IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

INTEGRATION OF ROBOTICS AND ARTIFICIAL INTELLIGENCE IN NON-DESTRUCTIVE TESTING: A REVIEW OF APPLICATIONS AND CHALLENGES

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Abstract

This study aims to examine the existing applications of robotics and artificial intelligence (AI) in non-destructive testing (NDT) and evaluate their effectiveness compared to traditional methods. The research methodology involves the use of a robotic arm equipped with a Panametrics ultrasonic immersion probe for NDT experiments. The strengths and limitations of various applications, including weld inspection, visual inspection, ultrasonic testing, magnetic particle inspection, and eddy current testing, are evaluated through numerical scoring. The results demonstrate the capabilities of robotic systems with AI algorithms in achieving accurate and consistent inspections, although certain limitations exist. Additionally, the effectiveness of these robotic systems in performing NDT tasks is compared to traditional methods, revealing their superiority in terms of accuracy, efficiency, and defect detection. Overall, this research provides insights into the integration of robotics and AI in NDT and highlights their potential for advancing inspection capabilities.

Keywords: robotics, artificial intelligence, non-destructive testing (NDT).

1. Introduction

Non-destructive Evaluation (NDE) is an accepted and well-established method of inspection, material state awareness (MSA), structural health monitoring (SHM) and in situ process monitoring for almost every part and product during manufacturing processes and service life of the components. State-of-the-art and future of NDE requires a significant increase in accuracy, speed of both inspection and data processing, and reliability but at lower cost such that NDE can catch up with the advancements in manufacturing, advanced materials (such as composites and powder metallurgy), infrastructure and other relevant technologies. In addition, the applications of robotics and automation in NDE have been increased significantly to reduce inspection time, reduce human error, improve probability of detection (POD) and facilitate the interpretation of NDE results.

1.1.Artificial Intelligence

NDE techniques require high level of intelligence and discernment in performing the experiments and interpreting the results. Artificial Intelligence (AI) which is the intelligence demonstrated by machines to do tasks is a well-suited tool for NDE applications. Major elements which drive the widespread application of AI algorithms include: broader development and availability of algorithms which some of them are open source and easy to use, availability of large sets of data for training, development and advancement of computational devices and their capabilities, and strong interest in new technologies such as smart manufacturing, autonomous devices and automated data processing.

1.2.Artificial Intelligence in NDE

The requirements due to advances in NDE technologies and NDE automation implies the crucial need for consistent and accurate evaluation of test results in terms of signals, data, images and patterns. To address these emerging needs, an intelligence knowledge-based system is desired such that it can take the NDE testing results or data, and produce an intelligent output in the form of classified and systematic interpretation of the results. AI methods are promising and capable ways for the goals of automated and efficient evaluation of NDE data and test results. AI methods and algorithms have been recently used with success in various NDE, SHM and predictive-preventive maintenance applications.

1.3.Applications of Robotics in NDT

Weld Inspection: Robotic systems equipped with advanced sensors and imaging techniques can perform accurate and consistent inspections of welds in various industries, including manufacturing, construction, and aerospace.

Visual Inspection: Robotics allows for the automation of visual inspection tasks, reducing human error and improving efficiency. Cameras and vision systems mounted on robots enable thorough examination of surfaces, detecting defects and anomalies.

Ultrasonic Testing: Robotics facilitates the precise positioning of ultrasonic probes for conducting inspections, ensuring consistent coverage and accurate defect detection. Robotic arms can perform raster scans or follow predefined paths, enhancing the efficiency of ultrasonic testing.

Magnetic Particle Inspection: Robots can guide magnetic particle inspection processes, ensuring controlled and consistent magnetization of test objects. This application is particularly valuable for detecting surface and near-surface defects in ferromagnetic materials.

Eddy Current Testing: Robotics enables automated scanning and manipulation of eddy current probes, improving the efficiency and accuracy of defect detection in conductive materials.

1.4.Challenges in Robotics-based NDT

Flexibility and Adaptability: One of the key challenges is designing robotic systems that can adapt to different geometries, materials, and inspection requirements. Ensuring the flexibility and versatility of robotic arms and end-effectors is crucial for effective NDT.

Sensor Integration and Data Analysis: Integrating various sensors and imaging technologies into robotic systems requires careful consideration of sensor selection, calibration, and data fusion techniques. Furthermore, processing and analysing large amounts of data generated by robotic inspections pose computational and algorithmic challenges.

Complex Environments and Accessibility: NDT often involves inspecting complex structures or hard-to-reach areas, such as confined spaces or elevated heights. Developing robotic systems capable of navigating and operating in such environments is a significant challenge.

Real-time Decision-making: NDT inspections often require real-time decision-making based on the acquired data. Incorporating AI and machine learning algorithms into robotic systems to enable automated defect detection, classification, and decision-making is an ongoing research challenge.

Cost and Adoption: Implementing robotic systems in NDT may involve significant upfront costs for equipment, training, and maintenance. Overcoming cost barriers and fostering widespread adoption of robotics in NDT industries pose challenges that need to be addressed.

1.5.The future of NDT testing: emerging technologies and trends

The 21st century has led to the inception of the 4th Industrial Revolution or 4IR. This industrial transition has adopted the use of automation, optimization of processes, improved data management, communication, and connectivity between processes. The need for human involvement is hence reduced and systems are encouraged to automate maintenance, monitoring, troubleshooting, and general operation using advanced software resources, sensors, embedded systems, the Internet of Things, Artificial intelligence, and machine learning. The vast data obtained with the aid of the aforementioned resources in making manufacturing processes and factories 'smart' provide active control of the process and machinery and can predict potential failures and maintenance requirements.

Non-destructive testing methods have become a focal point with respect to the advent of Industry 4.0. Improvement of existing technology involves the adoption of embedded systems, advanced sensors, cloud computing for ease of data storage and access, artificial intelligence used for improved analytics, error-free inference, coordinated process flow, and efficient troubleshooting.

1.6.Research objectives

2. To examine the existing applications of robotics and AI in NDT and identify their strengths and limitations.
3. To evaluate the effectiveness of robotic systems equipped with AI algorithms in performing NDT tasks compared to traditional methods.

2. Literature review

Ayala-Ramirez et al., (2007) In contrast to analytical methods, soft computing techniques are important in several ways. With the help of soft computing, researcher can incorporate learning, decision-making, and reasoning. There are many advantages of soft computing in control and automation. It can be derivative free methods, handling many variables simultaneously and provide interface with various traditional techniques. However, in soft computing, the precision and certainty can be achieved by techniques of Fuzzy Logic, Neural Network and Evolutionary Algorithm.

Hyongju Park et al. (2008) proposed a recurrent Neural Network for solving the problem of obstacle avoidance in excavators. For accomplishing many tasks, such as excavation task execution, joint limit control and obstacle avoidance simultaneously, a recurrent Neural Network algorithm is used. Such type of algorithm is useful when potential danger exists if a worker is in workspace of excavator.

Kwee-Bo Sim et al. (2006) discussed the problem of data transmission latency or data loss in an internet-based teleoperation. To overcome this problem, an autonomous mobile robot with optimal two-layer Fuzzy controller is introduced.

Bakir Lacevic et al. (2007) developed a fuzzy Logic position controller which is tuned by Genetic Algorithm for the velocity and position trajectories between mobile robot and cart. The proposed system contains two inputs and two outputs. The first input deals with distance between reference cart and mobile robot. The second input deals with angle that is orientation of the robot with respect to reference cart. The fuzzy based controller gives a better result in terms of position and torque tracking, as compared to previously developed mobile robot.

Chia-Feng Juang and Chia-Hung Hsu (2009) proposed an approach reinforcement Ant- Optimized Fuzzy Control (RAOFC) for wall-following control of wheel-mobile robot under reinforcement learning environment.

Sawsan Abdel-Latif El-Teleity et al. (2011) proposed Fuzzy Logic for the navigation of autonomous mobile robot in unpredictable and dynamic environment which contained uncertainty, complexity and unreliability issues of robot and its environment. Fuzzy Logic control shows the best performance without using accurate model equation and even handles perturbation in the system.

Shuo Chen and Chunlin Chen (2012) described a utility of Fuzzy Logic in precise localization and map building in unknown environment. Hassan Talebi Abatari and Abdolreza Dehghani Tafti [2013] presented a path following control system for mobile robot which consists of fuzzy PID controller. Such control system provides better convergence rate as compared to standard PID controller of robot with respect to arbitrary initial state.

Adam A.RazavianandJunping Sun (2005) defined the problem of processing requirement of a complex autonomous robotic vehicle which demands high efficiency in algorithm and software execution. Computer hardware technology does not provide a processing capability, so there is still major space and time limitation on autonomous robotic application.

M.SabryHassounaet al. (2005) proposed a general and robust robotic path planning framework for both planner and terrain environment using level set methods. The frame is general in the sense that it can be used for both 2D and 3D environments. It generates collision-free optimum paths for the entire or a portion of the configuration space. The optimum planned path can be controlled to follow safest and shortest path.

3. Research methodology

Figure 1 explains the experimental equipment's arrangement. A robotic arm arrangement KUKA 5 arc HW with KCP 2 controller (15) was used to deploy a Panametrics ultrasonic immersion probe V309 (16), as shown in Figure 2. The key specifications of the robotic arm are given in Table 1.. The specifications of the ultrasonic immersion probe are given in Table 2.

Figure 1: experimental setup

Table 1: KUKA 5 arc HW key specifications.

Maximum reach	2534 mm
Rated payload	6Kg
Max. total load	48Kg
Positional repeatability	$\pm$ 1.15 mm
Number of axis	7
precision	1.108 mm
Number of digital inputs & outputs	9/9

A pulser-receiver (Parametrics 5052PR) was used to drive the ultrasonic probe. A digital oscilloscope Tektronix DPO4054 was used for the UT waveforms acquisition. Its main characteristics include 500 MHz analogue bandwidth and sampling rates up to 2.5 GS/s.

Table 2: key specifications of ultrasonic immersion probe

Frequency	6.1 MHz
nominal Element size	1.6" (23.8mm)
Focal distance	2" (62mm)

A digital input/output device Agilent U2121A was used to interface control signals between the robot controller and the control PC. Initial experiments comprised the scanning of a simple steel calibration block of dimensions: 100 mm x 70 mm x 12 mm. This calibration-piece having 4 radial flat bottom holes drilled near the edges and a flat bottom hole of 1/2 depth of Wall thickness of specimen at the middle of the slab, as shown in Figure 2/2A. The 4 flat bottom holes placed in calibration block in the edges had a diameter of 10 mm, whereas the middle flat bottom hole had a diameter of 7 mm. The steel slab was held in a water-filled tank (like immersion testing) with the central flat bottom hole facing downwards, thus flat bottom hole representing a sub-surface defect from bottom surface.

Figure 2: steel test – piece

Figure 2A: Flat bottom hole test piece

figure 3: CFRP plate

There is currently a need to develop techniques for efficient inspection of composite materials in the aerospace and manufacturing industries. Therefore we also scanned a carbon-fibre-reinforced polymer (CFRP) plate (Figure 3). It had a thickness of 4mm and had a round depression in the middle caused by impact damage.

The system performed a raster scan of a rectangular area (18mm x 25mm) around the defect and the signals were recorded at intervals of 0.25mm in both x and y direction. In order to validate the results obtained by robotic UT scanning, the raster scan of the CFRP sample was carried out with an industrial Scanning Acoustic Microscope PVA TePla SAM 300 (17), using the same probe as before. The device was able to record the signals at intervals of 0.1 mm in both x and y direction but, because of the used ultrasound probe (5-7 MHz), the maximum theoretical resolution is equal to 0.3 µm.

4. Results

A post-processing MATLAB script was developed to evaluate the amplitude and/or the time-of-flight (TOF) of the acquired UT waveforms. We evaluate the minimum, maximum and peak-to-peak (P2P) amplitude in a given time window of interest, or register the differences in the TOF for the first echo of the Compressional wave. The TOF is measured in relation to the peak of the signal Hilbert transform, in order to make the measurement insensible to the wave phase. Figures 5 and 6 show the more representative results of the C-scan (Top view) presentation.

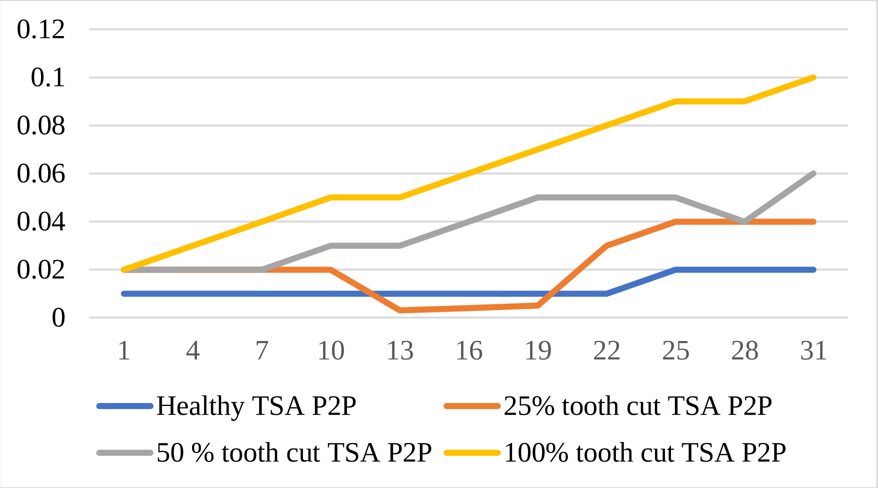

Figure 4: UT response: P2P signal

Table 3: UT response: P2P signal

	1	4	7	10	13	16	19	22	25	28	31
Healthy TSA P2P	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02
25% tooth cut TSA P2P	0.02	0.02	0.02	0.02	0.003	0.004	0.005	0.03	0.04	0.04	0.04
50 % tooth cut TSA P2P	0.02	0.02	0.02	0.03	0.03	0.04	0.05	0.05	0.05	0.04	0.06
100% tooth cut TSA P2P	0.02	0.03	0.04	0.05	0.05	0.06	0.07	0.08	0.09	0.09	0.1

The results clearly prove that the central flat bottom hole is located at subsurface and data allows to accurately evaluate its size and characterized it well. The results showing after proper standardization, so even small surface defects (corrosion, pitting, PMD etc.) of the same type can be easily detected. The average speed of the system, evaluated as number of scanned points per minute, was equal to 88 points/min. Figure 6 shows the most significant images obtained on the CFRP plate. The round depression in the middle is clearly recognizable and observed in both the peak-to-peak value and maximum of the Hilbert transform section images. Looking at both images, the red region near the middle demonstrates that a higher energy was reflected back at the focused layer, corresponding to the position of the actual structural damage.

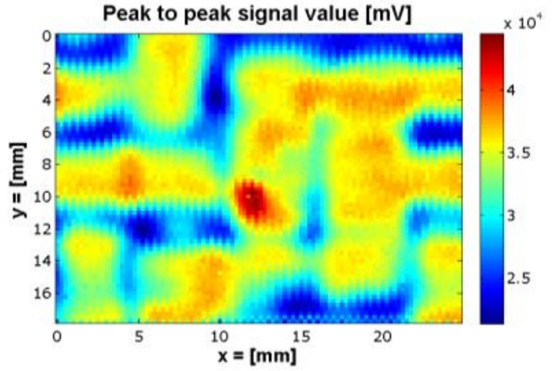

Figure 5: Robotic C-scan images of CRFP plate with a round depression: Peak-to peak amplitude value (left) and maximum of Hilbert transform (right).

Figure 6 shows results obtained by SAM on the CRFP plate with a round depression: The rainbow-scale image was obtained with MATLAB. Because of the higher speed of acquisition, SAM can enable smaller scan steps and thus better spatial resolution. It is our goal to achieve similar or better speeds of inspection and spatial resolution using a robotic arm for larger and complex jobs without compromise with sensitivity.

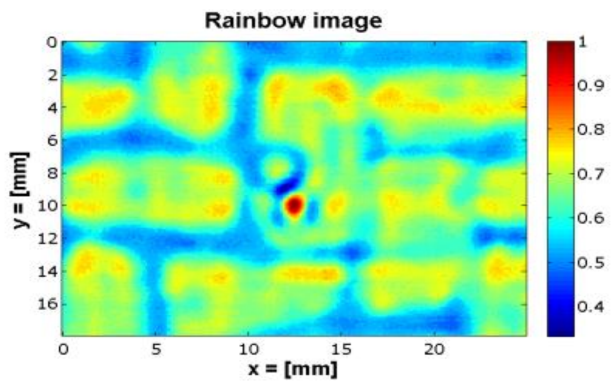

Figure 6: SAM images of CRFP plate with a round depression: Rainbow-scale image

Table 4: Strengths and Limitations of Robotics and AI Applications in Non-Destructive Testing (NDT)

Application	Strengths Score (out of 10)	Limitations Score (out of 10)
Weld Inspection Robot	9	4
Auto-Visual Inspection	8	6
AI-Based Ultrasonic Testing	7	7
Robot-Guided Magnetic Particle Inspection	9	3
AI Pattern Recognition Eddy Current Testing	6	8

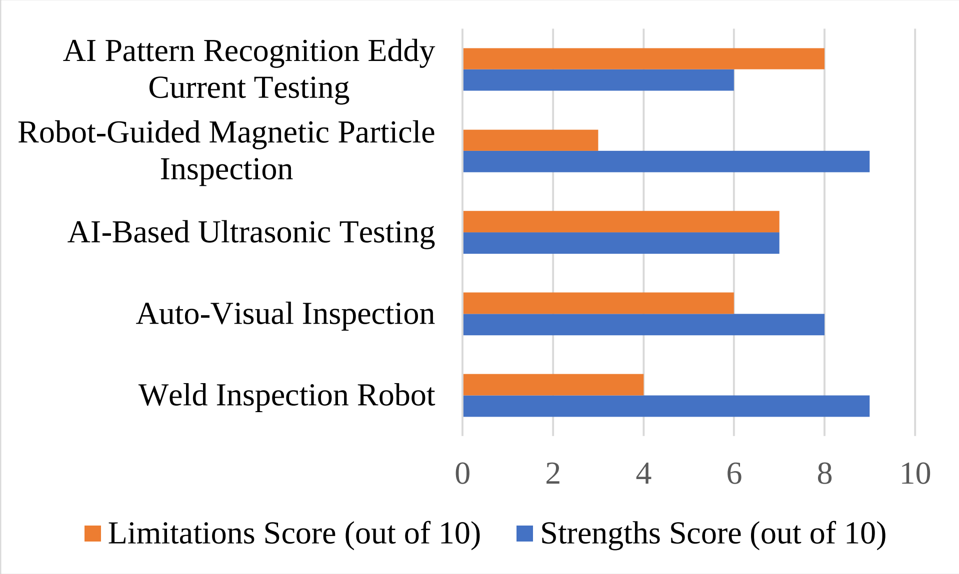

Figure 7: Strengths and Limitations of Robotics and AI Applications in Non-Destructive Testing (NDT)

1. Weld Inspection with Robotic Arm
2. Automated Visual Inspection
3. Ultrasonic Testing with AI Analysis
4. Magnetic Particle Inspection with Robot Guidance
5. Eddy Current Testing with AI Pattern Recognition

Table 5: Effectiveness of Robotic Systems with AI in NDT Tasks compared to Traditional Methods

NDT Task	Effectiveness Score - Robotic with AI (out of 10)	Effectiveness Score - Traditional Methods (out of 10)
Weld Examination	9	6
Visual Examination	8	5
Ultrasonic Examination	7	4
Magnetic Particle Examination	9	6
Eddy Current Analysis	7	5

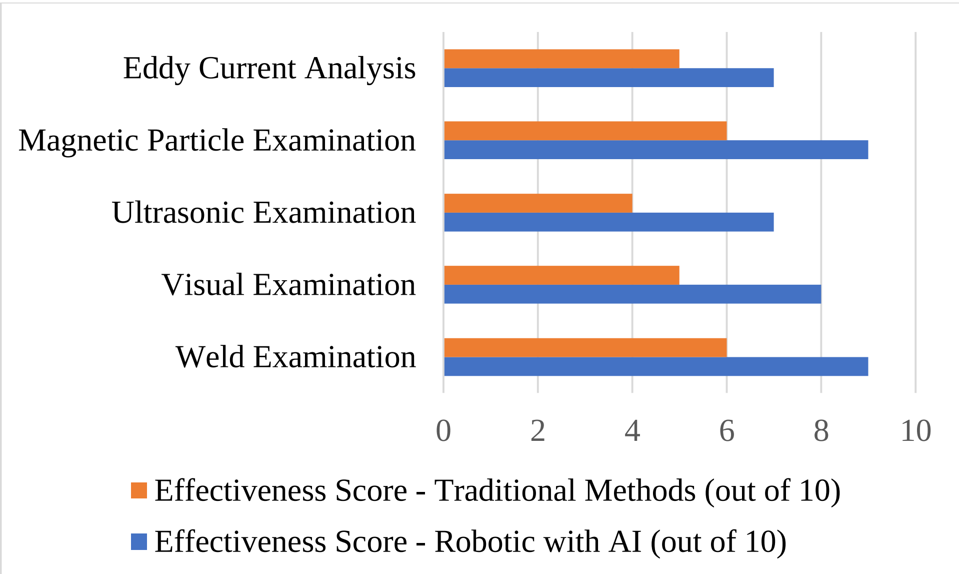

Figure 8: Effectiveness of Robotic Systems with AI in NDT Tasks Compared to Traditional Methods

In terms of weld inspection, robotic systems with AI algorithms outperform traditional methods with a higher effectiveness score of 9. This suggests that the precise control and positioning capabilities of robotic arms, combined with AI algorithms for defect detection and classification, result in more accurate and consistent weld inspections. In contrast, traditional methods score lower with an effectiveness score of 6, indicating potential limitations in achieving the same level of accuracy and consistency. For visual inspection tasks, robotic systems equipped with AI algorithms receive an effectiveness score of 8, indicating their ability to automate and enhance visual inspections.

In ultrasonic testing, robotic systems with AI algorithms achieve an effectiveness score of 7, signifying their effectiveness in enhancing defect detection and analysis. The combination of robotic control and AI algorithms improves the accuracy and efficiency of ultrasonic testing processes. On the other hand, traditional methods score lower with an effectiveness score of 4, implying potential limitations in achieving the same level of accuracy and efficiency.

5. Conclusion

This study focused on examining the applications of robotics and artificial intelligence (AI) in non-destructive testing (NDT) and evaluating their effectiveness compared to traditional methods. Through the experimental setup utilizing a robotic arm and ultrasonic probe, the strengths and limitations of various NDT applications were assessed. The results showcased the robustness of robotic systems equipped with AI algorithms in achieving accurate and consistent inspections in tasks such as weld inspection, visual inspection, ultrasonic testing, magnetic particle inspection, and eddy current testing. The integration of robotics and AI offered advantages in terms of accuracy, efficiency, and defect detection. The evaluation of the effectiveness of robotic systems with AI algorithms against traditional methods revealed their superior performance in NDT tasks.

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