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Investigation of Human Robot Collaboration Safety Based on Speed and Separating Monitoring

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The increasing focus on robotics safety underscores the importance of establishing rigorous standards to protect human operators. ISO/TS 15066 is a pivotal standard that reflects this concern, providing guidelines for human robot collaboration (HRC). This paper focuses on one out of four main techniques in safety standard, which is speed and separation monitoring. The novelty lies in the integration of Machine Learning (ML), Artificial Intelligence (AI), and Robot Operating System (ROS) to enhance decision accuracy. The test rig involves a 4-degree-of-freedom (DOF) serial robotic arm and Microsoft Kinect One, adept at recognizing gesture signs and tracking hand movements. Moreover, the system ensures safety by adjusting the robot's speed dynamically, even coming to a stop if necessary. The result shows improvement in decision-making. This demonstrates a significant contribution to advancing safety standards in robotics.

1. Introduction

The increasing interaction between humans and robots necessitates stringent safety protocols to mitigate risks and ensure the well-being of human operators [1]. To ensure human safety, a risk assessment must be completed prior to the operation of an industrial robot. One such crucial standard is the International Organization for Standardization (ISO) 10218 contains the fundamental safety regulations for robotics [2,3]. The ISO amended these requirements with the technical specification ISO/TS 15066 in 2016, which delineates guidelines for collaborative robot safety. It defines four fundamental types of collaborative operations, every one of them tailored to specific levels of human-robot engagement and risk tolerance [4]. These include:

i. Safety-rated monitored stop
ii. Hand guiding
iii. Speed and separating motoring
iv. Power and force limiting.

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Ensuring safety in HRC environment is paramount for widespread adoption across industries. The implementation of ISO 15066 guidelines, coupled with advanced technologies [5] such as 3D sensory depth machine vision and Robot Operating System (ROS) integration, mitigates risks and fosters trust between humans and robots. ROS serves as a fundamental framework for developing and integrating robotic systems [6]. It facilitates seamless communication between hardware components and software modules, enabling robots to process data efficiently and execute tasks effectively in dynamic environments. By prioritizing safety, organizations can harness the full potential of HRC, driving innovation and efficiency while safeguarding human well-being. Li *et al.,* [7] conducted a survey on safety standards and regulations in HRC, highlighting the significance of adherence to safety protocols.

Beyond safety standards in recent research, machine learning (ML) methods play a crucial role in enhancing the safety and efficiency of human-robot collaboration. Semeraro *et al.,* [8] presented a survey on ML in HRC, discussing recent advances and future directions in the field. Ongoing research aims to refine and customize these ML approaches to address specific challenges in HRC, such as real-time speed and separation monitoring. The integration of ML and artificial intelligence (AI) further enriches the capabilities of collaborative robotic systems. ML algorithms, such as You Only Look Once (YOLO) [9] and MediaPipe [10] empower robots with advanced perception and decision-making capabilities, including scene understanding, real-time object detection and tracking. As ML and AI technologies progress further [11,12], gesture recognition [13] remains a critical component in shaping the future of human-robot collaboration. By prioritizing safety, efficiency, and seamless integration into diverse work environments, gesture recognition technologies pave the way for enhanced collaboration between humans and robots across various industries and applications [14]. The ongoing development and refinement of gesture recognition algorithms promise to further enhance the capabilities of collaborative robotics, driving continued progress in human-robot interaction and collaboration.

Despite significant progress in HRC safety mechanisms, there exists a research gap in speed and separation monitoring using ML and AI methods. Recent studies have focused on developing advanced ML algorithms capable of dynamically adjusting robot speeds based on real-time environmental cues and human behaviors. Karagiannis *et al.,* [15] discussed the design and implementation of a hybrid cell using safety monitoring area camera and safety functions of speed and space monitoring. It highlights the development and implementation of a system that enhances the safety and efficiency of human operators working in close proximity to industrial robots. Zanchettin *et al.,* [16] proposed a methodology to improve the performance of speed and separation algorithm while dealing with finite and quantized 2D cost-effective sensing capabilities. The strategy was verified experimentally as applied on a palletizing application with a Comau SmartSix industrial robot. Rosenstrauch *et al.,* [17] Introduced a methodology that utilizes Microsoft Kinect V2 for real-time monitoring of the distance between humans and robots using the NITE library for skeleton tracking and algorithm in ROS. Byner *et al.,* [18] discussed the development and evaluation of Dynamic Speed and Separation Monitoring (dSSM) methods for enhancing productivity in collaborative robot applications while ensuring operator safety. The key focus is on continuously adapting robot speed based on the separation distance and direction of motion relative to the operator. Wang *et al.,* [19] presented a study on using laser scanners and inertial measurement units (IMUs) to ensure safe human-robot interaction by calculating minimum distances in dynamic environments using QR factorization. Secil *et al.,* [20] Presented a framework for real-time calculation of the minimum distance between humans and robots to enable safe interactions. It utilizes a Microsoft Kinect v2 sensor for human tracking and represents both human and robot geometries as capsules for efficient distance computation. While the framework integrates with ROS and utilizes libfreenect2, openNI 2 and Nite 2 open-source skeletal tracking software, alongside the Flexible Collision Library (FCL) for implementing the GJK algorithm. In addition, the vision system plays a pivotal role in real-time tracking and distance accuracy. Its deployment has been proven effective through various studies by several authors [21-26].

The literature review addresses several methods in human robot collaboration safety especially in speed and separation monitoring. Therefore, developing a simple and accurate method in decision-making is one of the main goals for the researchers. Hence, some of the works are conventional, but AI gives new capabilities and higher possibilities.

This paper aims to utilize ML and AI to develop a decision-making platform to enhance the safety of collaborative robots. Based on human hands proximity and human safety considerations, the robot takes three decisions: maintaining normal speed, decelerating or fully stopping. Based on these decisions, which are informed by machine vision inputs, a suitable action will be taken. The research contribution is intended to enhance the decision-making accuracy. It is expected that this approach will augment the efficiency of human-robot collaboration and hence increase the share of the robot in the human work environment.

Section 2 will introduce the collaboration platform. The ML and AI method details are explained in Section 3. The experimental work, including a discussion of the results, is presented in Section 4. Section 5 is the conclusions and contribution.

2. Experimental Setup

This section describes a test platform for collaborative robot. The experimental setup shown in Figure 1, is used to test the research hypothesis. The experimental system features a streamlined arrangement that integrates a Phantom-X Pincher robotic arm at its core. This system is complemented by a central processing unit (CPU) and a time-of-flight vision sensor. The robotic arm is distinguished by four revolute joints, which are sequentially connected through USB2Dynamixel. This robot offers an expansive range of motion, with a vertical reach of up to 350 mm and a horizontal span of 310 mm.

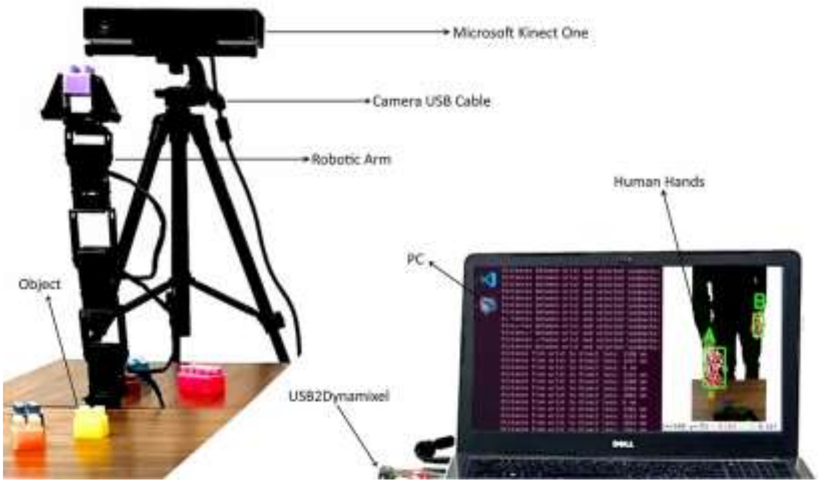

Fig. 1. Experimental Setup

The software and communication facilitate the utilization of ML and AI. The operation of the robotic arm is seamlessly managed *via* the ROS, utilizing Visual Studio alongside Python scripting. This combination offers accurate pick-and-place operation and enables the dynamic modulation of speed, which ensures versatile functionality. The connection between the robotic arm and the CPU is established through a high-speed USB 3.0 interface. The computing power supporting this setup is an Intel® Core™ i7-7500U CPU clocked at 2.70 GHz, backed by a substantial 32.0 GB of RAM, ensuring swift and efficient processing capabilities. The vision system employs a Microsoft Kinect One module, which is directly interfaced with the PC within the ROS environment via another USB 3.0 port. This camera needs to be calibrated before use [27]. It is implemented in an eye-to-hand configuration, which provides a comprehensive field of view 60 degrees vertically and 70 degrees horizontally. It has an effective detection range spanning from 0.5m to 4.5m. Moreover, it is optimally positioned to monitor the workspace and focusing on human hands in different views, as shown in Figure 2.

Fig. 2. Camera focusing on human hands

3. Method Description

The setup presented in this paper is powered by ROS Noetic, designed to monitor the environment and make decisions through ML and AI. In this section, the proposed approach is based on the following libraries: computer vision (OpenCv), machine learning and AI (MediaPipe), a speech synthesis engine (pyttsx3), and a robot interface (ROS serial). The script starts with monitoring and capturing images from the workspace, where human hands are designated as the region of interest (ROI). The camera footage is provided in both RGB image and depth map data. Once the hands are recognized, they will be highlighted by two boxes labeled with the letters A and B. Afterwards, the ML model successfully maps the corresponding landmarks for hands, with their connections represented in red dots and green lines, as shown in Figure 3.

Fig. 3. MediaPipe's hand landmarks model [10]

Moreover, MediaPipe employs AI gesture recognition using the camera feed to track and interpret the human hand. This is achieved by measuring the distances between specific landmarks.

Once a certain configuration is achieved, an input command is triggered. These commands can be executed by flicks or waves in any direction. For example, as shown in Figure 4 when the following landmarks 4, 8, 12, 16 and 20 are at zero distance from the wrist landmark, the gesture is triggered.

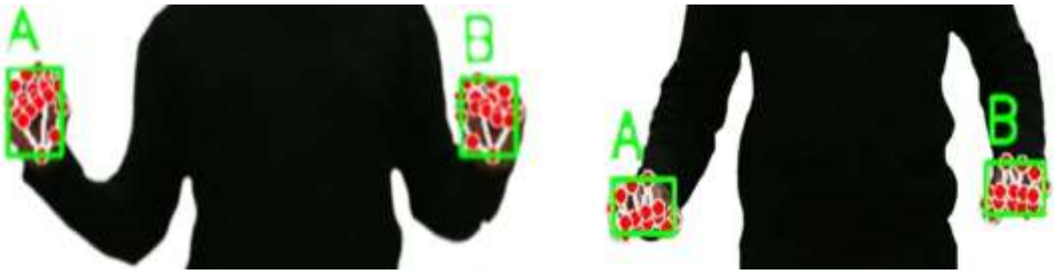

Fig. 3. AI Gesture Recognition

Upon triggering the gesture, the speech synthesis algorithm converts the pre-defined text "Hand tracking activated'' into a human-voice. This notifies the operator that the tracking function has been activated. Additionally, the wrist landmark is used as a reference point to measure the distance to the camera lens frame. Based on these distances, the robot joints adjust their speeds, as shown in Table 1 and Figure 5.

Table 1
Robot speed decisions

Decision #	Distance (mm)	Speed Ratio	Speed (r.p.m)
1	Above 3000	100 %	6.67
2	Between 1000 & 3000	50 %	3.33
3	Below 1000	Stop	Stop

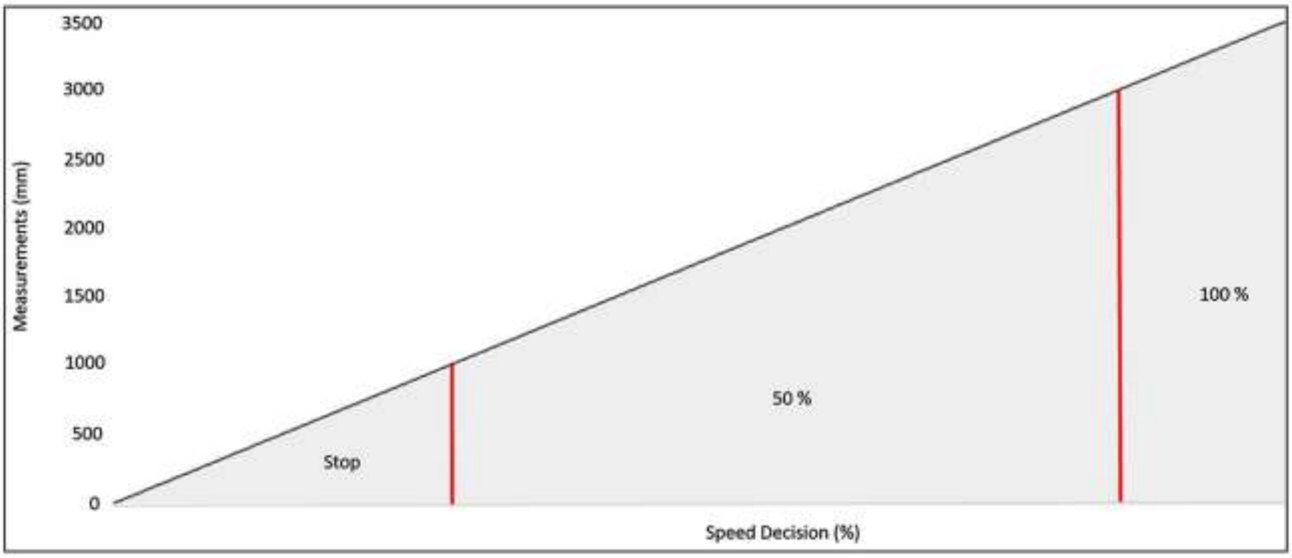

Fig. 4. Robot speed decisions limits

The robot operation primary objective is ensuring the connectivity between the robot joints and the PC through USB2Dynamixels. As well as, the continuity of a repetitive robot task while controlling the robot to achieve a pick and place process in real-time. Figure 6 illustrates the method flowchart.

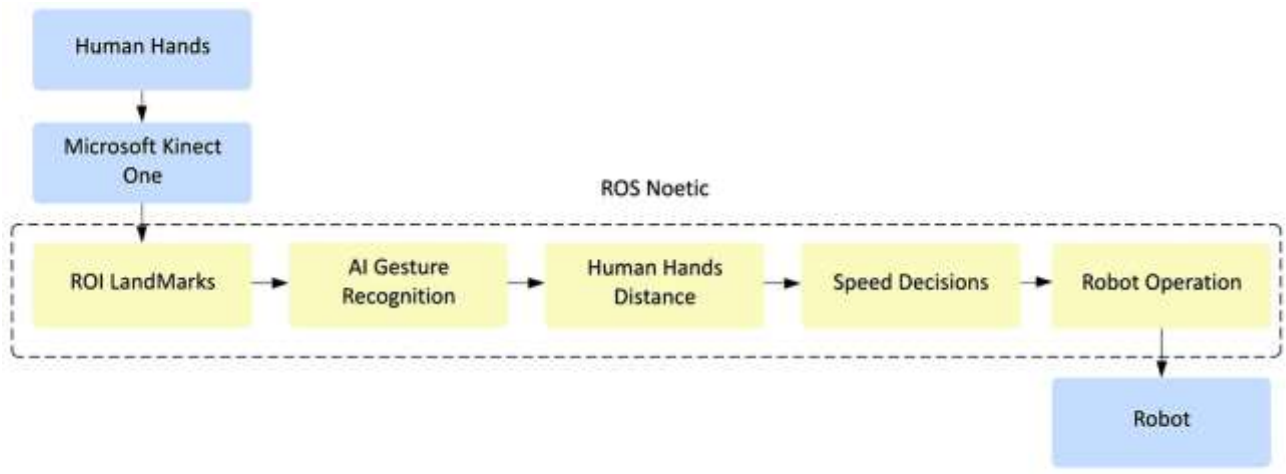

Fig. 6. Method flowchart

Ultimately, the script generates a log file that includes: the date and time, the robot's speed and the distance from wrist of the human hand to the camera lens.

4. Results and Discussions

In this study, a series of eight experimental groups conducted at two distance ranges: 1000 ± 200 mm and 3000 ± 200 mm. These ranges represent the margins for robot speed decisions. The robot's task in the experiments involved moving an object from point A to point B at its maximum allowable speed. During the process, the human operator interacted with an on-screen display to activate hand-tracking via AI based gesture recognition, using the Microsoft Kinect One. A snapshot in Figure 7 illustrates how the operator facilitated seamless collaboration within the robot's working environment.

Fig. 7. Human hands sharing robot workspace

Moreover, the absolute error is equal to the real-world measurement minus the camera measurements. These real-world measurements are taken from a measurement tape extending 3 m, to determine the distances from the human hand to the camera lens. The measurement tape was chosen for this study due to its simplicity, cost-effectiveness, ease of use, and sufficient accuracy for this research.

Due to camera calibration, which is a tool for this research. The first group of measurements results yielded an average of absolute error of 2.75 mm and a standard deviation of absolute error of 0.43 mm. These results indicate a consistent level of precision with the absolute error remaining relatively low. On the other hand, the second group measurements yielded an absolute error of 103.75 mm, and a standard deviation of absolute error of 4.92 mm. These findings demonstrate a slightly higher level of absolute error compared to the first group, yet it still remains reasonable for this study. As discussed in section 1, by employing calibration procedures, advanced filtering techniques and sensor fusion, it is possible to significantly enhance the precision of depth measurements. Consequently, the absolute error will be reduced, helping the robot make better decisions. Table 2 summarizes the associated errors for both ranges.

Table 2
Summary of ranges accuracy errors

	1000 ± 200 (mm)	3000 ± 200 (mm)
Average of error (mm)	2.75	103.75
Standard deviation of error (mm)	0.43	4.92

For the robot speed decisions, which are the focus of the main study. The system calibration is evaluated in the context of the robot speed decisions. These decisions rules are: adjust the speed to 100% if the measurements are above 3000 mm, to 50 % if the measurements lie between 1000 mm and 3000 mm, and stop if the measurements are less than 1000 mm. The results show an acceptable robot speed decision percentage in the range of 1000 ± 200 mm at 99.78 %, and 97.54 % robot speed decision in the range of 3000 ± 200 mm. Figure 8 shows the robot speed decisions results. These results meet safety requirements in ISO/TS 15066. Furthermore, the robot makes acceptable and suitable speed decisions in the two ranges.

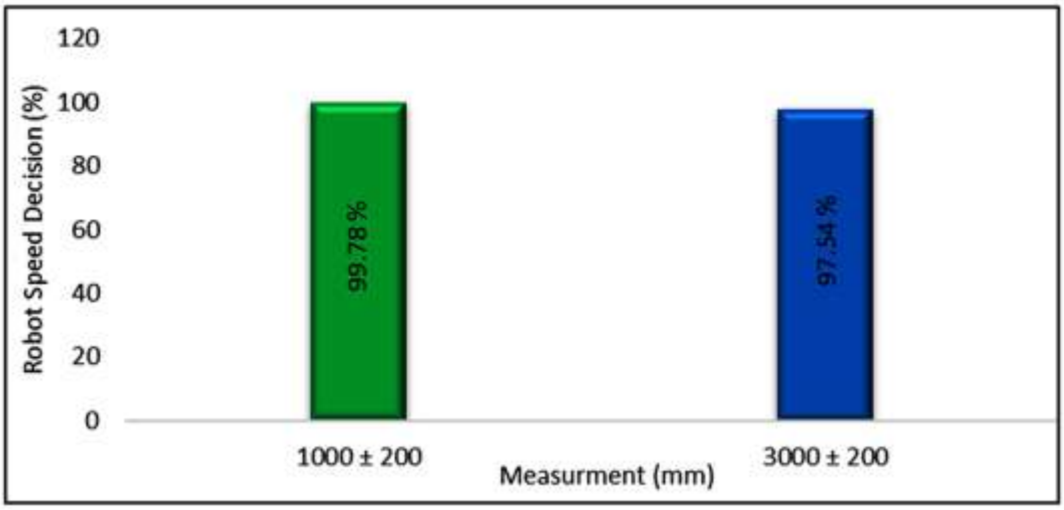

Fig. 8. Robot speed decisions results

5. Conclusion

In conclusion, this paper introduces a speed and separating monitoring based on ISO/TS 15066, using ML and AI with the assistance of machine vision as a tool. The novelty of this research is using

ML and AI for decision-making. The proposed approach is tested experimentally, applied on a 4-DOF arm robot for pick and place task. The code is developed specially for this research. A comparison between robot speed decisions is carried out. Yeilding 99.78 % within the range of 1000 ± 200 mm and 97.54 % within the range of 3000 ± 200 mm. The proposed approach meets the safety requirements in ISO/TS 15066 with acceptable robot speed decisions. Using ML and AI is suitable for programming robots used in small and medium enterprises. This will increase the robot's share in global industries and ensure safety between human and robots.

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