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Newsletter

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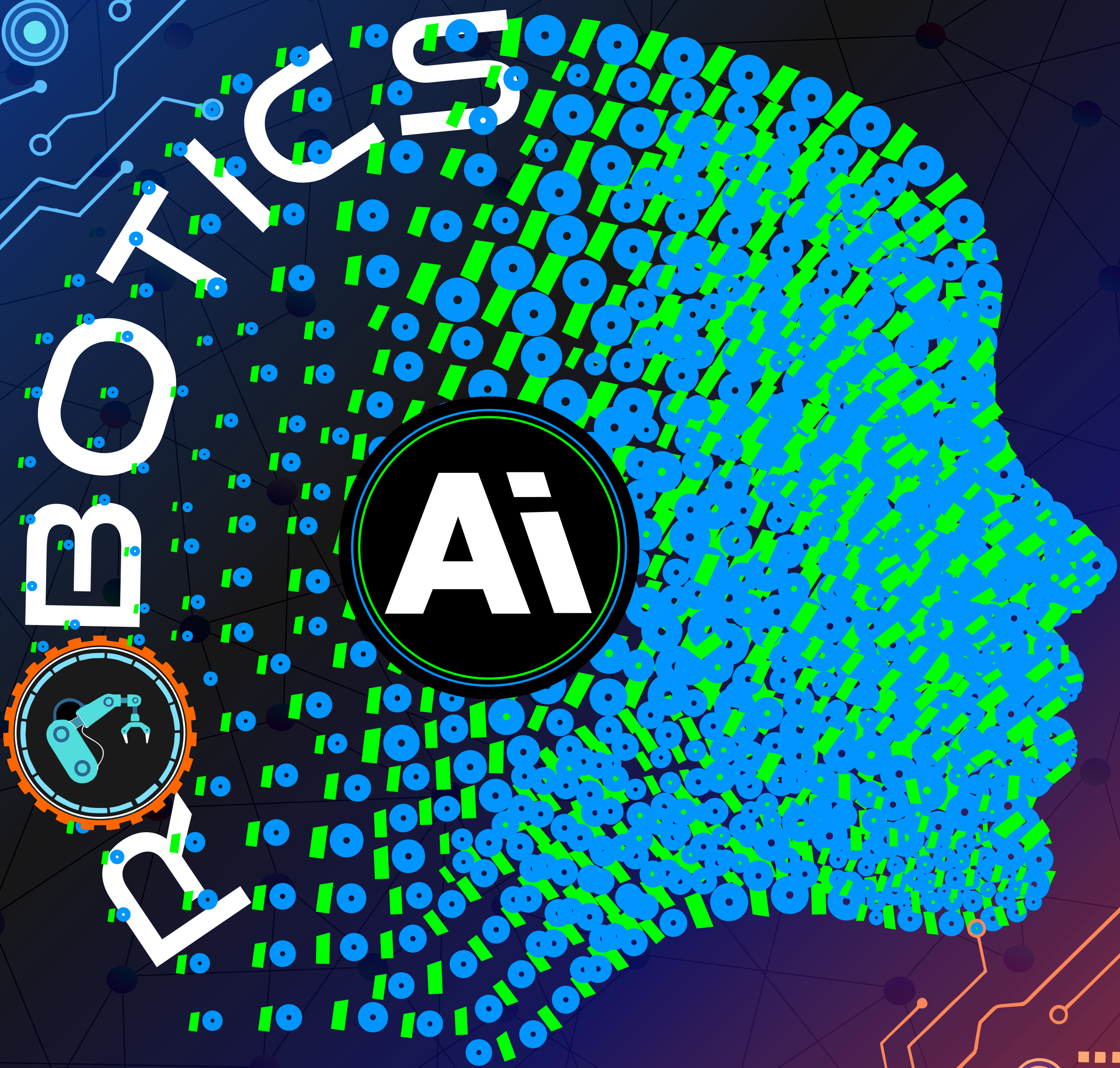

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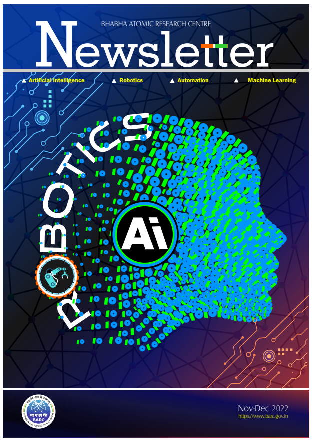

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वसुधैव कुटुम्बकम्
ONE EARTH • ONE FAMILY • ONE FUTURE

foreword

AI ROBOTICS

Modern Tools for Nuclear Energy

I am extremely happy to write this foreword for the thematic issue of BARC Newsletter, on Artificial Intelligence (AI) and Robotics. In recent times, the subjects of AI, Machine Learning (ML), Deep Learning, Big Data Science, Automation & Robotics have gained global importance. The recommendations of NITI Aayog, Govt. of India, also provide thrust to carry out extensive research work in these areas of Science & Technology, for the benefit of mankind. As India celebrated the completion of 75 years of Independence by launching the nation-wide Azadi Ka Amrit Mahotsav campaign, BARC organized a gamut of activities under this to propagate the country's multi-faceted achievements in the domain of science and technology.

A series of lectures on the theme AI & Robotics were delivered by eminent speakers from the field, on the occasion of National Science Day-2022 (NSD '22), on 28th February, 2022 in BARC, to mark the invention of the Raman Effect. These lectures in their true sense, further propagated the on-going research work in BARC, related to this theme. On 11th May, 2022, on the occasion of National Technology Day-2022 (NTD '22), BARC conducted various programs related to AI & Robotics, for the benefit of secondary school and junior college students of Mumbai. More than 300 students participated in the program and they showed very high interest and enthusiasm in these subjects. The centre of attraction was the exhibition and demonstration of AI & Robotic systems developed in BARC.

Subsequently, BARC planned to bring-out a thematic issue of BARC Newsletter on AI & Robotics covering the latest developments carried out in BARC, to demonstrate the capabilities of BARC in pursuit of the mission 'Atmanirbhar Bharat' (indigenization). It goes without saying that BARC is already committed to build the high performance scientific computing platform for facilitating AI/ML related activities. In view of the mandate of the Department of Atomic Energy (DAE), I am of firm belief that the research work being pursued in the fields of Deep learning, ML, AI, Automation & Robotics would certainly resolve many of the problems associated with Nuclear Power Plants, Back-End Technologies, Strategic areas, in addition to the Healthcare and Agriculture sectors.

I am grateful to Shri K. N. Vyas, Chairman, AEC & Secretary, DAE and Dr A. K. Mohanty, Director, BARC for their keen interest in the field of AI & Robotics and their kind support for the research activities in these areas of Science & Technology. I am sure that the readers would enjoy the range of articles on AI & Robotics chronicled in this issue.

Dr. S. Mukhopadhyay
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The Beginning of a NEW ERA

Psychologist, Robert Sternberg's triarchic theory of intelligence has three components namely Practical Intelligence: the ability to get along in different contexts; Creative Intelligence: the ability to come-up with new ideas and Analytical Intelligence: the ability to evaluate information & solve problems. Human cerebrum has these three components, evolved to the extent that, the quest for that extra intelligence and extra throughput for the automation, robotics and machines have driven mankind into the new fields of AI, ML, robotics and big data science.

Industry 4.0 has paved the interleaved path of IoTs; cloud computing; data analytics and AI-ML into the culmination of an efficient manufacturing capability. At the same time, *Industry 5.0* is about to arrive at our door-steps, for the usage of robots and smart machines on a very massive scale. Indian brains have always accepted new challenges to cope-up with and to harmonize newer methods & techniques, in solving problems, to meet the requirements of our country.

BARC scientists and technologists are also on the fore-front to catch-up with the latest concepts of robotics and AI-ML. The current issue of BARC Newsletter makes everyone aware that BARC has also initiated and adopted automation-robotics-AI-ML to solve some of the critical scientific problems of the Department of Atomic Energy. At a glance, one can observe that robots & cobots have been utilized for the three-stage nuclear program, back-end fuel cycle, healthcare, security & surveillance and for unmanned operations for hazardous areas. On the other hand, AI-Deep learning-ML have been utilized to solve the challenges in the field of identification process; healthcare; astronomical science; recognition of human features and extraction of automobile features for security purpose, biological and material studies and for video analytics.

The benefits of automation have been exploited for the critical applications in nuclear, space and defense industries and for specific applications in the field of civil engineering, transport sector, pharmaceutical, chemical process and advanced studies in Physics-Chemistry-Biology. We are sure that the big data science, cloud computing and data analytics are going to play a major role in the fields of simulation & modeling for the earth and environmental science, remote-sensing, agriculture and for economy and finance too. Therefore, it is an era of facing technological challenges within and outside the domain of expertise for the benefit of mankind. Have a fruitful experience, in reading the eighteen articles, penned down by BARC scientists and engineers, where they have shared some of their latest endeavors.

Dr. V. H. Patankar
Electronics Division

M. Padmanabhan
SESS Division

Dinesh M. Sarode
Computer Division

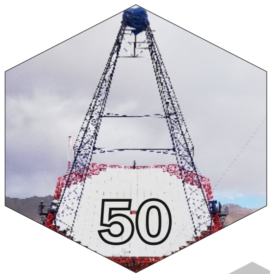
Chandan Dey
DRHR

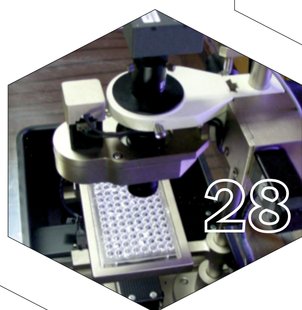
ARTIFICIAL INTELLIGENCE & ROBOTICS

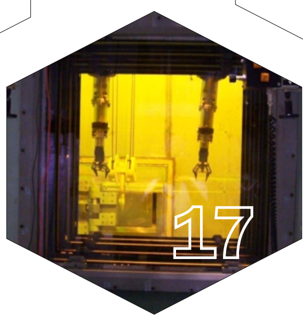
RESEARCH HIGHLIGHTS

AWARDS & HONORS

SCIENTIFIC SOCIAL RESPONSIBILITY IN DAE







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BARC Q&A

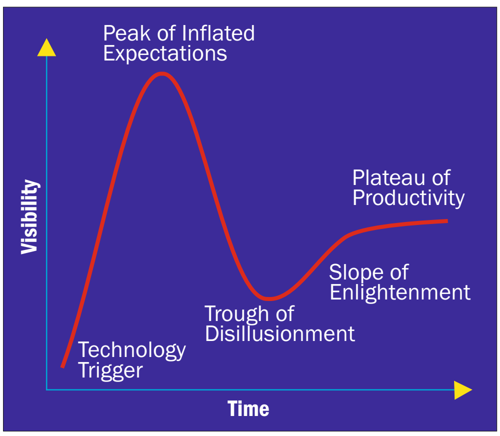
Tête-à-tête with

Dr. Shashank Chaturvedi

Director, Institute for Plasma Research

M. Padmanabhan: **It is recalled that in 1928 the famous French economist J.B. Say remarked "Nevertheless no machine will ever be able to perform what even the worst horses can - the service of carrying people and goods through the bustle and throng of a great city". Today we have driverless cars and hence it is very difficult to predict future impact that technology will have on the society. What is your comment on this? Is it just a bubble or the next big thing?**

Dr. S. Chaturvedi: AI is already in widespread use for a variety of applications. The well-known curve given below shows the expectation from any new technology as a function of time. Every innovation sees a rapidly-increasing expectation level, reaches a peak of inflated expectations, then crashes into a trough of disillusionment before reaching a plateau of "true" productivity. The AI revolution is likely to follow the same trend, and we may currently be near the peak. But the real-life contributions already made by AI clearly show that it is certainly not a bubble.



M. Padmanabhan: **The impact of the industrial revolutions has, undoubtedly, been substantial on all aspects of our society, quality of life and employment. Then came the digital revolution; use of computers and communication changed the way that we worked, interacted. It shaped the industries in transportation, automobiles, energy, finance and production of other consumer goods. Will the forthcoming AI revolution produce similar, far-reaching effects?**

Dr. S. Chaturvedi: The AI revolution has already produced major effects across a range of activities. Customer care services have been taken over by chat bots and the job of salesmen is being done by automated recommendation systems. In healthcare, it is transforming cancer diagnosis & treatment by improving data analysis, interpretation & planning. It is already part of technologies for analyzing crop yields & improving irrigation, and is now being adopted in precision agriculture (PA). Propagation of PA can be a game-changer for India, due to small-holdings of individual farmers so that major industrial tools & techniques cannot be applied. New drug discovery may be faster and cost-effective. Automatic text-to-text translation between arbitrary pairs of languages has transformed communication. Now, we are not bounded by the language differences as AI based real time translation tools are available. AI also finds application in fraud detection in financial transactions, etc. If and when driverless cars become reliable, they may help improve traffic flow in cities and reduce loss of life from traffic accidents. So it is very

(through) its power of analyzing complex patterns, it (AI) can assist in detecting potential anomalies and predict component failures in nuclear reactors well before they are imminent.

Dr. Shashank Chaturvedi

likely that the growth seen in the IT industry over the last 20 years (from 2000 – 2020) could be replicated in AI over the next 20 years.

M. Padmanabhan: **Content suggestions, response suggestions, filter suggestions for images are few common AI assists that has started influencing social media. Do you see human interpersonal communication and relations being influenced by this technology in near future?**

Dr. S. Chaturvedi: Content suggestions and recommendation systems certainly affect the thinking of individuals and their relationships. There is a major impact in the area of news & opinion dissemination. When people relied on newspapers & magazines, they were compulsorily exposed to news & opinions from a variety of areas/sources, and had to make a conscious decision to ignore certain kinds of news & opinions. However, AI-driven choice of news items means that people learn more-and-more about less-and-less; this could make them less-informed about other important areas. Also, they keep seeing articles that more-or-less match their existing opinions on certain subjects – a classic positive feedback system. This could lead to polarization of opinion, without people even being aware that their opinions are based on limited knowledge. With adolescents increasingly getting their news and opinions from Social Media driven by AI, this polarization will have a major effect in the coming years.

M. Padmanabhan: **Nuclear energy remained a sector where knowledge and innovation remains a key in producing electrical power in a safe and secure manner. How do you think AI led innovation is going to help the nuclear industry?**

Dr. S. Chaturvedi: AI is going to help the nuclear industry in terms of both science & technology. In nuclear science, AI techniques are helping in experiments, making new discoveries, developing new theories by helping researchers quickly analyze large amounts of data, finding new patterns and creating sophisticated data models. In nuclear power, it can help in improving reactor designs & optimizing processes. Through improved automation, it can improve operation efficiency and help increase reliability of components/sub-systems. Utilizing its power of analyzing complex patterns, it can assist in detecting potential anomalies and predict component failures well before they are imminent. A detailed discussion of AI applications in these areas is available from:

https://www.iaea.org/newscenter/news/seven-ways-ai-will-change-nuclear-science-and-technology

M. Padmanabhan: **You are shaping Indian participation in the Nuclear Fusion research in India as well as in the international collaboration at ITER. Are there applications of AI in fusion research?**

Dr. S. Chaturvedi: AI is already being applied in several areas of fusion research. These applications of AI are included in a new five-year IAEA coordinated research project aimed at accelerating fusion research and development. One of the important applications is the real-time prediction of

AI imposes a huge challenge to security as it has become difficult to distinguish between real data and fake data.

Dr. Shashank Chaturvedi

plasma disruptions in tokamaks, which is critical for timely deployment of disruption-mitigation techniques. Another area is the optimization of performance of emerging fusion concepts, based on large experimental datasets, without detailed modelling of the underlying physical phenomena. A third is the prediction of the time to failure of critical machine components. A fourth is the area of Remote Handling in fusion machines – for example, AI can be used for automatically detecting damaged in-vessel components like plasma-facing graphite tiles, so that they can be replaced by remote handling tools.

M. Padmanabhan: **AI is coming in a big way in health care, medical imaging and supporting geriatric care. However, it is seen that a majority of such devices are not produced in the country. What is your comment on that?**

Dr. S. Chaturvedi: Health care & medical imaging make use of equipment/machines that are normally imported from abroad. Such imported hardware, with integrated software, is generally costly, and is thus accessible only in cities and larger towns. The limited availability of healthcare specialists and sophisticated equipment in rural and semi-urban areas is thus a major issue in India. A multi-pronged effort may provide the solution. The first is to indigenously develop and deploy low-cost diagnostic equipment in all towns/villages, using mobile teams. The second is to digitize, at a National level, physical diagnostic reports like X-ray films and their diagnoses by specialists, and to train indigenously-developed AI-software based on this database. The third is to use this AI software through a National portal where X-ray images etc can be uploaded for an automated, high-speed diagnosis. An effort of this type is already underway in India based on chest X-ray images–IPR has developed a deep learning software 'DeepCXR' as a part of an ICMR led AI-TB program for training AI models for detection of chest ailments in Chest X-Ray images. We have also developed an automated system 'AIBacilli' for detection of TB using microscope images of the bacilli. The need for a coordinated National effort cannot be over-emphasised--in a country like India, there are large geographical variations, making a national database *essential.*

M. Padmanabhan: **How do you see the impact of AI on national security; cyber as well as physical?**

Dr. S. Chaturvedi: It is said that "Data is new Oil", and this data can be used in both ways. AI can help in analyzing abnormal behavior patterns among large datasets, highlighting anomalous behaviour for appropriate action. AI has major applications for Security agencies in high-speed automated analysis of speech, image, signal and video data. On the other hand, AI is now being perceived as major threat in cyber security due to its ability to operate 24/7 and because it is continuously adapting. AI imposes a huge challenge to cyber security as it has become difficult to distinguish between real data and fake data. Also, with advancement in digital technology, most of the data such as personal, private, confidential & financial are available online and become prone to cyber-attacks. In the

There's little point in preaching people about the ethical usage of AI, as anyone with access to data can do whatever he/she wants to. A legal framework is necessary but not sufficient.

Dr. Shashank Chaturvedi

defense sector, many countries are investing big time in AI-enabled systems such as autonomous drones, robot soldiers, training platforms etc.

M. Padmanabhan: **Use of AI and ethics remain often contradictory. Use of AI in various applications raises questions of issues with privacy. Possibly legal issues involving use of AI is also not firmed up. How should we address this?**

Dr. S. Chaturvedi: In the past, if you needed to spy on someone, it necessitated a physical effort to track, trace and follow, which required deployment of a considerable number of people. But today, you can gather information about someone just from his/her digital footprints. Usage of AI adds another layer, allowing you to know the likes/dislikes and perform behavioral analysis of any individual. There is little point in preaching to people about the ethical usage of AI, as anyone with access to data can do whatever he/she wants. A Legal framework is necessary but not sufficient. It is also necessary to restrict access to data. The data should only be shared with trusted individuals/organizations. AI ethics should be part of education, and schools should continuously alert students to the potential misuse of their data. In 2018, Niti Aayog released the National Strategy for Artificial Intelligence (NSAI) discussion paper which, while highlighting the potential of Artificial Intelligence (AI) for accelerating growth, also emphasized the social potential of large scale adoption of AI with a focus on themes of inclusivity, adopting the theme of 'AI for All' As AI is still developing rapidly, the risks associated with it are also increasing.

M. Padmanabhan: **What is your advice to the young budding engineers, scientists and social scientists on having a career interwoven with his area of work and application of AI?**

Dr. S. Chaturvedi: Young budding engineers/scientists must continuously update themselves about the applications of AI in their own areas of expertise. There is a large and growing body of literature in the open domain. At the same time, they should realise that the accuracy of AI is limited by the availability of large datasets which are not always available; also, available datasets may be limited in their scope, and AI models trained on this data may not be generally applicable. Hence it may turn out that a combination of physically-based models with AI would give the best results.

M. Padmanabhan: **Role of AI in Big Data Analytics and especially in LIGO?**

Dr. S. Chaturvedi: Given the large amounts of data generated by gravitational wave observatories, AI has an important role to play in gravitational wave analysis. The AI ensemble used is reported to be used for advanced LIGO data within just seven minutes and revealed no misclassifications. More details are available from: https://news.uchicago.edu/story/scientists-use-artificial-intelligence-detect-gravitational-waves.

Artificial Intelligence

1

Life with Artificial Intelligence

Prabir K. Pal

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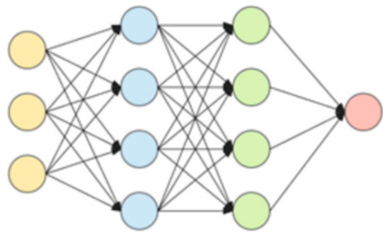

A Feedforward Neural Network

ABSTRACT

As the Artificial Intelligence (AI) technology grows in power, the question arises, can it ever give rise to an artificial mind? A mind which not only remembers facts and solves hard problems, but is conscious about its existence, and has a will of its own? Can such a mind surpass human intelligence? What can be the consequence of these mind boggling possibilities on our society? The present article provides a brief overview of AI as it stands today, and explores what lies ahead as this technology grows big and influences all aspects of our life.

KEYWORDS: *Artificial intelligence, Neural network, Superintelligent, Expert systems, Artificial general intelligence, Deep learning*

Introduction

Soon after the modern digital computer was invented, and the notion of a central processing unit fetching and executing instructions from a program stored in the memory became clear, quite a few visionary minds started speculating on the possibility of programming a human mind on such a machine. The idea was far too ambitious at that point of time, and the way forward was not at all clear. Nevertheless, the seed was sown. Alan Turing even laid down a procedure for testing such a machine, if ever it comes up. He suggested that a person engage in conversation with the artificial mind program and a human being separately using a keyboard, and if he is unable to say for sure which one is the human being and which one is the computer, then only the mind program can claim success.

Intelligence through Search

Human mind has diverse capabilities. Which feature do we pick-up to start building an artificial mind? Shaw, Newell and Simon started looking into ways in which a computer program could possibly solve a problem like proving a theorem of Geometry, or playing a game like checker, or even chess. They demonstrated that solving such problems boils down to searching through a maze of possible decisions to reach a desired goal. The sequence of decisions, that leads to the goal, forms the solution. Often the search space is potentially infinite. So there are strategies to search selectively through this space exploiting any prior knowledge about the nature of the problem. This was the first major breakthrough of Artificial Intelligence, which eventually led to the IBM Deep Blue Computer beating Grandmaster Kasparov in a game of chess in 1997. Even before that, in the eighties, there was an avalanche of Expert Systems in various domains, primarily triggered by techniques to capture domain knowledge in the form of facts and rules and use search to find an appropriate sequence of application of these rules to arrive at a solution.

Computers are extremely fast and efficient in certain matters, like numerical computations, storing and retrieving information to and from a database, etc. Humans fare very poorly in these tasks. However, there are certain other tasks that humans do effortlessly, like seeing and recognising objects in their environment, communicating in spoken and written languages etc., which the computers find very hard to perform correctly. Getting computers to carry out these tasks as effectively as humans do, or even better, has been the principal aim of Artificial Intelligence. Modelling these processes by appropriate facts and rules and searching for the right sequence of their application on input data has broadly been the approach to recognise an object, or a spoken word. These methods have improved considerably over time, but have not been able to reach the point where they can be used in daily life.

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Neural Network

There was a parallel effort for some time to build a computing system out of a network of artificial neurons. Each artificial neuron is a simple computing element whose output is a simple function of its input. Neurons form the building blocks of brains of living beings, so there was a strong suspicion that human-like capabilities may be easier to achieve using neuron like computing elements. The major difference in this case is of course the fact that we do not try to build any model for the process. We allow the network of neurons to learn to emulate the process by watching its input and output data under various circumstances. Thus we achieve the functionality of the process without knowing how it actually functions. In effect, we do not need the facts and rules any more. We only need input output data – and a lot of them covering almost all possible situations the process might encounter. The neural network deciphers the process and learns to produce the desired output for any input. Here the input may be an image data, while the object it represents can be the output. Similarly, a stretch of speech data can be the input, while the word it represents can be the output.

Artificial neurons can be connected and organised in many ways to exhibit diverse behaviours. One of them, called a Layered Feed forward Neural Network, in which the neurons are connected in several layers from input to output (Fig.1), has found many applications, and has been studied extensively to demonstrate their ability to emulate a process by observing its

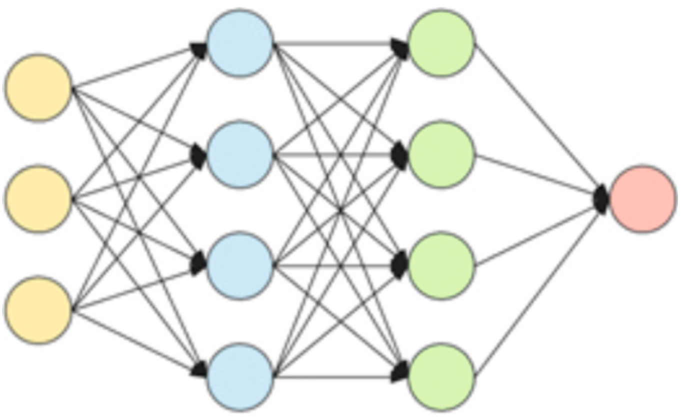

Fig.1: A Feedforward Neural Network of 4 layers with 3 neurons in the input layer, and a single neuron as an output.

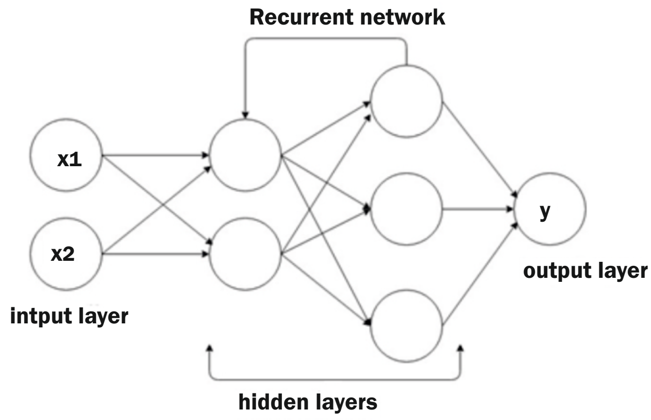

Fig.3: A Recurrent Neural Network (RNN) feeds a part of the output as input to a part of a preceding layer for the next cycle of computation, thus introducing a notion of memory.

input and output data. They were typically arranged in 3 to 4 layers, as a higher number of layers proved almost impossible to train. Because of the limitations on the number of layers, such neural nets could not emulate very complex processes. In 2004 however, ways to train deep neural networks with 30 or more layers of neurons were invented, resulting in the development of many successful applications of this technology in areas like object recognition, speech processing, natural language processing etc.

Image and speech have this property that they have a huge data to be presented as input, in which however only neighbouring data may be related in some ways. For processing such data efficiently, a Convolutional Neural Network (CNN) was devised, which permits only local connectivity among neurons in consecutive layers to identify certain basic patterns in different parts of the input data. This process progresses through several layers, ultimately creating a concise and abstract description of the input data. This is then fed as input to a deep neural network to produce the desired output. The entire Deep CNN so formed (Fig.2) was utilized with great success to identify objects in images and words in speeches.

There are some data that have an inherent notion of sequence in them, e.g., in a natural language, in which words appear in certain sequences to form meaningful sentences. A Recurrent Neural Network (RNN) was devised to process such data. In this, at any stage of computation, a part of the output is fed back and presented as a part of the input to one of the preceding layers of the Neural Network for the next stage of computation (Fig.3). This introduces a memory-like quality in the network. A word is no more interpreted in isolation. Instead, it is interpreted in the light of the words that have preceded it. Deep RNNs and their variants proved to be very useful in understanding and synthesising sentences and also in translating from one language to another. Translation of-course requires the network to get trained by reading many such documents which are published simultaneously in different languages.

Artificial General Intelligence

The recent spurt in AI applications have mainly been triggered by the advent of Deep Learning techniques. However effective they are, the old knowledge based search algorithms are not discarded either and are utilized freely in association with deep learning wherever appropriate. Some of the major achievements of AI in recent years have been the Google Translator which translates from one language to another (2006), IBM's Watson computer which unseated Jeopardy champion (2011), Deep CNN-based AlexNet which won Image Net Competition (2012) for recognizing images, Google voice for Automatic Speech Recognition (2015), Google Assistant /Alexa which answers your questions (2016),Google's AlphaGo which beat human Go champion (2016), and IBM's Debater which provided a spirited fight against human debater (2019). However intelligent these programs are, they operate well only within their domains. They are no substitute for the general intelligence exhibited by a human mind in varied circumstances. That is why there is a quest now for building Artificial General Intelligence (AGI) and to that end, it is pertinent to figure out how the human brain functions.

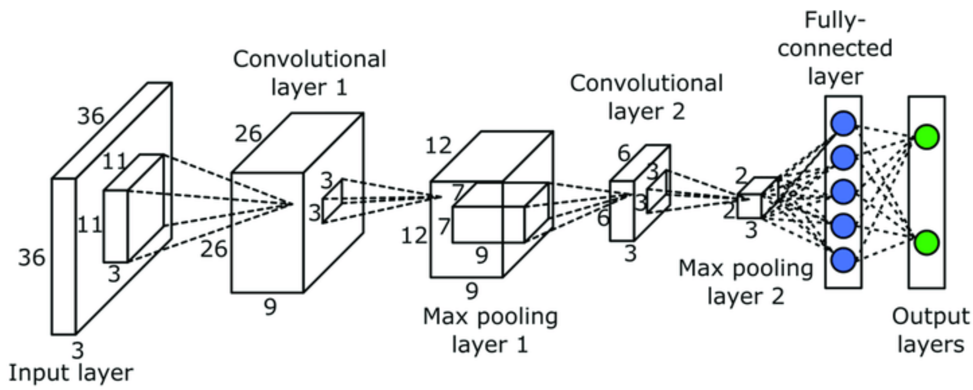

Fig.2: A Deep CNN comprises several stages of convolution and pooling, and finally a Deep Neural Network for training.

There are about 100 billion neurons in a human brain. They are arranged in clusters and these clusters are networked in layers. They receive signals through sensory nerves and these signals get interpreted by these neuronal layers to form a model of the environment. The outermost layer of human brain, called Cortex, has many regions in it corresponding to different functions of the brain. One of the regions recognises faces or objects and brings in corresponding emotions. Another region understands and forms sentences, an ability unique to humans. One creates an image of the body parts and helps maintain balance. Another does arithmetic, chooses words, creates metaphors and abstractions. Human qualities like ambition, vision, ethics and self-dignity are the prerogatives of one such region. There are also Mirror Neurons which enable us to feel for others, a quality that is possibly the origin of human culture. These cortex regions and their functions have been identified by associating abnormal behaviours exhibited by patients with regions of their brains that are injured, isolated, or dead, as indicated by MRI scans. It seems, all aspects of the personality of a human being are generated by the neuron clusters of the brain. This provides a mechanistic view of the human mind. And if mind is really a machine, it may not be impossible to simulate it.

One approach to emulate the human mind is to identify the components and processes of the human brain in sufficient details and simulate them on a machine. For that purpose, one has to get thin slices of the brain scanned to trace all neurons and their inter-connections in 3D format. This is easier said than done and at present it is possible only for brains of very small organisms with a few hundred neurons. This process must be mechanised so that it can be scaled up first for a mouse, then for a monkey, and ultimately for a human brain. An artificial neuronal model of the brain can be tried for creating AGI. If necessary, each cell or even each molecule of the brain may have to be simulated. But that is a gargantuan task, and far beyond the capacity of present day computers. Although this approach appears quite promising, AGI may also be achieved independently by means other than emulation of the brain.

Superintelligence

It is quite likely that at some point, computers will get smarter than humans. Smart computers will design even smarter computers with improved AI programs. Soon this may snowball into an intelligence explosion. Science, Technology, Defence, Business, International Relations, everything will undergo a rapid transformation with the advent of superintelligence. Even creative jobs will be performed by computers – faster and better. That will result in a life without jobs for humans! Even if everybody is provided for, this will bring in a major change in the way we live. Shall we become irrelevant and extinct as we lose our role in leading civilisation?

A Superintelligent System will take many decisions and actions to pursue the goals set by its creators. Even if some of them hurt us, we may not be in a position to restrain it from acting them out. Some experts feel that a Superintelligent System cannot be trusted and must be caged in a closed environment away from the Internet and all wireless communications. It may be provided with necessary information in digital storage medium, and its advice may be taken down in printed form, so that the machine does not get any opportunity to initiate actions or influence individuals to attain its goal. That sounds like a contradiction, since the whole purpose of building superintelligent machines is to obtain solutions of difficult problems faced by the human civilisation. Much of-course depends on the way Superintelligence is actually realized.

Conclusion

Max Tegmark in his book 'Life 3.0' describes three stages of our evolution. In the first stage, biological evolution from micro-organisms to humans took place over millions of years. Since this was a natural process, it was extremely slow. In the next stage, human civilisation quickened the pace of evolution of our lifestyle and culture through acquiring, storing and sharing of knowledge. We are at present going through that stage of evolution. In the penultimate stage, he predicts, superintelligent robots will take over humans and spread out to farthest corners of the Universe. We can mark them as our descendants.

That is of course only a prophecy. It is almost impossible to predict far into the future, as so many things change meanwhile. Whether humans will continue to have a role, or the machines will completely takeover is a big question that cannot be answered so easily. Possibility of superintelligence is strong, but how it may be realised is not clear at the moment. The future will unfold on its own. Hope, the journey will be beneficial and enjoyable to humanity.

Remote Handling

2

Remote Handling Tools for Radioactive Environments

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RDMs installed in hotcell

ABSTRACT

Department of Atomic Energy has been according high priority to safety, including radiation safety. Remote handling tools are used in radiation environments to eliminate or reduce radiation exposure to operators. The tools separate the operators from the task they are engaged in. The article describes a few types of general-purpose remote handling tools developed by BARC for operations in radioactive environments.

KEYWORDS: *Radioactive cells, Remote handling, Master slave manipulator*

Introduction

Radioactive materials and radiation have become unavoidable part of our life. We use them in power plants, industry, agriculture, research, etc. They are also used in medical fields for diagnosis, treatment and palliative care of cancer; and sterilisation of medical products. BARC and many other units of DAE regularly handle radioisotopes during their production and use. To protect human operator from exposure to high radiation, radioisotopes are handled remotely using remote handling tools. Remote handling tools enable the operator to perform the desired task in a hazardous area, while staying away at a safe location. The plants of nuclear fuel cycle, such as fuel fabrication, fuel reprocessing and waste management, as well as the facilities for production and use of radioisotopes, post-irradiation examination and nuclear research employ remote handling tools. In the initial period of DAE, all major remote handling tools were imported. Now, DAE is self-reliant in this technology and can meet all remote handling requirements of the Department.

Remote Handling Tools and Systems

BARC has developed a variety of remote handling tools and systems, such as remote handling tong, master slave systems, robots, automations systems, remote cranes and mobile robots for remote operations in radioactive environment. They include general-purpose and special-purpose systems; autonomous and manually controlled tools; and manipulators with mobility and those without mobility. They also vary in their level of dexterity, payload, proximity to the site, versatility, protective measures, etc. Remote handling strategy and selection of remote handling tool depend on the risks and the complexity associated with the task. The scope of this article is limited to non-autonomous (manually controlled) general-purpose remote handling tools developed at BARC.

Remote Handling Tong

The simplest form of remote handling device is long reach tools, which extend the length of standard tools, providing safe distance between the hazard and the operator. A remote handling tong consists of a gripper, a handle and a rod between them (Fig.1). Based on the requirement, tongs are designed for installation on shielded/sealed walls, for hanging on a carrying system (for use in a water pools), or for carrying directly by the operator.

Fig.1: Remote Handling Tong.

Radioactive Cells (Hot Cells)

Gamma-active materials are handled in heavily shielded rooms, called hotcells, using remote handling tools[1]. The cells are shielded with normal or high-density concrete walls and ceiling of thickness ranging up to 2 m. Hotcells handling alpha-active materials are sealed to prevent leakage of contaminated air into the surroundings. The cells are also maintained at lower pressure, compared to their surroundings. For remote operations, the cells are provided with in-cell cranes, power manipulators and/or master-slave manipulators (Fig.2). Operators can control these devices from operating area, viewing the cell through shielded glass windows or CCTV monitors.

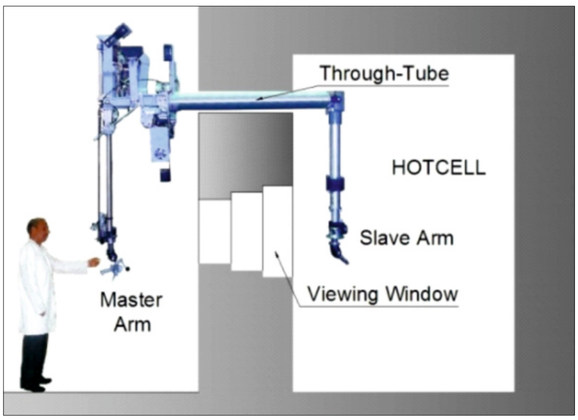

Fig.2: Layout of MSM in Hotcell.

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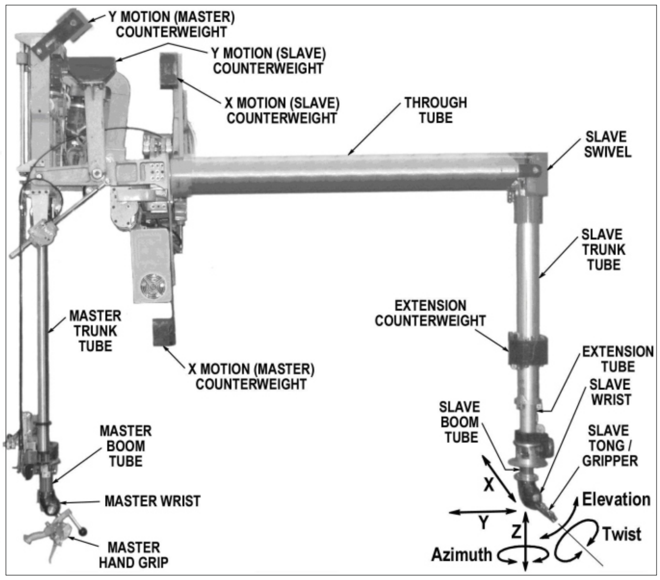

Fig.3: Parts and motions of an MSM.

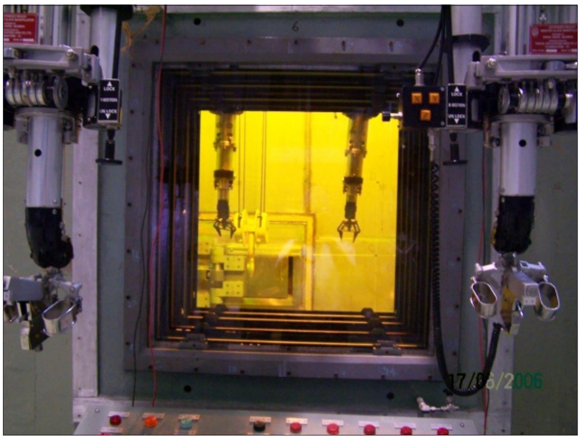

Fig.4: A pair of ERMs installed in a hotcell.

Fig.5: A row of RDMs installed in hotcell.

In-Cell Cranes and Power Manipulators

In-cell cranes and power manipulators are used for handling heavy objects in hotcells. Power manipulator has a series of links and joints, powered by electric motors. Usually, crane has a hook for lifting the load, while power manipulator has a gripper for handling the payload. In addition to positioning the gripper at the desired location, power manipulators can orient the gripper in the desired direction. They are usually controlled by push button switches or joysticks. Their modular construction enables easy maintenance/repair/replacement of components and sub-assemblies.

Master Slave Manipulators

Master slave manipulators (MSMs) are the most widely used general-purpose remote handling tools used in nuclear industry[2]. In master slave manipulation, human being is part of the process, and his/her manipulative abilities are extended to the remote site.

An MSM consists of two arms: the slave arm, which is usually located in the hotcell and the master arm in the operating area/control station. When the operator grasps and manipulates the master gripper, the motion of his/her hand is reproduced at the slave tong, performing the intended task. Usually, the master arm and the slave arm are made geometrically similar. MSMs are usually used in pairs, and operator manipulates the master arms using both the hands. MSMs may be Mechanical Manipulators or Servo Manipulators.

Mechanical Manipulators

A mechanical MSM provides a mechanical linkage between the operator at the control station and the hazardous task areas inside the hotcell. Most of the mechanical MSMs are of through-wall type, where the slave arm is located in the hotcell, the master arm in the control station and the through-tube connecting these arms in the shielded wall (Figs.2&3). They are complex mechanical systems with 6 to 9 degrees of freedom and a gripper. Six joints and the gripper of MSMs are powered and controlled directly by human operator. In addition, their major joints are provided with electrically actuated indexing motions to increase their range, to ease operation and to prevent loss of view of hotcell areas during handling. From the task area, operator gets visual feedback through a shielding window (Fig.4). Mechanical MSMs are suitable, where the work area is not too large and the force/torque requirements are within the capabilities of the operator.

Mechanical manipulator may be of articulated type or telescopic type. BARC has developed a variety of mechanical MSMs, such as Articulated Manipulator, Model-8 Manipulator, Extended Reach Manipulator (ERM) (Fig.4), Rugged Duty Manipulator (RDM) (Fig.5) and Three-Piece Manipulator (TPM)[3]. They vary in their payload (4.5 kg to 45 kg) and reach (1 m^3 to 20 m^3). Provision for shielding and sealing are offered in a few models. Also, in a few models, grippers of the slave arm are made remotely replaceable. In TPM, entire slave arm can be remotely replaced for its maintenance and repair. Often, the slave arms are provided with gaiter (booting) to protect it from contamination and to prevent leakage of contaminate air into the operating area. Using counterweights, all major joints of the manipulator are mechanically balanced to reduce operator's efforts for moving the arms in any direction.

Servo Manipulators

Unlike mechanical manipulators, which are mechanically powered by human operator, servo-manipulators are powered by electric (or hydraulic) actuators. A servo-manipulator system consists of two kinematically similar arms: master arm and slave arm. The mechanical power sources of the slave arm are electric motors, which are connected to all (usually six) joints and gripper of the slave arm. The controller continuously monitors the corresponding joint angles of the master and the slave, using the joint angle sensors, like synchro, potentiometer or encoder. It also drives all slave

Fig.6: Control station and master arm of indigenous Servo Manipulator at WIP, Trombay.

Fig.7: Slave arm in the hotcell, as seen by the operator in CCTV monitor.

Fig.8: Suspendable servo manipulator (SSM).

Fig.9: SSM retrieving waste pieces fallen on the floor of hot cell.

motors in real time to match the configuration of the slave arm to that of the master arm. In a few models, motors are provided on master joints also, to enable the operator to feel and control the forces/torques acting on the salve gripper.

Usually, slave arms are mounted on transporters to increase the reach of the slave arm. The transporter also allows the slave arm to approach hotcell equipment from different directions and provides flexibility in equipment layout in the cell. As the effective range of the slave arm is only limited by the range of the transporter, in general, single pair of slave arms can serve hotcells of any size. The presence of external power source reduces operator's handling effort and fatigue. In addition, servo-manipulator can be designed for high payload, as the force/ torque available at the slave arm is not limited by the strength of human operator.

In hotcells using servo manipulator, task area is viewed using CCTV cameras mounted on the slave arm and at different locations in the hotcell (Figs. 6, 7, 8, 9).

BARC has developed a few models of servo manipulators, such as Servo-Manipulator (Mark-1), Advanced Servo Manipulator (ASM), Four-Piece Servo Manipulator (FPSM), Portable Servo Manipulator (PSM) and Suspendable Servo Manipulator (SSM)[4,5,6].

Conclusion

BARC has developed the state-of-the-art remote handling tools for use in various radioactive areas of the department. Now, DAE is self-reliant in this technology and can meet all remote handling requirements of the Department.

Acknowledgements

The authors acknowledge the contributions of the present and retired officers and staff of DRHR, for their contributions towards development of the systems described.

References

[1] K. Jayarajan, B. Sony, V. K. Shrivastava, R. Sahu, S. Panda, A. N. Jha, M. N. Rao, V. Mahadev, A. K. Pradhan, S. Sethi, S. P. Dey, K. Karmakar, S. B. Gaikwad, V. R. Bhave, K. Sharma and A. Tariq, "Development of Hot Cells and their Embedded Parts," BARC News letter, Founder's Day Special Issue, pp. 142-144, October 2014.

[2] K. Jayarajan, "Advances in Remote Handling Technology in Nuclear Industry," Annals of the Indian National Academy of Engineering, vol. IX, April 2012.

[3] B. Sony, V. Mahadev, K. Jayarajan and M. Singh, "Development of Sealed Three-Piece Master Slave Manipulator," in Proc. of the National Conf. on Factory Automation, Robotics and Soft Computing (FARSC-2007), Warangal, 2007.

[4] D. D. Ray, K. Jayarajan and M. Singh, "Development of Advanced Servo Manipulator for Remote Handling in Nuclear Installations," BARC Newsletter, Founder's Day Special Issue, pp. 53-60, October 2010.

[5] B. Sony, P. V. Sarngadharan, K. Jayarajan and D. N. Bododkar, "Suspendable Servo-Manipulator for Hot Cell Applications," BARC Newsletter, Founder's Day Special Issue, pp. 61-64, October 2016.

[6] R. V. Sakrikar, U. Sarkar, D. D. Ray, B. Sony, D. C. Biswas and K. Jayarajan, "Development of Four- Piece Servo Manipulator," BARC Newsletter, Founder's Day Special Issue, pp. 60-65, October 2014.

Robotics

3

Parallel Mechanism based Cooperative Robots

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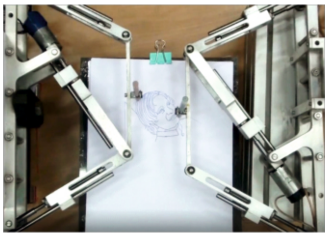

Trajectories of single caricature with complex geometry shared by two cooperating robots

ABSTRACT

The co-operation among a set of robots is for the purpose of achieving a common goal. The objective is to setup and delegate subtasks to individual robots to complete the task with optimum performance in a cooperative manner. The work presents trajectory planning algorithms based on inter-relationship among robots in achieving a goal in cooperation. Several general tasks are demonstrated in cooperative mode. Further, a novel idea of cooperation in the joint space to generate spatial trajectory using a single actuator is elaborated. The article validates the concept of cooperation through parallel mechanism-based robots, developed at DRHR, BARC.

KEYWORDS: *Robots, Mirror motions, Kinematic structure*

Introduction

To plan and program the participating robots individually towards a common goal at the task space is very complex[1]. The complexity is not only in programming the robots but also in operating and supervising them. This article explains a new trajectory planning scheme based on the inter-relationship that has to exist in achieving a goal in cooperation. The scheme deals with simple ways to divide and delegate the subtasks to the participating robots. Identifying the functional relationship and setting the motion of the cooperating robots on mirror mode would simplify the robot control, user interface and supervision. Many manipulations fall in the category of mirroring the motions at the task space of the cooperating robots. Two schemes of cooperation among robots are discussed. A scheme which serves as a *Cooperating Robots' Programming Interface* (CRPI) simplifies the task space trajectory planning among cooperating robots using mirror motions and its transformation. The other scheme is to cooperate functionally within the actuating axes (joint space) of a parallel mechanism to design a robot based on a single actuator to Generate "6D Trajectories". The key feature of the concept is to enhance the reliability by reducing the complexity.

This article deals with the planning and delegation of tasks among parallel mechanism based cooperative robots. The positional accuracy and stiffness of the parallel mechanism is relatively high in comparison to serial mechanism and hence parallel mechanisms are suitable as participating robots for cooperation in position and force domain. The concept of mirroring manipulation among cooperating robots and to illustrate the several tasks which can be programmed under this framework are explained. The context of the theme is to automate operations that take place in the inaccessible environment. The common tasks that are often encountered are pick and place, trace and cut, grip and hold, align and push, share payload and move. These tasks of cooperation are subtasks in applications like welding, cutting, bending, gripping, pick and place. Mirror motions can function in synchronised manner or can have specific time delay among participating robots. The concept of mirror manipulations can serve to automate several complex manipulations for various applications.

Cooperating Robots through Mirror Motions

The categorization of tasks helps to plan the cooperation. For a cooperation, dividing the work and delegating the work to participating robots become utmost important. The simple option is to look for mirroring the efforts of participating robots in jointly handling the given task. In the following sub-sections, all categories of tasks under the mirror motion scheme are addressed. It is assumed, that for entire planning purposes, the participating robots are identical in their kinematic structure and have a same dynamic capability. Two translations in plane and a rotation about any axis normal to the plane constitute the 3 Degree of Freedom (DOF) of the planar robot. The robot can perform coordinated translation along any line in a plane and a screw driver type rotation about any axis normal to the plane. The architecture of the manipulator is such that the major portion of the end effector is free of structural obstacles and can come face to face with its cooperating robot. Fig.1 shows a schematic of the two planar parallel robots. In a standard setup in the enclosed cell, a coordinate frame, M (X_M,Y_M,Z_M) is established at a point M and $[\hat{i},\hat{j},\hat{k}]^T$ are the unit vectors along X_M, Y_M and Z_M respectively. The plane normal to the axis, Y_M and containing the point M is referred as the mirroring plane. Based on the mirroring plane and the workspace of the robot, the base frames, $O_1(X_1, Y_1, Z_1)$ and $O_2(X_2, Y_2, Z_2)$ of the participating robots are fixed. The base frames in mirror symmetry serve as reference co-ordinate frames for the participating robots. The standard setup is shown in Fig.1. In the following subsection, the mirror motion scheme is explained by considering one task. Let us consider that the objective of the task is to generate a circular trace on the job as shown in Fig.1.

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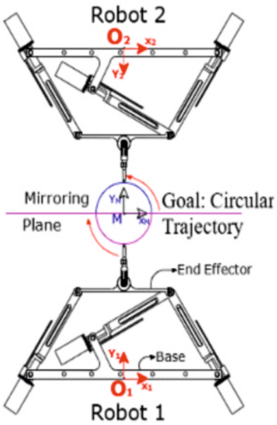


Fig.1: Two robots in mirror symmetry.

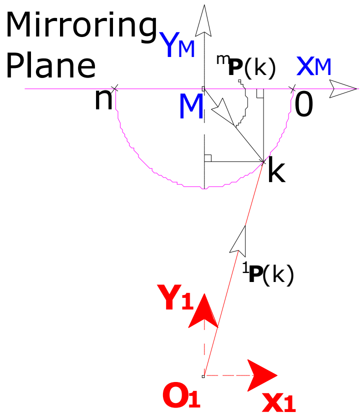
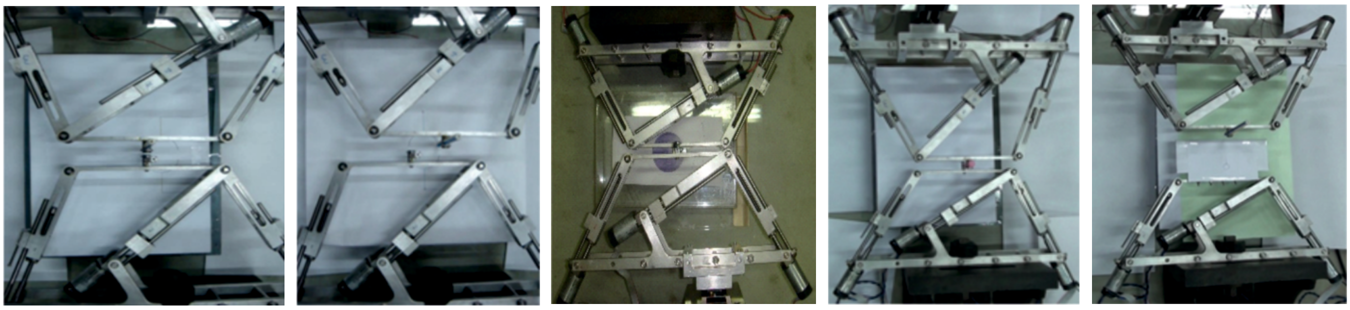


Fig.2: Task point description for Robot 1.



(a) Co. operation in tracing

(b) Trace-Flipping start, and end point

(c) Combined high precision trajectory trace

(d) load sharing while tracing

(e) Ultra-slow relative Motion

Fig.3: Different tasks performed in co-operation by two robots.

Tracing about a mirror plane

A task is shared by both the participating robots and the task is such that the manipulation required from the participating robots is mirror symmetric about a mirror plane (Z_M-X_M, normal to the page and Z_M extending out of the page). It is simple and many operations can be envisaged under this classification. The trajectory sharing about a mirror plane is explained by considering a circular trajectory and the description will hold true for any trajectory that is mirror symmetric to the mirror plane. The circular task space trajectory is divided into two semi-circular trajectories about the mirroring plane.

A point data, $k \in [0,n]$ is the point on the circumference of the semi-circle (see Fig.2) in the task space. The data delegation for the participating robots to trace a semi-circular trajectory is developed as follows.

$$^{m}P(k) = {}^{m}P(k)\hat{\imath},\ {}^{m}P(k)\hat{\jmath} \quad (1)$$

$$^{1}P(k) = O_1M + {}^{1}_{m}R\ {}^{m}P(k) \quad (2)$$

Where, $^{m}P(k)$ is the k^{th} point with respect to the mirror frame, O_1M is the known vector from O_1 to M. $^{1}_{m}R$ is the rotation of frame M with respect to O_1. $^{1}P(k)$ is the k^{th} point data in the task space for the participating robot 1, the parameters are as shown in the Fig.2. An Inverse Kinematic solution on $^{1}P(k)$ gives the joint data for robot 1. Similarly, all data points in the task space and the corresponding joint data for the participating robot 1 can be computed. The joint data and the corresponding instant of time is the control input for the robot motion. The same data serves as the motion input file for robot 2 for the above setup and is as given in equation 3.

$$[l_k]_{R2} = [I][l_k]_{R1} \quad (3)$$

$[l_k]_{Ri} = [l_{1k}, l_{2k}, l_{3k}]^T_{Ri}$ is the inverse kinematic solution of the k^{th} point of the robot I and [I] is a 3×3 identity matrix. The robots 1 and 2 will start from an initial point, $^{m}P(0)$ and move in a mirror motion in opposite directions to end the trace at a point, $^{m}P(n)$ to accomplish a circular trace in the task space.

Two prototype planar parallel robots are setup in skewed mirror configuration. Fig.3 illustrates different tasks performed in cooperation by two robots. The objective is to achieve simple and reliable ways to bring multiple robots to collaborate and conduct a task.

Ultra slow-motion using mirror algorithm

A single robot to realize an ultra-slow uniform motion at the end-effector is not feasible because the motors exhibit jerky motions at very slow velocity. Two cooperative robots are set to move near around most proficient speeds, yet the relative motion between their end-effectors can be

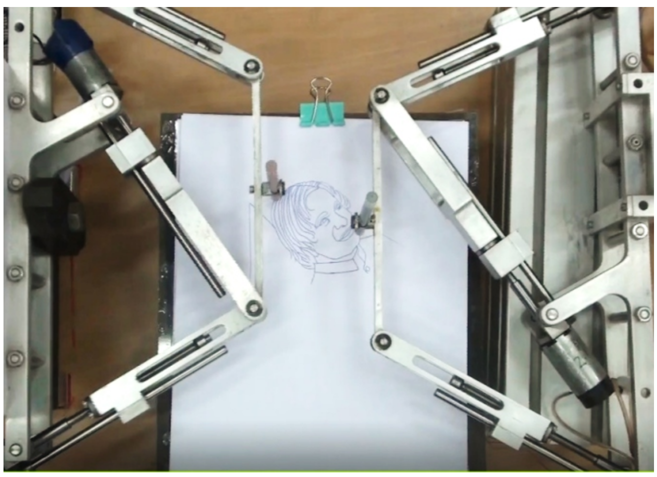
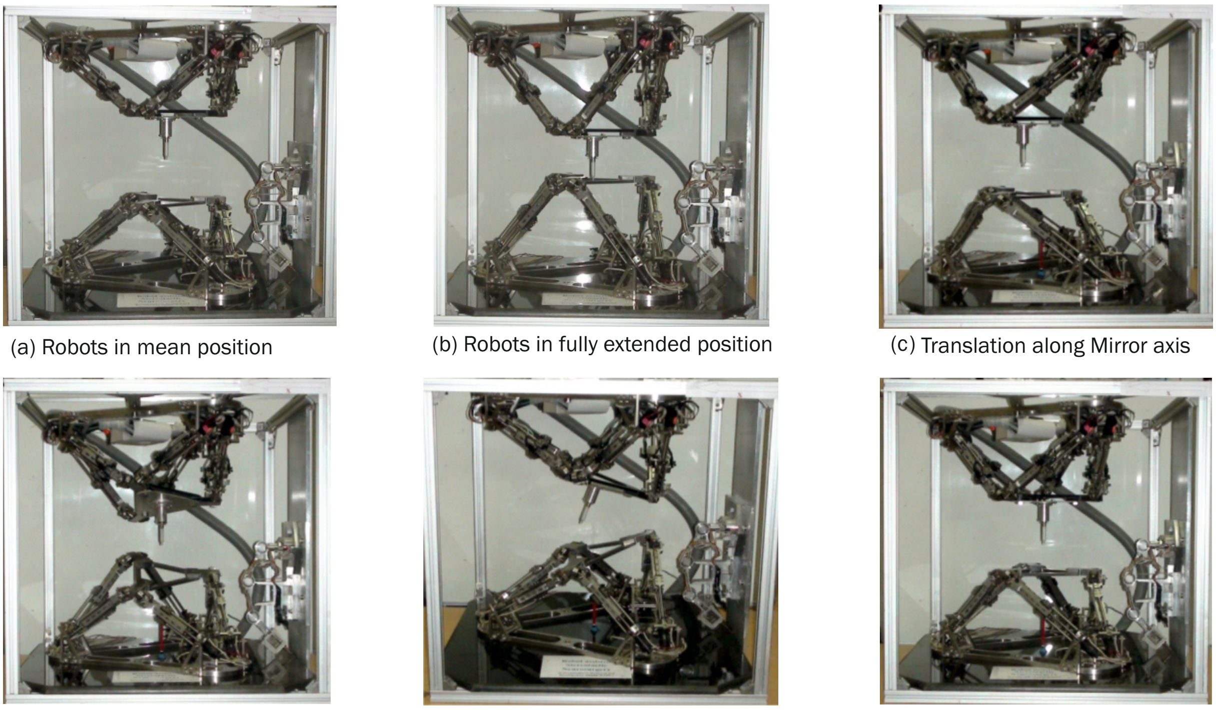


Fig.4: Photograph depicting high precision cooperation. Trajectories of single caricature with complex geometry shared by two cooperating robots.



(a) Robots in mean position
(b) Robots in fully extended position
(c) Translation along Mirror axis
(d) Rotation about a mirror axis
(e) Rotation a mirror axis
(f) Rotation, normal to mirror plane

Fig.5: Categories of subtasks of application under cooperation participating robots.

programmed to have ultra-slow velocity. Certain applications require a uniform, ultra-slow relative velocity. A typical application is laser cutting where ultra-slow velocity is required between the laser beam and the job being cut. In cooperative mode, the laser beam is manipulated by robot 1 and the job which has to be cut is manipulated by robot 2. The arrangement of co-operative robots is through mirror motions as discussed above. To realize ultra-slow uniform velocity at the interface of the beam and the job, both of them are set to motion along the same direction. It is like a laser beam following the job along the trajectory.

Let the task space velocity of robot 1 and 2 be T_1 and T_2 respectively. If the task space ultra-slow velocity between the interface of the beam tip and the job is ΔT.

The CPRI code should achieve $(T_1 - T_2) = \Delta T$

The task space velocities of robot 1 and 2 in terms of the components are written as

$$\{T_1\}=[v_{x1}\ v_{y1}\ \omega_1]^T \ ; \qquad \{T_2\}=[v_{x2}\ v_{y2}\ \omega_2]^T$$

The Jacobian, relating the task space velocity to the leg velocity for robot 1 and 2 is given as

$$\{v_1\} = [\,J_1]^T \{T_1\} \ ; \qquad \{v_2\} = [\,J_2]^T \{T_2\}$$

where, $\{v_i\} = [v_{1i}\ \ v_{2i}\ v_{3i}]^T$ is the vector containing leg velocities of the robot i [i=1,2]. $[J_1]$ and $[J_2]$ are the 3×3 Jacobian matrix of robot 1 and 2 respectively. The relationship between $\{V_1\}$ and $\{V_2\}$ can be obtained as discussed above for the cooperating robots.

Six DOF Parallel Robots in Cooperative Mode

The CPRI discussed above is extended to the in-house developed 6 DOF parallel mechanisms-based robots. Three translations and three rotations constitute the 6 DOF for the robot. A representative arrangement of the 6 DOF parallel mechanisms for mirror manipulation in cooperative mode is shown in Fig.5. All the categories of subtasks of applications mentioned in the earlier section can be performed in spatial mode.

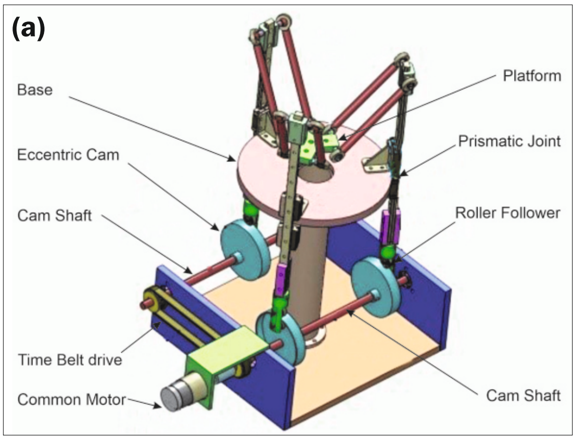
Single Actuator Parallel Mechanism to Generate "6D Trajectories"

The Prismatic-Spherical-Spherical (PSS) connector type of robot has fixed active axes. The model of 3-DOF Delta Parallel robot and 6-DOF PSS parallel robot along with the prototype is shown in Fig.6. The fixed active axes show specific advantages in building spatial trajectories using single actuator and constraining other active axes in a cooperative function rule. This is perceived not as a cooperation of robots but as a cooperation of joints within a robot to generate a unique spatial trajectory. The purpose is to generate repeating "6D motion trajectories" using a single actuator. The scheme is to functionally cooperate within the joint space of a robot to design a single actuator parallel mechanism-based robot to Generate "6D Trajectories". For a given spatial task space trajectory, the simple way to generate it is through the combination of the six cam-follower displacement at the joint space in a cooperative mode. The kinematic design, prototype development and algorithm to generate a 6D motion trajectory is elaborated in reference[3]. The concept shows feasibility of newer application domains for the mechanism.

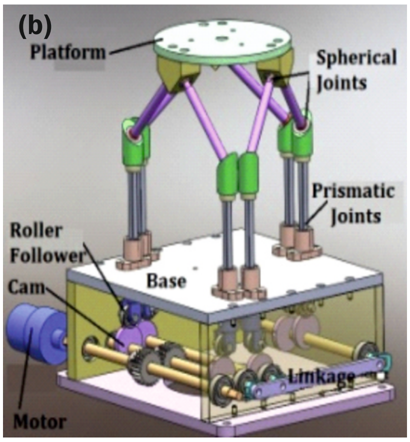
The cam and the follower for a joint space prismatic displacement is proposed. The various combinations of cam and the follower methods for motion transmission are possible. The common shaft transmission for an array of PSS Parallel Manipulator based robots to follow a specific trajectory is discussed in reference[3]. Fig.6 shows model and prototypes of PSS based mechanism-based robots on a single actuator. Fig.7 shows the Mechanical Master-Slave, a passive manipulator, intuitively in cooperation at joint space.

Conclusion

High positional accuracy and the stiffness of the parallel mechanism-based robots are suitable for cooperation in position and force domain. The concept of mirroring manipulation through typical cooperative tasks using parallel robots are useful for large number of scientific applications.



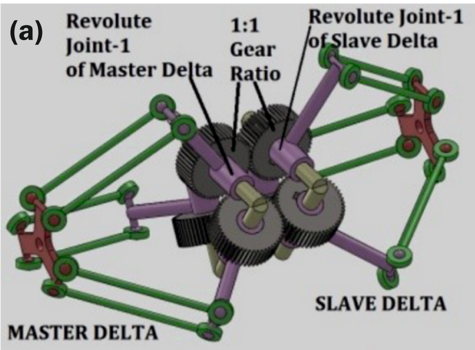
(a) Joint space Co. operation for 3-DoF Delta



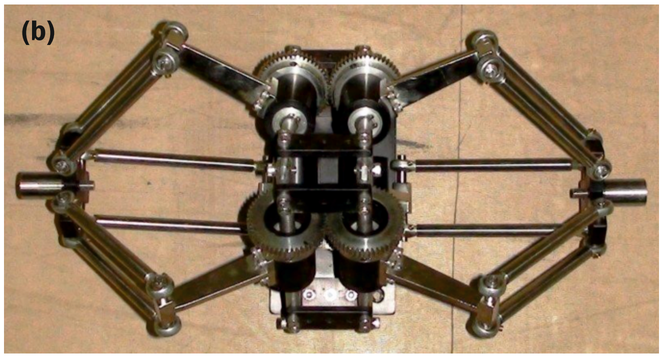
(b) Joint space Co. operation for 6 DoF in PSS configuration

(c) Joint space Co. operation for 6 DoF PKM Prototype

Fig.6: Cooperation of joints in a parallel robot to generate a unique spatial trajectory.



(a) 3 DoF Delta in Mechanical Master-Slave, Configuration



(b) Prototype of 3 DoF Delta in Mechanical Master-Slave Configuration

Fig.7: Parallel mechanism based Mechanical Master-Slave Manipulator.

The mirror manipulations can provide a simple cooperative scheme for participating robots.

References

[1] A. Banerji, R. N. Banavar, D. Venkatesh, “A Non-Dexterous Dual Arm Robot’s Feasible Orientations along Desired Trajectories: Analysis & Synthesis,” 44th IEEE Conference on Decision and Control, Spain, 2005.

[2] T. A. Dwarakanath, Gaurav Bhutani and Puneet Srivastava, “Task space trajectory planning among cooperating robots through mirror motions”, 15th NaCoMM 2011, IIT, Madras, Dec. 2011.

[3] K. D. Lagoo, T. A. Dwarakanath and D. N. Badodkar, “Single Actuator Shaker Design to generate Infinite Spatial Signatures”, 2nd Int. & 17th iNaCoMM 2015, IIT Kanpur, Dec. 2015.

Robotics

4

Robots in Healthcare

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Radiotherapy Simulator

ABSTRACT

Robots have revolutionised industrial production and are now increasingly being used in other areas like space, research, defence, agriculture, underwater etc. Use of robots in healthcare is slow but for some of the applications robotic devices are now almost indispensable. It is important to note that most of the devices discussed here are remotely-operated, computer-controlled machines designed for specialized medical applications. In some cases, where robots are used, doctors always remain in the loop. Involvement of experts during such applications is important, particularly because every patient is unique, and parameters are expected to be different when someone seeks medical intervention.

KEYWORDS: *Medical robots, Bhabhatron, Radiotherapy, Localized cancer, Brachytherapy, Multi leaf collimator*

Introduction

Human cancer is one of the leading causes of death worldwide and is increasing at an alarming rate. Radiotherapy is an established and cost-effective treatment modality for the management of localized cancers. Since radiation is equally harmful to surrounding healthy tissues/organs and those coming in the path of the radiation beam, utmost care has to be taken to restrict the prescribed radiation exposure only to the affected organ/region. Additionally, it is essential to protect the operator, other hospital staff and the environment from the harmful effects of radiation. This requires specialized devices and some of these are discussed below.

In teletherapy, also termed as external beam radiotherapy, radiation dose is delivered from a distance to the affected region of a patient. For the source of radiation, there are two options: either it can be generated as and when required using devices like x-ray tubes, or using certain radioisotopes which emit radiation continuously. Bhabhatron is an indigenously developed teletherapy machine and uses high-energy gamma radiation emitted by Cobalt-60 radioisotope for the treatment of localized cancers[1]. It has 10 motorized and remotely operated motions for accurate patient positioning and radiation field shaping. A source capsule containing Cobalt-60 radioisotope of activity upto 15kCi is controlled remotely to toggle between the shielded and treatment positions. Since the geometry of the cancer-affected organ/region is highly irregular, a Multi Leaf Collimator (MLC) System has been developed and integrated with Bhabhatron. Thin divergent leaves made of tungsten alloys are grouped into two banks (30 in each) and are driven independently by individual electric motor. A computer program controls the leaves and independently positions each of the leaves to generate required radiation field geometries conforming to the irregular tumour boundaries. The accelerator based imported teletherapy machine is similar except the source of radiation is replaced by a compact linear accelerator emitting high-energy x-rays.

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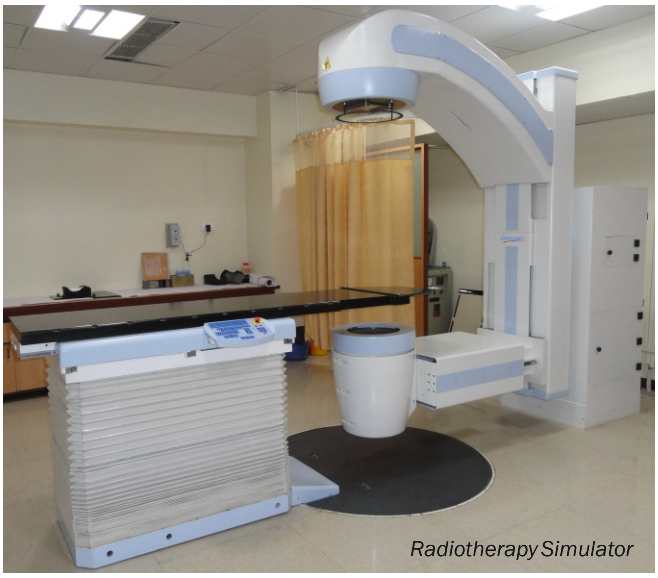
Safe and effective radiation therapy necessitates proper planning through delineation of the tumour and identification of the organs at risk for accurate delivery of the planned radiation dose. Radiotherapy simulation to determine the shape, size and orientation of the high-energy radiation field(s) to which the patient will be exposed later during the radiation therapy treatment is performed prior to the radiation therapy treatment, using a machine called radiotherapy simulator which has mechanical and radiation beam geometry identical to that of a teletherapy machine. In the indigenously developed system[2], there are 18 remotely controlled movements to reproduce the geometric movements of a teletherapy machine. However, unlike a teletherapy machine that delivers high-energy Gamma radiation beams for treatment, a Radiotherapy Simulator uses low-energy X-ray beams for imaging, either in radiography or fluoroscopy mode.

Indigenous Cobalt-60 Teletherapy Machine - Bhabhatron.

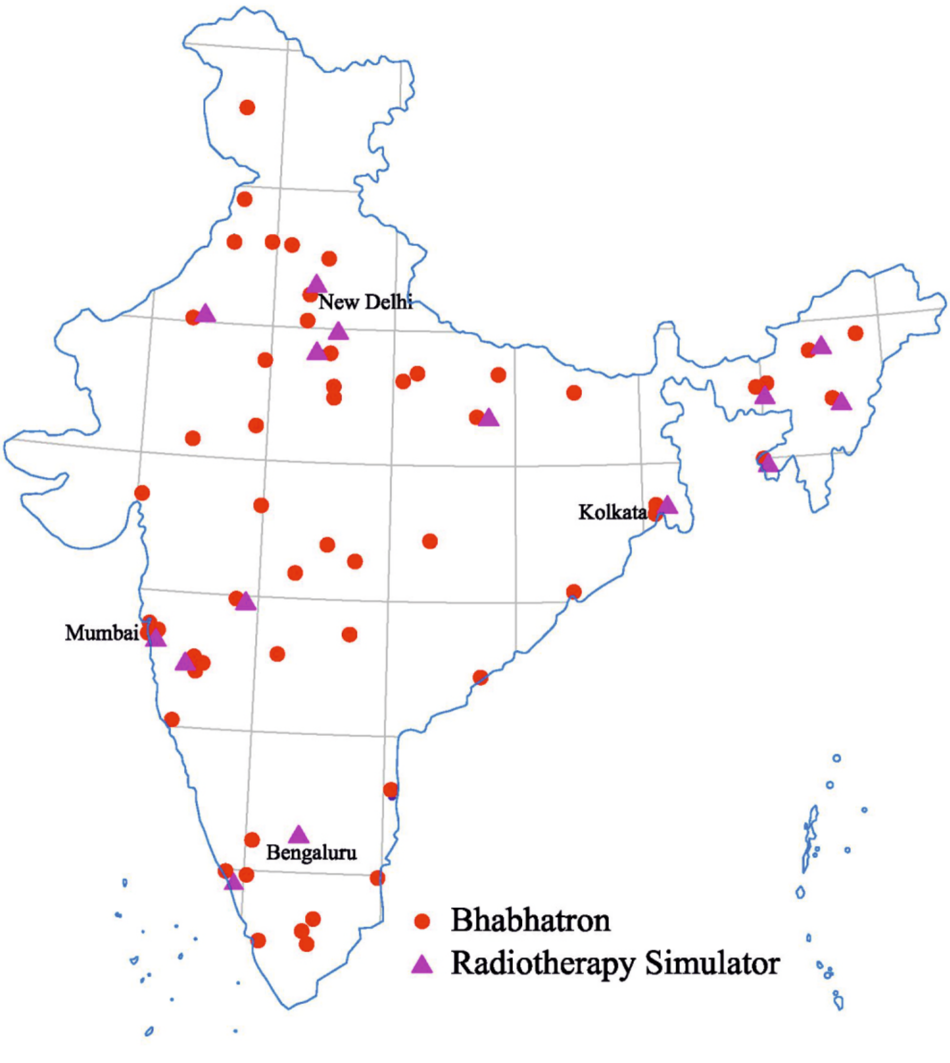

Radiotherapy Simulator

Both the machines, namely Bhabhatron and the Radiotherapy Simulator are designed to conform to the requirements of the International Electrotechnical Commission Standards. Additionally, these are approved by Atomic Energy Regulatory Board (AERB) for clinical use. The technologies have been transferred to industries for commercialization. More than 70 units of Bhabhatron and more than 20 units of Radiotherapy Simulator are in operation in various Cancer Hospitals in India and abroad.

Cyberknife®[3], originally developed by the Stanford University, USA, is a robotic teletherapy device in which a compact linear accelerator is mounted on an articulated robotic arm for precise delivery of high-energy x-ray beams concentrating to the tumour from wide range of positions and angles. Image-guided operations, coupled with robotic precision help in delivering very high dose to the tumour while limiting exposure to adjacent healthy tissues make it particularly suitable for the treatment of brain tumours.

Another mode of treatment for localized cancers using ionizing radiation is Brachytherapy which involves placement of miniature sealed radioisotope inside or in close proximity of the affected tissues/organ. In high dose rate remote after loading brachytherapy, the tiny capsule containing Iridium-192 or other radioisotope is remotely driven to the preset locations inside the organ through guiding tubes placed inside the body before the treatment. One such device has been developed by Board of Research in Isotope Technology (BRIT), an independent unit of Department of Atomic Energy (DAE).

In the Robot Assisted Neurosurgical Suite[4] developed by BARC, a compact parallel mechanism based six degrees of freedom robot can be programmed to access small deep rooted tumors and extract samples for biopsy. Image guided navigation of this high-precision mechanism provides tool position in real time during the procedure.



Installations

Use of robot for surgery was first started with replacement of hip joint. In the Robodoc surgical system[5] developed jointly by the University of California and IBM, the robot was programmed to drill hole into the femoral shaft for precise fitting between the bone and the artificial implant for improved performance of the joint. Subsequently, robots were used in many other healthcare applications, but the most significant is in minimally invasive surgical applications.

Minimally invasive surgery allows surgeons to perform surgery through small incisions instead of large abdominal cuts. There are significant benefits to the patient in terms of reduced post-operative complications and quicker return to normal physical activities. However, the laparoscopic tools have limited dexterity restricting the procedure to relatively simple operations. Also, these operations are quite demanding for the surgeons. Robot-assisted devices like *da Vinci* Surgical System[6] developed by Intuitive Surgical Inc., USA, allows a surgeon to perform surgical operations using miniature robotic arms (in master-slave mode), sitting comfortably at a remote location. Technologically, these are similar to the servo-manipulator systems used in DAE for nuclear (Hot-Cell) applications. Improved 3D view of the surgical site, force reflection, tremor-filtration etc. can drastically improve the surgical performance.

Brain-Computer Interfaces (BCI) are demonstrated to operate robotic devices for assisting persons with neurodegenerative disorders. The electroencephalography (EEG) signal from non-invasive BCIs are decoded to assign specific tasks for a robotic device enabling the disabled person to interact with their environment, communicate, and reduce dependence. These systems are still in the development stage and have potential to significantly improve the lives of many people with physical disabilities.

During the Covid-19 pandemic, when the proximity of the caregivers was risky, machines were perceived to be safer alternatives. Numerous robotic devices with wide range of sophistications were developed for applications like managing patient admissions, acquisition and monitoring of vital parameters of patients, drawing samples for pathological investigations, delivery of food and medicine, sanitization etc. Probably, a few of these will continue to be used in the post-pandemic era.

Apart from the devices discussed above, there are numerous robotic systems being used indirectly, namely in biological research, pathological investigations etc.

Conclusion

The use of Robotic and other automated devices is increasing rapidly in healthcare applications. Such tools are not to replace the humans but to extend human skills and improve performance. These systems are evolved to protect humans, to reach to locations which are otherwise unreachable, to improve performance and in some cases to perform tasks which are otherwise not feasible. There was an era when human used to be cautioned to stay away from robots/machines. But now, particularly in some healthcare applications, robotic touch is for the benefits of humans.

References

[1] K. Jayarajan, D. C. Kar, R. Sahu, M. G. Radke, and Manjit Singh, (2005), BARC develops cobalt-60 teletherapy machine for cancer treatment, BARC Newsletter, No.253, February 2005.

[2] D. C. Kar, R. Sahu, K. Jayarajan, D. D. Ray and Manjit Singh (2011), Development of Digital Radiotherapy Simulator: A Device for Tumor Localization, Radiotherapy Planning and verification. BARC Newsletter, No.318, January-February, pp.63-69.

[3] CYBERKNIFE® TREATMENT DELIVERY SYSTEM, accessed 16 October, 2022 <https://www.accuray.com/wp-content/uploads/cyberknife-treatment-delivery-system_-technical-specifications.pdf>

[4] Abhishek Kaushik, T. A. Dwarakanath, Gaurav Bhutani, S. Dwarakanath (2020) Robot-based Autonomous Neuroregistration and Neuronavigation: Implementation and Case studies, World Neurosurgery, Vol. 134, pp. e256-e271.

[5] N. G. Hockstein, C. G. Gourin, R. A. Faust and D. J. Terris (2007) A history of robots: from science fiction to surgical robotics. Journal of Robotic Surgery, vol.1, pp.113–118.

[6] F. Pugin, P. Bucher, and P. Morel, (2011) History of robotic surgery: from AESOP® and ZEUS® to da Vinci®, Journal of Visceral Surgery, vol.148, no.5, pp.e3-e8.

Deep Learning

5

Deep Learning & Robotics for Biomedical, Nuclear Applications

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Spot Picker Robot

ABSTRACT

Recent advances in the computation capabilities, Artificial Intelligence (AI) has opened up new dimensions for solving real-world problems. Vision-based automation systems have been indigenously developed comprising of AI capabilities to cater to the needs of robotics, biological and nuclear science. In this article, we have discussed four such systems i.e., Biochip reader system, Spot picker robot, Protein crystallography imaging system and In-cell video microscopic system. These systems are in active use at various laboratories of BARC and thus enhancing the fields of biomedical and nuclear science research.

KEYWORDS: *Biomedical and nuclear applications, Artificial intelligence, Robots*

Deep Learning based Fluorescence Signal Detection for Biochip

A novel fluorescence-based portable biochip reader system has been developed, which has deep learning algorithms for fluorescence measurement of multianalyte. It is used for reading DNA/protein biochips in clinical diagnosis and basic research. The compact designed system having size of 13 cm x 13 cm x 16 cm is shown in Fig.1. The system consists of a monochromatic light source (LEDs), excitation and emission filters, dichroic mirror or beam-splitter and a CCD/CMOS camera. It can read the whole biochip at a time. Depending upon the excitation and emission maxima of the fluorescent label used, LEDs and filters can be easily changed. The focusing collimator also contains a beam shaper causing excitation light to carry an almost uniform distribution, instead of Gaussian. Images obtained by the camera are stored with 16-bits gray scale levels and analyzed using in-house developed software that exploits the deep learning method.

Deep learning Network for Biochip Data Quantification

To meet the challenge of detection and quantification of low contrast signals, a specific deep learning network as described in Fig.2 has been developed[1] and deployed. Each block in the contracting path of the network consists of two successive 3 x 3 convolutions followed by batch normalization, a Rectified Linear Unit (ReLU) activation function and a max-pooling layer. This arrangement is repeated several times. The expansive path of the network replaces the max-pooling layer with the up-sampling layer and also concatenates the high-resolution information coming from the contracting path. The network has several advantages over other similar available networks. It is asymmetrical, i.e., the decoder side of the network has fewer feature maps than encoder to reduce the number of parameters and computation time. The original skip connection which transfers high-resolution features to deeper layers has been modified by introducing "processing blocks" on it without making any changes to feature maps. Each processing block is a residual block consisting of a sigmoid layer sandwiched between the two Convolution layers. This arrangement is intended to help in denoising and contrast enhancement features and resulted in better detection of low-intensity spots. The depth wise separable convolution filters are also used instead of standard convolution filters, which

Fig.1: Biochip Reader.

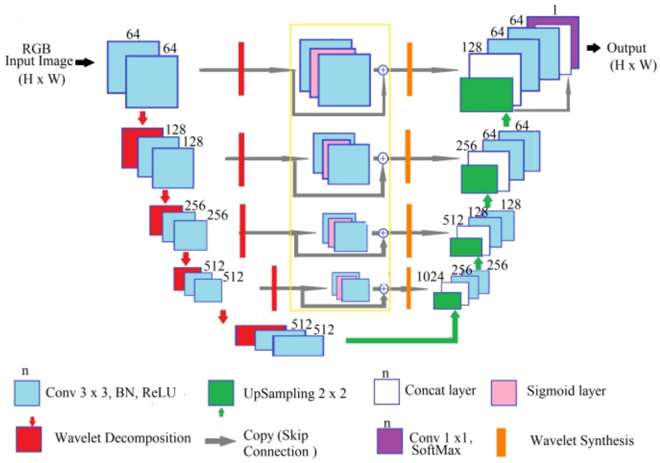

Fig.2: Deep learning Network-Bio-UNet.

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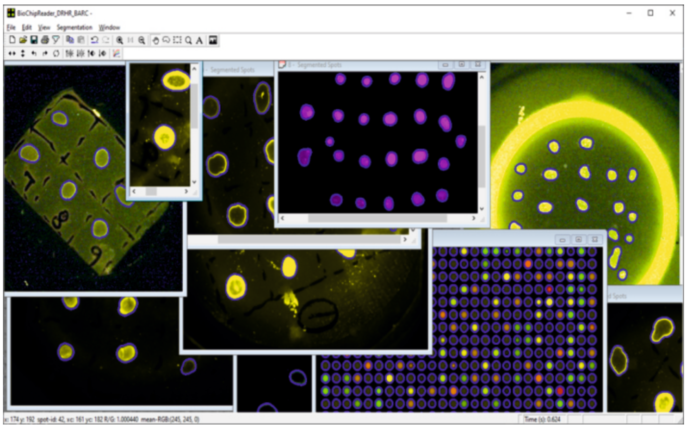


Fig.3: Results & User interface software.

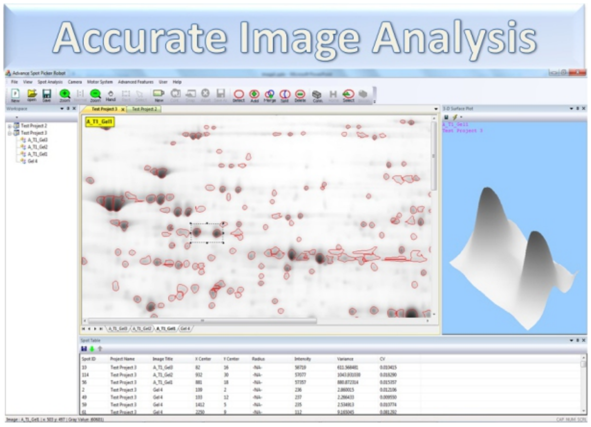


Fig.5: 2DGE Image Analysis Software.

Fig.4: Spot Picker Robot.

reduces the number of parameters in the network by a large factor (from 13M to 2 M) without any significant adverse effect on the segmentation results of biochip images. To enhance the accuracy of detection, a hybrid loss function having a combination of binary cross entropy and a dice loss has been adopted for training. Our deep learning method has been compared with the other available deep learning networks and traditional methods and it is found to be superior by a large margin. It has been demonstrated to provide hierarchal feature segmentation with an accuracy of 98.4%. The results and user interface have been illustrated in Fig.3. The developed bio-chip reader has been clinically tested with DNA as well as antibody biochips and is under clinical use at RMC, Mumbai.

Spot Picker Robot for Proteomics Applications

This robotic system has been indigenously developed and it demonstrates the state-of-the-art technology in precise positioning and powerful imaging algorithm in the field of proteomics as shown in Fig.4 & Fig.5 respectively. It accurately locates and identifies the protein spots from 2D gel electrophoresis (2DGE) and picks and transfers the proteins for further analysis, thus enhancing data quality and reliability in the field of proteomics. The application of this robot has helped in discovering new proteins to develop biomarkers for new diagnostic tests.

The nature of 2-D Gel Electrophoresis (2DGE) images poses difficulties, such as a very noisy and inhomogeneous background with several irregular protein spots. These irregular protein spots are of varying size, shape and intensity. A novel non separable wavelet based image processing algorithm as described in Fig.6 has been developed to detect complex and faint protein spots in non linear background[2], where the available commercial imaging software is not suitable for such detection.

This algorithm is implemented in the Spot Picker Robotic system to provide automation for screening of large number of proteins. Presently the system is in experimental use at RMC.

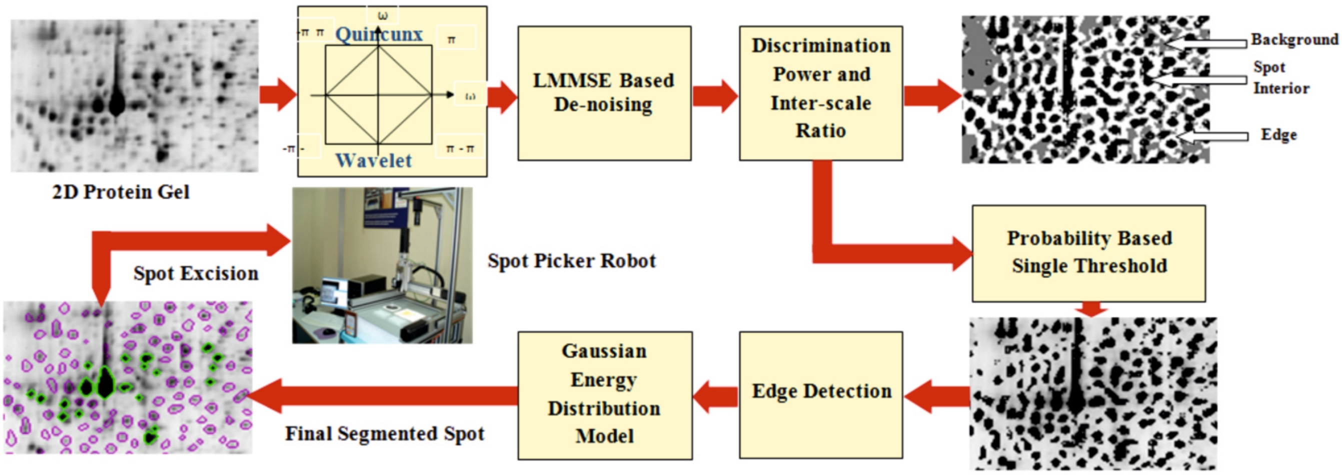


Fig.6: Analysis of 2D-Gel Images for Detection of Protein Spots Using Non-Separable Wavelet.

Real Time Crystal Classification using Deep Convolutional Neural Network for Protein Crystallography Imaging System

X-ray crystallographic technique provides the atomic positions of biological macromolecules for the development of new drugs and vaccines. Correct combination of numerous factors like protein purity, pH, temperature, protein concentration, the type of precipitant and the crystallization methods is essential for the formation of crystals. However, it is difficult to predict these exact conditions for protein crystallization. Therefore, thousands of trials are often required for successful crystallization experiment. Because of the high throughput crystallization approach, manual inspection becomes tedious and prone to errors. Therefore, automated image classification system has been developed to acquire and classify the crystallization images.

Bench-top imaging system[3] has been indigenously developed to monitor the real time protein crystal growth and classification of different state of crystals for X-ray crystallography (Fig.7). Robotics and custom designed microscopic imaging system are used for capturing multi focal images of protein crystals of few microns in size. Advanced computation methods based image processing algorithms have been developed to generate 3D slices of the crystal images. The crystal images acquired by the system are shown in Fig.8.

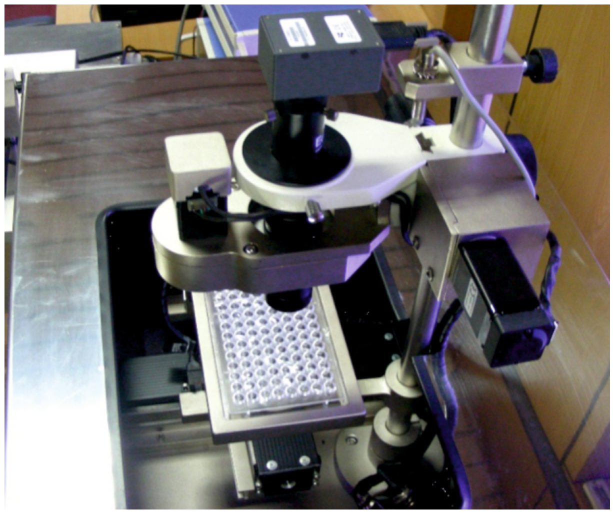
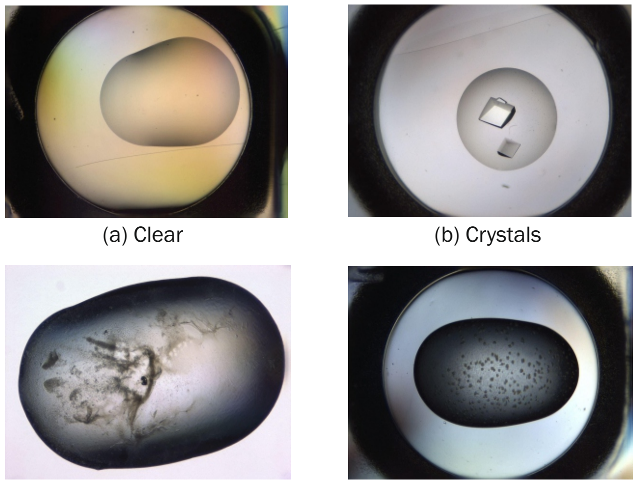


Fig.7: Protein Crystallography Imaging System.



(a) Clear (b) Crystals

(c) Precipitate (d) Other

Fig.8: Different state of the crystals captured by Imaging System.

Image classification during crystallization process

Automated image classification system has been built to classify the images into four classes (Crystals, Precipitate, Clear and Other) to reduce the time in labeling the crystals. The CoAtNet architecture[4] was conceptualized by combining convolution and self-attention to develop fast and accurate neural networks for large-scale image recognition.

Dataset has been randomly partitioned into 75000 training, 7000 tests and 5000 validation images. Each image was resized to 1200x1200 and was centrally cropped. Then, they are randomly flipped in horizontal and vertical directions. The saturation, hue and brightness are randomly adjusted in the ranges of [0.3, 1.5], [0, 0.5], and [0.1, 0.5], respectively. CoAtNet model was modified and tuned for our classification task and the network is shown in Fig.9. For training purposes four Nvidia 3080 RTX 10 GB GPUs are used. The optimizer was Adam with a batch size of 8, a decaying learning rate with an initial setting of 0.045 and maximum epochs of 30. The total time taken for training was 7 hours. Overall test accuracy achieved was 94.1% and validation accuracy of 92.11%. Two systems with software containing real time crystal classification are in used at RBHSD, BARC. The CNN network was found working efficiently for accurate classification thus minimizing the manual efforts and time for predicting the correct crystal category.

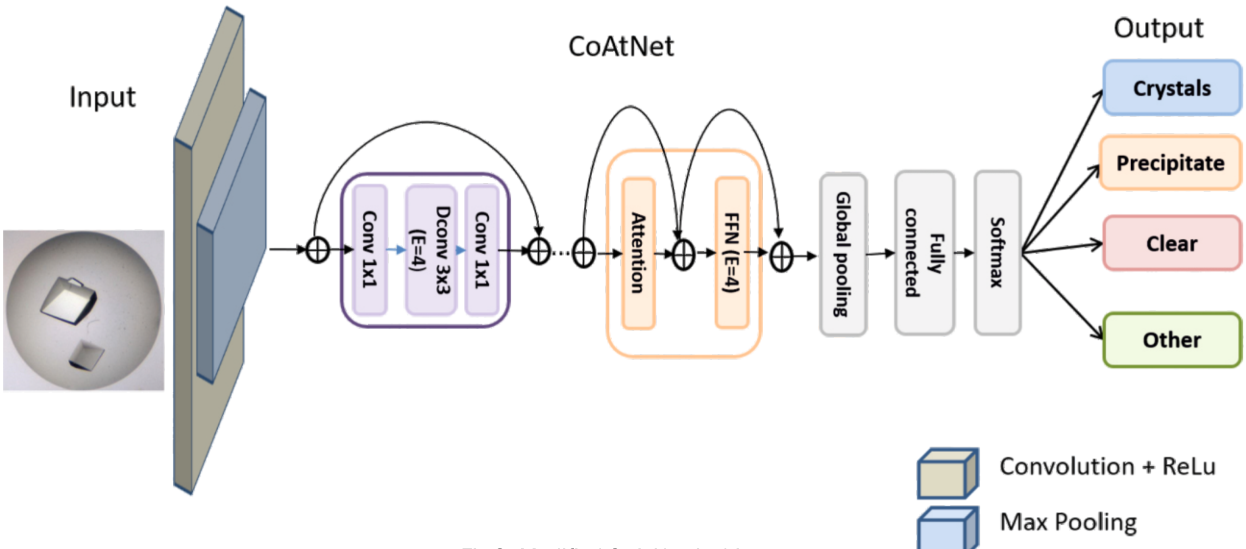


Fig.9: Modified CoAtNet Architecture.

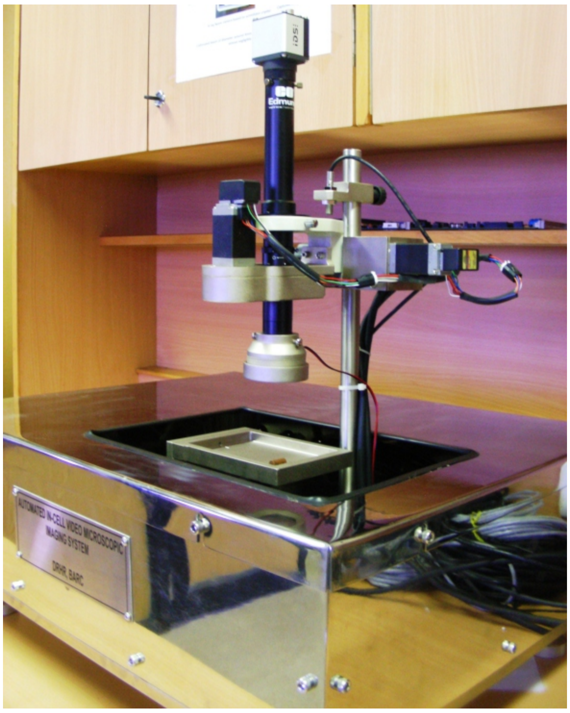


Fig.10: In-cell Video Microscopic Imaging System.

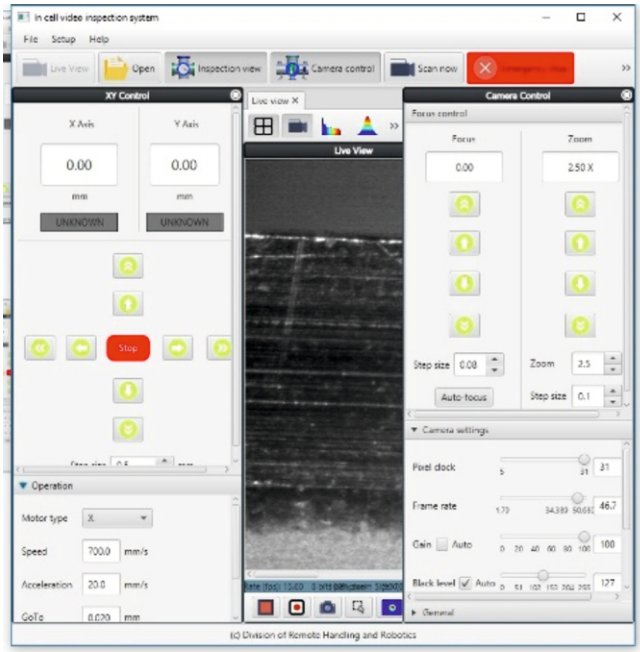


Fig.11: Control Software GUI.

In-cell Video Microscopic Imaging System

The in-cell video microscopic imaging system (Fig.10) has been indigenously developed for automated analysis and dimensional measurements of various reactor core components inside the hot cell. It provides visual inspection and automated analysis of reactor core components at different zoom levels (up to 100x). The system is useful for observing the nodule on Inner Diameter (ID) and flaw characterization in the pressure tubes and defects in the low burn-up fuels of PHWR type nuclear reactors.

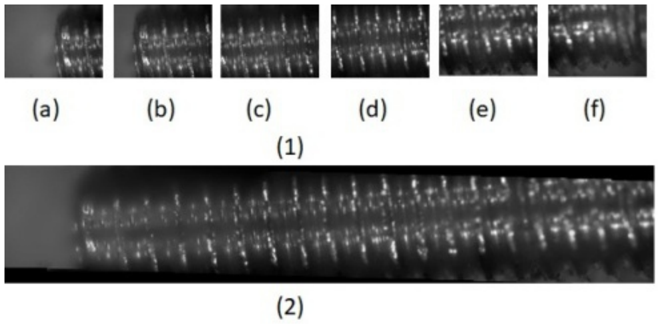


Fig.12: Images captured at different scan positions (1) and stitched image mosaicing (2).

The system consists of a precise robotic system with custom design radiation resistance motorized microscopic imaging system and illumination source. It provides motion travel of 100x100x50mm with positional accuracy of 5µm and the system automatically captures images of reactor core components at different heights and zoom levels. A control system has been developed for stable operation. The multi axis robotic motion is controlled remotely by Ethernet-IP based PLC through PC. This assembly provides a fully automated and optimized multidimensional imaging of the nuclear reactor core components. The proper shielding is provided to the lens and illumination source for working in a radiation environment.

Control GUI software as shown in Fig.11 has been developed for the movement of different axes in various positions, mapping of image magnification to robotics coordinates, automatic scan of inspection material by selecting the region of interest (ROI) and live view of scanning process. Scanning results images are stored in the database in various formats. The system hardware has been integrated with control software and tested with 2D and 3D objects for automated analysis and visualization as demonstrated in Fig.12.

Conclusion

The article presents that the robotics and AI techniques have been implemented in biomedical and nuclear applications for high throughput systems. It is aimed to build more technologies by a combination of both robotics and AI for better perspectives of intelligent automation.

References

[1] Ratnesh S Sengar, A. K. Upadhyay and B. Jain, “Deep Learning Aided Small-Sized Portable Fluorescence Biochip Reader,” IEEE Transactions on Instrumentation and Measurement, 2022, Art no.2507709, vol. 71, pp. 1-9.

[2] Ratnesh S Sengar, A. K. Upadhyay, M. Singh, V. M. Gadre, “Analysis of 2D-Gel Images for Detection of Protein Spots Using a Novel Non-Separable Wavelet Based Method”, Biomedical Signal Processing and Control (Elsevier),2016, Vol.25, pp62-75.

[3] Ratnesh S Sengar, R. Sharma, K. Madhusoodanan and A. Das, “Real Time Protein Crystal Monitoring System”, 2022 IEEE 7th International conference for Convergence in Technology (I2CT), 2022, pp. 1-6, doi: 10.1109/I2CT54291.2022.9825287.

[4] Zihang Dai, Hanxiao Liu, Quoc V. Le, Mingxing Tan. (2021). “CoAtNet: Marrying Convolution and Attention for All Data Sizes”. Computer Vision and Pattern Recognition, 2021. doi: 10.48550/arXiv.2106.04803.

Robotics

6

AI-powered Decision Making in 'Robotic Solutions'

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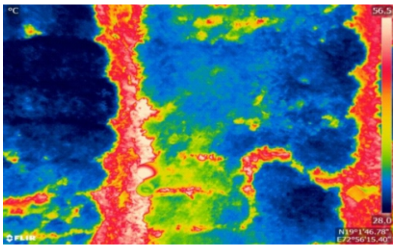

Thermal image of the plantation

ABSTRACT

Artificial Intelligence (AI) based decision making enables robotic solutions to perform intellectual tasks. In robotics, AI solves many complex problems which are otherwise difficult to solve. In this article, some of the robotic solutions developed at BARC,wherein AI powered decision making had been used, are described. AGV based material transfer system is one of the instances, where AI-powered decision-making hasbeen applied to enable autonomous operation. Drone based system, developed for land survey and research in nuclear agriculture, uses AI to build models that provide crucial information for decision making. Perception is a challenge in self-driving robots. Deep Learning based data driven AI approach has been used to build perception system with sensorpacks containingLiDAR, monocular camera and stereo camera.

KEYWORDS: *AI powered decision, Robotic solutions, Artificial Intelligence, Autonomous operation, Aerial robotics, Perception system*

Introduction

System designers use different degrees of AI in decision making such as '**decision automated**', '**decision augmented**' or '**decision supported**' approaches in the overall scheme of solution[1]. Irrespective of the approach, AI part is to attain the reasoning ability needed to take rational conclusions for decision making. AI uses deductive and inductive reasoning for problem solving and it includes methods like heuristic algorithms, probabilistic algorithms, machine learning methods and many more. Some of the algorithms conclude the result with certainty while others conclude with associated probability. Robots in real-world face challenges similar to what a human face in decision making. But the evolutionary advantage and the vast amount of prior information human has, is missing in robots. Robots rely on the knowledge passed on by the system designer or have to extract useful information from the data received through a variety of sensors they possess. AI models help to use 'the prior knowledge passed on' as well as 'to make sense out of raw data' from the sensors. With the current state of AI technology, all decision making cannot be made fully autonomous. System developers need to bring human in the loop and make compromise in autonomy for effectiveness of the solution. Based on the level and the nature of human intervention apt for the robotic solution, system developers have a range of choices of concepts. Some of these concepts are as follows[2].

- **Human in the loop** - The human actor makes the decision and the AI part provides only support in taking decision.
- **Human in the loop for exceptions** – Most of the decisions are automated and the human actor handles exceptions alone.
- **Human on the loop** – AI part makes micro-decisions and human is only assisting AI.
- **Human out of the Loop** – AI part makes every decision. Human intervenes only to set new objectives, constraints etc.

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With this background, further sections will describe some of the robotic solutions developed in-house wherein AI powered decision making had been utilized.

Autonomous Material Transfer System

Nuclear industry requires automation not only for improving the efficiency of the process but also to reduce the occupational hazards to workers. Automated guided vehicle (AGV) based Autonomous pellet boat transfer system (APBTS) developed at DRHR, BARC as shown in Fig.1 and Fig.2, aims to improve on both the fronts[5,7]. It is an AGV based system which can transfer materials in an industrial facility without the need of an operator to drive it. APBTS has adopted 'Human Out of the Loop' model in the implementation. Based on the real time data from the network of sensors located in the shop-floor, the system decides from where to pick-up and where to drop-off the material. AGV does the transportation of material from pick-up stations to drop-off stations. An effective planning solution[3,4] is required to achieve certain goals like 'efficient utilization of AGVs', 'optimal task assignment' etc.

Search algorithms are crucial to path planning which involves finding the best possible route for the AGV in terms of cost, time, energy or any other user defined parameter. Although, traditional uninformed search algorithms are useful in many cases, for mobile robot-based applications, their utility is limited. Algorithm like "Dijkstra's" are optimal; however, they are not fast enough to solve the problem and automate the overall solution in practical environment. So, for this application, a heuristic-based search algorithm which is fast to solve the problem is essential and if it is optimal, that is an added advantage. Algorithms like A*, D* fall in this category and are popular for the problem domain. Both are deterministic planning algorithms, A* is a complete and optimal, under certain conditions and D*, which is based on A*, is used for

Fig.1: AGV trial at NFC, Hyderabad.

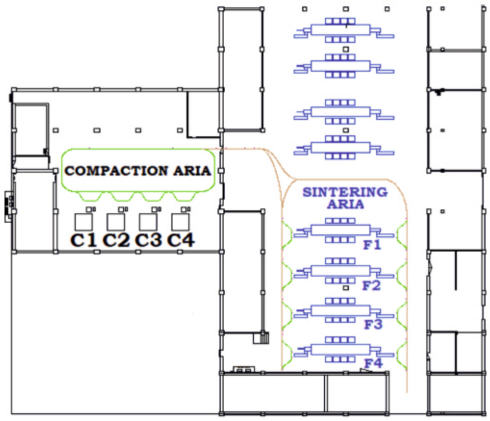

Fig.2: Layout of the plant.

dynamic planning in partially known and dynamic environment. In this line, a customized software solution[4] has been developed for planning the path for AGVs.

The whole process of material transportation on the factory floor is executed without the intervention of human. System utilizes the prior information about environment and process, which is provided by the designer or operator. This includes map of the area, know-how of the process being automated, constraints etc.

Drone based System for Land Survey & Agricultural Research

Aerial robotics, empowered with AI, is changing the face of various application domains including the geographical survey and agriculture for betterment. Drones can navigate to the places where a human can't, provide new information affordably and cover large area in short span of time. DRHR, BARC has developed drone-based solutions to conduct' photogrammetric survey' of land and 'thermal & multi-spectral imaging' for agricultural research as shown in Fig.3 to Fig.6.

With a drone and an onboard camera, it is possible to carry out land survey with the same quality of highly accurate traditional methods. This takes only a fraction of time required by traditional methods. It uses photogrammetry technique, bundle-adjustment based optimization which minimizes the reprojection error, to combine images that contain the same point on the ground from multiple vantage points to yield detailed 2D and 3D maps. Quality of the result depends on various factors like planning, image quality, weather pattern, control points, expertise of the surveyor etc. Drone captures Multispectral/Thermal/Colour images of survey site using high-resolution multispectral, thermal and visible-spectrum onboard imager. It autonomously navigates along a pre-defined path and captures images along the trajectory. Some decisions like defining way points, postprocessing of data etc. are left to the human operator.

For agriculture applications, some of the prominent areas are yield prediction, crop health, field phenotyping of plant response to drought etc. Thermal imaging is now an established technology for the study of stomatal responses and for drought phenotyping. This could be helpful for the development of drought tolerant varieties of different crops through mutation breeding. Computing vegetation index maps, by means of drone based multispectral imaging, helps to assess health of the crop. Such a system together with other solutions help to perform relative biomass analysis, drought stress assessment, agricultural production prediction, nutrition monitoring, identification of pests and diseases that are affecting the crop etc.

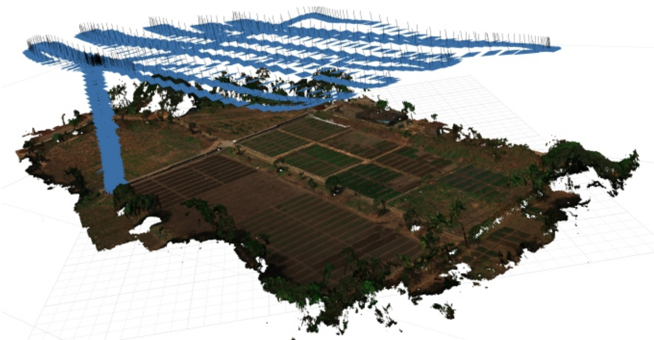

Fig.3: Digital Elevation Model of a Farm.

Fig.4: Vegetation Index map of a Farm.

Fig.5: A patch of the plantation .

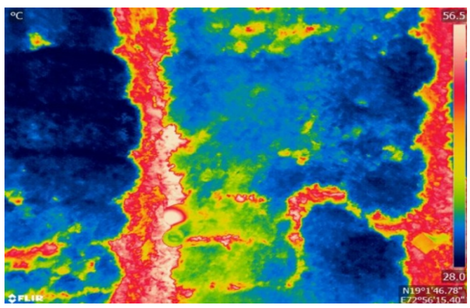

Fig.6: Thermal image of the plantation.

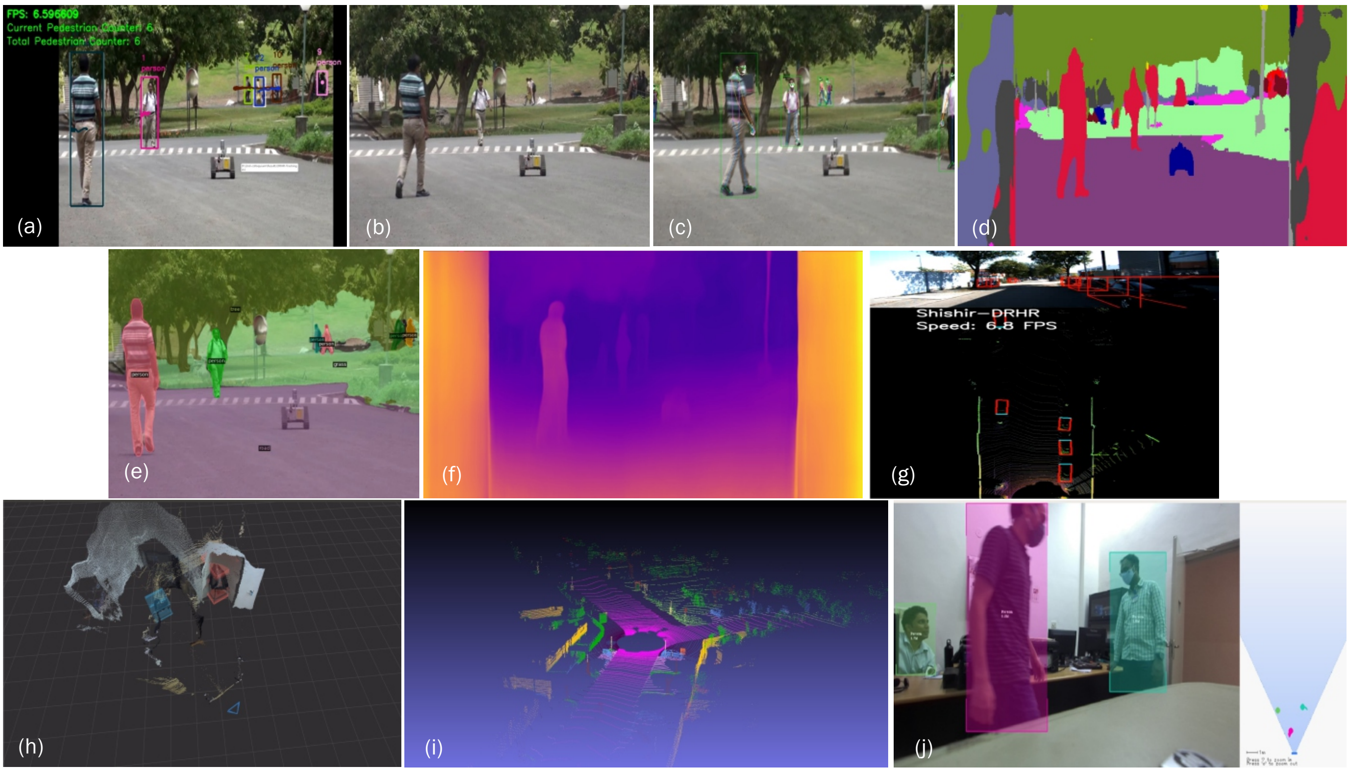

Fig.7: (a) 2D Multi Object Tracking (b) Pose estimation (c) Raw image (d) Semantic Segmentation (e) Monocular depth (f) Panoptic Segmentation (g) 3D object detection in LIDAR (h) 3D detection in stereo camera point cloud (i) LIDAR based semantic Segmentation (j) Real-time 3D tracking.

Perception system for Mobile Robots

Autonomous mobile robots navigate and make decisions without the help of any external agent. The ultimate aim of this technology is to achieve driving capability of human or better and delegate the task to AI engine. Any industry will benefit from such technology in material transportation in factories[5], security & surveillance[6],disaster management etc.

Sensing the environment is a prerequisite for navigation. Just like humans use their senses to probe the environment for safe navigation, mobile robots have sensors such as cameras, LIDAR, radar, sonar, GPS, IMU etc. DRHR, BARC has developed solutions to process data from such sensors using deep learning techniques (Fig.7). This includes detection of objects commonly found in indoor/outdoor environment. Semantic segmentation (SS), which tags each pixel of the image with a category like road, footpath, vegetation, building etc. This is useful in outdoor applications, where the robot needs to travel on road. Panoptic segmentation (PS) combines the task of semantic and instance segmentation which helps to reduce computational cost. Monocular depth estimation and optical flow identifies depth, flow vector for each pixel in an image. It helps in 3D understanding of the scene and motion. Multi object tracking (MOT) provides the temporal information and full body pose estimation is helpful for human activity recognition and tracking.

Conclusion

Future of robotics is intertwined with the progress in the field of artificial intelligence as AI is in the core of intelligent behavior of robots. Advanced robotic solutions inherently demand the development of AI based components to solve challenging real-world problems. Deep Learning (DL) based solutions have achieved a performance level in many applications which makes them a viable option to use in the practical conditions. The new paradigm for future research in robotics is end-to-end sensorimotor learning with reduced intervention from human actor.

References

[1] Laura, Starita ‘Would You Let Artificial Intelligence Make Your Pay Decisions?’, Garter Insights Information Technology Article, 2021. https://www.gartner.com/smarterwithgartner/would-you-let-artificial-intelligence-make-your-pay-decisions (accessed September2, 2022).

[2] Michael, Ross; James, Taylor ‘Managing AI Decision Making Tools’, Harvard Business Review, 2021. https://hbr.org/2021/11/managing-ai-decision-making-tools (accessed September2, 2022).

[3] N. Singh, P. V. Sarngadharan, P. K. Pal, AGV scheduling for automated material distribution—a case study, J. Intelligen. Manufact. 20(4) (2009).

[4] N. Singh, V. Dave, J. Kota, S. Singh, R. Sakrikar, P. V. Sarngadharan, Modular Mission Control for Automated Material Handling System and Performance Analysis-A Case Study, 3rd International & 18th National Conference on Machines and Mechanisms (2017).

[5] P. K. Pal, R. Sakrikar, P. V. Sarngadharan, S. Sharma, V. K. Shrivastava, V. Dave, N. Singh, A.P. Das, Development of an AGV-based intelligent material distribution system, Curr. Sci. J. 101(8) (2011).

[6] S. Singh, N. Singh, J. Kota, P. V. Sarngadharan, Building Autonomy in Outdoor Mobile Robots for Radiation and Video Survey, 3rd International & 18th National Conference on Machines and Mechanisms (2017).

[7] V. Dave, S. Singh, J. Kota, N. Singh, R. Sakrikar, V. K. Shrivastava, P. V. Sarngadharan, Tuning procedure for correcting systematic errors in a quad configuration AGV, 3rd International & 18th National Conference on Machines and Mechanisms (2017).

Robotics & Deep Learning

7

Robotics & Deep Learning for Intelligent Storage of PFBR Fuel Pins

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Articulated robotic arm

ABSTRACT

Nuclear fuel pins for Prototype Fast Breeder Reactor (PFBR) are transferred from the fuel fabrication facility to the reactor site in transport magazines. This article presents a framework for automated loading of nuclear fuel pins into transport magazines. This development aims to close the gap between the manual and fully automated loading systems. This article discusses the vision-guided robotic system for precise alignment of fuel pins with empty slots and accurate insertion by a robot. The article also presents an innovative deep learning technique for recognizing and recording fuel pin numbers engraved on end plugs. The system has pin alignment accuracy of ± 20 microns and repeatability of ±30 microns for automatic insertion.

KEYWORDS: *Robot, Vision guided alignment, Deep learning*

Introduction

The industrial environment needs robotic systems that intelligently makes autonomous decisions based on the physical environment. Vision-based systems can now robustly detect position and orientation of the mechanical components with a monocular camera even with imperfect illuminations [1,2]. Vision-guided alignment for tight tolerance assemblies can be achieved by precise robotic systems [3,4]. Further, a deep learning approach for number recognition can enable tracebility[5] of industrial components. Rapid developments in active environmental sensing techniques have enabled the development of high-performance robotic systems for challenging requirements[6,7].

This article describes the various system components and innovative methodologies used to develop a robotic system for autonomous loading of fuel pins into transport magazines.

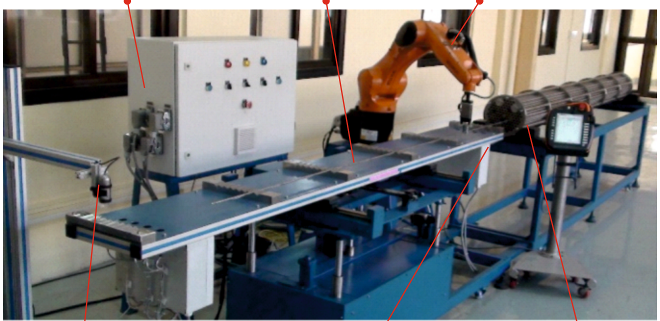

Fig.1: Robotic system for insertion of PFBR pins into transport magazine.

System Description

The robotic system(Fig.1) has a precise position control system, an articulated robotic arm, a number identification system, and a magazine orientation measurement system. Presently, the system can place eight fuel pins on the pin-loading platform. The pin position control system performs precise alignment of the fuel pins with the transport magazine before loading a pin. After that, a robotic arm fitted with a specially designed gripper pushes the fuel pin into the assigned slot. As a part of the automation, a deep learning-based methodology extracts fuel pin numbers from the end-plug curved surface. Also, the image-based system computes cage orientation. All the developed sub-systems are working on the production floor.

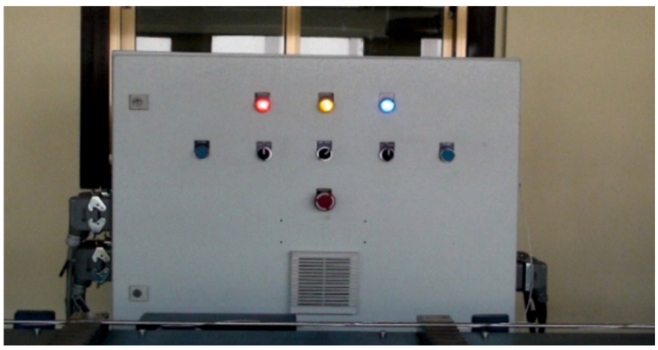

Fig.2: Controller for positioning of pin tray.

Pin position control system

We have designed and developed a two axes linear position control system (Fig.2) with ±20 microns accuracy. Tight tolerance between pin and slot necessitates the development of a system for accurate alignment. The control system issues commands for controlling the pin tray position using two servo motors (Fig.3).

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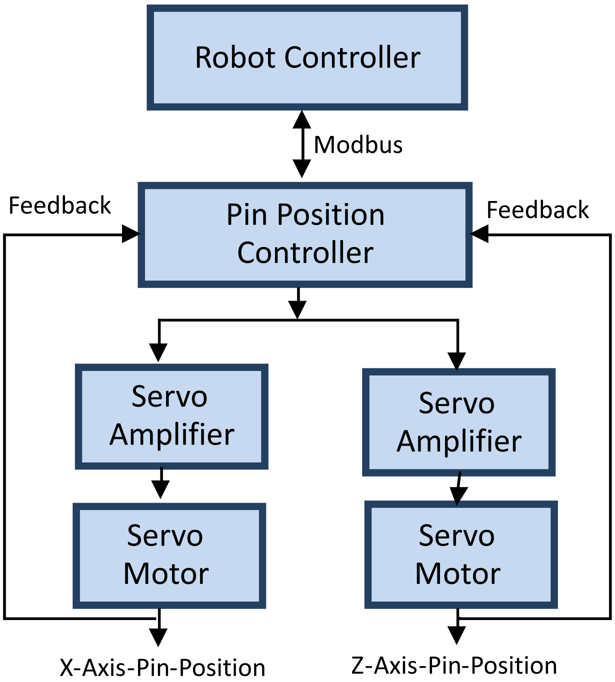

Fig.3: Pin Control System.

Fig.4: Articulated robotic arm.

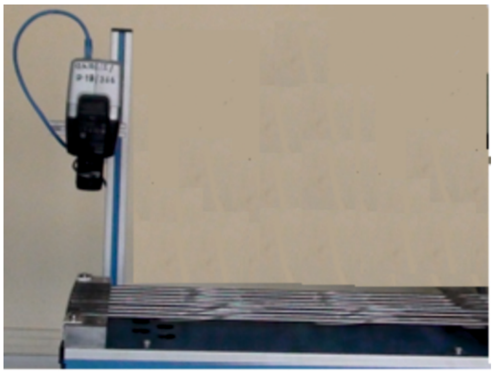

Fig.5: Camera for reading pin number.

Articulated Robotic Arm

A robotic arm with a maximum reach of 900 mm, performs insertion operation (Fig.4). The robot controller pre-computes all insertion positions. Loading of one pin requires six successive robotic pushing operations, and the robot controller completes all the processes within 24s with repeatability of ±30 microns. The robot also performs deep pin insertion into the slot, thus ensuring that fuel pins are not overhanging.

Pin Number Reading Camera

All the fuel pins have unique numbers engraved on the end plugs. This number ensures the traceability of the pin. A Bosch Dinion IP camera of 1280 (H) x 720 (V) resolution (Fig.5) captures the image of the end plug for extracting the pin number. The Control system performs scanning of all the pin numbers before initiating the loading operation. After insertion of each pin into the magazine, the software saves the pin number and corresponding magazine slot number.

User interface

Loading fuel pins into a transport magazine requires pin number scanning, pin positioning, insertion with the help of robot, and database preparation. Graphical User Interface software controls all the operations for pin insertion (Fig.6). The operator can validate extracted pin numbers before storing them in the database. The user interface depicts filled, empty, or block status for all the slots during the entire loading operation. Also, mapping information of pin number vs. slot number is displayed.

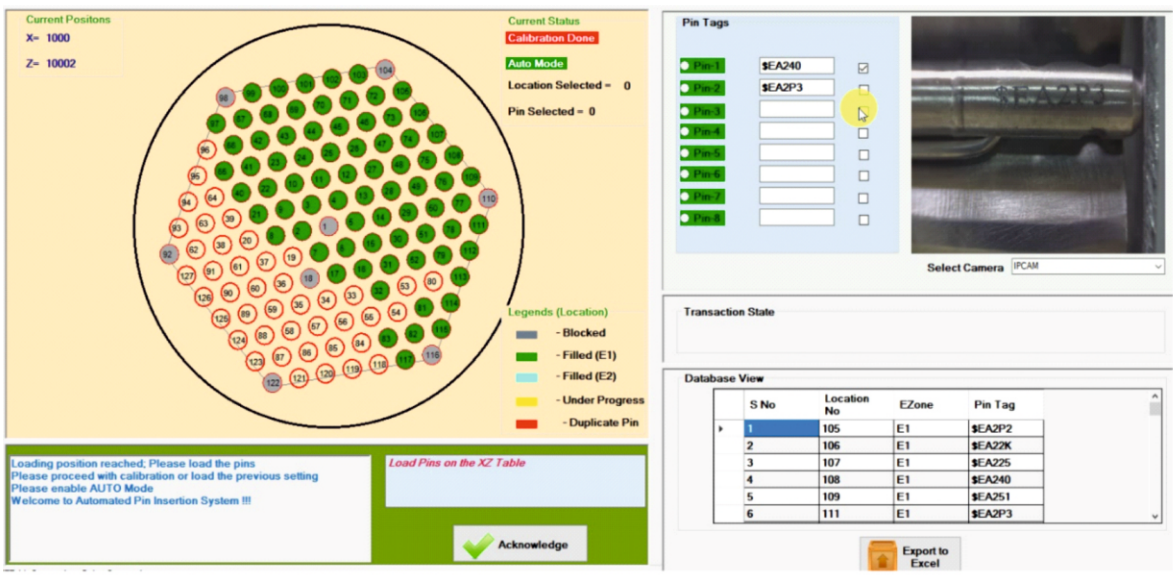

Fig.6: Graphical User Interface for Robotic Pin Insertion system (i) Status of 120 slots: Green(filled), No color (empty) (ii) End plug image and number detected by deep neural network (iii) Database for slot number and corresponding inserted pin number.

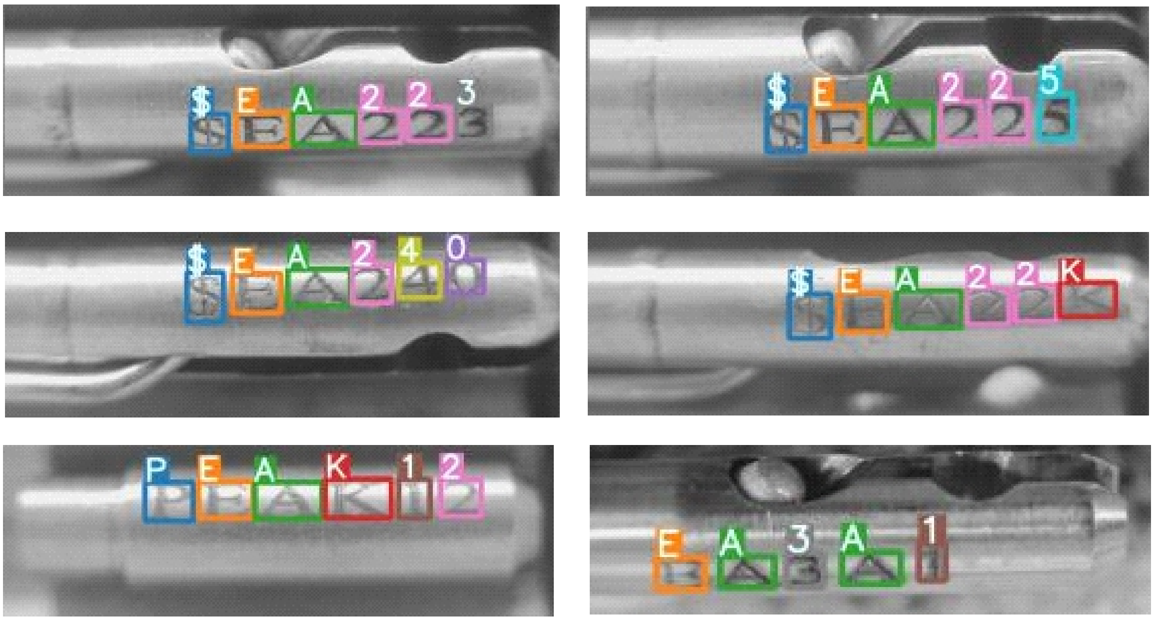

Fig.7: Recognition of fuel pin number with deep learning system.

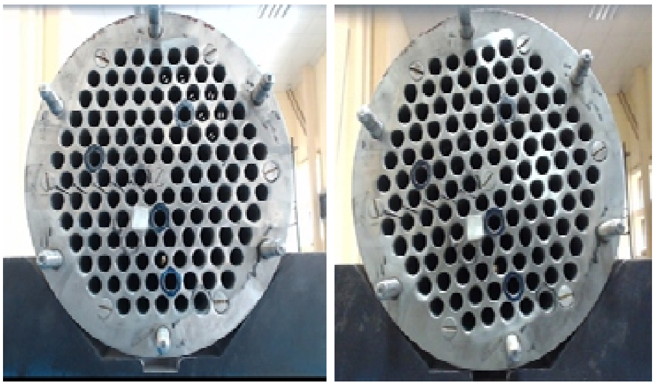

Fig.8: Orientation error because of variable transport magazine placement.

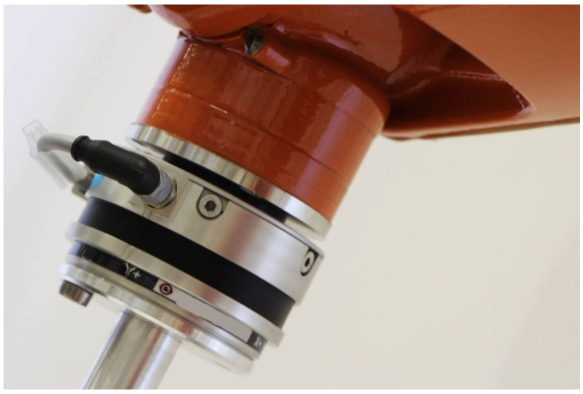

Fig.9: Force/Torque sensor for monitoring excess forces.

Innovative Techniques

Traditional industrial image processing solutions for number reading are unsuitable because of specular reflections, inconsistent number position, and the possibility of distorted and partial images. Hence, we have developed a novel deep learning technique using supervised learning. Further, estimating transport cage orientation was challenging, as installing sensors on the transport cage is not feasible. Therefore, we developed a unique vision-based technique for identifying features from the image for orientation measurement.

Deep Learning for Number Reading

A deep learning system for recognizing alphanumeric code from images (Fig.7) is one of the critical components of the automation system. The developed deep learning network identifies the engraved code sequence with an accuracy of 99.7%. We have performed supervised learning for identifying and classifying alphanumeric digits with more than 10000 images. The trained network recognizes and displays fuel pin numbers on the user interface in less than 500 msec. The operator validates this number before updating the database. The developed system helps to prevent unnecessary exposure as it is not required to go near to the pins for reading respective numbers.

Orientation Measurement System

Small orientation error (Fig.8) is possible after placement of transport magazine by a crane. The orientation error needs to be measured to modify pin position commands appropriately. A homography matrix extracts the features from images to compute rotation information. The system has a rotational measurement accuracy of $\pm 0.01^{\circ}$. We have verified the system's performance on the production floor with transport magazines in different orientations.

Online Force Monitoring for Safe Insertion

Safe insertion of fuel pin is critical as any undue forces on it may lead to bending of fuel pin. Inaccurate fuel pin alignment with the assigned magazine slot may cause forces to exceed the threshold safe limit. Therefore, during the robotic pushing of the fuel pin, force and torque values at the robot's end effector are continuously monitored. A force/torque sensor (Fig.9) between the robot and the gripper communicates with the robot. The robot halts operations when the force and torque values exceed the predefined threshold levels.

Conclusion

We have installed the robotic system (Fig.10) at PFBR fuel fabrication facility. The system provides active aid to human operators and protects them from radioactive hazards.

Fig.10: Robotic system installed at PFBR fabrication facility.

References

[1] D. Tish et al., "Highly accessible platform technologies for vision-guided, closed-loop robotic assembly of unitized enclosure systems," Construction Robotics (2020),19-29.

[2] V. Putz et al., "Computer Vision Approach for the Automated Tool Alignment of an Orbital Sanding Robot," International Federation of Autonomous Control (2019),19-24.

[3] C. Shegyong et al., "Active Vision in Robotic Systems: A Survey of Recent Developments," Int. Journal of Robotics Research (2011), 1343–1377.

[4] B. Zhang et al., "Vision-guided Robot Alignment for Scalable, Flexible Assembly and Automation," IEEE International Conference on Robotics and Biomimetic (2011), 944-951.

[5] R. Ptucha et al., "Intelligent character recognition using fully convolutional neural networks," International Journal of Pattern Recognition (2019), 604-613.

[6] R. Jain et al., "Picking of Cylindrical Fuel Pellets from a Boat Using 3D Range Sensor," International Journal of Mechatronics, Electrical and Computer Technology (2016), 2682-2688.

[7] A. Jaju et al., "Autonomous Robotic Rearrangement of Nuclear Fuel Pellets for Formation of Fixed Length Stacks," International Conference on Advanced Computation and Communications Paradigms, (2019), 1-6.

Deep Learning

8

Deep Learning based Face Recognition System

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Face recognition system developed in-house

ABSTRACT

Today, face recognition systems are able to achieve the state of the art performance using machine learning. Computer Division, BARC has designed and developed in-house face recognition system using deep learning. It recognizes more than 20,000 registered persons in an unconstrained environment. In this article, we discuss a life cycle of machine learning project with the help of the developed system. We discuss selection of performance metrics, datasets, and neural networks for achieving satisfactory performance. We talk about model deployment using edge computing. We emphasize the importance of data-centric AI development and model monitoring for maintaining an acceptable level of performance.

KEYWORDS: *Face recognition, Deep learning, Data-centric AI development, Model monitoring*

Introduction

Bhabha Atomic Research Centre (BARC) is an organization of strategic importance. Security cameras have been installed in the organization premises for video surveillance. Online intelligent face recognition systems support as well as enhance the power of manual video surveillance. Computer Division, BARC has designed and developed a face recognition system using in-house machine learning framework. Numbers of machine learning design patterns[1] are utilized during the development. It has achieved the state of the art (SOTA) accuracy using the large composite data sets. It contains 20,000 persons from open dataset and representative persons from Computer Division, BARC. In-house field trials have shown ~0% false negative and ~3% false positive rates in an unconstrained environment. A life cycle of a machine learning project starts with project scoping. It involves identifying candidate problems and defining the scope of the project with performance metrics and required resources. Then appropriate open dataset is selected or in-house dataset is collected. Then neural network models are selected, trained, and evaluated in modeling stage. These trained models are continuously monitored for acceptable performance in monitoring stage. Model retraining and dataset curation are essential to address performance degradation due to data drift or concept drift. In this article, we discuss a life cycle of machine learning project with the help of the developed face recognition system.

System Architecture

In-house face recognition system uses a full HD camera connected to a workstation with a high end graphics card for edge computing. The process is divided into three stages as shown in Fig.1. Initially, human faces are detected within input image stream. Then facial features are extracted for these detected faces. Finally these features are utilized for face classification or recognition. Intersection over Union (IoU) and Mean Average Precision(mAP) are used to track the progress of face detection. Accuracy metric is utilized to evaluate face classification.

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Dataset

Deep learning models require large datasets to achieve the state of the art performance. Open dataset such as Image Net dataset is driving force for research, where as in-house datasets are essential for local adaptations and continuous model monitoring and improvement.

Open datasets

WIDER FACE dataset[2] is a benchmark dataset for face detection. It is used for training a deep neural network. It contains 32,203 images with 3,93,703 annotated faces for bounding boxes and attributes such as scale, pose, occlusion and so on.

Microsoft dataset [4] is utilized for training of deep neural networks for facial feature extraction and face classification. The base dataset contains approximately 12 lakh aligned facial images for 20,000 celebrities. The novel dataset contains 1,000images for 1,000 celebrities.

In-house dataset

A standard operating procedure is established for in-house dataset collection. Representative employees from Computer Division, BARC have been registered. Pre-processing is performed to align facial images. In-house dataset is combined with open dataset for further processing. Rebalancing design pattern[1] is employed to reduce dataset imbalance.

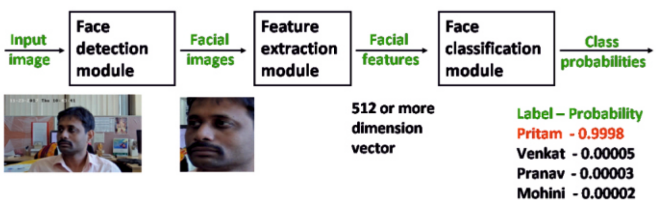


Fig.1: Overview of face recognition system.

Modeling

Numbers of neural network models are studied for face detection and face or image classification in the modeling stage.

Face detection

In-house Multi Task Cascaded Convolutional Neural Networks and You Only Look Once (YOLO)[5] are trained using WIDER FACE dataset for face detection. 94.5% accuracy is achieved on FDDB dataset[3]. YOLO provides better performance for full HD image stream.

Model centric AI development

Inception model is selected as the baseline model for performance evaluation. Inception, Inception-ResNet, and ResNet[6] models are selected for model centric AI development.

Transfer learning

Transfer learning design pattern[1] is utilized to fine-tune models trained using Image Net dataset. As shown in Table 1, comparable test dataset accuracy is observed for all models.

Table 1: Model centric AI development using transfer learning.

Models	Inception	Inception-ResNet	ResNet50-v2	ResNet152-v2
Accuracy	98.5%	98.6%	98.6%	98.65%

Without transfer learning

Models are trained from scratch using Microsoft dataset. As shown in Table 2, the accuracy is marginally better than respective models trained using transfer learning. It is mainly due to the use of Microsoft dataset as it matches better than Image Net dataset for face classification.

Table 2: Model centric AI development without using transfer learning.

Models	Inception	Inception-ResNet	ResNet50-v2	ResNet152-v2
Accuracy	99.1%	99.2%	99.2%	99.3%

Data centric AI development

Data centric AI development is performed using in-house ResNet18-v2 model. As shown in Table 3, just 75% accuracy is observed without using any data augmentation. Random crop and resize is the most dominant data augmentation for face or image classification.

Table 3: Data centric AI development using data augmentations.

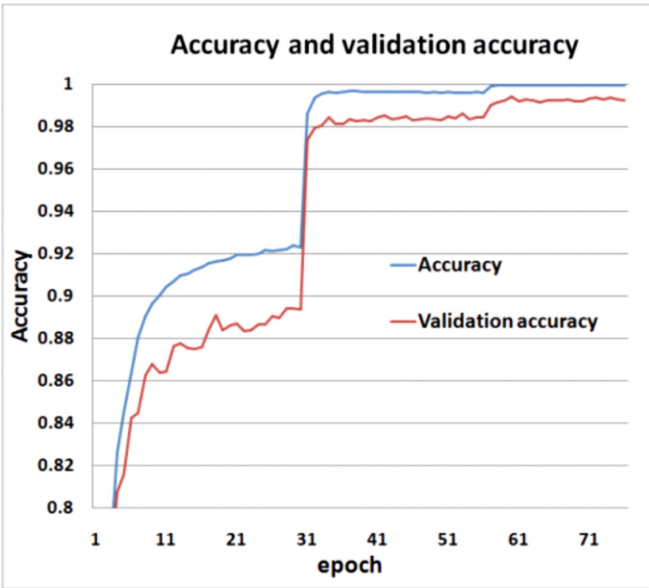
Data augmentation	No data augmentation	Random crop & random resize	Colour augmentation	Horizontal flip augmentation
Accuracy	75.0%	97.5%	98.2%	98.3%

Data curation

Rebalancing design pattern[1] is employed to reduce dataset imbalance. Microsoft dataset is pre-processed to match the deployment images. As shown in Table 4, maintaining aspect ratio and native image resolution provides the best performance.

Table 4: Data centric AI development using data curation.

Data augmentation	Native dataset	Aspect ratio	Aspect ratio plus native image resolution
Accuracy	98.75%	99.6%	99.8%



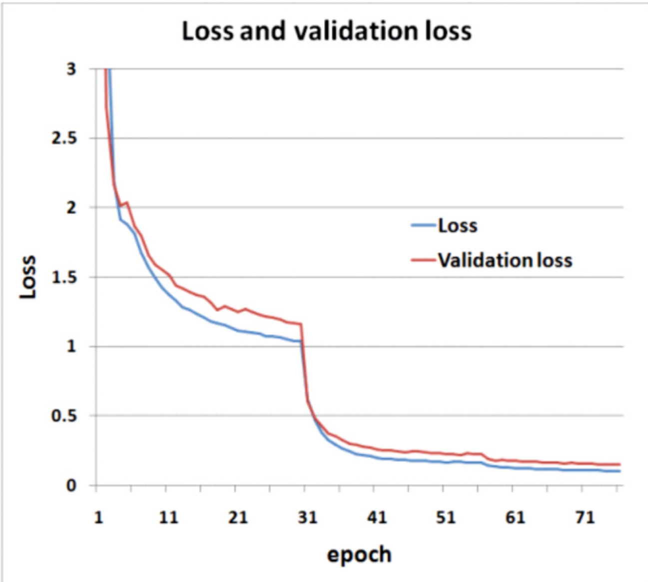


Fig.2: Model performance on training and validation datasets.

As shown in Fig.2, the low model bias and the competency of in-house ResNet18-v2 model is indicated by nearly 100% training accuracy. Data augmentations and model regularizations have reduced the gap between training and validation accuracy as well as the model variance. Training and validation losses are initially reduced sharply and then saturated with epochs.

Field Trials and Monitoring

Field trials conducted at Computer Division, BARC helped us to get more insight about the working environment and arriving at important considerations about camera, optimization of the in-house model and identifying failure cases and thereby improving the overall system.

Camera Selection

Various types of cameras are assessed for quality of acquired image stream. Image quality is improved and motion blur is reduced using appropriate camera placement and parameters. Camera is installed to cover the shortest and the tallest person without operational constrains.

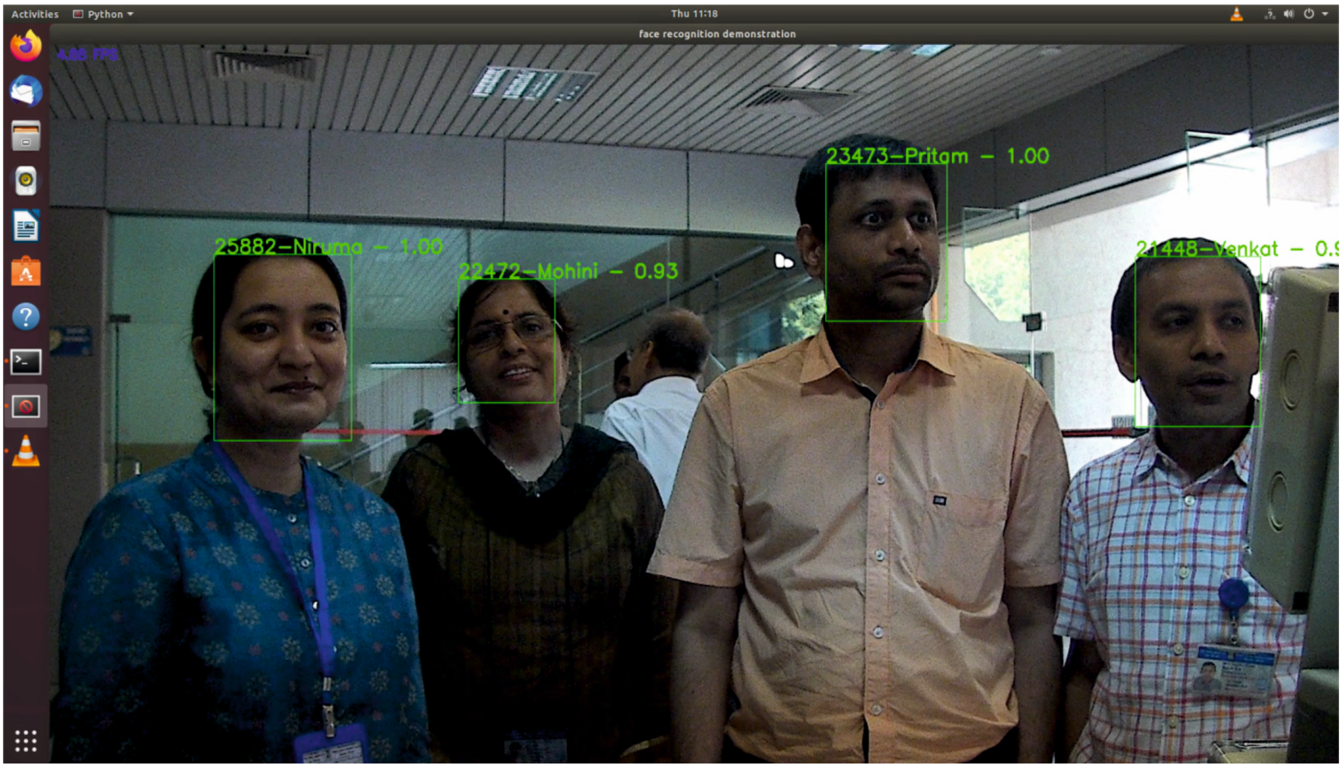


Fig.3: In-house face recognition system in action at Computer Division, BARC.

Post training optimization

Software level optimization is performed using Open CV-DNN and Tensor RT based compiler. Model quantization is utilized for algorithm level optimization for faster inference.

Edge computing

Edge computing is employed as compared to prediction server for live processing and low prediction latency. It has 100 ms latency and runs live with 10 to 15 frames per second.

Model monitoring

System performance is continuously monitored for more than 9 months. Failure cases due to eye blinking, face occlusion, facial poses, and lighting conditions are identified. These are corrected using the in-house dataset and exhaustive data augmentations.

Results

The developed system recognizes persons with eye-glasses, turban, cap and so on. It also identifies persons with different ages and different facial poses. As shown in Fig. 3, it is able to recognize multiple persons using images acquired from full HD camera. The field trials conducted in an unconstrained environment achieved ~0% false negative and ~3% false positive rate.

Conclusion

In this article, we have discussed a workstation based face recognition system developed in-house based on deep learning techniques and its full life cycle. During the field trials we have demonstrated the competency of system even in an unconstrained environment. The system achieved ~99.8% accuracy on open datasets containing more than 20,000 persons.

References

[1] Valliappa Lakshmanan and et. al., Machine Learning Design Patterns: Solutions to Common Challenges in Data Preparation, Model Building, and MLOps, O'Reilly Media, October 2020.

[2] Yang and et. al., "WIDER FACE - A Face Detection Benchmark", in Proc. of IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016.

[3] Vidit Jainand et. al., "FDDB - A Benchmark for Face Detection in Unconstrained Settings", Technical Report UM-CS-2010-2009, University of Massachusetts, 2010.

[4] Yandong Guo and et. al., "MS-Celeb-1M - A Dataset and Benchmark for Large-Scale Face Recognition", in Proc. of European Conference on Computer Vision, ECCV 2016.

[5] Alexey Bochkovskiy and et. al., "YOLOv4 - Optimal Speed and Accuracy of Object Detection", arXiv, 2020.

[6] Kaiming He and et. al., "Deep Residual Learning for Image Recognition", in Proc. of 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016.

Deep Learning

9

Deep Learning based Head Pose Estimation & Fiducial Localization for Neuro Navigation

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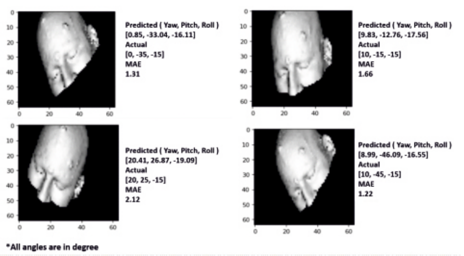

Predictions over 3D head volume (MRI data) with ground truth

ABSTRACT

Image guided neurosurgical systems have proven very effective in terms of reducing hospitalization and recovery time due to their minimally invasive and precise nature of neurosurgical procedures. In this regard, an initiative has been undertaken by DRHR and CD[1]to extend affordable high-quality neurosurgical practice in India. Estimation of head pose of patient and establishing its relationship with medical imaging data is crucial for surgery planning and patient placement. Once the patient is in surgical setting, fiducial markers affixed on patient's head are localized[2] to establish a complete process of registration between the patient and medical imaging data. Deep learning-based head pose estimation system described in this article has achieved an accuracy of 4-degree MAE (Mean Absolute Error)over a typical patient as well as for medical imaging data. Further, fine sub-slice based fiducial localization technique has achieved 30% reduction in localization time with significant improvement in precision and recall.

KEYWORDS: *Medical imaging, Head pose estimation, Image guided brain surgery, deep residual network, Fiducial localization*

Introduction

Minimally invasive surgery can be performed with distinctness, less bleeding and having faster healing time using robots. Owing to the anatomical complexities of the brain, application of robotic systems in neurosurgery is limited as compared to other medical fields. Even a minor mistake during surgery can lead to disastrous effect. Hence, the biggest problem faced by the neurosurgeons is the visibility inside the patient's skull while performing the brain related procedures. To have visibility of the brain interiors, surgeons are heavily dependent on the medical imaging data both for diagnosis as well as for surgery planning.

Head pose of patient during medical imaging and surgery may not be same. Also, due to constrained motion of robot, sometimes we need to orient patient to ensure reachability of robot and surgical tool. Hence, we need to align the medical imaging head pose with the head pose of patient during the surgery, i.e., registration. This article presents two crucial components of Neuro navigation system,

1. Head pose estimation of patient and medical imaging data
2. Gross localization of fiducials

The estimated head pose information is utilized to accomplish coarse alignment of patient and medical imaging head volume, where as the localized fiducial coordinates are utilized to provide guidance in establishing a fine registration between patient and medical imaging data.

Head pose estimation for patient and medical imaging data

Head poses of both patient and medical imaging data are required to establish correspondence between them. This correspondence is required in surgery planning, patient placement and successful execution of surgery. For estimating the pose angles, Deep learning based CNN architectures are used. The following sections will provide details of the data sets, architecture, training of the model and results.

Dataset

For human head pose estimation, we have used open source labelled data sets like BIWI Kinect head pose[4], 300W_LP[5] and AFLW 2000[6]. For medical imaging head pose we have generated two different data sets (of different sizes, 50k and 150k) using anonymized MRI samples.

Solution architecture

Proposed method for patient head pose estimation takes RGB frame as input and applies face detection over it. Detected face data is passed to a Convolutional Neural Network to predict Yaw, Pitch and Roll angles. In our initial experiments, we have modified AlexNet architecture for prediction, where we observed accuracy saturation below our desired level (Fig.2). In our later experiments, we have used a modified ResNet50[3] architecture to predict the corresponding pose angles. Fig.1

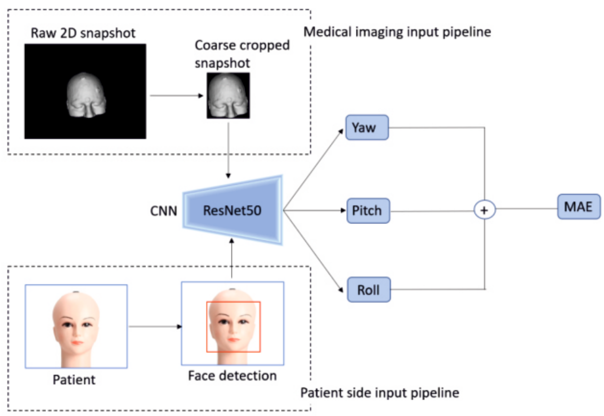

Fig.1: Head pose estimation pipeline for patient and medical imaging data.

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depicts the graphical representation of patient and medical imaging head pose estimation pipeline.

3D reconstruction of MRI data contains only half of the face; hence the use of face detector is restricted. In this case, we have applied a coarse cropping mechanism to crop out the face area from medical imaging data. This cropped part is provided to backbone CNN to predict the yaw, pitch and roll angles.

Evaluation metric

The evaluation work estimates yaw, pitch and roll angles associated with head pose and attempts to minimize mean absolute error(MAE) across all the three angles as given in Equation 1.

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \quad (1)$$

Equation 1: Formula to calculate Mean Absolute Error, in our case n=3 (yaw, pitch, roll), y (predicted angle) and x (true angle)

Training

Fig.2 represents validation loss for different training experiments conducted using modified AlexNet architecture for patient's head pose estimation. Here, we can observe the variation of Mean Absolute Error(MAE) with respect to epochs (the number of passes of the entire training dataset through neural network). Fig.2 also compares the variation of MAE for different batch sizes (BS). Fig.3 depicts the training and validation loss achieved during experimentation with ResNet50 architecture for the same problem, where we can observe significant reduction in validation loss compared to AlexNet.

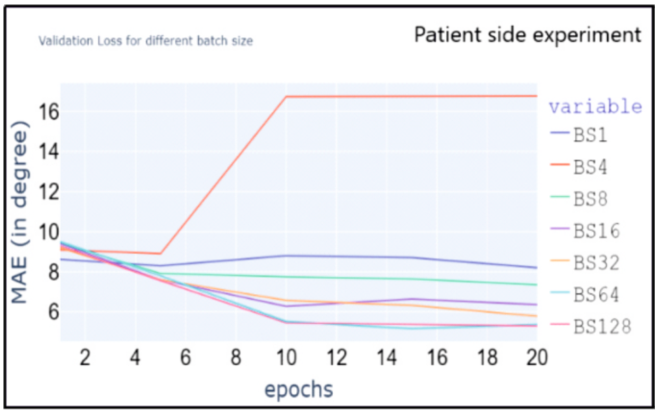

Fig.2: Validation loss-AlexNet.

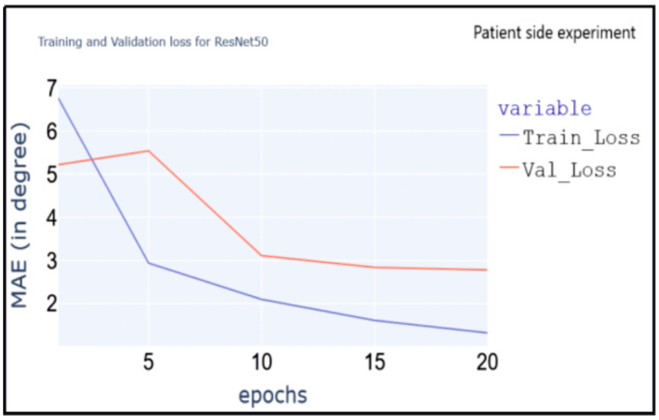

Fig.3: Validation loss - ResNet50.

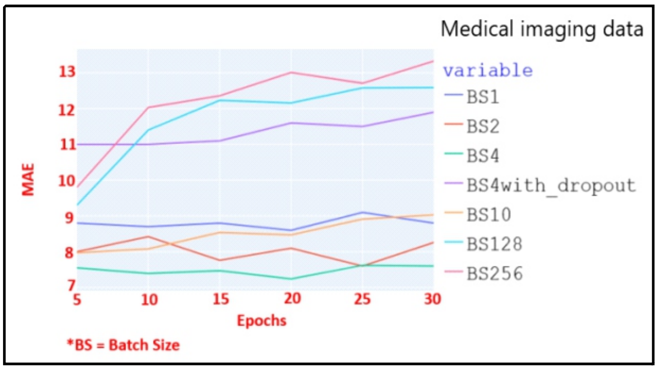

Fig.4: Validation loss-AlexNet.

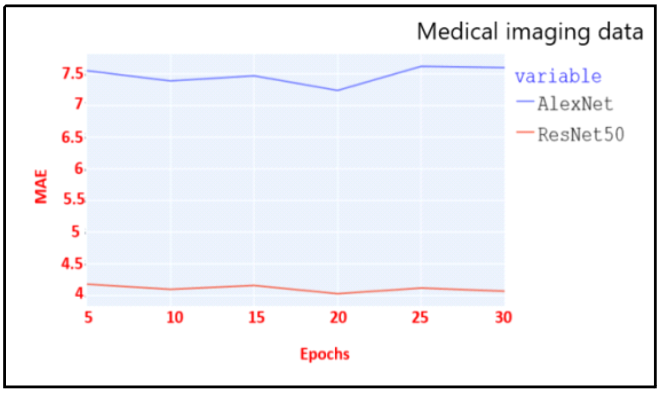

Fig.5: Comparison of AlexNet and ResNet50.

Table 1: Comparison of MAE over BIWI dataset for patient head pose.

Method	MAE (in degree) over complete BIWI dataset
Modified AlexNet trained over BIWI	3.58
Modified AlexNet trained over 300W_LP	7.77
Modified ResNet50 trained over 300W_LP	4.31

Fig.4 represents validation loss for different training experiments using modified AlexNet for medical imaging data. We can observe a significant reduction in validation loss using ResNet50 architecture for medical imaging head pose as depicted in Fig.5.

Results

Table 1 shows the performance of patient head pose estimation models over BIWI dataset, while Fig.6 depicts the predicted yaw, pitch and roll angles for medical imaging data.

Gross Localization of Fiducials

Fiducial localization is a complex and critical process, which requires manual annotation of fiducials over entire MRI volume. Gross localization of fiducials results in a bounded region of interest where fiducials are located. This accelerates the localization process and improves the overall efficiency of surgery. For gross localization of fiducials, deep learning based CNN architectures are used. The following sections will detail the data sets, architecture, training of the model and results.

Dataset

We have anonymized MRI data as received from a Hospital. Each MRI volume has 256x256x84 voxels with a resolution of 1mm x 1mm x 2mm.

Solution architecture

This work takes an axial slice of MRI as input and extracts the boundary (pronounced) of the slice which may contain

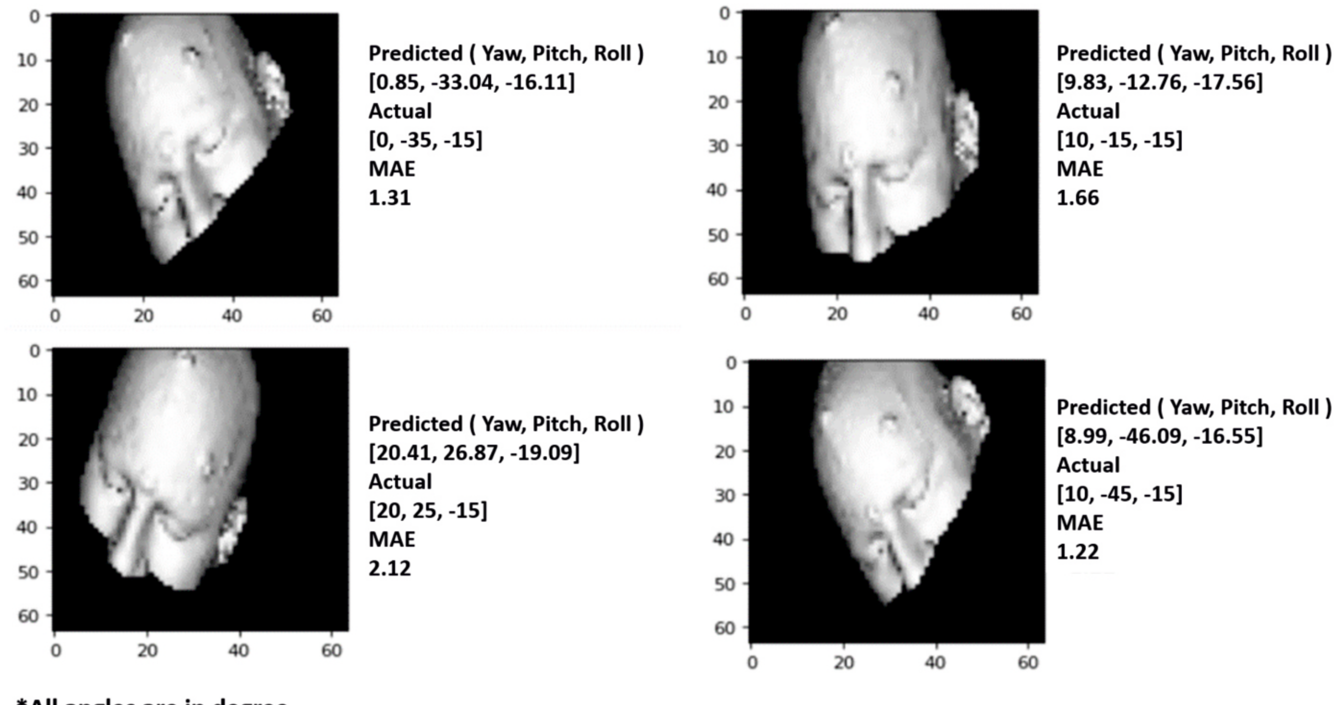

Fig.6: Predictions over 3D head volume (MRI data) with ground truth.

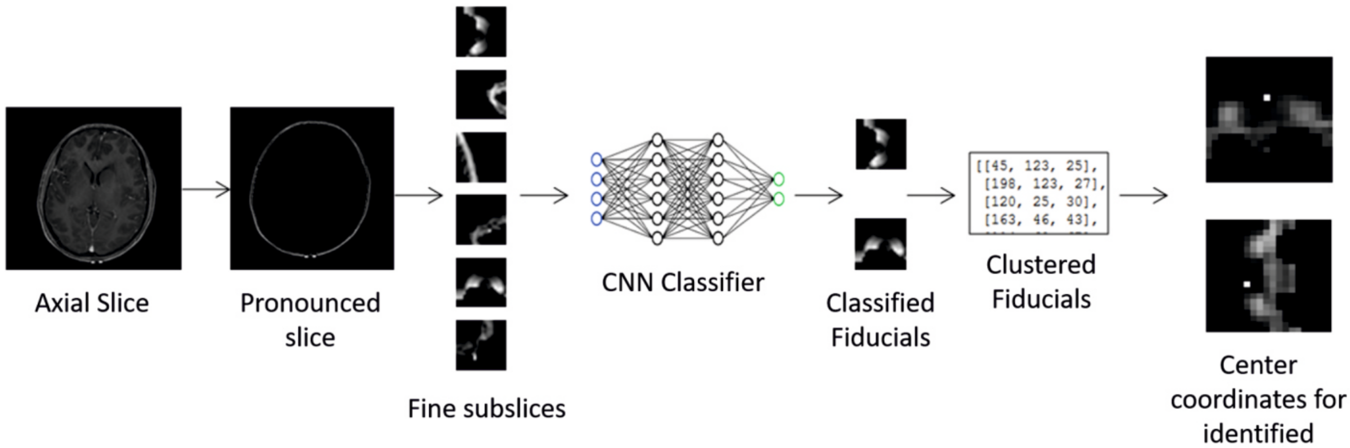

Fig.7: Solution architecture for fiducial localization.

fiducials. The pronounced slice is then divided into small fine sub-slices and passed on to the sub-slice classification network. Fig.7 depicts the solution architecture for gross localization of fiducials.

The sub-slice classification network as shown in Fig. 8 is built by aggregating the standard Deep Learning blocks viz. Convolution-Relu-Pooling (CRP), CR (Convolution-Relu), FCR (Fully Connected Relu) etc. The final sigmoid layer provides probability of whether the input sub-slice contains fiducial or not. We have used DBSCAN[7] clustering algorithm to identify the number of fiducials in an input volume by merging the neighborhood sub-slices(or fiducial candidates). The center of cluster of fiducials is taken as localized fiducial.

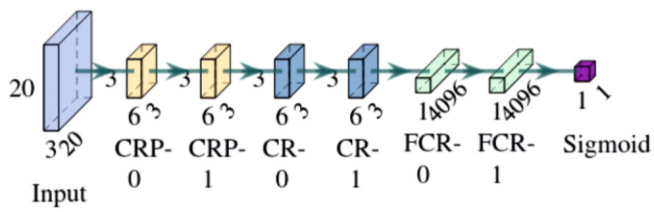

Fig.8: Sub-slice classification network.

Results

This method achieved a fiducial localization error of 4.3 mm, which implies a bounded 4.3mm spherical region of interest where fiducial is located. Now the doctors can refine the localization within the bounded region instead of scanning through the entire MRI volume, which reduces the localization time by 30%. Fig. 9 shows the localized fiducials over 3D head volume.

Conclusion

This article is a step towards head pose estimation for a neurosurgery and it presents a solution to establish a coarse alignment between patient's head and medical imaging data by estimating the head pose. Further, gross localization of fiducials reduces the localization time hence providing an assistance to doctors. The software modules developed here are currently under integration phase with the Neuro navigation system developed by BARC.

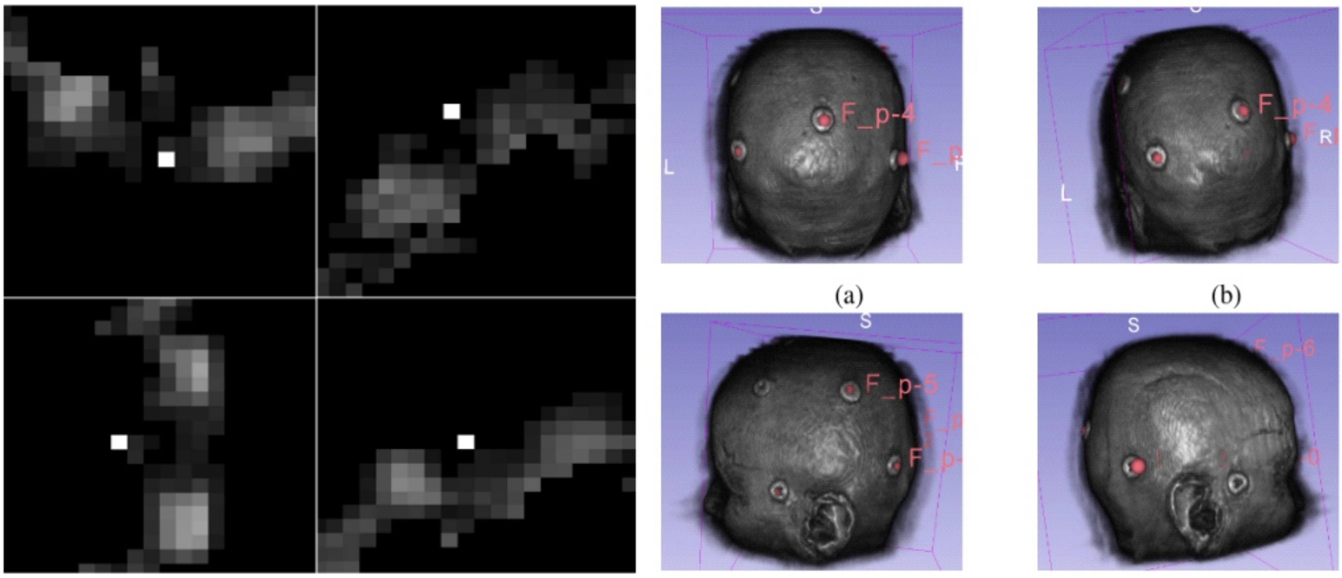

Fig.9: Fiducial localization in MRI sub-slices (left), Fiducial localization over test dataset (right).

References

[1] Gaurav Bhutani, T. A. Dwarakanath, K. D. Lagoo, Aliasgar Moiyadi and Venkata P P K: Neuro-Registration and Navigation Unit for Surgical Manipulation. In: 1st International and 16th National Conference on Machines and Mechanisms (iNaCoMM2013), IIT Roorkee (2013).

[2] Gaur, P., Bhardwaj, A., Venkata, P., Sarode, D. and Mahajan, A.: Assistance technique for Fiducial Localization in MRI images with Subslice Classification Neural Network. 6th International Conference on Intelligent Computing and Control Systems (ICICCS) (2022).

[3] He, K., Zhang, X., Ren, S. and Sun, J.: Deep Residual Learning for Image Recognition. In: IEEE Conference on Computer Vision and Pattern Recognition (CVPR).(2016)

[4] BIWI Dataset https://www.kaggle.com/datasets/kmader/biwi-kinect-head-pose-database

[5] 300W_LP Dataset https://www.tensorflow.org/datasets/catalog/the300w_lp

[6] AFLW Dataset https://www.tensorflow.org/datasets/catalog/aflw2k3d

[7] Deng, D. "DBSCAN clustering algorithm based on density," 2020 7th International Forum on Electrical Engineering and Automation (IFEEA) (2020).

Deep Learning

10

Dataset Preparation for Deep Learning based Applications

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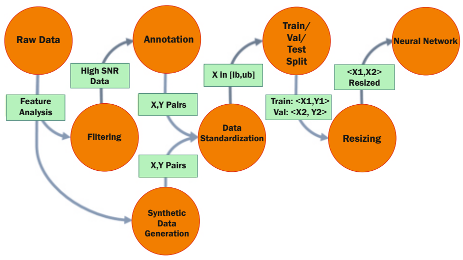

Stages of data-preparation for Deep Learning applications

ABSTRACT

State-of-art Deep learning model implementations for various forms of classification and regression tasks are publicly available. The biggest roadblock in adapting such implementations for the "use-case" arises from the unavailability or unsuitability of raw dataset acquired from the field for model training. A dataset preparation strategy assists in reliably transforming the raw-data acquired from field-sensors to the input for training the Deep learning models. We have introduced data-preparation process for Deep Learning based applications in context to the development of an Automatic Number Plate Recognition (ANPR) model. We have demonstrated the impact of strategizing dataset generation on the performance of the resulting ANPR model. We observed that systematically enhancing the number of text-fonts while keeping other image-generation parameters fixed, resulted in Word-error-rate(WER) dropping from 100% to 10%, whereas, merely increasing the number of training examples randomly, did not have any significant effect on the model performance.

KEYWORDS: *Dataset, Automatic number plate recognition (ANPR), Data-Augmentation, Ablation experiment*

Introduction

Deep learning based methods have pushed the state-of-art in various problem domains of academic interests. Implementations, pre-trained models and datasets for common-tasks are readily available. However, the specific versions of such tasks which are often encountered in the industry do not have public availability of corresponding assets owing to the narrow scope of these problems. For instance, in context of the automation to the generic visual inspection tasks, assets like object-detection, Optical Character Recognition (OCR) and object-tracking algorithm implementations, pre-trained models and datasets are readily available. However, no diverse *annotated* dataset for Indian Automatic Number Plate Recognition model exists in the public domain, requiring manpower involvement to prepare dataset first so as to be able to leverage benefits of AI for Indian ANPR. The current article is motivated by the fact that most research-works in the domain of image-to-text conversion task (like ANPR) state results on publicly available datasets[1] and the ones releasing public datasets give little insight into the impact of dataset preparation on the model training performance[2]. We have discussed the stages of dataset preparation in context to ANPR model development process along with the evaluation metrics. Experiment section of this article presents the quantitative evidence towards the significance of strategizing dataset preparation for fine-tuning model performance. Discussion section of this article highlights the implications of the results followed by the conclusion section which culminates the article outlining future directions.

Methodology

Dataset preparation process for Deep learning applications is depicted in Fig.1. Subsequent sections discuss details of the stages in context to the ANPR application and culminate into a discussion of the evaluation metrics.

Raw data collection and analysis stage

The raw data generated by sensors is collected and its distribution is analyzed in order to assess and quantify the features relevant to the target application. For instance, for vehicle number recognition application, IP camera stream from the deployment site can provide collection of images of incoming vehicles from which the number-plate text-color, background, font and orientation can be analyzed to identify the probable range of variations for each feature. The identified range of variations for these image-parameters can assist in realistic synthetic dataset generation.

Synthetic dataset generation and augmentation stage

Data augmentation and synthetic dataset generation can assist in utilizing the available dataset on large-scale for sample-efficient model training. The raw data samples and the analysis drawn earlier serve as key-inputs for this stage. Synthetic dataset generation involves varying the data-set

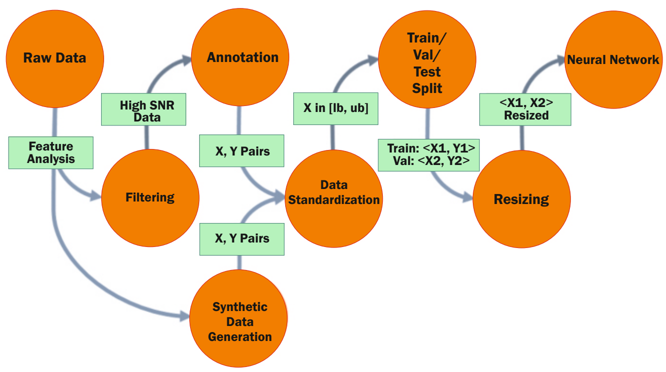

Fig.1: Stages of data-preparation for Deep Learning applications.

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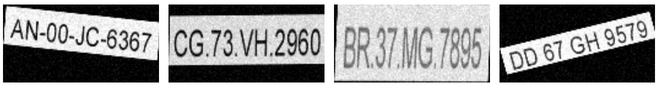

Fig.2: Some samples from synthetic number-plate dataset, showing variation in number-plate orientations, text-font, number-format, number-plate backgrounds.

parameters across a range and generating artificial annotated samples. To achieve an overlap between the distribution of the generated and real datasets, the empirically derived range of variation for each feature of real data is crucial. Dataset augmentation, on the other hand, assumes existing dataset samples over which the feature variations could be applied to generate more dataset samples. In ANPR application, synthetic number-plate images could be generated through a program using image-synthesis software libraries.

Realistic number-plate images, as shown in Fig.2, could be generated by varying number-plate text background, font, size, color, orientation as per the real-image data distribution inferred from the last stage.

Data filtering stage

Given raw data feed and the feature analysis from the last stage, we can selectively sample the raw-dataset by filtering noisy (or low-information) samples, thereby boosting its signal-to-noise (SNR) ratio. In ANPR application, images with vehicles are more relevant than background images for training number-plate recognition model. Further, if an area is marked as the region-of-interest (ROI) in the camera image-view, then the images with a vehicle in ROI are more relevant than the images with vehicle outside ROI. Similarly, for vehicle class prediction, if the current model performs well for ‘Jeep’ and ‘Car’ recognition, while predicts ‘Bus’ and ‘Motorcycle’ with low confidence, we can use the current model to semi-automatically filter-out images with only Jeeps and Cars from the raw dataset.

Dataset annotation stage

The filtered dataset can be used for model training after it has been annotated with the corresponding ground-truth labels, thereby generating sample(X) and label(Y) pairs as shown in Fig.1. In ANPR application, for each number-plate image, the number-plate text defines its ground-truth annotation. Program scripts leveraging previously trained number-plate prediction models could be used to semi-automatically label the number-plate images and can then later be manually fine-tuned.

Dataset standardization stage

As with any numerical optimization method, model training convergence for Deep learning applications is critical. Dataset features--identified in the first stage--have wild variation in the value ranges they acquire which often negatively affects the stability of model training and render it biased towards features with higher magnitudes. Dataset normalization counters this by explicitly defining a common fixed range of values (the lower and upper bounds) across all features of the dataset, shown as [lb, ub] in the Fig.1. In ANPR application, input number-plate images from RGB color-space are mapped to a more limited grayscale color-space thereby reducing the possible values each pixel can acquire.

Dataset splitting stage

The process of partitioning the available annotated dataset into train, validation and test datasets is called dataset-splitting. The test-dataset often comes from the end-user and is kept hidden during model-development, therefore, often this stage involves partitioning the available dataset into train and validation dataset, shown as <X1, Y1> and <X2, Y2>, respectively in Fig. 1. The validation dataset is supposed to test the model during training and is therefore not exposed to the model for training. In ANPR application, 80%-20% dataset split strategy is followed to generate train and validation datasets respectively from the available annotated dataset. The validation samples are drawn randomly from the dataset to avoid distribution bias.

Dataset resizing stage

Neural networks assume their input to be fixed in size, whereas the raw-data from field sensors comes in variety of resolutions. The normalized dataset, is therefore, resized to

Table 1: Ablation study of ANPR model performance with respect to number of text-font.

Index	Training data	Validation data	CER and WER
1	128 K frontal images with 1 font class	12.8K frontal images with 1 font class	100, 100
2	1.28 M frontal images with 1 font class	128K frontal images with 1 font class	100, 100
3	100 K images with 1 font class, random rotation, translation and Gaussian noise	20 K images with 1 font class, random rotation, translation and Gaussian noise	66.29, 100
4	50 K images, 5 font - classes	10 k with 5 font - classes	18.38, 98.57
5	50 K images, 5 font - classes, test- image background	10 kwith 5 font -classes, test-image background	10.05, 71.43
6	100 K images, 5 font - classes	20 kimages, 5 font -classes	5.22, 41.43
7	100 K images, 10 font - classes	20 kimages, 10 font-classes	3.80, 28.57
8	200 K, 10 font- classes	40 k images, 10 font -classes	**1.62, 10.0**

the network input size. For instance, in ANPR application, YOLOv3 model-based vehicle number-plate detector assumes input image to be of size 416 x 416 pixels, whereas the input image from IP camera has a resolution of 1920x1080 pixels, therefore input image needs to be resized from original resolution to 416x416. Further, notice that the network input size has 1:1 aspect ratio, while most image formats have 6:4, 4:3 aspect ratios, therefore, a resizing strategy which preserves the original aspect ratio-like the letterbox resizing-needs to be adopted to preserve the legibility of relevant features.

Evaluation metrics

For quantitative assessment of the effect of a data-preparation strategy on model-performance, an evaluation metric is crucial. Evaluation metric represents the objective of a target application against which various data-preparation and model training strategies could be assessed. For ANPR application, Word error rate (WER) and Character error rate (CER) [4] over a test-dataset are used to assess the effectiveness of a trained model against vehicle number prediction task.

Experiments

An ablation experiment demonstrating the impact of text font as a synthetic dataset generation parameter for vehicle number recognition task is reported in Table-1. The experiments are conducted on a PC with Intel Core processor (2GHz), 8GB RAM, NVIDIA Quadro M4000 GPU, Ubuntu 18.04 OS and TensorFlow 1.14 library. The test-dataset contains 100 images of vehicle number-plate collected from an IP camera installed at the ANPR system deployment site.

Discussion

Progressively incrementing the number of text fonts used to generate synthetic vehicle number-plate dataset reduced the WER from 100% to 10% as shown in experiments Sr. no. 4 through 8 of Table-1, indicating that merely exposing the model to variations in text font helps in generalizing it over number-plate text in test-dataset. However, adding more images without content variations did not affect the WER as can be observed in experiments Sr. no. 1 and 2 of Table-1. In experiment Sr. no. 5, adding a number-plate text background drawn from real number-plate images, significantly brought down the WER, which indicates the impact of bringing realism to the synthetically generated number-plate images, as can be achieved using Pix2Pix GANs[3].

Conclusion

We have described a generic data-preparation process for deep-learning in context of an ANPR application. The significance of data-preparation process is experimentally demonstrated with an ablation study over the effect of number-plate text-font on resulting Word-error-rate (WER) of the underlying number-plate recognition model. The experiment highlights the importance of aligning the synthetic dataset-distribution to be as close to real-dataset as possible, which we would like to explore in the context of ANPR application by leveraging generative models.

References

[1] Changhao Wu, Shugong Xu, Guocong Song, Shunqing Zhang, How many labeled license plates are needed?, arXiv:1808.08410, 2018.

[2] Zhenbo Xu, Wei Yang, Ajin, Meng, Nanxue Lu, Huan Huang, Changchun Ying, Liusheng Huang Towards End-to-End License Plate Detection and Recognition: A Large Dataset and Baseline, ECCV 2018.

[3] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, Alexei A. Efros, Image-to-Image Translation with Conditional Adversarial Networks, arXiv:1611.07004, 2017.

[4] Neudecker, C, Baierer, K, Gerber, M, Clausner, C, Antonacopoulos, A and Pletschacher, SA survey of OCR evaluation tools and metrics, HIP '21: The 6th International Workshop on Historical Document Imaging and Processing, 2021.

Artificial Intelligence

11

Applications of AI Methods for Driving Innovation in Modern Astronomy

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MACE telescope operated by BARC at Hanle in Leh

ABSTRACT

Astronomy is the oldest branch of science which evolved through the observations and data logging of the key studies of the solar system. As telescopes grew more powerful, the study expanded to the entire Universe thereby generating "astronomical" volumes of data. Artificial Intelligence is a new branch of science that astronomers are using as a powerful discovery tool to study rich but complex data and sift through data in search of signals. A whole new world of unexplored objects is being experimented with, thus generating a new world order-the "AI-powered Astronomy". In this article, we discuss general and mega-science applications of AI-based study of astronomy.

KEYWORDS: *Artificial intelligence, Machine learning, Astronomy*

Introduction

Artificial Intelligence (AI) name was proposed by J. McCarthy in 1956. AI can be considered as science that enables machines to take decisions as opposed to natural intelligence, similar to what humans would do. The AI methodology involves learning from the human intelligence and then developing computer algorithms for its execution. Based on the problem at hand, a flexible but efficient approach is used for problem-solving. The human intelligence is a manifestation of the biological brain which consists of a massively parallel set of neurons that can succeed at cognitive and control tasks. The advantage of the brain is its effective use of massive parallelism, a highly parallel computing structure with imprecise information processing capability. The human brain is a collection of ~11 billion interconnected neurons, where each neuron receives, processes and transmits information. The neurons use chemical reactions to process information. This collective model and processing is referred to as the biological neural system. AI are computational models which have been developed as generalizations of the mathematical models of the biological nervous system[1]. AI models e.g like the Artificial Neural Networks (ANN) have been developed as generalizations of mathematical models of biological system.

Need for Artificial Intelligence in Astronomy

Astronomy is one of the oldest branches of science which humans studied while AI is one of the newest branches of science. Study of astronomy is an observational science which developed due to mankind's quest for observing the night sky, which was not only fascinating, but also helped in day today tasks like creating calendars and navigation. An important development was the use of mathematical and geometrical models to study motion of the planetary objects. Early astronomers maintained a detailed record of the position of the celestial bodies. It is since then that data analysis has played a pivotal role in astronomy. Astronomers required the formulation of theories and mathematical equations in order to explain the universe. As the interest in astronomy grew, especially in last 100 years or so, it lead to generation of voluminous data which started becoming extremely cumbersome to analyze. Fortunately, due to the incredible progress in computational field due to availability of highly efficient processors, coupled with theoretical understanding of techniques such as Machine Learning (ML) have allowed AI to advance at a frantic rate. The exponentially increasing astronomical data raises the requirement for an efficient paradigm. Data analysis must become more automated and efficient, particularly through AI. In our efforts to understand the Universe, mankind is developing satellites and telescopes which will yield hundreds of tera-bytes of data/year. It will become impossible for scientists to sift through the data to generate meaningful science. This is where AI has proved to be God-sent, with its capability to automate almost anything. It is thus certainly an understatement that artificial intelligence (AI) has taken the astronomy by storm, with breakthroughs appearing on a daily basis.

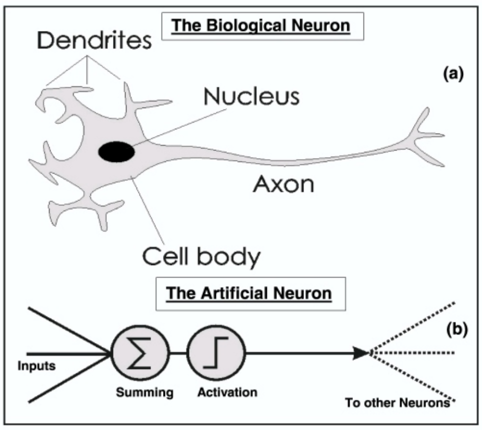

Fig.1: Schematic diagram of a typical neuron or a nerve cell in a biological neuron and the artificial (computer) model of a biological neuron.

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To quantify the above, as a thumb-rule in astronomy, the information we collect is roughly doubling every year[2]. The Hubble Telescope e.g., operating since 1990 gathers ~20GB of data/ week, the Large Synoptic Survey Telescope (LSST), is expected to gather ~30 TB of data/night. This however is negligible compared to the ambitious Square Kilometer Array (SKA). With its 2000 radio dishes and 2 million low-frequency antennas, it is expected to produce ~1Exabyte/day (~ more data produced in a day in comparison to what internet produces in a year)[3].

General AI applications in Astronomy

Historically, the first astronomical application of AI was the star-galaxy recognition problem and the spectral and morphological classifications of galaxies[4,5]. AI has also been applied to planetary data for prediction of solar activity phenomena[6]. This study enables us to understand the interplanetary magnetic field and stellar astrophysics.

AI application in astronomy can broadly be classified into time series analysis, identification of peculiar objects (QSO's, IR galaxies and Gamma-ray Bursts) and determination of photometric redshifts. Additionally, the new generation mega-science projects like LIGO, James Webb, and SKA have generated interest in AI application to data analysis.

Time series analysis: It concerns finding the variable signal in the time domain of data which was previously thought to be constant. This can be accomplished if and only if the observation and analysis techniques become more sensitive. Typical examples can be found in the study of light curves of variable stars and the study of Active Galactic Nuclei, the extragalactic sources powered by a central black hole[7]. Tools based on the use of Fourier analysis have been employed for such analysis[8,9] but if the astronomy data is unevenly sampled, the above techniques lead to erroneous results. Resampling of the data has been attempted via interpolation but it introduces amplification of the noise and hence Fourier, which is critically dependent on noise, cannot be used. Oppehium & Schafer[10] proposed the use of an algorithm based on a frequency estimator and a Neural Network for finding the Principal Component Analysis (PCA) & auto correlation matrix. After Neural Network training, the signal frequencies estimated are obtained for the weight matrix and eventually fed to the frequency estimator for final analysis.

Object detection using AI

For processing the astronomical data/image, the goal here is to make a catalog of astrometric/geometric morphology and estimate the photometric parameters of the image. However, the problems encountered are related to the low, comparable, or even fainter surface brightness compared to the image threshold. Also, many fainter objects that are present in the image are not detected by the analysis procedure due to extremely faint glow/signal, while others that are not present in the image are spuriously detected (spurious objects). The Neural Network package implemented by the group[11], performs object detection, de-blending and star/galaxy classification through mapping pixel intensities through PCA. Software package 'NExt' is employed to lower the dimensionality of the input pattern and an unsupervised PCA-Neural Network is used to identify significant features.

The photometric redshift of galaxies

The redshift of a galaxy which is recession velocity from the observer is of great importance in astronomy as it provides an estimate of the galaxy distance. Conventionally, redshift is measured spectroscopically, which is time-consuming or via photometry, which is less accurate and has more systematic errors. Baum et.al.,[12,13,14] used the Sloan Digital Sky Survey Early data which has photometric data for ~16 million galaxies and spectroscopic redshift for ~50,000 objects distributed over a large redshift range. They used unsupervised Self-Organizing Maps (SOM) to cluster the data in the training and test set to ensure complete coverage of the input parameter space. A MultiLayer Perceptron (MLP) neural model in the Bayesian framework is then used to estimate the photometric redshifts. A labeled SOM is used to derive the completeness and contamination of the final catalogs. To build the training/test sets, a set of parameters consisting of star magnitudes (namely u, g, r, i&z), flux levels, surface brightness and extinction coefficients,[14] were extracted from the data.

Application in Mega Science Projects

Laser Interferometer Gravitational-Wave Observatory

The Laser Interferometer Gravitational-Wave Observatory (LIGO) is a large-scale physics experiment for the detection of cosmic gravitational waves. LIGO-India is a planned advanced gravitational-wave observatory to be located in India as part of the worldwide network. The LIGO project operates three gravitational-wave (GW) detectors [15]. Two of these are situated in Hanford, Washington, and one is in Livingston, USA. The LIGO-India project is an international collaboration between the LIGO Laboratory and DAE institutes IPR-Gandhinagar, IUCAA- Pune and RRCAT- Indore.

Information extracted by the transmitted waves will help to address unsolved questions and mysteries of physics and astronomy. Gravitational waves were first detected in 2015 by LIGO, which marked the birth of gravitational wave astronomy. As LIGO continues to upgrade detector sensitivity to gravitational waves, it will be able to probe a larger volume of the universe-making the detection of gravitational wave sources a daily occurrence rather than weekly or monthly, thereby generating huge volume of data. Recently, Argonne National Laboratory (ANL, USA) along with collaborators developed a new AI framework that allows for accelerated and reproducible detection of gravitational waves. This new framework indicates that AI models could not only be very sensitive as traditional template matching algorithms but also orders of magnitude faster. Furthermore, these AI algorithms would only require an inexpensive GPU, to process data faster than in real-time [16]. The AI ensemble used for this study processed e.g., an entire month (August 2017) of advanced LIGO data in less than 7 minutes. In a significant study, the AI ensemble used for this analysis identified all four binary black hole mergers previously identified in that dataset and reported no misclassifications.

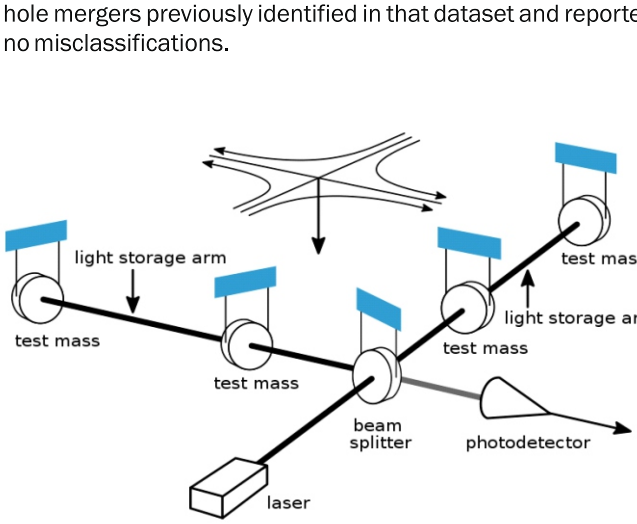

Fig.2: A Schematic of the LIGO Detector (Source: Nuclear Instruments and Methods in Physics Research A517, 1–3, 2004).

James Webb Space Telescope

James Webb Space Telescope (JWST) is the largest and most powerful space-based telescope ever constructed. It is an infrared space observatory with a 25 m^2 aperture (6 m class) telescope that will achieve diffraction-limited angular resolution at a wavelength of 2 μm[17]. The observatory will have four instruments: a near-IR camera, a near-IR multi-object spectrograph, and a tuneable filter imager which will cover the wavelength range $0.6 < \lambda < 5.0$ μm, while the mid-IR instrument will do both imaging and spectroscopy from $5.0 < \lambda < 29$ μm. The key science objective is to determine how galaxies and the dark matter, gas, stars, metals, morphological structures, and active nuclei within them evolved from the epoch of re-ionization to the present day. Keeping the above science goals in view, a rough estimate is that JWST will yield ~60GB of data/day. It will be an extremely cumbersome without any realistic methods for the scientific community to analyse such voluminous data.

To do away with the above difficulty, a machine learning model called Morpheus will be used to detect and classify galaxies in deep space and to map the earliest structures in the universe. Morpheus is a deep-learning-based AI model for image analysis of astronomical sources. It uses powerful AI models for detecting and classification of galaxies. Morpheus was trained on UC Santa Cruz's Lux supercomputer - which has 28 GPU nodes with two Nvidia V100 Tensor Core GPUs each. As data and images are sent from the telescope to Earth, that information will be fed into the AI models. The UC Santa Cruz's Computer Science and Astronomy department has created the deep learning framework that classifies astronomical objects, such as galaxies, based on the raw data streaming out of telescopes on a pixel-by-pixel basis. About half a million galaxies will be surveyed using multiband near-infrared imaging and 32,000 galaxies in mid-infrared imaging, a mammoth task that cannot be accomplished without the application of AI methods.

Square Kilometer Array

The Square Kilometer Array (SKA) project is an international effort to build the world's largest radio telescope, with over a square kilometer of collecting area. The SKA scale is a huge leap forward in engineering, research & development towards building and delivering a unique instrument.

In the first phase there will be about 200 dishes in South Africa and over 130,000 low frequency antennas in Western Australia, to monitor the Universe in unprecedented details, since no similar studies have ever been conducted with such a large array of detectors.

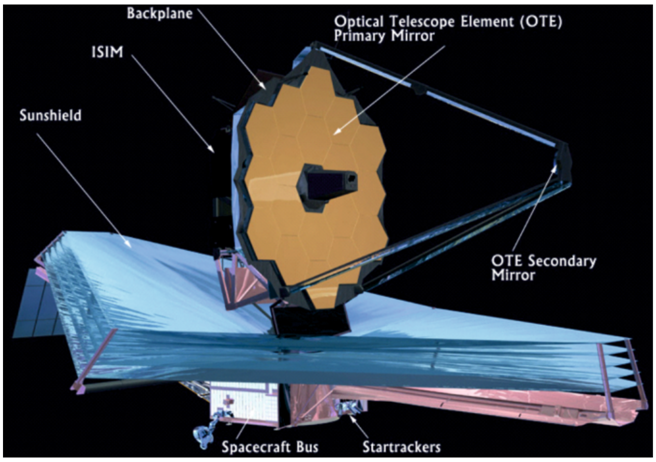

Fig.3: Various components of JWST (courtesy: https://astrobites.org) . AI based analysis is an important part of JWST data analysis.

The unprecedented sensitivity of the SKA receivers will allow insights into the formation and evolution of the first stars and galaxies just after the Big Bang, the nature of gravity and possibly even life beyond Earth. In addition, there could be several serendipitous discoveries to be expected owing to the sheer magnitude of SKA.

The expected volume of data from the SKA has motivated the expanded use of semi-automatic and automatic machine learning algorithms for scientific discovery in astronomy. The robust and systematic use of machine learning, however, faces several specific challenges including a paucity of labeled data for training (although enough data is there, it may still not be sufficient), a clear understanding of the effect of biases introduced due to observational and intrinsic astrophysical selection effects in the training data, and motivating a quantitative statistical representation of outcomes from decisive AI applications [18]. There will be specific challenges in recovering well-calibrated uncertainties from Bayesian neural networks when classifying radio galaxies which are a canonical example of AI application to radio astronomy. Table 1 below gives a summary of a direct comparison of the time taken by experts and by AI methods to analyze the SKA images. It is evident from the figure that AI methodology is the only viable option for analyzing the SKA data.

Fig.4 based on a survey of the arxiv data related to astronomy publications that contain keywords like "machine learning", "deep learning", or "artificial intelligence" in the abstract or title. An exponential increase can be seen in the field since 2010 onwards which is expected to grow at a faster rate once more data becomes available in the next few years within the astronomical community.

*Table 1: Demonstration of the actual time taken by human experts, web analysis and AI methods. (*Radio Galaxy Zoo is an internet crowd sourced citizen science project that seeks to locate supermassive black holes in distant galaxies. It is hosted by the web portal Zooniverse).*

Resource	Time	Remarks
Human Experts	1 source/min	~1,25,000/yr (full time work)
Radio Galaxy Zoo*	3,00,000 sources	12,000 users (5.5 yrs)
AI	100 million sources (15 mins)	AI offers viable solution

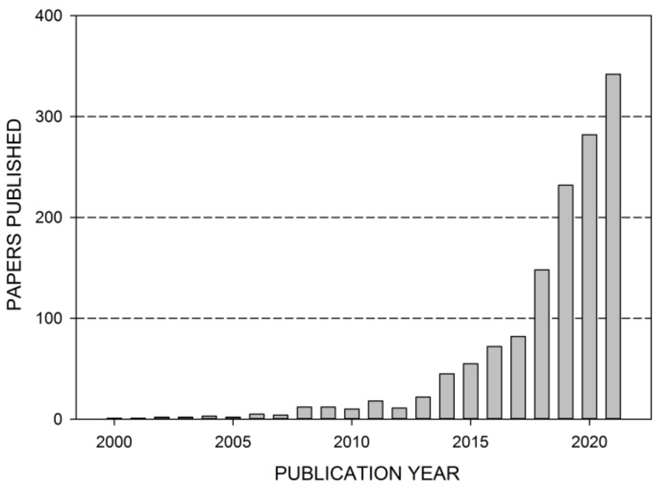

Fig.4: Astronomy research papers with AI title. Figure demonstrates the exponential increase in last decade.

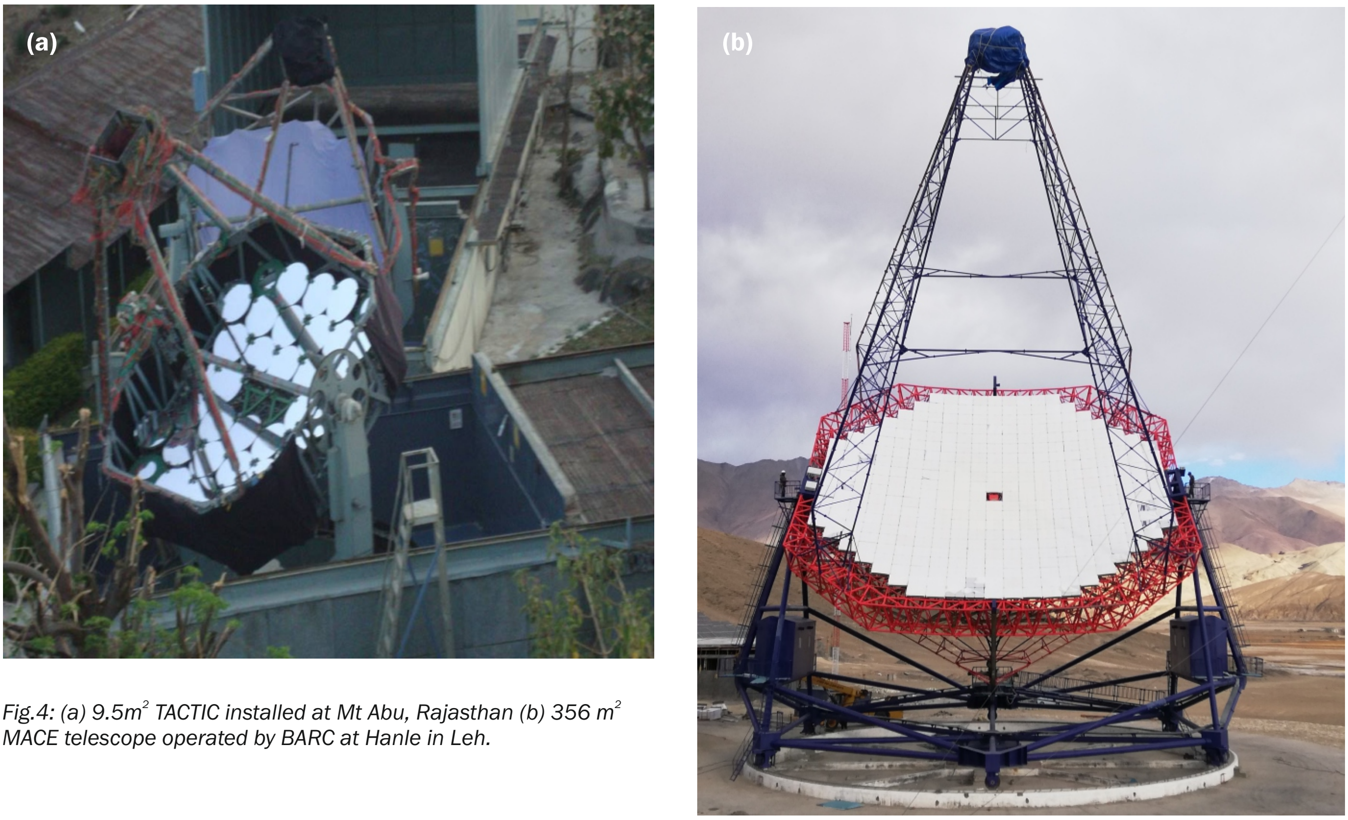

Fig.4: (a) 9.5m^2 TACTIC installed at Mt Abu, Rajasthan (b) 356 m^2 MACE telescope operated by BARC at Hanle in Leh.

Gamma-ray Astronomy applications at BARC

In the last few years, we have explored the application of Artificial Intelligence methods to the ground-based Gamma-ray astronomy activity of the department. While as TACTIC telescope, with a light collector of ~9.5m^2(Fig.5) is operational at Mt Abu, Rajasthan for more than 20 years, it is very recently that a high sensitivity telescope MACE has been commissioned at Hanle, Leh for the study of GeV-TeV γ-ray emission from celestial sources. AI-based methods have been employed for the gamma/hadron segregation and energy estimation of data from the TACTIC telescope. For TACTIC data, we have successfully utilized ANN and Random forest AI methods which have resulted in acceptance of ~ 20% more gamma-ray-like events in comparison to the conventional Dynamic Supercuts Method [19][20]. A novel ANN method was applied for energy estimation of the recorded gamma-ray events obtained with the TACTIC telescope and we have been able to improve energy resolution from ~35% to ~ 25% [21]. For the MACE telescope, we have applied RF & ANN techniques for the estimation of the Gamma-ray signal. For primary energy estimation of the detected events too, we are currently applying the two techniques. In the future also, we have plans to apply more sensitive techniques like deep-learning-based AI techniques for Gamma-hadron segregation for the MACE data.

References

[1] R Beale T Jackson, Adan Higler, An introduction to neural computing, Bristol, England (1990).

[2] Dunham, M., Data Mining Introductory and Advanced Topics. Prentice-Hall (2002).

[3] Jamie Farnes, Ben Mort, Fred Dulwich, StefSalvini, Wes Armour. Science Pipelines for the Square Kilometre Array. Galaxies, doi: 10.20944/preprints201810.0115.v2.

[4] Odewhan, S. C., & Nielsen, M. L Star galaxy separation using neural networks Vistas in Astronomy, 38, (1994), 281.

[5] Andreon, S., Gargiulo, G., Longo, G., Tagliaferri, R., & Capuano, N. Wide field imaging. I. Applications of neural networks to object detection and star/galaxy classification MNRAS, 319, (2000), 700.

[6] Birge, B., Walberg, G A Computational intelligence (CI) approach to the precision mars lander problem, Technical Report, North Carolina State University. (2002).

[7] Tagliaferri, R., Ciaramella, A., Milano, L., Barone, F., & Longo, G. Spectral analysis of stellar light curves by means of neural networks Astronomy and Astrophysics Supplement Series, 137, (1999a), 391.

[8] Fourier analysis with unequally-spaced data Astrophysics and Space Science, 36, (1975), 137.

[9] Deeming, T. J, Horne, J. H., & Baliunas, S. L. A prescription for period analysis of unevenly sampled time series Astrophysical Journal, 302,(1986), 757.

[10] Oppenheim, A. V., & Schafer, R. W. Discrete-time signal processing. Englewood Cliffs-NJ: Prentice-Hall (1989).

[11] Bishop, C. M. Neural networks for pattern recognition Oxford: Clarendon Press. (1995).

[12] Baum, W. A. Problems of extragalactic research IAU Symposium no. 15, (1962), 390.

[13] Pushell, J. J., Owen, F. N., & Laing, R. A. Astrophysical Journal, 275, (1982).

[14] Tagliaferri, R., Longo, G., Andreon, S., Capozziello, S., Donalek, C., Giordano, G Neural networks and photometric redshifts Astroph/0203445 (2002).

[15] Stoughton, C., Lupton, R. H., Bernardi, M., Blanton, M. R., Burles, S., Castander, F. J., Connolly, A. J., Eisenstein, D. J., Frieman, J. A., Hennessy, G. S., Sloan digital sky survey: early data release. Astronomical Journal, 123, (2002), 485.

[16] https://news.uchicago.edu/story/scientists-use-artificial-intelligence-detect-gravitational-waves.

[17] Pranshu Chaturvedi, Asad Khan, MinyangTian, E. A. Huerta, HuihuoZheng Inference-Optimized AI and High Performance Computing for Gravitational Wave Detection at Scale, Frontiers in Artificial Intelligence, 16 February 2022 Sec. Big Data and AI in High Energy Physics.

[18] A Bonaldi, T An, M Brüggen, S Burkutean, et al., Square Kilometre Array Science Data Challenge 1: analysis and results MNRAS, 500 (2021),3.

[19] V. K. Dhar, A. K. Tickoo, M. K. Koul, R. Koul, B. P. Dubey, R. C. Rannot, K. K. Yadav, P. Chandra, M. Kothari, K. Chanchalani, K. Venugopal Artificial Neural Network based γ-hadron segregation methodology for TACTIC telescope Nuclear Instruments and Methods in Physics ResearchA,708,(2013), 56.

[20] M. Sharma, J. Nayak, M. K. Koul, S. Bose, Abhas Mitra, V. K. Dhar, A. K. Tickoo, R. Koul Validation of a new background discrimination method for the TACTIC TeV γ-ray telescope with Markarian 421 data Nuclear Instruments and Methods in Physics Research A, Volume 770, (2015), 42.

[21] V. K. Dhar, A. K. Tickoo, M. K. Koul, R. C. Rannot, K. K. Yadav, P. Chandra, B. P. Dubey, R. Koul ANN-based energy reconstruction procedure for TACTIC γ-ray telescope and its comparison with other conventional methods Nuclear Instruments and Methods in Physics Research A 606 (3), 2009, 795.

Artificial Intelligence

12

Transient Identification & Operator Decision Support System for PHWR (Diagnostic System)

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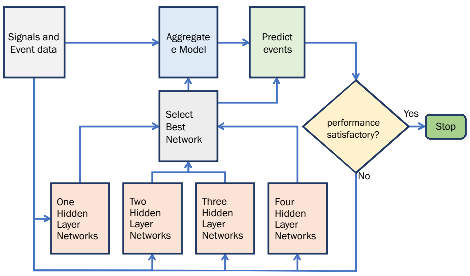

Schematic diagram of ANN approach

ABSTRACT

Artificial intelligence based transient identification and operator decision support system for 220MWe Pressurized Heavy Water Reactors (PHWRs) is developed and tested on a high speed computing facility at RSD, BARC. The transient identification module of diagnostic system employs Artificial Neural Network (ANN) model trained by a large database of plant transients simulated via core (RELAP5) and containment (CONTRAN) thermal-hydraulic code. The best-performing neural network model selection framework has been implemented in several stages with a highly random selection in the intial stage through the evolution of robust and efficient network in the final stage via recursive training scheme. The final ANN model has been obtained by creating an ensemble of the best-performing networks for identification of Loss of Coolant Accident (LOCA) and Main Steam Line Break (MSLB) scenarios. Blind validation exercises carried out on the best-performing models demonstrates thorough validation and testing of ANN models. The current version of Diagnostic system is capable of identifying a wide range of LOCA and MSLB scenarios in standard 220MWe PHWRs. Diagnostic system is built on a Remote Method Invocation (RMI) protocol concept for communication and integration of remote servers from the field (e.g. integration of Computerized Operator Information System (COIS)) for real-time transient identification.

KEYWORDS: *Operator decision support system, Diagnostic system, Neural networks, Nuclear power plant*

Introduction

Nuclear power plant (NPP) houses complex systems that are operated and monitored by human operators. When a transient occurs in the NPP (e.g. LOCA or MSLB), operator has to carry out diagnostic and corrective actions based on the available alarms/annunciations. Depending on the severity of the transient, readings of the instruments' may not always provide a clear indication of an anomaly at its incipient stage to the operator. In order to assist operator during such circumstances and to take timely corrective action, an Artificial Intelligence (AI) technique is useful. In view of this, development of AI based transient identification and operator decision support system (Diagnostic system) is the prime objective for accident management. The objective of the diagnostic system in any potentially unsafe scenario is to provide the operator suitable information about the evolving transients in terms of intensity of break in Primary Heat Transport (PHT) system, location of the break, etc. Transient identification is a decision making process based on a number of process parameters/alarm states in order to avoid/minimize the consequences associated with the specific transients. Analysis of an event/transient involve determination of the consequence of a specified event such as LOCA in terms of fuel temperature, PHT storage tank level, containment temperature and pressure, etc. Diagnosis is the identification of transients from the process signals selected from COIS. The event identification can be classified as a pattern recognition problem[1]. By properly selecting the plant parameters, a specific event can be identified by observing values/ variations of the relevant parameters. For this purpose, around 45 COIS signals have been selected from respective Emergency Operating Procedures (EOPs) for identifying LOCA and MSLB scenarios in PHWRs. The time-dependent transient data pertaining to the reactor core and the PHT has been generated using RELAP5[2] and CONTRAN[3] thermal hydraulic codes. There are a number of linear and non-linear pattern recognition techniques available in the literature[4]. However, ANN is one of the most widely employed machine learning techniques for solving such complex problems which involve a large number of input signals and output events. General characteristic of a neural network is the ability that quickly recognizes the various conditions or states of a complex system once it has been fully trained. The final ANN model has been integrated with Diagnostic system which provides most suitable information about the evolving transient and assists the operator to take corrective actions to mitigate the accident condition. The current version of the Diagnostic system is able to identify 33 LOCA and 18 MSLB scenarios in 220MWe PHWRs.

Simulation of LOCA and MSLB

PHT system depressurizes rapidly upon the occurrence of large breaks in PHT system thereby causing voids in the reactor core. This coolant voiding in the core causes positive reactivity addition and consequent power rise of reactor. Several trip signals will be activated namely high log rate, low PHT pressure, high neutron power, low PHT coolant flow and high reactor building pressure, etc. one after another in a short time. The sequence of trip actuation is largely dependent upon break location. In general, for breaks at Reactor Inlet Header

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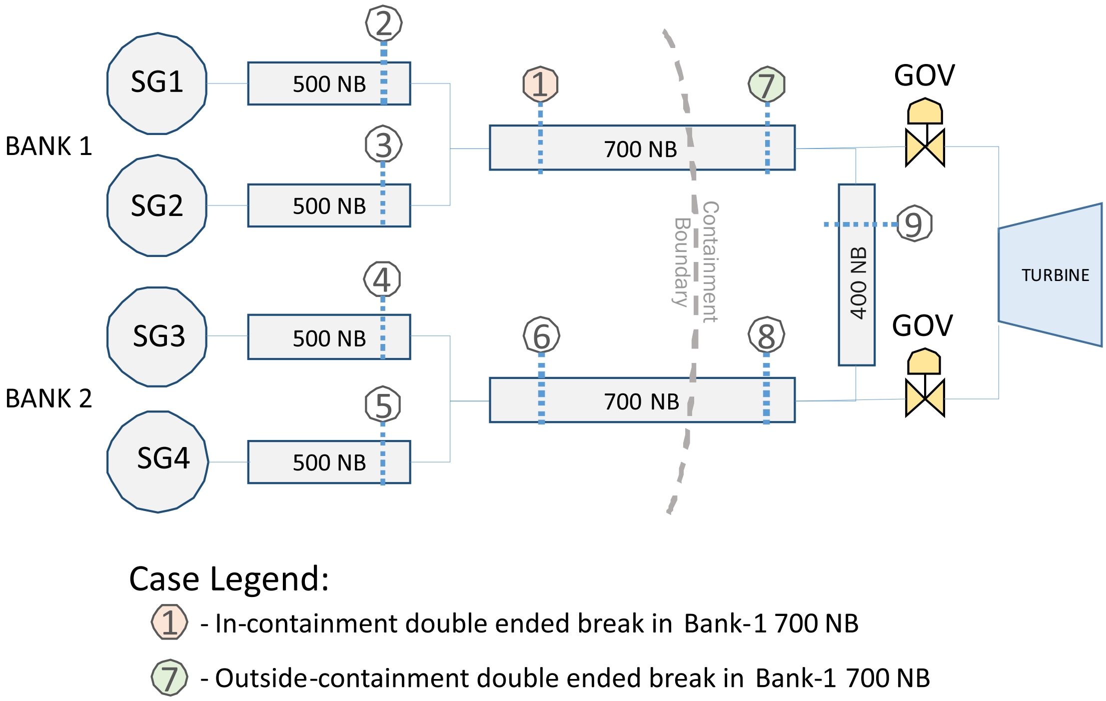

Fig.1: Schematic of main steam lines showing break locations.

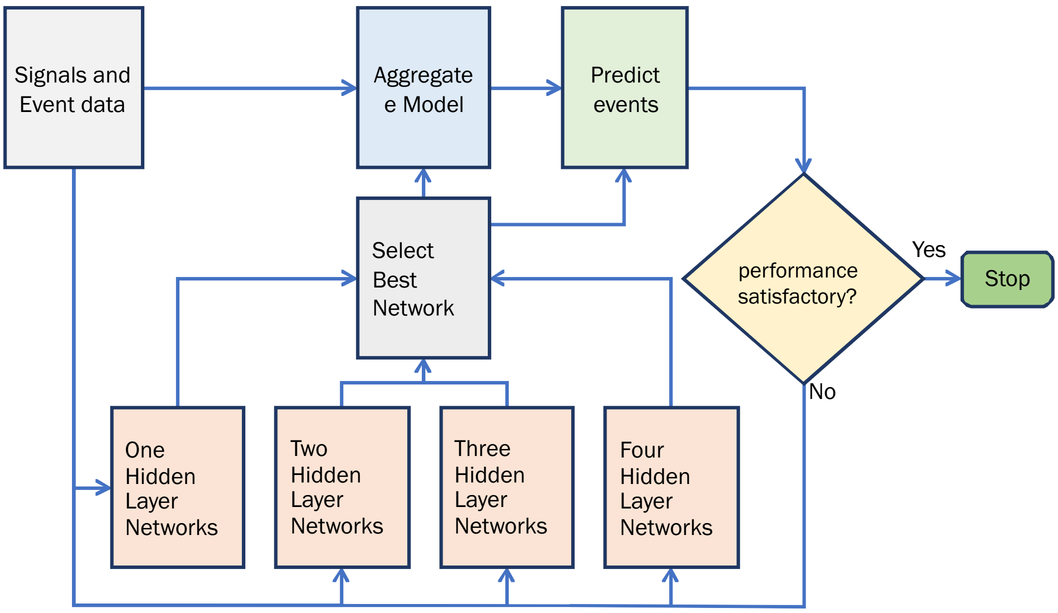

Fig.2: Schematic diagram of ANN approach.

(RIH) side, high log rate signal is a first signal followed by high neutron power, while for breaks at Reactor Outlet Header (ROH) side, low pressure signal is usually the first signal followed by high log rate. RELAP5 and CONTRAN thermal-hydraulic codes have been used to simulate 33 LOCA scenarios of pipe break at RIH and ROH, ranging from 20% to 200% double ended guillotine break.

MSLB scenario has also been modelled using RELAP5 and CONTRAN codes for simulating core and containment thermal-hydraulics for postulated pipe break in 400NB, 500NB and 700NB steam pipelines. Fig.1 shows the simulation carried out for 9 break locations. Transient data for two subsets each of 9 postulated cases with and without availability of Emergency Core Cooling System (ECCS) has been generated. Thus, a total of 18 cases have been analysed covering the possible break sizes, location and availability of ECCS. Transient results for COIS parameters in primary and secondary loops have been used in the development of ANN models.

Model Development

The transient identification can be classified as a pattern recognition problem and neural networks are found to be suitable for such problems. There is no pre-determined criterion for choosing a specific structure of neural network and development of a best-performing network is based on the trial and error approach. The schematic diagram describing the model development approach is shown in Fig.2. Random sets of 1-hidden, 2-hidden, 3-hidden and 4-hidden layer neural networks are generated and a best-performing network from

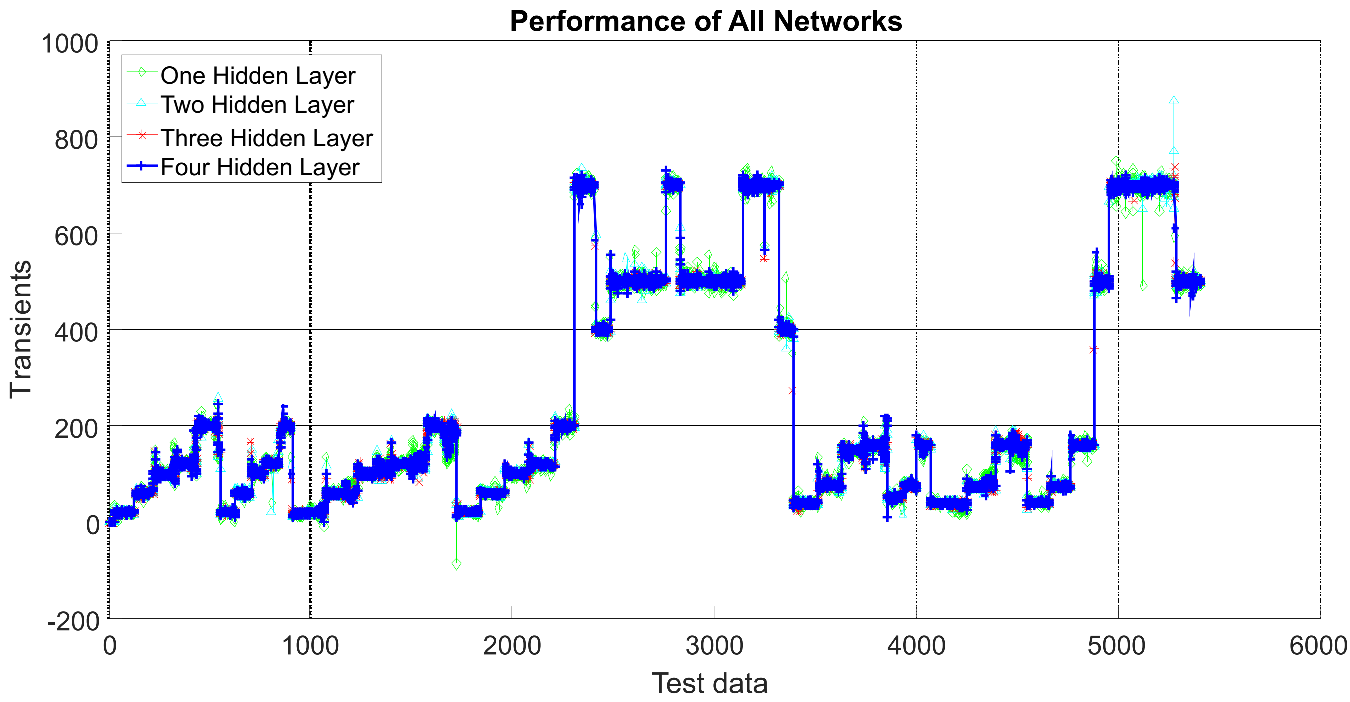

Fig.3: Performance of all networks .

each category is selected based on the lowest Root Mean Square Error (RMSE). Depending on the individual network's performance, a set of best-performing networks will be selected for creating an aggregation model. If the performance of the aggregate model or any individual network is satisfactory then the model development process is terminated. This process is repeated until reasonably acceptable model is evolved.

Training data

Artificial neural networks are widely known as data-driven techniques which rely on a large database of the input signals. In other words, ANNs require large amount of data to learn and recognize a particular input-output pattern. The transient data generated from RELAP5 and CONTRAN codes is randomly split into 70% training set, 15% validation set and 15% test set using the random sub sampling with no replacement method. This creates a balanced training, validation and test sets which are non-overlapping subsets of the transient dataset. The advantage of using a balanced training set is that this would ensure that the trained neural network would make unbiased estimation of different break sizes in the test set. In contrast, a network trained on an imbalanced training set may tend to result in the break size target corresponding to the majority class of the training set which leads to poor generalization of the network. Validation check is performed during the training phase to control the over-fitting. An event is identified by assigning a suitable event identification code in the input file. The final neural network model consists of 45 inputs and 4 output parameters for predicting LOCA and MSLB scenarios.

Performance of neural network

Levenberg-Marquardt Back-propagation algorithm is one of the most efficient and fast converging algorithms[5]. The Levenberg-Marquardt Back propagation algorithm is used for training the networks with the maximum epochs set to 1000 and the learning rate parameter set to 0.001. Various types of 1-hidden, 2-hidden, 3-hidden and 4-hidden neural networks were generated randomly by fixing the minimum and maximum neurons, and also fixing the total number of weights. The termination criterion is either fulfilling the validation checks or reaching to number of epochs or converging to the pre-set performance level (mean square error) which is set to 1e-4. From the performance evaluation study it is found that 3-hidden and 4-hidden layer networks performed well in predicting all the events over the entire dataset with RMSE less than 3. The prediction performance of all the networks for LOCA and MSLB on test data is shown in Fig.3. In order to further improve the prediction rate, a weighted-average aggregation model from these two networks has also been created. It is observed from the results that the networks are able to capture the distinct feature from the training data to distinguish LOCA and MSLB scenarios which share many common process parameters.

Operator Decision Support System

Diagnostic system employs AI model to predict the accident scenario well before the operator action is anticipated. Continuous monitoring of COIS parameters by AI model enables Diagnostic system to predict the evolving accident scenarios in their early stage[6-7]. Whenever an event is detected, this system will display the type of the event, time at which the event has occurred and the relevant process parameters and their values at the time of initiation of the event. In addition, the trend of important process parameters during accident progression is displayed on the operator screen along with relevant EOPs. Currently, Diagnostic system has been set up on high speed distributed computing servers (Intel i7-2600 CPU @ 3.4GHz with 4GB RAM) for fast processing and real-time response. It has been tested successfully for real-time identification of LOCA and MSLB scenarios in 220MWe PHWRs. Fig.4 shows the screenshot of operator screen of Diagnostic system indicating the identified MSLB scenario inside the containment.

The important process parameters and their values in red background colour indicate an abnormal reactor state. The complete details of the identified scenario are displayed at the bottom panel of the screen.

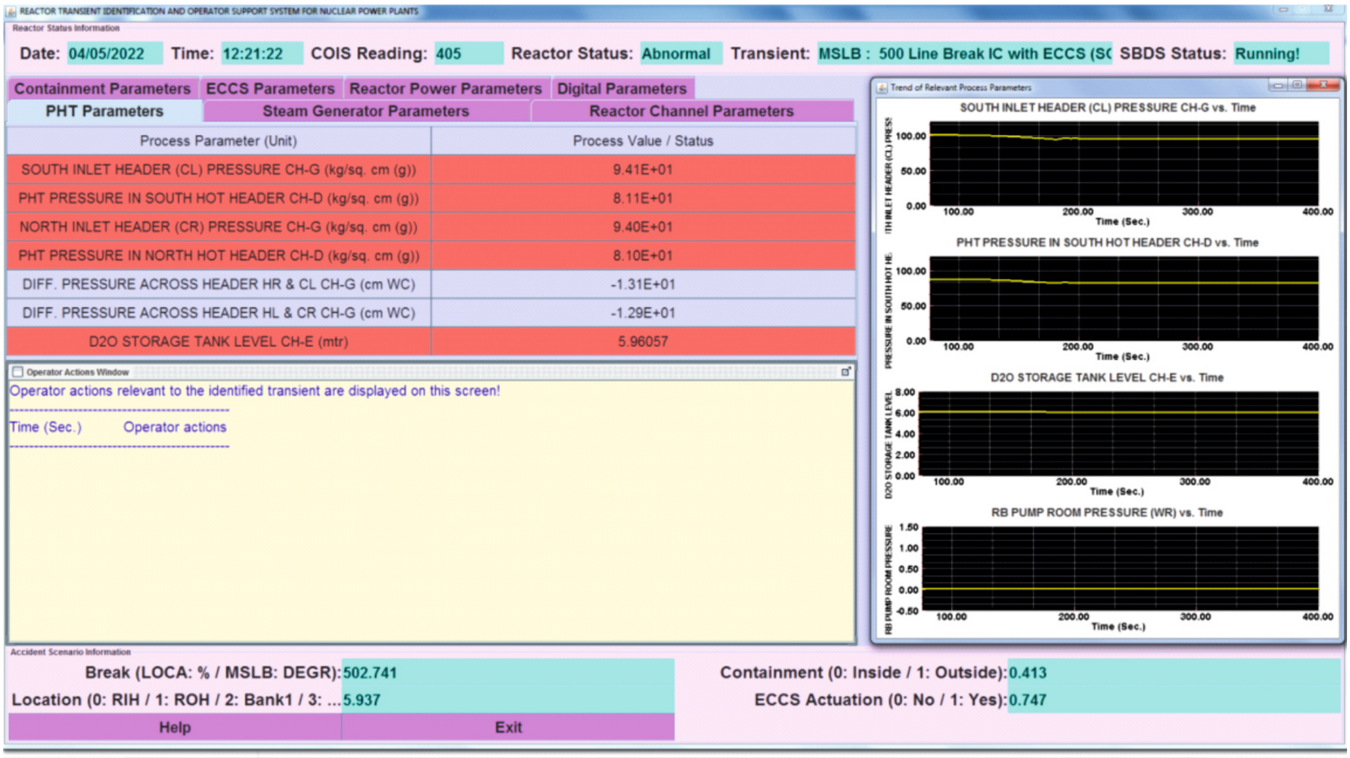

Fig.4: Screenshot of Diagnostic system showing 500NB line break inside containment with the availability of ECCS.

Conclusions

Robust and efficient neural network model has been developed for identification of LOCA and MSLB scenarios in 220 MWe PHWRs. A three-tier learning scheme is followed in developing a single yet efficient ANN model for predicting entire set of LOCA and MSLB transients for real-time application in plant considering the signals from COIS. Blind case validation exercises have been carried out to test the performance of ANN model against generality check. Break size, break location (i.e. distinguishing break inside or outside containment; RIH or ROH, etc.), and also the status of ECCS actuation can be known from the tool. Around 33 LOCA and 18 MSLB scenarios can be predicted from the current version of the Diagnostic system. The Diagnostic system provides confidence to the operator in effective identification and handling of events so that subsequent management of events becomes easier. Diagnostic system can be a useful aid for training the plant operators. This AI based method will reduce dependence on human skill and thus the human reliability factor can improve by reducing stress factor on operator during any event/transient.

References

[1] Bishop CM, "Neural networks for pattern recognition". Oxford university press, New York, USA, 1995.

[2] Fletcher G. D., Schultz R. R., RELAP5/MOD3.2 Code manual, Idaho National Engineering Laboratory, Idaho, 1995.

[3] S. K. Haware, S. G. Markandeya, A. K. Ghosh, V. Venkat Raj, Assessment of multi-compartment containment analysis computer code CONTRAN with the experiments on containment response during LOCA conditions, First ISHMT-ASME Heat and Mass Transfer Conference and 12th National Heat and Mass Transfer Conference, BARC, Bombay, India, January, 1994.

[4] Khalil Moshkbar-Bakhshayesh, Mohammad B. Ghofrani, Transient identification in nuclear power plants: A review, Progress in Nuclear Energy, pp. 23-32, no. 67, 2013.

[5] Martin T. Hagan and Mohammad B. Menhaj, Training feed forward networks with the Marquardt algorithm, IEEE Transactions on Neural Networks, vol. 5, no. 6, 1994.

[6] T. V. Santosh, A. Shrivastava, V. V. S. Sanyasi Rao, A. K. Ghosh and H.S.Kushwaha, "Diagnostic System for Identification of Accident Scenarios in Nuclear Power Plants using Artificial Neural Networks" Reliability Engineering and System Safety, pp. 759-762, vol.54, 2009.

[7] Silvia Tolo, EdoardoPatelli, Xiange Tian, Nils Bausch, Victor Becerra, T. V. Santhosh, Gopika Vinod, Robust on-line diagnosis tool for the early accident detection in nuclear power plants, Reliability Engineering and System Safety, no. 186, pp. 110-119, 2019.

Machine Learning

13

Machine Learning and Data Science for Accelerated Materials Discovery

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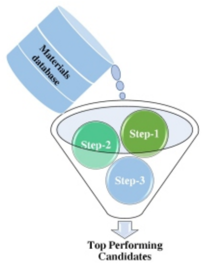

High-throughput screening of materials database for identifying top performing materials

ABSTRACT

Invention of advanced functional materials plays a great role in technological advancements and industrial revolution which ultimately improves living standards of mankind. Traditional materials discovery through experimental, theoretical and computational studies makes the process of materials discovery very expensive and time consuming. With the tremendous increase in available open materials database and advanced algorithms along the exponential growth in computational infrastructure, data science and machine learning became the fourth pillar of the materials discovery. In this article, current state of the materials informatics and challenges are discussed along with few important studies in designing advanced materials using machine learning and high-throughput screening techniques.

KEYWORDS: *Data science, Accelerated materials discovery, Machine learning, Metal organic frameworks*

Introduction

In recent years, revolution in artificial intelligence (AI) and big data have shown potential applications in accelerating the discovery of new molecules and materials[1]. Beyond the traditional methods of materials exploration using the trial and error experiments, theoretical and computational studies, data driven materials discovery is emerging as the fourth paradigm of material science which can improve the pace of materials innovation[2,3]. With the intention of accelerating the discovery of new materials, "Material Genome Initiative" (MGI) project was launched by the USA[4]. In machine learning (ML), a subclass of AI, machine extracts the knowledge from data (of materials) through mapping the structure-property relations which can be quite complex and beyond human intelligence in most of the cases and the knowledge gained can be applied for future predictions. One of the early attempts to use data for materials informatics was the development of CALculation of PHAse Diagrams (CALPHAD) to calculate the phase diagrams of alloys using the computed data of phase diagrams[5]. Data can be considered as the key component for material informatics and the amount of open-source data of materials has been rapidly increasing over the years. A large number of open materials databases like Inorganic Crystallographic Structural Database (ICSD)[6], Cambridge Crystallographic Data Centre (CCDC)[7], AFLOW[8], NOMAD[9], Materials Project[10], MARVEL NCCR[11], etc. composed of both experimental and computational data are openly available. Apart from the existing database, with different possible chemical compositions and structures, the chemical space of materials is virtually unlimited and many more new materials can be explored. In addition to the easily accessible open data resources, explosive growth in the computational infrastructure along with the development of efficient algorithms like deep learning methods accelerated the field of data driven materials innovation.

Challenges in ML for Materials Science

Fig. 1 depicts the typical supervised ML model trained using labelled data to predict the material properties. Major components of such ML model are (a) Defining a problem (b) Data acquisition and selecting appropriate feature space, (c) Data processing or Exploratory Data Analysis (EDA) and (d) Training and validating the model using a suitable algorithm. Though many open-source materials databases are available, data is composed of different categories and data of each category is relatively limited when compared to other fields of data science. In most of the experimental data, studies were conducted at different experimental conditions and hence the data depends on various control parameters like temperature, time, humidity, raw chemicals used, etc. Once the data is selected, next key challenge is to select appropriate set of features (fingerprints) of the materials to map with the target property. Open-source libraries like Pymatgen[12], Matminer[13], Atomic Simulation Environment (ASE)[14], DScribe[15], etc. are highly useful for extracting different site, bond and global (lattice) features of molecule and materials. EDA includes verifying any outliers, imputing the missing data, encoding the object type parameters to numeric type, checking for any duplicate copies in the data, etc. Once the data is ready, selecting a particular algorithm for a given problem is another challenge and it should consider different factors like size of data, feature space, complexity of problem etc. If a too complex (high variance) model like deep learning algorithm is selected with limited data points, it can lead to over fitting. Interpretability of the trained model is another important factor to understand the features that attribute the most to overall prediction[16]. Accuracy of the model can be further tuned using the hyper-parameter tuning methods like random search cross validation and grid search cross validation. Other than

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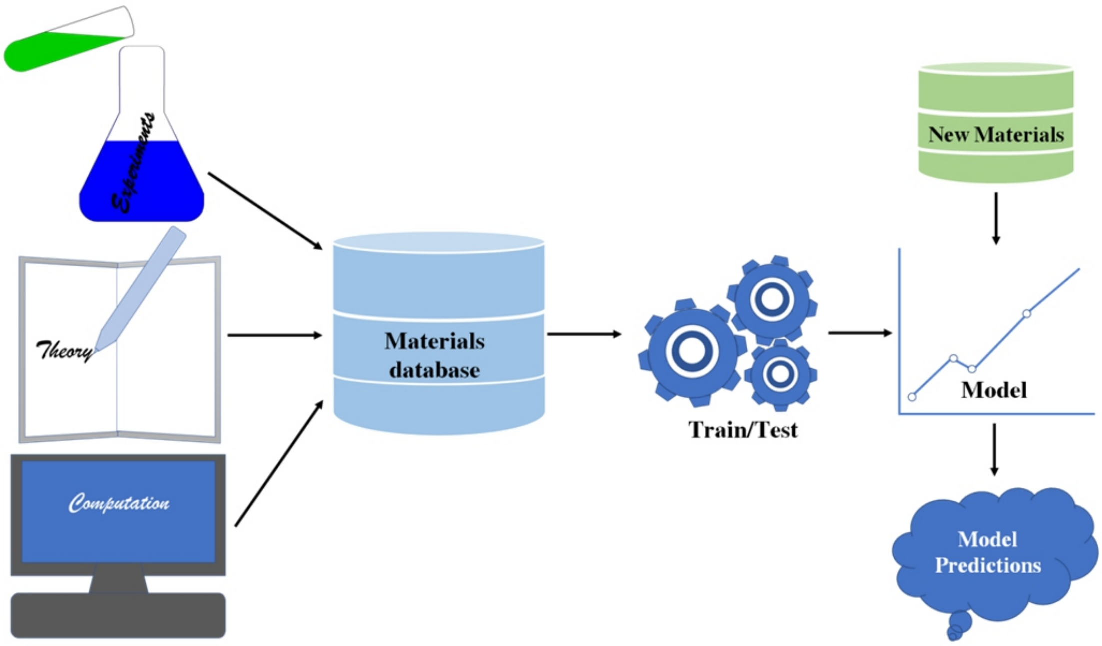

Fig.1: Schematic representation of training a supervised machine learning model for materials property prediction.

training ML models for predicting properties of materials, High-Throughput Screening (HTS) techniques are shown to be potential tool to identify top materials for a particular application from large database of materials which is schematically shown in Fig.2. Recently, self-driving experimental laboratories were developed where robots can perform autonomous experiments very precisely to discover advanced functional materials.

Materials for Energy related Applications

With ever increasing energy demands and adverse environmental effects of burning fossil fuels, great attention has been given to the clean and renewable energy technologies like solar, wind, hydrogen, nuclear energy, etc.[17] Progress in these new and advanced energy sectors is highly dependent on the design and development of advanced functional materials to withstand specific conditions like high temperature, corrosive conditions, high pressure, high energy radiation, etc. where data driven materials discovery has shown potential applications. Band gap of materials is an important property for designing materials for optical and electronic applications and the conventional Density Functional Theory (DFT) methods are inefficient in producing the accurate results whereas the hybrid functional methods which can provide reasonably good results are highly expensive. Zhuo et al.[18] developed a ML model to predict the band gap in inorganic solids where, support vector classification model was first used to classify metal and semiconductors followed by a support vector regressor to predict the band gaps. Kim et al.[19] trained a ML model using the Least Absolute Shrinkage and Selection Operator (LASSO) methods for predicting the dielectric breakdown strength in perovskite materials. Rajan et al.[20] trained a Gaussian process regressor model for predicting the band gaps in two-dimensional (2D) transition metal carbides and nitrides, MXenes. Through the ML guided DFT studies, Sendek et al.[21] discovered many crystalline solid materials with high Li ion conductivity at room temperature which is highly important in designing efficient Li-ion batteries. Using the DFT results on 104 graphene-supported single atoms catalysts, Lin et al.[22] trained random forest ML model to predict the overpotentials associates with the oxygen reduction reaction, oxygen and hydrogen evolution reactions over the selected catalysts. The trained model was used to predict the catalytic activity of other 260 graphene supported single atoms catalysts. Using the first principles based HTS study, Wu et al.[23] screened nitride and oxynitride compounds to identify the novel water splitting photocatalyst. Through the DFT based HTS study, Greeley et al.[24] screened 700 binary alloy surfaces for hydrogen evolution reaction and identified BiPt with better activity as compared to Pt and same was synthesized and the experimental results also shown improved catalytic activity compared to pure Pt surface. Developing advanced and safe fuel materials for nuclear reactors is one of the challenging problems in nuclear energy. Predicting properties of nuclear materials under operational and accidental conditions is a challenging task and difficult to carry out experiments where ML has shown potential applications. Kobayashi et al.[25] constructed a machine learning potential for thorium dioxide fuel materials using the first principles molecular dynamic studies with limited number of atoms and the developed potential was used to simulate the high temperature thermodynamic properties of ThO_2. Using the available experimental data, Jin et al.[26] trained a machine learning model to predict the radiation induced void swelling in different steels.

Porous Materials for Adsorption/Separation of Gases

Designing porous materials for adsorption and separation of gas mixtures is another important area for energy, environment and many other industrial gas separation applications. Metal organic frameworks (MOFs) are reported to have potential applications in separation/storage of various important gases[27]. CO_2 capture is an important technique which can be installed at stationary emission points to restrict the CO_2 levels in the atmosphere as the conventional capture through aqueous amine scrubbing is an energy intensive process. Li et al.[28] screened a database of 5109 MOFs for CO_2 capture from wet flue gas mixture through grand canonical Monte Carlo (GCMC) simulations using framework charges calculated from the extended charge equilibration (EQeq) method. Comparison of the CO_2/H_2O selectivity in the top

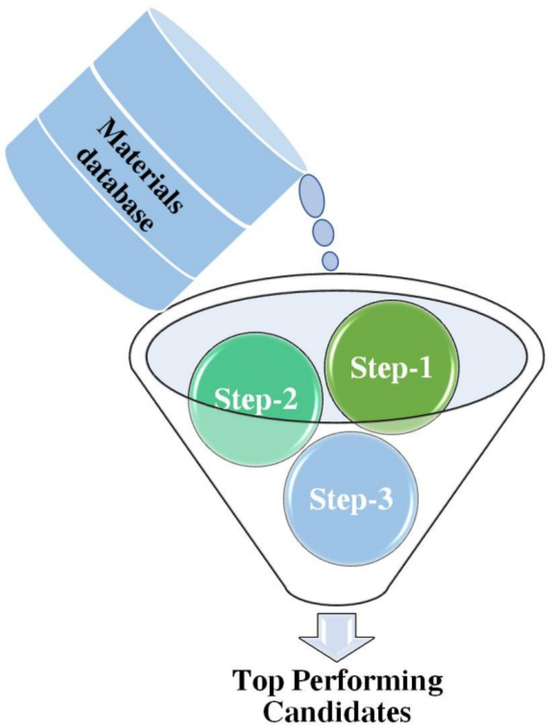

Fig.2: Schematic representation for multi step high-throughput screening of materials database to identify the top performing materials for a particular application .

15 MOFs calculated using the two different charge methods, EQeq and DFT based Repeating Electrostatic Potential Extracted ATomic (REPEAT) revealed that the CO_2/H_2O selectivity values using EQeq charges were overestimated and the K_H (Henry's constant) of H_2O is more sensitive to the charge method than that of CO_2 and N_2. Though the DFT based atomic charges are accurate as compared to empirical methods like EQeq, it is not practical to use for screening large database of MOFs.

To answer this issue, we trained a Random Forest based ML model to predict the atomic charges of MOF atoms using a limited yet meaningful set of features representing both the atom site properties and the local bonding environment and the atomic charges calculated using the Density Derived Electrostatic and Chemical (DDEC6) method[29]. The trained model predicts accurate atomic charges in MOFs with R^2 value of 0.9952 and a mean absolute error of 0.019 at a fraction of the computational cost of DFT. In another interesting study, Boyd et al.[30] screened a library of 325,000 hypothetically generated MOFs and proposed that MOFs with parallel aromatic rings separated by around 7 Å as effective for CO_2 capture in presence of water vapor. It was also experimentally validated by synthesizing such MOFs with optimal CO_2 binding environment which have shown minimal influence of water on the CO_2 capture capacity. Simon et al.[31] screened a database of 670,000 porous materials for Xe/Kr separation and identified aluminophosphate zeolite analogue and a calcium based coordination network as the two most selective materials. HTS of 137,000 hypothetical MOFs for Xe/Kr separation by Sikora et al.[32] concluded that MOFs with pores just enough to fit a xenon and having tubular morphology of uniform width are ideal for Xe/Kr separation.

In summary, this review article elaborates the importance and future scope of data driven materials discovery. Major steps involved in a typical supervised machine learning model for materials property prediction have been discussed with different challenges associated with them. Few data driven materials discovery reports especially for energy related materials have been discussed.

References

[1] Butler, K. T.; Davies, D. W.; Cartwright, H.; Isayev, O.; Walsh, A., "Machine learning for molecular and materials science." Nature 559 (7715), (2018):547-555.

[2] Hey, A. J.; Tansley, S.; Tolle, K. M., The fourth paradigm: data-intensive scientific discovery. Microsoft research Redmond, WA: 2009; Vol. 1.

[3] Pilania, G.; Wang, C.; Jiang, X.; Rajasekaran, S.; Ramprasad, R., "Accelerating materials property predictions using machine learning." Sci. Rep.3 (1), (2013):2810.

[4] https://www.mgi.gov. https://www.mgi.gov

[5] Saunders, N.; Miodownik, A. P., CALPHAD (calculation of phase diagrams): a comprehensive guide. Elsevier: 1998.

[6] https://icsd.products.fiz-karlsruhe.de/.

[7] https://www.ccdc.cam.ac.uk/.

[8] Curtarolo, S.; Setyawan, W.; Hart, G. L.; Jahnatek, M.; Chepulskii, R. V.; Taylor, R. H.; Wang, S.; Xue, J.; Yang, K.; Levy, O., "AFLOW: An automatic framework for high-throughput materials discovery." Comput. Mater. Sci.58, (2012):218-226.

[9] Zacharias, N.; Monet, D. G.; Levine, S. E.; Urban, S. E.; Gaume, R.; Wycoff, G. L. In The Naval Observatory merged astrometric dataset (NOMAD), American Astronomical Society Meeting Abstracts, 2004; p 48.15.

[10] Materials Project, https://materialsproject.org.

[11] Materials Cloud, https://www.materialscloud.org.

[12] Ong, S. P.; Richards, W. D.; Jain, A.; Hautier, G.; Kocher, M.; Cholia, S.; Gunter, D.; Chevrier, V. L.; Persson, K. A.; Ceder, G., "Python Materials Genomics (pymatgen): A robust, open-source python library for materials analysis." Comput. Mater. Sci. 68, (2013): 314-319.

[13] Ward, L.; Dunn, A.; Faghaninia, A.; Zimmermann, N. E.; Bajaj, S.; Wang, Q.; Montoya, J.; Chen, J.; Bystrom, K.; Dylla, M., "Matminer: An open source toolkit for materials data mining." Comput. Mater. Sci.152, (2018):60-69.

[14] Larsen, A. H.; Mortensen, J. J.; Blomqvist, J.; Castelli, I. E.; Christensen, R.; Dułak, M.; Friis, J.; Groves, M. N.; Hammer, B.; Hargus, C., "The atomic simulation environment—a Python library for working with atoms." J. Phys.: Condens. Matter 29 (27), (2017): 273002.

[15] Himanen, L.; Jäger, M. O.; Morooka, E. V.; Canova, F. F.; Ranawat, Y. S.; Gao, D. Z.; Rinke, P.; Foster, A. S., "DScribe: Library of descriptors for machine learning in materials science." Comput. Phys. Commun. 247, (2020):106949.

[16] James, G.; Witten, D.; Hastie, T.; Tibshirani, R., An introduction to statistical learning. Springer: 2013; Vol. 112.

[17] Armaroli, N.; Balzani, V., The Future of Energy Supply: "Challenges and Opportunities." Angew. Chem. Int. Ed.46 (1-2), (2006):52-66.

[18] Zhuo, Y.; Mansouri Tehrani, A.; Brgoch, J., "Predicting the Band Gaps of Inorganic Solids by Machine Learning." J. Phys. Chem. Lett. 9 (7), (2018):1668-1673.

[19] Kim, C.; Pilania, G.; Ramprasad, R., "Machine Learning Assisted Predictions of Intrinsic Dielectric Breakdown Strength of ABX3 Perovskites." J. Phys. Chem. C 120 (27), (2016):14575-14580.

[20] Rajan, A. C.; Mishra, A.; Satsangi, S.; Vaish, R.; Mizuseki, H.; Lee, K.-R.; Singh, A. K., "Machine-Learning-Assisted Accurate Band Gap Predictions of Functionalized MXene." Chem. Mater.30 (12),(2018):4031-4038.

[21] Sendek, A. D.; Cubuk, E. D.; Antoniuk, E. R.; Cheon, G.; Cui, Y.; Reed, E. J., "Machine Learning-Assisted Discovery of Solid Li-Ion Conducting Materials." Chem. Mater.31 (2), (2019):342-352.

[21] Lin, S.; Xu, H.; Wang, Y.; Zeng, X. C.; Chen, Z., "Directly predicting limiting potentials from easily obtainable physical properties of graphene-supported single-atom electrocatalysts by machine learning." J. Mater. Chem. A8 (11), (2020):5663-5670.

[23] Wu, Y.; Lazic, P.; Hautier, G.; Persson, K.; Ceder, G., "First principles high throughput screening of oxynitrides for water-splitting photocatalysts." Energy Environ. Sci.6 (1), (2013):157-168.

[24] Greeley, J.; Jaramillo, T. F.; Bonde, J.; Chorkendorff, I.; Nørskov, J. K., "Computational high-throughput screening of electrocatalytic materials for hydrogen evolution." Nat. Mater.5 (11), (2006):909-913.

[25] Kobayashi, K.; Okumura, M.; Nakamura, H.; Itakura, M.; Machida, M.; Cooper, M. W. D., "Machine learning molecular dynamics simulations toward exploration of high-temperature properties of nuclear fuel materials: case study of thorium dioxide." Sci. Rep.12 (1), (2022):9808.

[26] Jin, M.; Cao, P.; Short, M. P., "Predicting the onset of void swelling in irradiated metals with machine learning." J. Nucl. Mater.523, (2019):189-197.

[27] Zhou, H.-C.; Long, J. R.; Yaghi, O. M., "Introduction to Metal–Organic Frameworks." Chem. Rev.112 (2), (2012):673-674.

[28] Li, S.; Chung, Y. G.; Snurr, R. Q., "High-Throughput Screening of Metal–Organic Frameworks for CO2 Capture in the Presence of Water." Langmuir 32 (40), (2016):10368-10376.

[29] Kancharlapalli, S.; Gopalan, A.; Haranczyk, M.; Snurr, R. Q., "Fast and Accurate Machine Learning Strategy for Calculating Partial Atomic Charges in Metal–Organic Frameworks." J. Chem. Theory Comput.17 (5), (2021):3052-3064.

[30] Boyd, P. G.; Chidambaram, A.; García-Díez, E.; Ireland, C. P.; Daff, T. D.; Bounds, R.; Gładysiak, A.; Schouwink, P.; Moosavi, S. M.; Maroto-Valer, M. M.; Reimer, J. A.; Navarro, J. A. R.; Woo, T. K.; Garcia, S.; Stylianou, K. C.; Smit, B., "Data-driven design of metal–organic frameworks for wet flue gas CO^2 capture."Nature 576 (7786), (2019):253-256.

[31] Simon, C. M.; Mercado, R.; Schnell, S. K.; Smit, B.; Haranczyk, M., "What Are the Best Materials To Separate a Xenon/Krypton Mixture?" Chem. Mater.27 (12), (2015): 4459-4475.

[32] Sikora, B. J.; Wilmer, C. E.; Greenfield, M. L.; Snurr, R. Q., "Thermodynamic analysis of Xe/Kr selectivity in over 137,000 hypothetical metal–organic frameworks." Chem. Sci.3 (7), (2012):2217-2223.

Artificial Intelligence

14

AI in Video Analytics and Security

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Zones are marked up to 50m. Red line is virtual fence and green is zone

ABSTRACT

The surveillance of critical infrastructures and installations are typically based on multiple video cameras via a centralised manual monitoring station, among other modalities. The continuous monitoring of the video inputs from multiple cameras by human is error prone due to fatigue. Assistance from automated systems for detecting various malicious activities and movements can increase the surveillance performance. Due to the huge success of Artificial Intelligence (AI) based systems in analysing the images for various computer vision tasks, the same can be extended for analysing live surveillance videos. This article provides details of the AI based video analytics systems under development at SESSD, BARC.

KEYWORDS: *Deep learning, Computer vision, Video analytics, Object detection, Stereo vision*

Introduction

Video cameras are found inevitably in all modern surveillance systems of all critical installations and infrastructures. However, monitoring the feed from all these large number of video cameras at a centralised monitoring/operator room with a video wall is tedious and error-prone task. Studies[1] have shown that a human operator, watching a single video monitor for more than 20 minutes loses 95% of his ability to pay sufficient attention to differentiate between normal and malicious events. This has, hence, largely restricted the usage of this highly rich live data content only to be used during post-event analysis of the recorded video feed, in most scenarios. This has inspired the need to have automated solutions for analysing the live surveillance video feeds for detection of malicious events viz., loitering, crowd gathering, entering exclusion zones, abandoning baggage etc.

The application of artificial intelligence (AI) algorithms, especially Deep Neural Networks (DNNs), in the fields of image processing/computer vision has drastically improved after 2012. DNNs have been extensively studied and applied for various computer vision tasks like image classification, object detection, pose estimation etc. and has even achieved human level accuracies in few of these tasks. The availability of the high computation hardware like GPUs and the availability of large datasets for computer vision tasks like ILSVRC[2] have enhanced the development of deep learning techniques in recent years. Relying on the huge success of deep learning in analysing the images, it is possible to extend the same method to analyse video stream for detecting malicious events in real time. This can help in assisting the security personnel in surveillance and reduce the errors caused due to fatigue.

SESSD, BARC is involved in the development of various deep learning based automated system for assisting surveillance. These systems will be deployed for field testing within BARC. The Deep Learning based systems under development are as below:

1) Physical Intrusion Detection System
   a) Stereo Camera based
   b) Single Camera based
   c) Virtual Fence
2) Suspicious Behaviour Detection System

Each of these systems are briefly described in the following sections.

Deep Learning based Video Analytics Surveillance Systems

Many surveillance cameras are already installed along the fence/boundary of a critical installation. Typically, the modern-day cameras are digital IP based cameras and hence the video feed from all these cameras is available at a centralised monitoring station. The primary objective of the proposed video analytic systems is to identify activities like, any human approaching the fence, crossing the fence, Loitering in an exclusion zone etc.

Physical Intrusion Detection System (PIDS)

PIDS is a vision-based system, which detects human intrusions and also finds the 3D coordinates of the location of the intrusion w.r.t to camera coordinates system (CCS). CCS is defined using Geographic Information System (GIS) with x-axis pointed towards the geographic east, y-axis towards

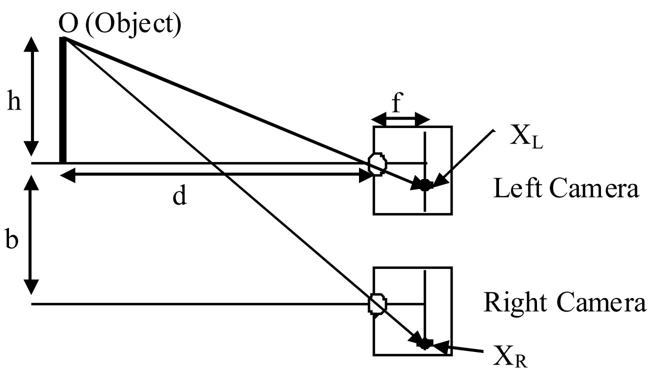

Fig.1: Representation of Stereo camera setup.

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Fig.2: Image showing a blue coloured bounding box marked over a detected intrusion. The depth, width and height (in meters) of the intrusion are also indicated over the bounding box as text.

geographic north and z-axis pointing up from the ground; camera feet location as origin of CCS. This kind of orientation assumption helps in integrating the live intrusion information from multiple camera feeds on to a single fused map.

In PIDS, the video feed received from each camera is analysed to find the intrusions per-image basis. The objective of finding the intrusions in a frame is realised by a deep learning model trained to detect objects in the given frame. The deep learning model is trained on large publicly available MS-COCO[3] dataset and the model architecture is based on SSD[4]. All the deep learning models are trained using Pytorch framework . Once the 2D-location of the humans is obtained in pixels, it is mapped to 3D coordinate system (CCS). Two different approaches are adopted for 2D to 3D recovery.

Stereo based Approach

In the stereo approach[6], two cameras (denoted as left and right cameras) are placed in a stereo fashion, with parallel optical axes, as shown in Fig.1. Assuming a pin-hole camera model, the depth of any object (O) in 3D space, whose 2D pixel locations are known in both the cameras, (X_L and X_R) can be estimated using the equation-1.

$$d = \frac{(f * b)}{(X_R - X_L)} \qquad (1)$$

Where *f* is the focal length of the cameras & *b* is the baseline of the setup. The term X_R- X_L is called disparity i.e., the shift in the pixel location of the corresponding 3D point in 2 images.

This system is deployed for field testing within BARC. Results are shown in the Fig.2 below. The system also has panning capability and hence system rotates to cover a larger field of view. The execution time for processing one frame is around 20msec on a PC with GeForce RTX-2080 graphic card (4352 CUDA cores and 11GB RAM).

Single Camera Approach

A stereo vision based setup requires two cameras which are arranged in precise parallel fashion to estimate the depth. The precise alignment of the cameras is mechanically tedious which increases deployment time. In order to avoid the usage and task of aligning of two cameras, a single camera approach is also developed[7]. Under a valid assumption that human stands on the ground, the 3D coordinates of the human are estimated. Feed from any existing surveillance camera can be utilised to detect intrusions using the trained deep learning model for object detection. The 3D location of the feet of a human is estimated from 2D pixel location of feet.

This system is deployed for field testing within BARC. Results are shown in the Fig.3. It can be seen that the z-coordinate of the human feet location is always zero; this assumption is made because human stands on the ground as shown in Fig.3. The execution time for processing one frame is around 20msec on a PC with GeForce RTX-2080 graphic card (4352 CUDA cores and 11GB RAM).

Virtual Fence

The idea of recovering the 3D coordinates of the points of a plane from their 2D pixel locations, is applied to draw virtual fences. This is shown in Fig.4. This application detects a person and also tracks the person. Here, the zones are virtually

Fig.3: Images showing intrusion with their 3D coordinates of feet and height(in meters) of the intrusion.

Fig.4: Zones are marked up to 50m. Red line is virtual fence and green is zone. It detects persons and tracks them. As soon as the person enter the zone, a bounding box is drawn around him and the tracking of the movement is performed.

marked on the ground, as zone-1 and zone-2. If the person enters into one of the exclusion zones, an alarm is generated. This also detects the zone crossing, if the person moves from one zone to other zone. This is deployed within BARC for field testing.

Suspicious Behaviour Identification System (SBIS)

The objective of this application is to find a suspicious action of a person or other objects from the video feed. An end-to-end deep learning architecture is under development to predict suspicious actions. The spatio-temporal features of the key joints of the human in small video clips are used to identify the actions and to further classify into normal or suspicious action. Other possible way is to model a self-learning AI model to learn the normal and suspicious behaviour of a person.

Other Applications

The model obtained from training on MS-COCO[3] dataset for object detection is fine-tuned to perform object detection on the thermal images. These thermal images of human-beings are obtained from FLIR[8]. This process is called transfer learning. The results are shown below in Fig.5. In areas where there is no/low light, it is possible to detect the objects using thermal images.

Summary

Manually monitoring the video feed from several surveillance cameras for detecting any intrusion or suspicious behaviour is a tedious task for security personnel. Deep Learning based models are yielding promising results in various computer vision tasks, viz, object detection and image classification. This article summarises few surveillance systems which are under development where deep learning concepts are being applied. Object detection models are used in Physical Intrusions Detection System and virtual fence systems. Object tracking models are used in virtual fence. These models are trained using publicly available datasets and then these models are fine-tuned using local datasets for surveillance applications. Few of these systems are deployed at BARC perimeter for field testing.

References

[1] M. Green, “The appropriate and effective use of security in schools,” US Department of Justice, 1999.

[2] http://www.image-net.org/challenges/LSVRC/ (accessed Sep 5, 2022).

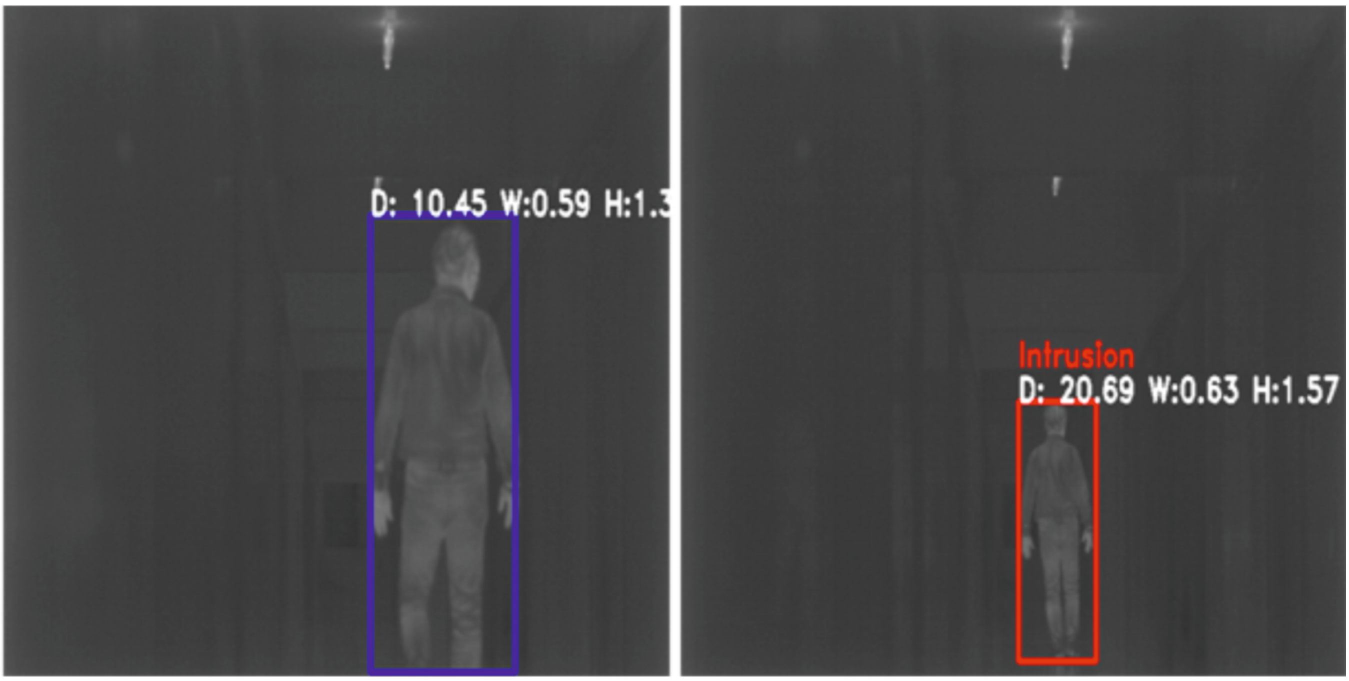

Fig.5: Results of Transfer learning on Thermal Images. The depth, width and height (in meters) of the intrusion are also indicated over the bounding box as text. The experiment was conducted to detect the humans from thermal images placed in stereo-fashion and find the dimensions of the human. Depending on the depth (or distance) of the human from camera, the colour of the bounding box changes. The colour of the bounding box is kept as blue for depths less than 20m and red for depths greater than 20m.

[3] L. T. e. al., "Microsoft COCO: Common Objects in Context," in Computer Vision – ECCV, 2014.

[4] Chengcheng Ning, Huajun Zhou, Yan Song and Jinhui Tang "Inception Single Shot MultiBox Detector for object detection," in IEEE International Conference on Multimedia & Expo Workshops (ICMEW), Hong Kong, 2017.

[5] http://www.pytorch.org (accessed Sep 5, 2022).

[6] Aravamuthan, G., Rajasekhar, P., Verma, R. K., Shrikhande, S. V., Kar, S., Balur, S. "Physical Intrusion Detection System using Stereo Video Analytics," in CVIP-2018-IIITDM Jabalpur, 2018.

[7] R. Punna, G. Aravamuthan and S. Kar, "Recovering 3D from 2D image points (calibrated camera approach for surveillance)," in 2022 IEEE 7th International Conference on Converging Technologies (I2CT), Pune, 2022 .

[8] https://www.flir.in/oem/adas/adas-dataset-form/(accessed Nov 5, 2021).

Remote Handling & Robotics

15

Advances in Remote Handling & Robotics in Backend of Nuclear Fuel Cycle

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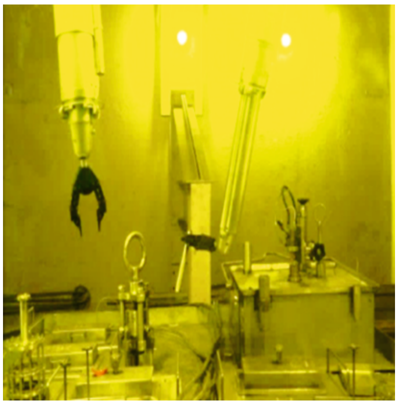

Mechanical manipulator arm inside the cell

ABSTRACT

Nuclear energy plays a crucial role in expansion of the horizons of green technology. It provides access to clean, reliable and affordable energy, mitigating the negative impacts of climate change. A three-stage nuclear power programme, based on a closed nuclear fuel cycle due to modest uranium reserves, was then stated out by the founder father of the department of atomic energy and the program comprises of the design & commissioning of Natural uranium fuelled Pressurized Heavy Water Reactors (PHWRs), Fast Breeder Reactors (FBRs) utilizing plutonium based fuel and Advanced nuclear power systems for utilization of thorium. To sustain this Closed Fuel Cycle, reprocessing of spent fuel to extract useful Pu & U for its further utilization in second stage, and management of High-Level Waste (HLW) for waste minimization have been adopted. Radiochemical Processing of spent fuels necessitates handling of high radioactive material behind heavy shielding, where it also requires highly reliable and safe remote handling gadgets. A variety of remote handling gadgets have been deployed by BARC in Indian Back-end facilities as per different process treatment requirements. This article discusses existing remote handling systems and recent advances made in remote handling and robotics of Backend of Nuclear Fuel Cycle deployed for better reliability, productivity and safety.

KEYWORDS: *Robotics, Remote viewing, Advanced servo manipulator, Wireless camera, Gantry mounted Power manipulator*

Introduction

The used spent fuel undergoes a series of steps including temporary storage, reprocessing & recycle, waste management known as Back-end of Nuclear Fuel Cycle. In reprocessing, Uranium & Plutonium, constituting bulk of spent nuclear fuel are separated and subsequently recycled. Remaining portion constitutes High Level Radioactive Liquid Waste (HLRLW) containing most of the fission products & minor actinides etc. Radiochemical plants in back end of fuel cycle depends heavily on remote technology for operation and maintenance. These functions have been achieved by way of operating general type remote handling gadgets and special customized equipment. Design of various manipulators, special equipment for handling & viewing devices, specially designed cranes etc. developed indigenously adapting modern technologies are the key for increasing reliability & availability of these plants.

Remote handling of Back end fuel cycle

Major operations in Radiochemical Plants are carried out in heavily shielded thick structures known as hot cells, to reduce radiation exposure. 'Hot cell' term refers to cells or areas where radioactivity is very high with highly acidic or corrosive, hot and humid environment, and also with no manual access inside for Operation and Maintenance (O&M). Remote Technology for O&M of such plants is under development with several objectives where the technology ensures increased operation, safety against hazards of radiation exposure to operating personnel, availability of Radiochemical plants at Back-end for continued production, overall reduction in secondary waste generation and effect on operating cost/life of the plant. List of major operation activities of Nuclear back end cycle have been shown in the Fig.1.

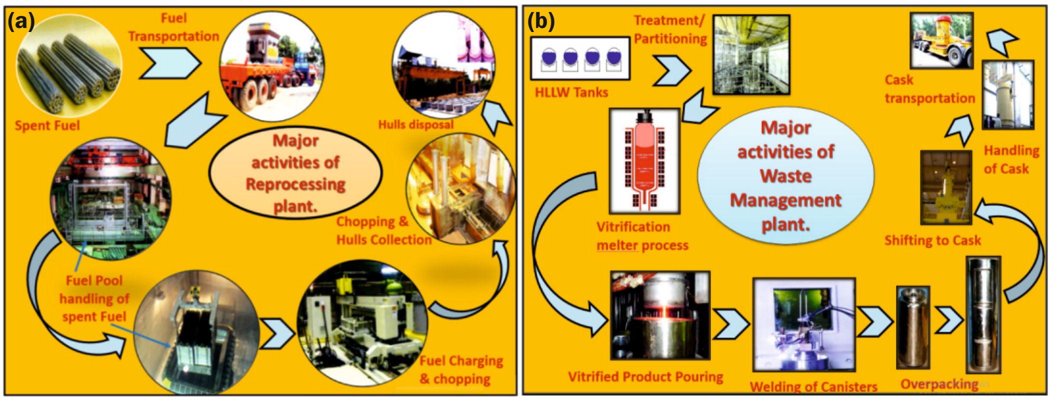

Fig.1: List of activities involved: (a) Reprocessing cycle (b) Waste management cycle.

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Table 1: Major Terminology of Robotics.

Payload-	Maximum load, equipment can handle at end of arm in any configuration.
Degree of freedom(DOF)-	No. of independent parameters required to define configuration of a mechanism.
Kinematics-	Study of motion without regard to forces.
Dynamics	Study of motion with regard to forces
Actuator-	Provides force for motor/ joints motion.

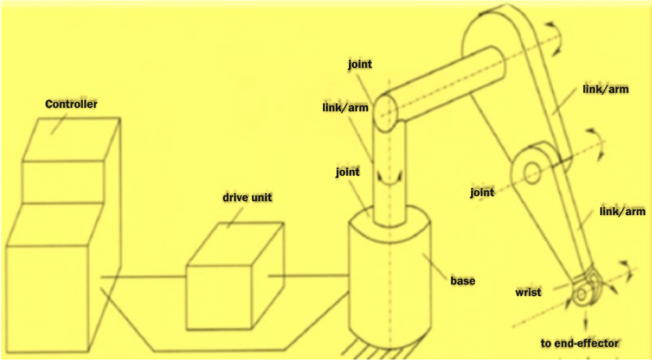

Fig.2: Robotics mechanism showing controller to end effector.

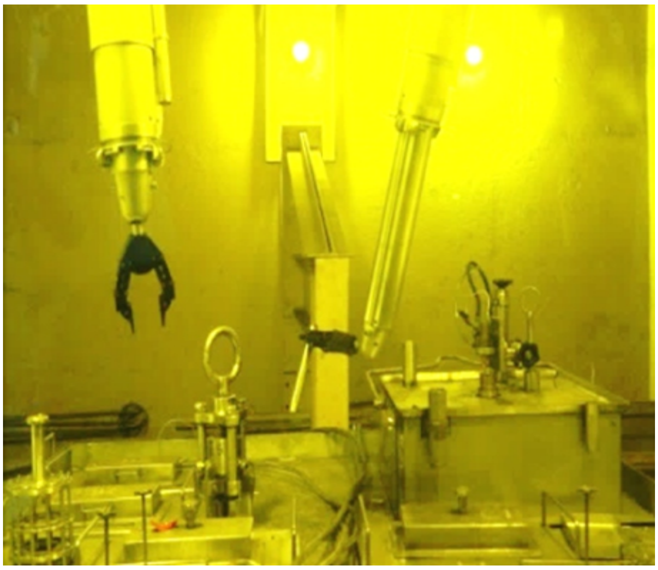

Fig.3: Mechanical manipulator arm inside the cell.

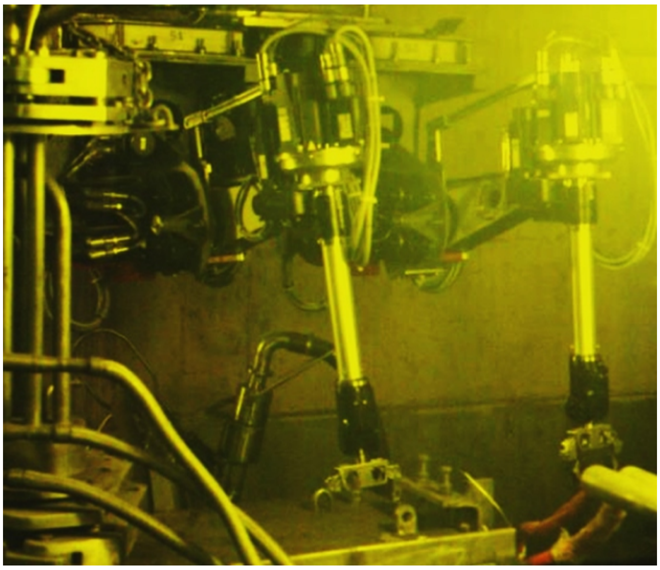

Fig.4: ASM arm inside the cell.

Present Robotics & Remote handling equipment

Mechanical and electrical Master Slave Manipulators (MSM), special cranes & trolleys & transfer systems, remote viewing systems, specially designed grapplers etc., are the major remote handling tools and systems utilized in the present facilities. Methodology behind design of any remote handling equipment or robotics is to replicate operator as detailed in next section.

Linkage between Robotics and Human

Robotics refer to the field of machines that can be substituted for human and replicate human actions. Hence, to replicate a human being, 3Hs of Human being have been translated into Robotics. Hand which refers to arm, Head which controls & guide all motion refers to brain of a Robot (Controller) and Heart which pumps blood, refers to drives for power transmission which can be mechanical, electrical or pneumatic etc. Robotic sensors same as Human ear, eyes, nose etc. are used to estimate the robot's condition and environment. Sensors in the manipulators collect information from the environment, and send this information to the controller. The drives work, based on this feedback. Manipulator refers to a robot with fixed base and are composed of an assembly of links & joints. Links are rigid members between joints and these joints provide mobility or degrees of freedom in the system as shown in Fig.2. Two major types of manipulators are being used in Back end cycle: - Mechanical such as three piece manipulator (as shown in Fig.3), articulated manipulators etc. and Electrical manipulators such as servo manipulators, power manipulator etc. In mechanical manipulator, motion generated by operator's hand is mechanically transmitted to end effector of slave, through linkages of master arm, through tubes & slave arm and whereas electrical actuators such as different motors are being used for transmission of motion in electrical manipulators.

Recent Advances in Remote Handling Systems

Several developments have been carried out recently with advanced mechatronics, by utilizing multiple operation feedbacks and as they are discussed in next sections.

Advanced Servo Manipulator

Advanced Servo Manipulator (ASM) as shown in Fig.4 is an Electro-mechanical bridge mounted type of manipulator. It is a dual arm & kinematically similar arm, bilateral, force reflecting system using digital control system and servo feedback system as shown in Fig.5.

There is no direct mechanical links connecting the master arm and the slave arm. Slave arm has been installed inside the Hot Cell & the master arm in the workstation. Slave arm is basically used in precision remote handling, such as handling of thermocouples, airline connectors or alignment of impact wrench inside the hot cell.

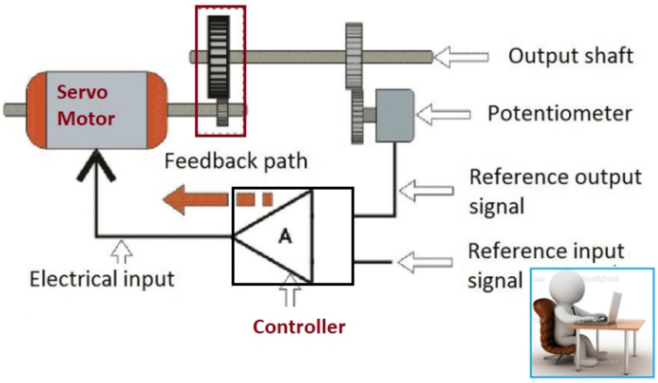

Fig.5: Servo motor working principle.

Table 2: GMPM Technical specification.

Travel length	2350mm to 5100mm
Gripper payload	30Kg
Gripper opening	80mm
First roll/swivel	+/- 180°
First pitch	0 to -120°
Second pitch	+/- 90°
Wrist pitch	+/- 90°
Wrist roll	+/- 180°

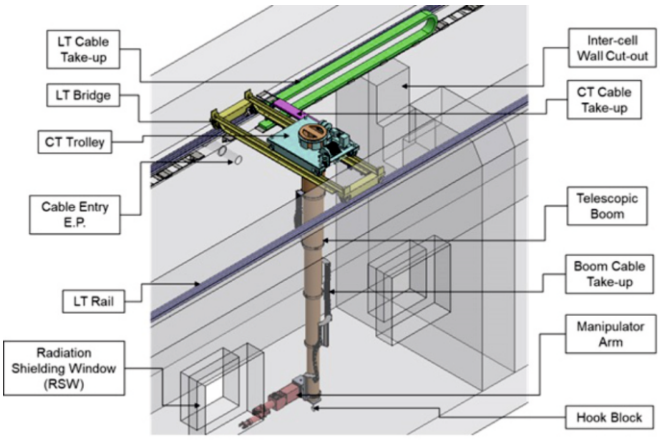

Fig.6: General Layout of the GMPM in Hot-Cell.

Fig.7: Remote handling Workstation.

Slave arm assembly is mounted on transporter inside the hot cell, providing large effective area of hot cell. All ASM operation are CCTV assisted and operated through master control station from outside hot cell (i.e. work station). Payload of the installed ASM is 25kg and it has an adjustable type gripping force control with feedback provision. All joints are operated using Servo motors.

Gantry Mounted Power Manipulator for Hot-cell

Gantry mounted power manipulator (GMPM) is an electrically actuated system utilized for remote handling operations of materials and maintenance activities inside hot-cell. GMPM consists of a gantry with long travel (LT), cross travel (CT), a telescopic boom, a hook for lifting loads and 6-axis articulated manipulator arm fitted to the boom assembly for object handling. Major technical specifications of GMPM are listed in Table 2. GMPM will be operated through pendant from multiple locations outside the cell/bay, by viewing it through the radiation shielded glass windows and remote viewing system. GMPM can also be controlled from a control station through a Human Machine Interface (HMI) interface. Fig.6 shows a general arrangement of the GMPM in the hot-cell.

Limiting design parameters of telescopic boom and articulated arm of GMPM are: Collapsed length which is restricted by inter-cell wall opening of the hot cells and the extended length to reach the cell floor during operation. Designing the gantry for GMPM was also constrained by the in-cell crane installed on the same LT rails in the work space. It is designed for remote maintenance, replacement of components/sub-assemblies. Five telescope tubes have been utilized for telescopic movement. Manual override is also being provided for gantry operation during emergency. The control system is designed for long lead operation with cable length of 100 m.

Remote viewing system

Remote viewing system in conjunction with radiation shielding windows are the key for efficient and safe remote handling inside hot cell. Reliable remote viewing system allows to optimum utilization of hot cells for design of equipment layout. In general, CCTV based remote viewing system as shown in Fig.7, has been used due to its cheaper cost and availability. CCTV based system consists of camera (lens & sensor) with cabling, Digital Video Recorder (DVR)/Network Video Recorder (NVR) & Video Monitor etc. Three types of CCTV camera system - Analog, Digital & IP network are in use. Image sensors used in these are either Charge Coupled Device (CCD) or Complementary Metal Oxide Semi-Conductor (CMOS).

These types of cameras in hot cell have limited life if used in direct exposure to radiation, resulting in frequent failure and downtime. In order to enhance the life of cameras, different customized mechanisms have been designed and developed for handling of cameras, to bring it into shielded environment in the hot cell during inoperative condition. These are Retractable Type (motorized and pneumatic), telescope type & wireless Cameras.

Retractable camera system

Special customized retractable camera systems have been designed, developed and tested for mounting on

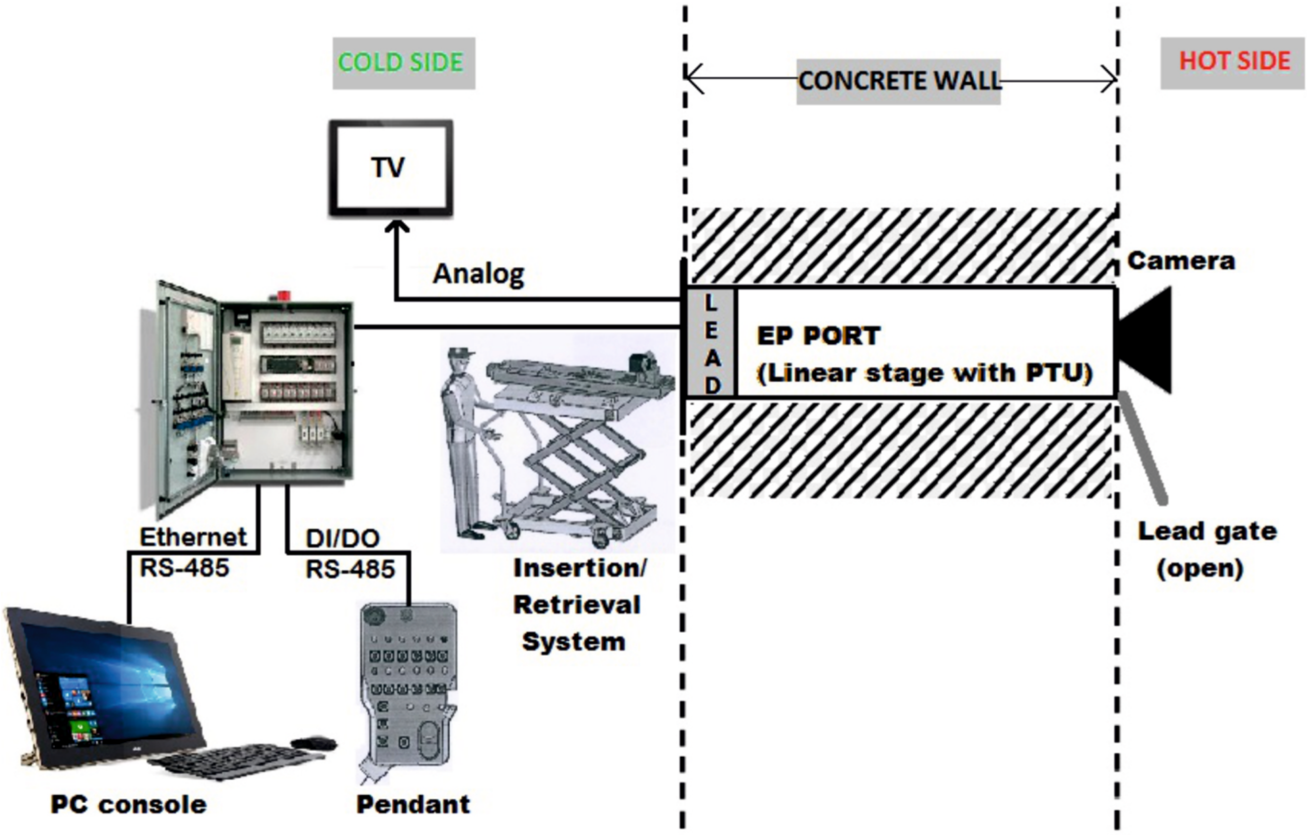

Fig.8: System Architecture.

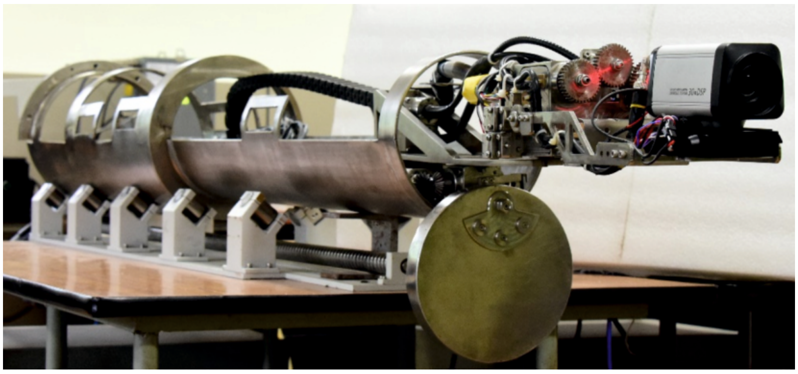

Fig.9: Motorized CCTV camera system.

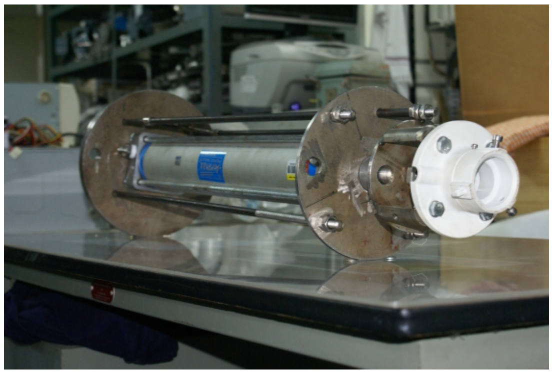

Fig.10: EP Camera pneumatic actuator mechanism.

Embedded Plugs (EPs) of hot cells. The system comprises of 1.5-meter SS tube housing which dwells inside the wall port and has a provision of rotating the shielding inside the hot cell to prevent radiation streaming on camera sensors.

The overall architecture of the system's final design is shown in Fig.8. The system comprises of tube housing having a motorized linear trolley as shown in Fig.9, to facilitate extension and retraction of camera mounted on a pan-tilt pedestal for viewing of the hot cell view. This system can be operated directly using a control pendant or PLC based system which incorporates safety interlocks using hardwired relay circuitry. The system has a provision for manual retrieving from hot cell in case of any motorized movement of components which fails inside hot cell. Similar type of remotely operated pneumatic mechanism has been developed using standard IP based camera system for hot cells. The system comprises of a pneumatic actuator which provides forward and retrieval motion inside the 1.5-meter-long EP of the Hot Cell wall as shown in Fig.10.

This system has no other moving parts and hence it does not need high maintenance. Shielding blocks have also been designed to avoid any radiation streaming towards cold side (operating gallery). It has been commissioned inside the hot cell and has provided maintenance free operation for long time.

Remotely replaceable IP based Wireless Camera System

A remotely replaceable IP based wireless camera system is one of the recent developments for the existing in-cell crane mounted camera inside the hot cells of Waste Management Plant of BARC. The development has resulted in the negligible man-rem exposure, as well as reduced system downtime due to its remote replaceability and auto latching connector design features.

Conclusions and Future Challenges

Remote handling mechanisms play a vital role in the Back-end of Fuel Cycle. Several campaigns have been

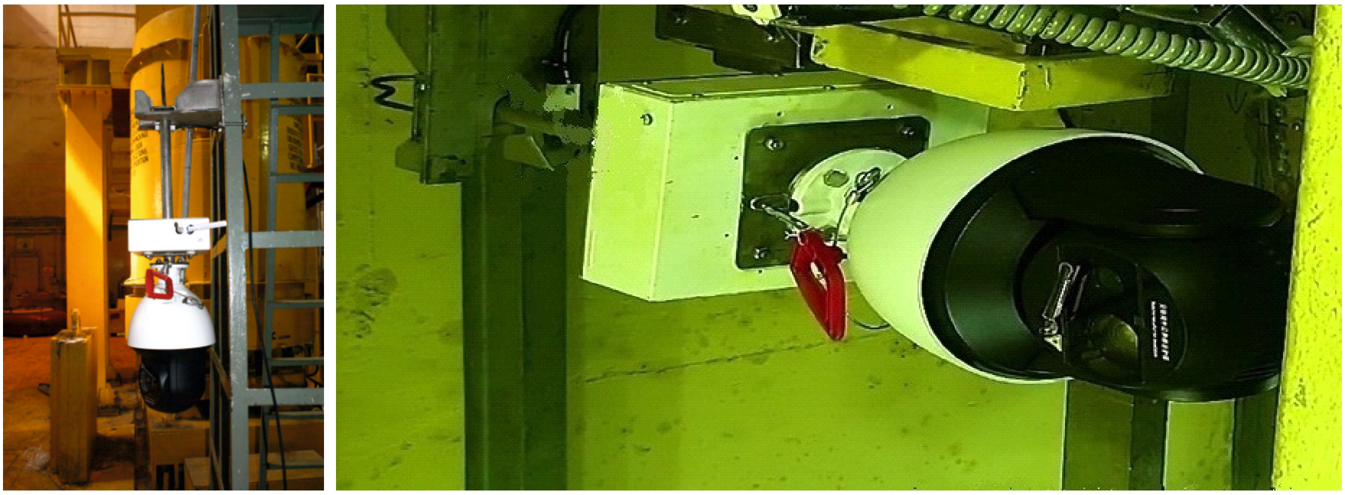

Fig.11: Wireless camera assembly during testing and inside view during commissioning.

performed by utilizing indigenously developed remote handling equipment. This matured indigenous remote handling equipments have reduced man-rem exposure, decreased down time by reducing the maintenance frequencies, and also reducing disposal quantities of malfunctioned gadgets/ equipment, thus decreasing radioactive waste.

To summarize, major future challenges are ahead in the designing of robotics for cell manipulation, decommissioning, dismantling of facilities, indigenous & reliable remote handling equipment with advanced automation for reducing downtime with increasing availability & operability at rated capacity. In this era of modern technologies, virtual reality modelling for better understanding during hot cell planning and designing of plant for higher level of remote operability & maintainability etc. will be adopted.

References

[1] C. P. Kaushik "Indian Program for Vitrification of High Level Radioactive Liquid Waste", Procedia Materials Science, 2014, 16-22.

[2] S. Wadhwa et al., "Challenges in Installation of Advanced Servo Manipulator (ASM) at Hotcell, WIP, Trombay, BARC", BARC Newsletter (2018), 24-30.

[3] S. Wadhwa et al.,"Advances in Remote handling and robotics in Vitrification Facilities", BARC Newsletter (2022), 38-41.

Homeland Security

16

AI based Object Detection in X-Ray Images for Homeland Security

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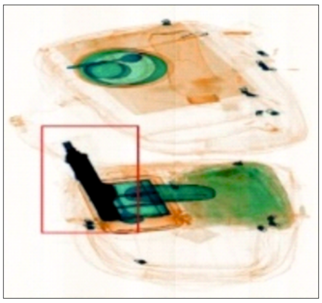

Auto detection of Guns

ABSTRACT

X-Ray baggage scanners and Cargo scanners are used at critical checkpoints to screen the item under inspection to reveal concealment of threats, contra-bands, illicit materials and prohibited items. Manual screening by human operators plays a vital role in their detection. Although experience and knowledge are the key factors for confident detection, external variables such as personnel fatigue, increase in traffic volume and cluttered items under inspection adversely impact manual screening. A more viable solution is automatic analysis of scanned images to assist the human operators to accurately identify anomalies. Recently a modern technique namely, Deep Learning has demonstrated remarkable success in automated object detection. Hence we have used AI based deep learning approach, with a particular focus on object classification, detection, segmentation and anomaly detection tasks for Auto-threat detection and Auto Content verification.

KEYWORDS: *Automated object detection, X-Ray image inspection, Baggage scanner, Cargo scanner automated content verification, Data augmentation for X-Ray images, Feature visualization*

Introduction

X-ray Radiography is a non-destructive imaging technique used to scan baggage and to inspect scanned images for anomalies, threats and prohibited items. Manual Inspection of X-ray images for high risk prohibited items is largely dependent on operator alertness and expertise. Automating the X-Ray image classification into threat and non-threat classes requires intelligence to be integrated into image processing. Due to variation in shape and size of threat objects, background and occlusion, it is difficult and impractical to create an exhaustive set of rules for threat object detection, rendering numerical models unsuitable to model threats. A better solution is to use machine learning techniques and train models to learn the most important rules by themselves. Convolutional Neural Network (CNN), is chosen for threat detection, as it scales well for images and considers spatial correlation. This article is divided in three parts:

- Automated threat recognition in X-Ray baggage scanner images
- Automated threat detection in X-Ray baggage scanner images
- Automated Content verification for cargo scanner

Automated Threat Recognition

Automated threat recognition discusses classification of dual energy X-Ray baggage image into threat or non-threat class based on presence of a threat item, using CNN.

Data Augmentation for Threat Recognition

CNN requires a large and balanced dataset to learn a generalizable model. The dataset obtained from X-Ray baggage scanner was imbalanced as the majority of the images do not contain a threat leading to a bias in the learning algorithms based on this dataset towards non-threat class. To balance the dataset, data augmentation based on Threat Image Projection technique[1] is utilized to artificially generate training images containing threat item. A dataset of 110 non-threat baggage images and 94 images of the featured threat item was split into (i) base training set consisting of 80 non-threat baggage images and 73 featured threat images and (ii) base test set consisting of 30 non-threat baggage images and 21 featured threat images.

The dataset was obtained from dual energy single view ECIL make X-Ray baggage scanner ECX6040:SVXBIS. Class preserving translation and rotation variations were applied to existing data to expose the CNN model to natural variations during training. Feasibility of projection was calculated to determine whether the featured threat image after transformation lies completely inside baggage region. Translated and rotated featured threat images were projected onto the clean image patches using Threat Image Projection technique. The intensity of a pixel in a threat scan was split into contributions from the threat and its background using Beer-Lambert law. Threat mask was calculated using the attenuation caused by the background in threat scan without any container. The threat mask was then projected into X-ray images by multiplication.

The training set and test set derived from the base set using data augmentation contained around 1.24 lakh images and around 18,000 images respectively. The validation set was formed by randomly choosing 5000 test set images from the above images. The training and testing dataset also included toy guns, which belonged to negative class. Toy guns have shape similar to real guns but made of different material. This introduced the material variation in the training set.

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Table 1: Model Performance using Adam Optimizer.

Model	Tr. A	VA	TA	FP	FN	Precision	Recall	F - measure	AUC - ROC	Accuracy on toy guns
Gradient Descent	0.9881	0.985	0.9846	85	121	0.9867	0.9812	0.9839	0.9845	0.896
Adam Optimizer	**0.9972**	**0.992**	**0.9905**	**32**	**95**	**0.9949**	**0.9852**	**0.9904**	**0.9924**	**0.972**

Table 2: Variation in VGG-19 layers.

Model	Tr . A	TA	FP	FN	Precision	Recall	F - measure	AUC - ROC
VGG - 19	0.9881	0.9846	85	121	0.9867	0.9812	0.9839	0.9845
VGG - 20	**0.9912**	**0.9864**	**90**	**93**	**0.9860**	**0.9855**	**0.9857**	**0.9836**
VGG - 21	0.9917	0.9847	25	180	0.9960	0.9669	0.9720	0.9842
VGG - 22	0.9908	0.9793	65	213	0.9896	0.9669	0.9781	0.9788
Google Net	0.9983	0.9386	27	226	0.9956	0.9649	0.9800	0.9803

CNN Training and Optimization

The Current state of the art CNN models such as AlexNet, VGGNet were considered for threat detection. Four channel input (-log HE, -log LE, HE + LE, HE - LE), derived from 2 channel (High Energy (HE) and Low Energy (LE)) was selected considering the occlusion characteristics and material discrimination in dual energy X-Ray baggage scanner images. AlexNet, VGG-16 and VGG-19 were trained on a Tesla K80 GPU, using mini batch gradient descent approach with batch size of 32. Dropout with probability of 0.5, in addition to weight decay (lambda=0.0001), was used in fully connected layers as a regularization technique. The performance of CNN models has been reported in terms of training accuracy (Tr. A.), testing accuracy (TA), false positives (FP), false negatives (FN), precision, recall, F-measure and AUC-ROC.

CNN Optimization

Among AlexNet and VGGNet models, VGG-19 achieved highest testing accuracy of 98.4% with four channel inputs. We further explored three different approaches for improving accuracy i) use of Adam optimizer[2] instead of vanilla gradient descent as CNN loss optimization algorithm, ii) Varying the number of layers in VGG-19 architecture and iii) ensemble of trained models.

Adam Optimizer: Adam Optimizer is a variant of stochastic gradient descent (SGD) which adapts the learning rate based on recent gradient magnitudes. Adam Optimizer improved the training accuracy from 98.81% to 99.72%. High testing accuracy (99.05%) which is close to training accuracy and improved toy gun classification (97.2%), also indicate good generalization achieved by trained model. (Table 1).

Variation in number of layers: VGG-20, VGG-21 and VGG-22 architectures were designed by varying number of layers in VGG-19 architecture with gradient descent. (Table 2). Considering the trade-off between higher learning capacity provided by deeper networks and overfitting due to large number of parameters in deeper networks, peak is found at 20 layers (VGG-20). Model starts overfitting and losing its generalization capacity beyond 20 layers.

Ensemble Network: VGG-19 and AlexNet achieved threat detection rate of 98.52% and 97.96% respectively using Adam Optimizer. Analysis of false negative images revealed that AlexNet was able to detect some of the guns among 1.48% guns, which were not discovered by VGG-19. Considering the importance of reducing false negatives for automated threat detection, AlexNet and VGG-19 models were combined to increase threat detection rate. The combined Ensemble Network reduced false negatives by 36% as compared to both the base models (Table 3). Out of all the tested models, Ensemble network of four channel AlexNet and VGG-19 had the highest accuracy (99.37%) and threat detection rate of 99.06%. Also, the model had F-measure value 0.9934 and 0.9936 AUC. Thus, the ensemble network of AlexNet and VGG-19 was found the most suitable for automated threat recognition.

Visualization of detected features

Visualization of CNN gives insight into the function of intermediate feature layers and the operation of the classifier. Deconvolutional Network[3] is one way to visualize the input pattern that caused given activation in feature maps by mapping the activation back to input space. Fig.1 shows the features of the threat item evolved over the layers of CNN.

Automated Threat Detection

The fixed input size (256x256) Ensemble network was unsuitable for real time prediction required in security applications as sliding window detection needs to be applied for variable sized X-Ray baggage scanner images. Also, the

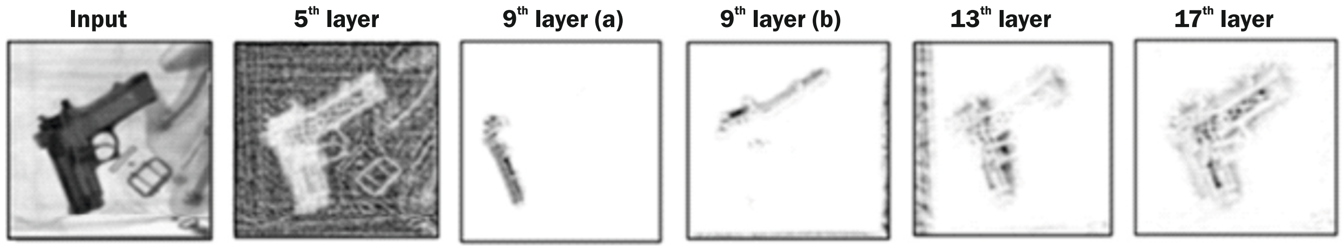

Fig.1: 5th Layer: Detection of edges, 9th Layer: parts of object, 17th Layer: Detection of object ignoring background.

Table 3: Ensemble Network Performance.

Model	VA	TA	FP	FN	Precision	Recall	F - measure	AUC - ROC	Accuracy on toy guns
VGG -19	0.992	0.9905	32	95	0.994	0.9852	0.99	0.9924	0.9720
AlexNet	0.986	0.9845	77	131	0.987	0.9796	0.9837	0.9851	0.9702
Ensemble Network	**0.995**	**0.9937**	**24**	**60**	**0.9962**	**0.9906**	**0.9934**	**0.9936**	**0.9825**

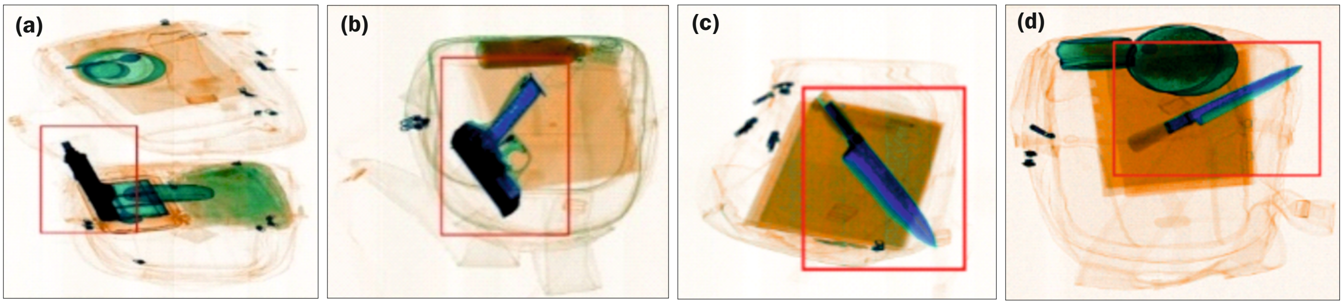

Fig.2: Auto detection of Guns (a, b) and Knives (c, d).

localization could only be as accurate as the bounding box provided by sliding window size (256x256). Thus, object detection (i.e. both, object recognition and object localization) model with variable input size, was required for automated threat detection in X-Ray images in real time. Such a model is also more effective in detecting multiple threats in a single image. Hence, YOLOv2, its improved version YOLOv3 and the smaller version Tiny-YOLOv3 for constrained environments, were considered for its applicability in threat detections in dual energy X-Ray baggage images.

Data Augmentation and Threat Projection as discussed in section 2.1 was used to obtain a balanced dataset. Ground truth labels for training object detection models were assigned to each threat object projected image. The low energy and high energy channels of clean bag images and threat object projected images were fused together to form pseudo coloured RGB images identifying material categories (Organic, Mixture, Inorganic and Dense). 'Spot the difference'[4] using threat and benign pairs was applied to the training set and testing set of 2280 images and 772 images respectively.

Results and Discussion

YOLOv2, YOLOv3 and Tiny-YOLOv3 models, initialised using pre-trained ImageNet weights, were trained on the training dataset created as explained above in 'Data augmentation for threat recognition' section. Table 4 shows the comparison of YOLOv2 model and YOLOv3 model trained with input resolution 416 x 416 pixels and YOLOv3 model trained with random input resolution, using multiscale training. In multiscale training, for every 10 batches, the network was trained on randomly chosen image sizes from range 320x320 pixels to 608x608 pixels as multiple of 32 pixels. The improvement in mAP (99.17%), accuracy (98.18%) and F-1 score (98.17%) shows that YOLOv3 model trained using multiscale option is most suitable for automated threat detection in material discriminated X-Ray baggage images.

While scanning a typical baggage in X-Ray inspection system, the baggage is displayed on the inspection screen for 2.5 seconds on an average. The best performing YOLOv3 model detects the threat in real time using GPUs (0.125 sec), but takes significantly more time without GPUs (around 3.6 sec). Tiny-YOLOv3 a compact variant model takes around 0.0149 sec on GPU and 0.369 sec on CPU which is well within the real time prediction limit for X-Ray baggage inspection system. Thus, trained YOLOv3 model with 99.17% mAP was found best performing for automated threat detection task, whereas Tiny-YOLOv3 was found best suitable for real time threat detection in non-GPU environments. A Trade-off was observed between model performance in terms of mAP and average prediction time. Table 5 shows average prediction time of YOLOv3 and Tiny-YOLOv3 trained models on: Intel 4th generation (Haswell) i-7 processor non-GPU system and NVidia Tesla K80 GPU with 4096 cores.

Table4: Performance of YOLO models.

Model	Resolution	mAP	Accuracy	F 1- score	IOU
YOLOv2	416 x 416	97.99%	96.89%	96.92%	73.98%
YOLOv3	416 x 416	98.63%	97.80%	97.79%	78.68%
YOLOv3	608 x 608 Multiscale	99.17 %	98.18%	98.17 %	78.01%

Table4: Average Prediction Time.

Model	mAP	Accuracy	F 1-score	IOU	Prediction Time sec (GPU)	Prediction Time sec (CPU)
YOLOv3	99.17 %	98.18%	98.17 %	78.01%	0.125	3.598
Tiny YOLOv3	96.34%	94.30%	96.72%	73.82%	0.0149	0.369

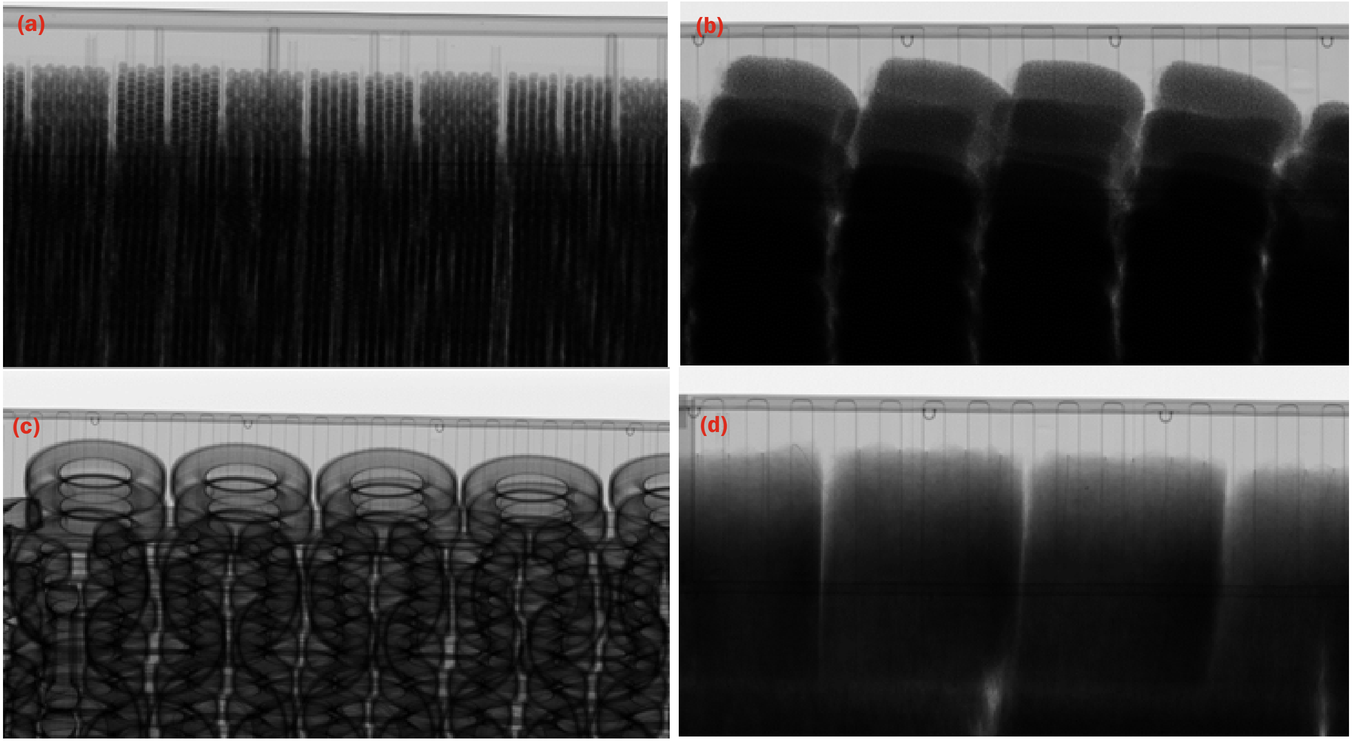

Fig.3: Content classification: A) Apple, B) Dates, C) Tyre, D) Paper.

Integration with XBIS Software

The model has been integrated as a pluggable add-on with the Single View X-ray Baggage Inspection System software(XBIS) developed by Electronics Division. Real scanned bag images obtained from XBIS machines deployed at site were superimposed with threat images and continuous scanning of a mixture of benign and threat-containing bags was done to evaluate performance during real scans. YOLO model could successfully detect guns and knives in real-time (Fig.2).

Auto Content Verification

Volume of cargo containers is several times larger than a regular luggage. Moreover, cargo images are cluttered and they maybe homogeneous or heterogeneous. Mutual overlap between objects and different stacking modes increase image complexities and makes manual inspection of cargo images a visually challenging task. Machine learning based object classification approach for autocontent verification of the Cargo under inspection has been used. A dataset containing over 3000 images per category of Apples, Dates, Tyre and Paper was subjected to automated image segmentation and classification using machine learning. Segmentation was done using texture, morphological and Statistical Region Merging algorithms. Classification of images using Bag of Words and Bayesian methods gave 86% accuracy. Second approach using deep learning (VGG-19 model) achieved accuracy of 97.8%. Fig.3 shows the classification.

Conclusions

In this article, following are presented i) Convolutional Neural Networks to classify dual energy X-ray images of baggage in threat and non-threat classes for threat object, ii) YOLO models to recognise as well as localize threat object in dual energy X-Ray baggage images and iii) Classical machine learning and deep learning models for automated content verification in cargo scanner X-ray images. It is found that, when trained on a large and balanced dataset, deep learning models prove to be a practical tool for automated image classification and object detection. In this study, it is concluded that, the use of ensemble network improved the accuracy over base models. We studied the trade-off between learning capacity and generalization capacity of a model by varying the number of layers of VGG-19 model and found that testing accuracy reached its peak at 20 layers.

References

[1] T. Rogers, J. Nicolas, J. Ollier and L. Griffin, “Threat Image Projection (TIP) into X-ray images of cargo containers for training humans and machines,” in Security Technology(ICCST), 2016 IEEE International Carnahan Conference, Orlando, FL, USA, 2016.

[2] D. P. Kingma and J. Ba, “Adam: A Method for Stochastic Optimization,” in International Conference for Learning Representations, San Diego, 2015.

[3] M. D. Zeiler and R. Fergus, “Visualizing and Understanding Convolutional Networks,” in ECCV 2014, Zurich, 2014.

[4] T. Rogers, N. Jaccard and L. Griffin, “A Deep Learning Framework for the automated inspection of complex dual energy x-ray cargo imagery,” in Anomaly Detection and Imaging with X-Rays (ADIX) III, Orlando, 2017.

Automation

17

Automation in Ultrasonic Imaging of Under-water Concrete/RCC Structures

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4-channel Ultrasonic Imaging System for Concrete/ RCC

ABSTRACT

There has been a rapid increase in the construction of under-water concrete structures all over the world and the maintenance and rehabilitation of these concrete structures pose a major concern for estimating the quality and the useful remaining life of these structures. This article provides brief details of the in-house developed Automated 4-Channel Ultrasonic Imaging System for the detection of flaws, porosities and rebar locations inside the concrete/Reinforced Cement Concrete (RCC) structures, and the system is interfaced with 2-axes automated mechanical scanner, for operation either in Pulse Echo (PE) or Transmit-Receive (T-R) mode. The imaging system performs data acquisition and temporal averaging of the RF bipolar signals using Spartan-6 FPGA to achieve high Signal-to-Noise Ratio (SNR) (> 20 dB).

KEYWORDS: *Ultrasonic Imaging, Concrete/RCC, Automation, Under-water,z UPV, Pulse-Echo*

Introduction

Ultrasonic wave propagation is sensitive to distributed damages in concrete structures and ultrasonic testing (UT) technique can be applied in-situ for inspection of large structures. However, the inhomogeneous and porous nature of concrete gives rise to scattering and absorption of propagating ultrasonic waves. As a consequence, the wave attenuation and structural noise are predominant in the received signals, which mask reflections received from flaws which are required to be detected. Low frequency ultrasonic transducers (50 kHz to 250 kHz) are routinely employed for the inspection of non-homogeneous structures like Concrete/RCC etc, to avoid the attenuation due to divergence and scattering of ultrasonic waves within the material[1]. However, with low frequency ultrasound also, the concrete still acts as an excessive at tenuative material which makes the inspection of Concrete/ RCC structures a challenging task. Ultrasonic Pulse Velocity (UPV) testing is an effective and indirect method as per BIS standard IS 13311 (Part-1) [2] & IS 516 (Part-5/Sec 1) [3], for the assessment of material homogeneity, providing information about the compressive strength and the existence of internal flaws and anomalies. At the same time, evaluation of UPV result is a specialized field activity, which requires careful data collection and expert knowledge and experience to obtain reliable diagnosis. In order to map the homogeneity of a concrete structure, it is necessary to acquire and interpret a large number of UPV values for the concrete structure under test[4]. Therefore, the automated ultrasonic imaging technique is needed which provides internal details of the Concrete/RCC structure under test and the estimation of flaw size and flaw characterization.

Automated 4-channel Ultrasonic Imaging system

Due to a rapid progress in the computing technology, many imaging techniques like Synthetic Aperture Focusing Technique (SAFT), Reverse Time Migration (RTM) technique, Total Focusing Method (TFM) etc., are widely utilized by the researchers for the ultrasonic imaging of Concrete/RCC structures. The SAFT algorithm has been applied extensively by researchers on ultrasonic data to image the tendon ducts, defects and rebars inside concrete structures. Many commercial instruments utilize these digital techniques using phased array shear wave transducers for imaging of the concrete structures[5]. But for imaging of under-water concrete structures, instruments which are generally based on shear-wave transducers cannot be employed due to the non-feasibility of shear wave propagation in water.

The water-immersion based and automated 4-channel Ultrasonic Imaging System has been designed & developed by Electronics Division (ED), BARC for the acquisition of B-Scan images of the under-water concrete and RCC blocks using Pulse-Echo (PE) mode as shown in Fig.1(a), which needs access from one side of the concrete structure under test. The linear array fixture using commercially available narrow band, longitudinal-wave type water-immersion, 92 kHz ultrasonic transducers have been fabricated at workshop, ED as shown in Fig.1(b). Four transducers are sequentially energized as transmitters to enable image data acquisition by utilizing same transducers as receiver of ultrasound. The technique is completely contactless as ultrasonic immersion transducers with fixed stand-off distance between transducer's front face and top surface of concrete block are employed for imaging purpose[6]. The four-channel imaging system consists of four-channel high voltage (HV) tone-burst square-wave bipolar pulser[7], four-channel pre-amplifiers with maximum gain of 66 dB for each pre-amplifier channel and a common main amplifier with 66 dB maximum gain; multi-channel data acquisition module which includes in-house developed 100 MSPS, 8 bits high speed digitizer, commercially available Spartan 6 FPGA module which controls the timing of the entire

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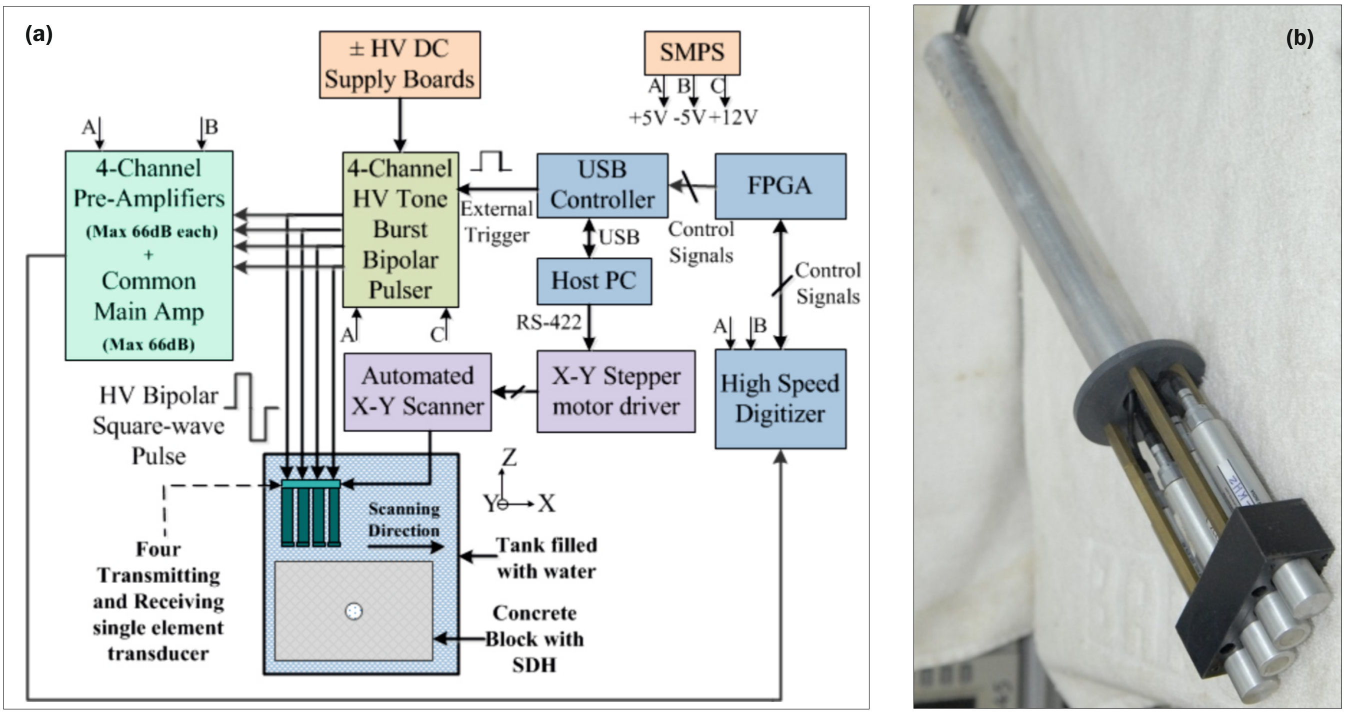

Fig.1: (a) Schematic Block Diagram of Automated 4-Channel Ultrasonic Imaging System for inspection of under-water Concrete/RCC structures in PE mode; (b) Photograph of linear array transducers assembly.

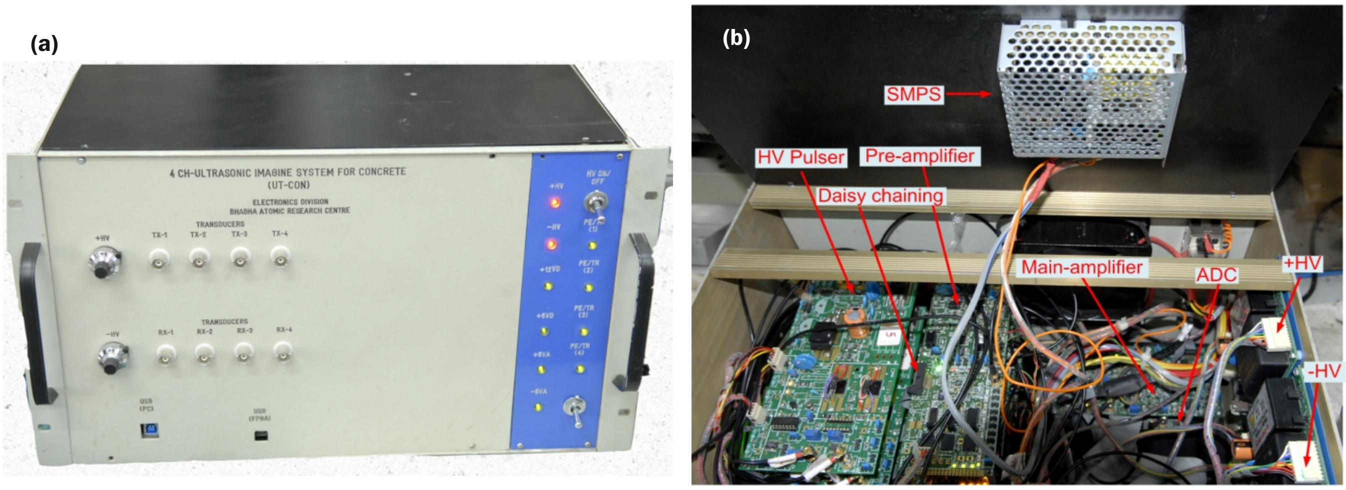

Fig.2: Photographs of (a) Four-channel ultrasonic imaging system hardware mounted inside 19”×6U×300 mm sub-rack, (b) Inside view of imaging system and built-in HV and LV DC power supplies.

system and USB controller module for the communication with computer; immersion type four longitudinal-wave transducers with central frequency of 92 kHz and an automated X-Y scanner mounted onto 300 mm (L) x 300 mm (W) x 500 mm (D) water tank for manoeuvring the transducer assembly inside the water tank for the acquisition of A-Scan 1D waveforms and B-Scan 2D cross-sectional front view images. The automated scanner is controlled through RS422 interface using GUI software developed on C# platform, for PC. Photographs of the 4-channel ultrasonic imaging system are shown in Fig.2[8].

Automated B-Scan imaging is carried out using four numbers of 92 kHz immersion transducers, keeping them perpendicular to the test block's top surface for PE mode. All the transducers utilised for experimentation are Canopus Instruments, Kalyan, Thane, India make. B-Scan image represents the cross-sectional front view along a particular axis for the Concrete/RCC specimen under test. The depth of the test block is shown along the Y-axis, while the position of the 92 kHz longitudinal wave transducer is shown along the X-axis in the B-Scan image shown in Fig.3 (c) and (d) and Fig.4 (g) and (h). Fig.3 and Fig.4 provides the schematic, photograph and B-scan images for two types of concrete test blocks reinforced with High Yield Strength Deformed (HYSD) steel rebars. The binary offset data received from the 8-bits parallel ADC is utilized to represent the data, in the form of coloured pixels for each A-Scan waveform using the GUI software, developed using visual environment. The four-channel data is first processed by temporal averaging in the FPGA hardware to minimize the effects of random noise and then the stored data is routed through the software-implemented 1-D bandpass filter (BPF) with -3dB cut-off of 80 kHz and 120 kHz. The BPF eliminates the high frequency noise and provides a speckle free B-Scan image of the concrete test block under test. The raw B-Scan image is always superimposed with undesired artifacts due to electromagnetic interference (EMI) of motor drive unit and EMI masks the identification of internal reflectors such as voids, inclusions, etc as they are

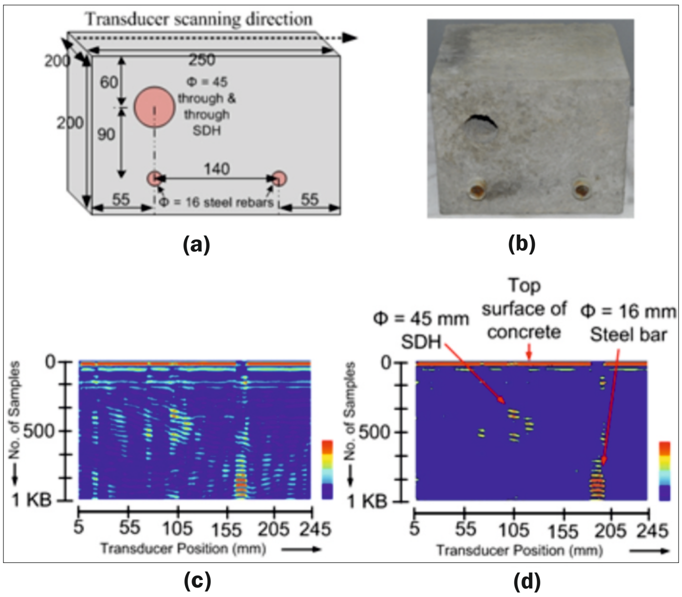

Fig.3: M35 grade concrete reinforced with HYSD two steel rebars of 16 mm diameter each with through & through 45 mm diameter hole (a) Schematic diagram of test block, (b) Photograph of test block, (c) B-Scan image of test block, (d) Gated and processed B-Scan image of test block.

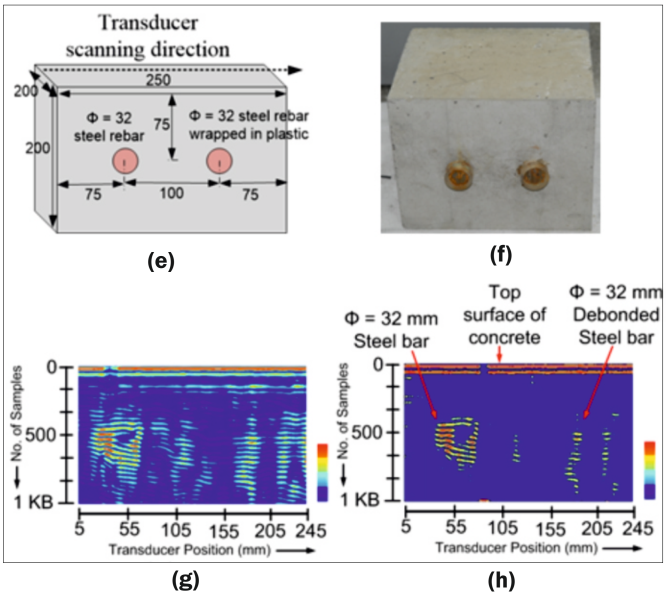

Fig.4: M35 grade concrete reinforced with HYSD steel rebar of 32 mm diameter and another is a plastic wrapped HYSD steel rebar of 32 mm diameter, (e) Schematic diagram of test block, (f) Photograph of test block, (g) B-Scan image of test block, (h) Gated and processed B-Scan image of test block.

corresponding to the received feeble echo signals. Therefore, a software-implemented 1-D band-pass filter has been implemented to minimize the effects of undesired reflections/artefacts, as an off-line process, to enhance SNR more than 20 dB. The system also operates in UPV mode to compute acoustic velocity of unknown Concrete/RCC material.

Key features of the automated ultrasonic imaging system are as below:

- Transducer frequency – 92 kHz
- 4-Channel Preamplifier (individual) Gain - 66dB (maximum)
- 4-Channel Common Main amplifier (individual) Gain - 66dB (maximum)
- Temporal averages - 64 (fixed) (To enhance SNR)
- Operating mode - Pulse Echo (PE) or Transmit-Receive (T-R) mode
- 4-Channel Tone-burst Square-wave Bipolar Pulser - [50-350V with max. 5 no. of bursts]
- Digitizer - 100MSPS @ 8-Bits, 12kB data/A-scan
- Interface to Computer – USB 2.0

Conclusions

An automated, 4-Channel Ultrasonic Imaging System has been designed and developed and it was employed for the imaging and visualization of inclusions and various flaws such as voids and debonding in M35 grade under-water concrete and RCC test blocks reinforced with HYSD steel rebars, using 92 kHz longitudinal wave, immersion type ultrasonic transducers. The FPGA-based four-channel ultrasonic imaging system has been indigenously developed to image under-water Concrete/RCC materials and structures and also measures UPV for unknown Concrete/RCC structures. The system is stand-alone with FPGA as a control device with USB interface to computer for storage and offline analysis of A-Scan 1D data and B-Scan 2D images. The test setup for imaging of concrete test blocks of various dimensions has been designed and manufactured by Workshop, Electronics Div., BARC and concrete sample blocks of M15-M35 grade, embedded with various inclusions and defects have been designed and manufactured by Civil Engg. Div., BARC.

References

[1] H. Jain, V. H. Patankar, & M. S. Kulkarni, "Ultrasonic testing of concrete structures: a review", (BARC–2021/E/017), India, 2021. [https://inis.iaea.org/search/52097777].

[2] IS 13311 (Part 1): Non-destructive testing of concrete – Part 1 Ultrasonic Pulse Velocity test, BIS, India, 1992.

[3] IS 516 (Part-5/Sec 1): Ultrasonic Pulse Velocity Testing, BIS, India, 2018.

[4] International Atomic Energy Agency, "IAEA-TCS-17: Guidebook on Non-Destructive Testing of Concrete Structures", Vienna: 2002, 231 p.

[5] D. Clayton, C. Smith, & C. Ferraro, "Evaluation of Ultrasonic Techniques on Concrete Structures", (ORNL/TM-2013/430), USA, 2013. [https://info.ornl.gov/sites/publications/files/Pub46126.pdf].

[6] H. Jain and V. H. Patankar, "Embedded system for ultrasonic imaging of under-water concrete structures," Journal of Instrumentation (JINST), vol. 16, no. 07, p. P07049, Jul 2021. [https://doi.org/10.1088/1748-0221/16/07/p07049].

[7] H. Jain, E. G. Tarpara, and V. H. Patankar, "Design and development of ultrasonic bipolar square-wave pulser for non-destructive testing of concrete structures," Review of Scientific Instruments, vol. 91, 094704, Sep 2020. [https://doi.org/10.1063/5.0006782].

[8] H. Jain and V. H. Patankar, "FPGA-based four-channel embedded system for ultrasonic imaging of under-water concrete structures", Review of Scientific Instruments, vol. 93, 114706, Nov 2022. [https://doi.org/10.1063/5.0101490].

Automation

18

Automation in Ultrasonic Gauging & Imaging of Tubes and Pipes

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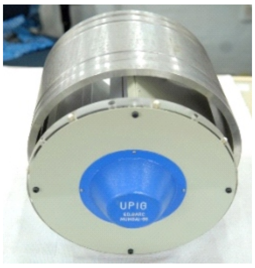

Inspection head assembly inside pipe

ABSTRACT

Automated ultrasonic imaging and gauging systems are employed for the inspection of tubes and pipes in strategic applications due to systems automated operation without the intervention of an operator; repeatability in measurements and better measurement accuracies. This article provides brief details of the two systems namely the in-house developed Water-immersible 2-channel ultrasonic pipe inspection and gauging system for inspection of long length pipes and the water-immersible system modules can float along with the flow of fluid. Another system is, the Automated 5-Channel Ultrasonic Gauging System (UGS) suitable for inspection of pressure tubes of PHWR, where the system was interfaced to the automated 2-axes mechanical precision scanner.

KEYWORDS: *Ultrasonic Gauging System (UGS), Water-immersible, Pressurised Heavy Water reactor (PHWR), Post-Irradiation-Examination (PIE), Tubes/pipes*

Introduction

Metallic Tubes/pipes play an extremely important role in strategic and critical applications like defence, nuclear and petrochemical industries. Tubes and pipes are employed in these industries to work under high temperature, high pressure, high flow rates, radiation and/or gas-liquid environment. Metal loss, corrosion and erosion cause wall-thinning of such tubes and pipes. The tubes and pipes are also inspected for volumetric and planar flaws which are hidden inside the material of tubes and pipes. To provide a high level of safety, reliability and quality assurance, there is a need to inspect flaws and to measure the ID, OD and WT of such tubes and pipes. There are some references available from national and international researchers and manufacturers who have developed automated ultrasonic inspection systems for tubes and pipes[1-5]. A water-immersible 2-channel IP 67 grade water-immersible ultrasonic pipe inspection and gauging instrumentation system (UPIG-250) is suitable for gauging and imaging of long-length metallic pipes and an automated 5-channel Ultrasonic Gauging (UGS) system suitable for post-irradiation examination of pressure tubes of 220MWe PHWR have been designed and developed by Electronics Division (ED) of BARC[6,7].

Water-immersible 2-channel Ultrasonic Pipe Inspection and Gauging System (UPIG-250)

The water-immersible 2-channel Ultrasonic Pipe Inspection and Gauging System (UPIG-250) has been designed & developed, as shown in Fig.1 (a). The system operates on the principle of Pulse-Echo mode and consists of water-immersible IP67 grade two modules comprising of ultrasonic instrumentation hardware. The modules of UPIG-250 system are namely the 2-Channel Ultrasonic Spike Pulser module, Fig.1 (b) and the DAQ module, Fig.1 (c). The DAQ module comprises of 2-Channel wideband Pre-amplifier, 100MSPS/8-Bits Digitizer, Artix-7 FPGA and USB controller modules. UPIG-250 hardware enclosures are mounted inside the inspection head assembly and the inspection head assembly is designed at Workshop, ED, BARC. The inspection head has 8+8 spring-loaded Teflon balls at the front & rear sides for proper centring of the inspection-head inside the 12" diameter sample SS pipe, having 12.75mm wall-thickness. The inspection-head has been mounted with spherically focused ultrasonic immersion two transducers placed 180 degree apart for the measurement of WT, ID and OD of the pipe under testing[8]. 2KB of A-Scan 1D data Fig.1(d) is stored per transducer with a time latency of 200 msec between two channels. Considering the transducer diameter of 10 mm, the UPIG-250 can provide acquisition for a fluid velocity of 100 mm/sec inside the pipe. At present, the two modules have been tested inside the pipe, filled with water, for a period of five hours and more than 180MB of data has been stored in a static condition. A time slot of 10 minutes has been provided before the actual acquisition starts inside the pipe to complete the installation of UPIG-250 system inside the water-filled pipe. Once the data acquisition of five hours is completed, the DAQ module will be opened and the USB board is connected externaly to the PC via USB 2.0 cable. At present the water-immersed UPIG-250 system has been tested for five hours inside the pipe. The modules are operated by Li-ion batteries that are mounted in another IP67-grade two enclosures. Subsequently, the entire water-immersible UPIG-BARC system will be tested inside the pipe with a fluid velocity of 100–500 mm/sec. Such system is one of the first kind of indigenously designed & developed battery-operated system available for the inspection & gauging of pipes and tubes. For inspection & gauging of tubes, customised inspection-head is inserted inside the tube under test and system hardware will remain outside the tube.

Key features of the 2-Channel ultrasonic inspection and gauging system of for tubes and pipes:

- Transducer frequency: 2MHz/ 5MHz/ 10MHz (focused & damped)

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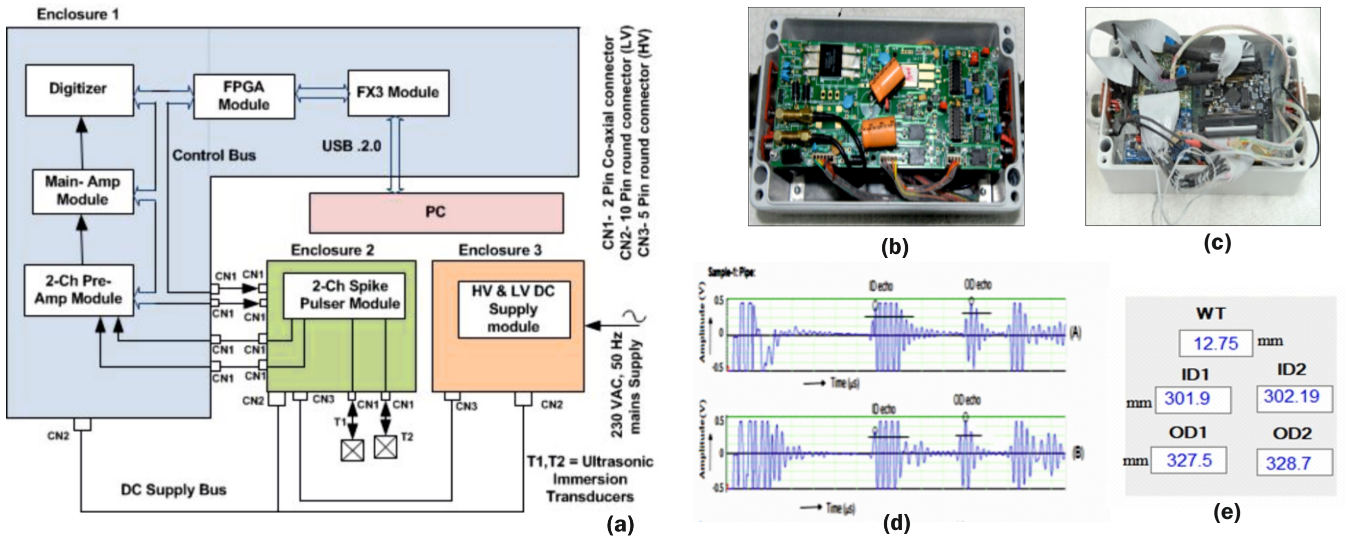


Fig.1: (a) Schematic Diagram of UPIG -250 system (b) Pulser module (c) DAQ Module (d) 2-Channel A-Scan waveforms received by 5 Mhz immersion transducers of EEC make, Mumbai (e) Gauging Data of sample pipe.

- 2-Channel Pre-amplifier (individual) Gain: –66dB (maximum)
- Temporal averages: – 32 (fixed) (To enhance SNR)
- Operating mode: Pulse Echo (PE)
- 2-Channel Spike Pulser: -100V@ 100nsec[9]
- Digitizer: 100MSPS @ 8-Bits, 2Kbytes/A-Scan Data
- Interface to Computer: USB 2.0
- Mech. Dimensions of IP67 grade modules: Pulser Module: 120x220x91mm; DAQ Module: 160x260x90mm: Battery Module-1: 120x220x91mm (DC supply for FPGA) and Battery Module-2: 160x260x90mm (DC supply for DAQ module)

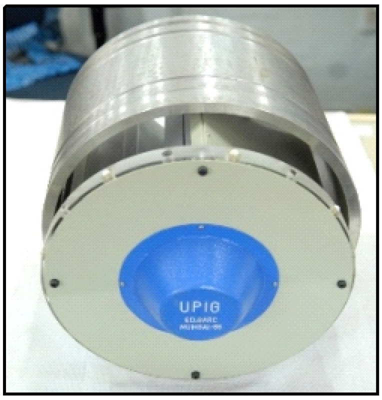


Fig.2: Inspection-Head inserted inside Pipe.

Automated PC-Based 5-channel Ultrasonic Gauging (UGS) system

There are two major aspects related to the accurate measurement of ID and WT of Pressure Tubes (PT) of Pressurised Heavy Water reactor (PHWR). Firstly, it is very important to assess the remaining life of the coolant channels of the PHWR while in-service and secondly, it is to analyse the post-service i.e. post irradiation dimensional variations in a PT due to fatigue and stresses[6]. Automated scanning mechanisms are widely employed for ultrasonic imaging and gauging of tubes due to automated operation without the intervention of an operator with repeatability in measurements and minimization of measurement inaccuracies. To meet the requirements of the Post-Irradiation-Examination (PIE) activity of PHWR, an automated ultrasonic-based X-Theta scanning mechanism has been designed and developed at ED, BARC for Post-Irradiation Examination (PIE) of pressure tubes of 220MWe PHWR, as shown in Fig.3 and Fig.4. The 5-Channel Ultrasonic Gauging System (UGS) H/W and 'Control & DAQ' S/W are major constituents of the system. The Z-Theta, 2-axes scanning mechanism could measures the ID, OD and WT of a sample PT of 5100mm length and the system also performed automated profilometry of the sample PT as shown in Fig.4(b). UGS comprises of 5-channel ultrasonic spike Pulser-Receiver,

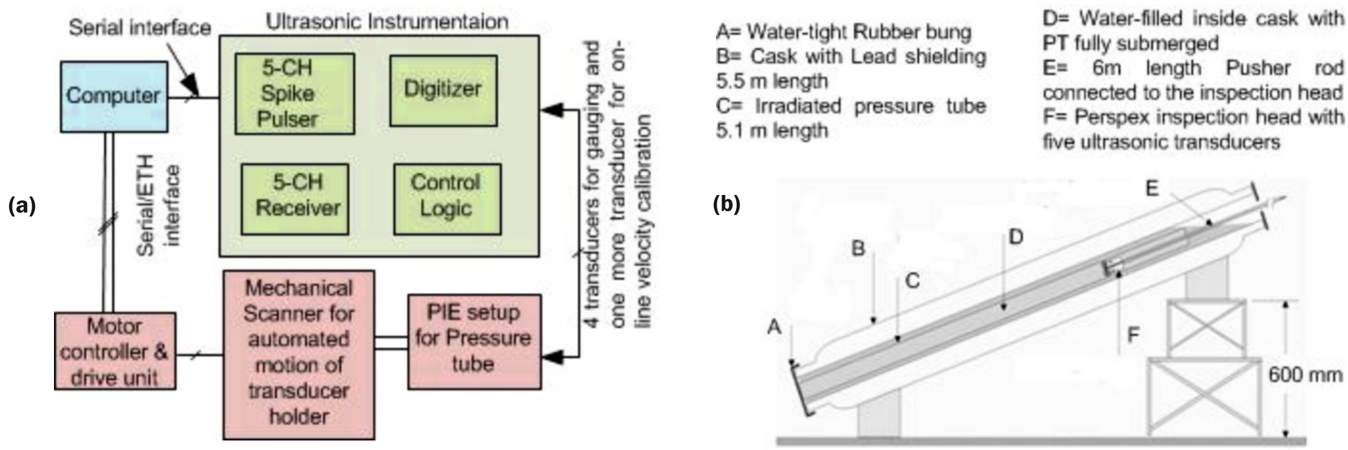


Fig.3: (a) Schematic Block Diagram of Automated 5-Channel Ultrasonic Gauging System(b) Dummy Cask filled with water which contains 5.1 mtr long sample Pressure Tube and X-Theta motions are imparted to inspection head for Gauging and profilometry.

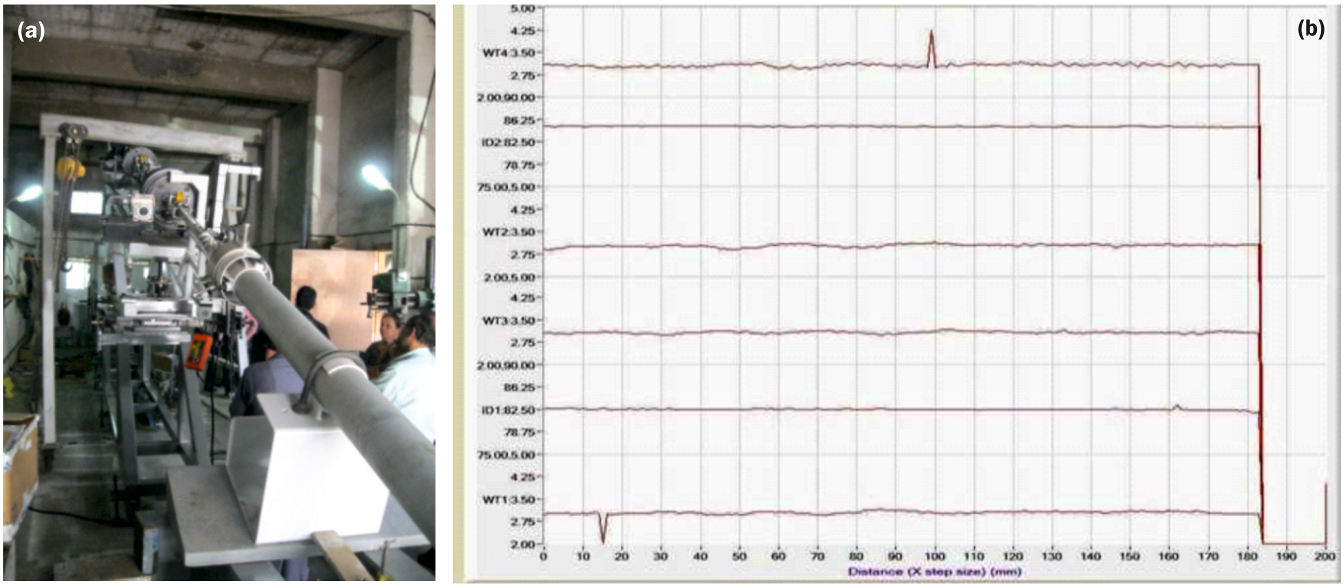


Fig.4: (a) Automated X-Theta mechanical Scanner (b) ID and Wall-Thickness Profilometry of 5.1mtr long sample Pressure Tube.

PCI-based 500 MSPS, 8-bits digitizer and control & data acquisition GUI software, for measurement & analysis of gauging data. Each Pulser channel provides a spike type pulse of 300V for excitation of high frequency spherically focused 10 MHz ultrasonic transducers of Roop Telsonic, Mumbai make, and user selectable HV pulse amplitude &amplifier gain and sampling rate and depth range in Pulse-Echo mode. Each receiver channel has user programmable gain and the digitizer provides sampling rate up to 500MSPS. Gauging and profilometry data are stored and displayed for on-line computation of ID, OD and WT of the PT, as well as to acquire and display profilometry. i.e., a cross-sectional view of the PT in terms of variation in ID and WT over a length of 5100 mm of the sample PT.

Conclusions

A water-immersible IP 67 grade 2-channel Ultrasonic Pipe Inspection and Gauging System (UPIG-250) has been designed and developed for the gauging and imaging of long-length metallic pipes utilized petrochemical and other strategic industries. Another system is a an automated, 5-Channel Prototype Ultrasonic Gauging System (UGS) was developed for the profilometry of the pressure tube (PT), using 10MHz focused transducers and water-immersion technique. A technique was developed which can be adopted for the Post-Irradiation-Examination (PIE) of irradiated Pressure tubes of 220MWe PHWR, inside a hot-cell. ID of 82.55mm of PT was measured with an accuracy of 100 microns, using X-Theta automated mechanical scanner and 5.1-meter-long dummy pressure tube. The technique established by using the prototype development, is suitable in a hot-cell area for the PIE of an irradiated Pressure Tubes of PHWR.

References

[1] M. P Dolbey, "CIGAR - An automated inspection system for CANDU reactor fuel channels", In: Proceedings of the 8th International Conference on NDE in the Nuclear Industry, (Kissimmee, Florida,USA: 17–20 November 1986), Metals Park: American Society for Metals, pp. 105-112, 1986.

[https://inis.iaea.org/search/searchsinglerecord.aspx?recordsFor=SingleRecord&RN=21076255]

[2] Karl Deutsch, W.A. et al. "Automated ultrasonic pipe weld inspection", In: 17th World Conference on Nondestructive Testing, (Shanghai, China: WCNDT 2008, 25- 28 October 2008), NDT.net Issue: 2008-11, 2008.

[https://www.karldeutsch.de/wpcontent/uploads/2019/01/AutomatedUT-WeldedPipes-WCNDT-Shanghai-WD-Jan08.pdf]

[3] H. Lei, Z. Huang, W. Liang, Y. Mao, and P. W. Que, "Ultrasonic PIG for submarine oil pipeline corrosion inspection," Russian Journal of Nondestructive Testing, vol. 45, pp. 285–291, 2009.[https://doi.org/10.1134/S106183090904010X]

[4] K. Reber, M. Beller, H. Willems, and O. Barbian, "A new generation of ultrasonic in-line inspection tools for detecting, sizing and locating metal loss and cracks in transmission pipelines," in 2002 IEEE Ultrasonics Symposium, 2002. Proceedings., vol. 1, pp. 665–671 vol.1, 2002. [doi: 10.1109/ULTSYM.2002.1193490]

[5] N. Pavan Kumar, V. H. Patankar, M. S. Kulkarni "Ultrasonic gauging and imaging of metallic tubes and pipes: a review", (BARC--2020/E/012), India, December 2020.[https://inis.iaea.org/search/search.aspx?orig_q=RN:52019727]

[6] V. H. Patankar, R. K. Jain, N. Varier Vijayan , P.P. Selvam, Makrand Rajhans, K Binoy, LV Murali Krishna and Kumawat Nitin "Development of an Automated Scanning Mechanism for Profilometry of Pressure Tubes of PHWR", NDE-2015, Hyderabad, 26-28 November, 2015. [https://www.ndt.net/search/docs.php3?id=21077]

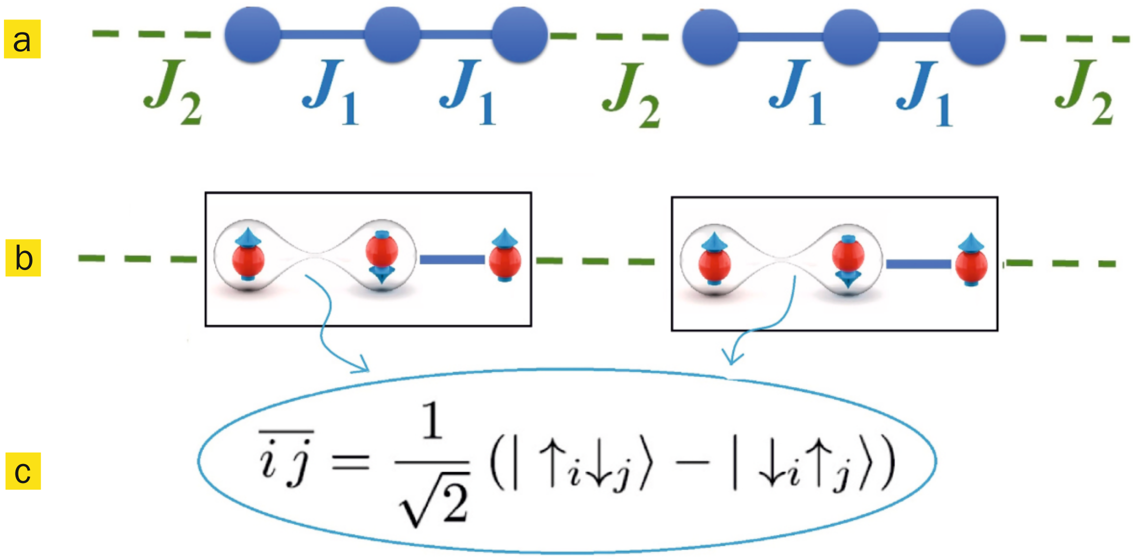
[7] J. L. Singh, S. Ananthraman, E. Ramdasan and D.N. Sah, "Ultrasonic Measurement of Wall Thickness and Internal Diameter of Irradiated Zircaloy Pressure Tubes", NDE-2006, Hyderabad, 2016. [https://www.ndt.net/article/nde-india2006/files/TP-106.pdf]

[8] N. Pavan Kumar, E. G.Tarpara and V. H. Patankar, "Experimentation for Sag and Dimension Measurement of Thin-Walled Tubes and Pipes Using Multi-Channel Ultrasonic Imaging System", Journal of Nondestructive Evaluation 40, 2 (2021). [https://doi.org/10.1007/s10921-020-00726-w]

[9] N. Pavan Kumar and V. H. Patankar, "Design and development of water-immersible two-channel high-voltage spike pulser for under-water inspection and gauging of pipes", Review of Scientific

Quantum technology applications

Spin Quantum Entanglement Near Room Temperature



A schematic snapshot of the quantum entangled spin state (b) of a trimer spin-chain having periodic quantum mechanical magnetic exchange interactions J1-J1-J2 along the spin chain (a) involving the wave function (c).

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Entangled spin states are found to be very stable against temperature and persist up to near room temperature (~250 K), which has a special importance for practical device applications in the upcoming quantum technology.

Quantum entanglement has drawn a tremendous attention of researchers for its importance in quantum technology. Quantum entanglement phenomenon occurs when a group of quasi-particles interact and share spatial proximity in a way such that the quantum states of each particle of the group cannot be described independently of the states of the other particles.

Recent study [A. K. Bera, S. M. Yusuf* et al., Nature Communications 13, 6888 (2022)] has demonstrated for the first time the novel quasi-particle excitations of strong spin entangled ground state [Fig. (b)] of a quantum spin-1/2 trimer-chain antiferromagnet [Fig. (a)]. Such a model spin-1/2 trimer-chain antiferromagnet has been achieved in the compound $Na_2Cu_3Ge_4O_{12}$ where the group of three spin-1/2 of Cu^{2+} are strongly coupled to form a spin-trimer, and such trimers are magnetically weakly coupled to make a spin-chain [Fig. (a)]. The ground state of such a spin-trimer system involves a quantum entangled [Fig. (b)] wave function of two spins (out of the three spins) as shown in [Fig. (c)]. Most importantly, such entangled spin states are found to be very stable against temperature and persist up to near room temperature (~250 K), which has a special importance for practical device applications in the upcoming quantum technology.

Dr. S.M. Yusuf, Director, Physics Group, BARC has been elected as a Fellow of New Delhi headquartered prestigious Indian National Science Academy (INSA). Dr. Yusuf is recognized internationally for his outstanding contributions in the area of advanced magnetic materials and neutron scattering. He has published nearly 300 research papers in internationally reputed peer reviewed journals. He has one US patent and one European patent to his credit. Dr. Yusuf is also a Fellow of the Indian Academy of Sciences, and the National Academy of Sciences. He was a post-doctoral fellow at Argonne National Laboratory, USA, and a visiting scientist at the Institute of Materials Science, Spain. Dr. Yusuf is a recipient of U.S. Department of Energy Fellowship as well as the Spanish Ministry of Science & Education Fellowship.

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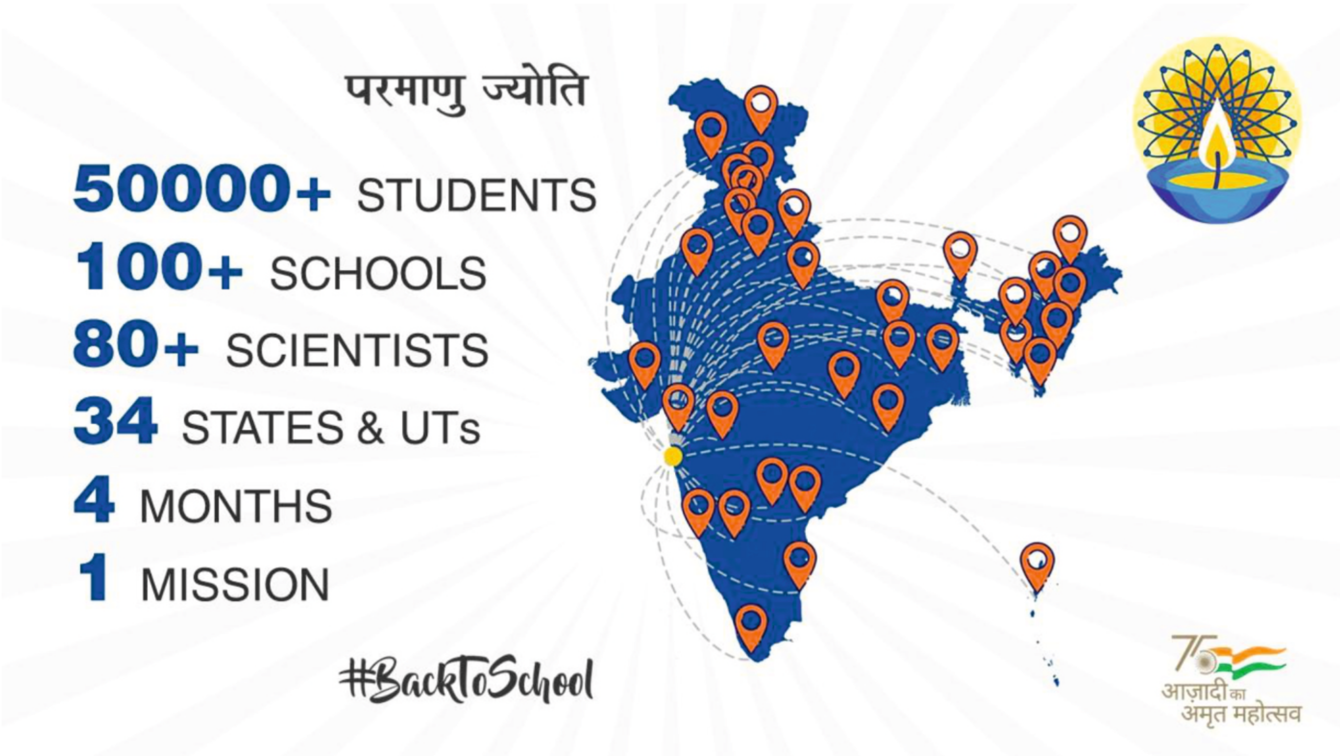

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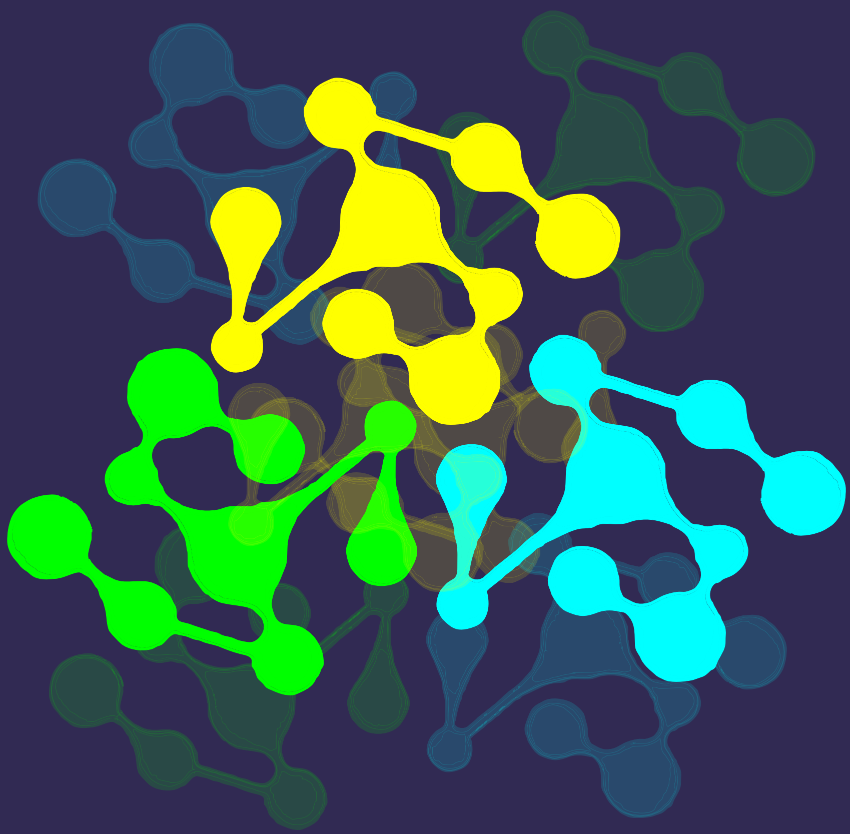

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