# Assessing Latency Cascades: Quantify Time-to-Respond Dynamics in Human-Robot Collaboration for Speed and Separation Monitoring


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***Abstract*—Advancements in sensing technology and artificial intelligence have revolutionized industrial settings by introducing robots that work alongside humans, enhancing productivity and flexibility. However, ensuring safety in human-robot interactions has become more challenging. Established safety standards emphasize risk assessment, protective measures, and real-time monitoring systems, where safety complexities arise from intricate industrial interactions. The study focuses on "Speed and Separation Monitoring" (SSM), a collaborative type defined by ISO/TS 15066. The research addresses unknowns within SSM, particularly on the parameter accounting for the robot system to respond to the operator's presence, crucial for decision-making on speed and separation limits. A proximity sensor was utilized to assess the overall delay of a classic industrial network between the sensing node for the operator detection (AI-based vision system) and the triggering of the safety node to the robot. The methodology was tested on a cohort of 23 subjects and evaluated under various lighting conditions. The study identified bottlenecks and the impact of each subsystem composing typical industrial control networks, highlighting the need for precise methodologies to assess latency as a critical factor in safety and productivity as sensing technology, collaborative robots and safety networks keep evolving.**



***Index Terms*—Latency, collaborative robotics, safety, speed and separation monitoring**


## I. Introduction

Human-robot collaboration is rapidly gaining traction within the evolving field of robotics, serving as a pivotal enabler for a wide array of applications [1]. This collaborative dynamic not only enhances existing scenarios where robots work alongside human operators but also extends into traditionally human-exclusive domains. While safety remains a paramount concern whenever humans and robots share a common workspace, the increasing integration of collaborative robots (cobots) with advanced AI-driven sensing technology presents new challenges for policymakers and legislators in developing robust and adaptable safety standards. The high repeatability, precision, and velocity in cobots, coupled with advancements in AI-driven sensing, underscores the need for proactive measures to ensure safe and sustainable deployment of collaborative robotic systems [2].

Safety in human-robot interaction (HRI) can be broadly categorized into two crucial dimensions [3]. The first and more intuitive dimension is physical safety. Here, the overarching objective is to prevent any undesired contact between humans and robots. However, if contact is required or not avoidable by the task for other reasons, the forces exerted by the robot on the human must be meticulously controlled to remain within limits that preclude discomfort or injury.

The second, often underestimated dimension is psychological safety. In the context of human-robot interaction, this usually refers to excessive stress and discomfort that could be induced by collaborative tasks over extended periods. Consider, for instance, a hypothetical robot operating with a sharp end effector capable of swift movements in close proximity to a human operator's hand. While physical barriers or light curtains may effectively prevent physical contact, therefore any chance of injury, the constant stress and discomfort experienced by the human operator pose significant long-term health concerns [4].

Several standards are being implemented to address safety in collaborative robotics scenarios, such as the ISO/TS 15066


This work was carried out with the support of Enterprise Ireland and Science foundation Ireland through the DTIF project SafetyBot (DT20200274), the SFI Centre VistaMilk (SFI 16/RC/3835) and the student mobility scholarship of Politecnico di Torino.

[5] that identifies four types of collaboration, including "Speed and Separation Monitoring" (SSM), which is the focus of this research. In this collaborative scenario, a minimum protective distance $S_P$ between a robot and an operator within the collaborative workspace, is established by the following equation:

$$S_{\mathrm{P}}(t_0) \geq \left( \int_{\tau=t_0}^{\tau=t_0+T_{\mathrm{R}}+T_{\mathrm{S}}} v_{\mathrm{H}}(\tau)\, d\tau \right) + \\ + \left( \int_{\tau=t_0}^{\tau=t_0+T_{\mathrm{R}}} v_{\mathrm{R}}(\tau)\, d\tau \right) + \left( \int_{\tau=t_0+T_{\mathrm{R}}}^{\tau=t_0+T_{\mathrm{R}}+T_{\mathrm{S}}} v_{\mathrm{S}}(\tau)\, d\tau \right) + \\ + C + Z_{\mathrm{S}} + Z_{\mathrm{R}}$$

where $v_H$ is the directed speed of the operator, $v_R$ is the directed speed of the robot in the direction of the operator, and $v_S$ is the directed speed of the robot in the course of stopping. $T_R$ is the time for the robot system to respond to the operator's presence, while $T_S$ is the time to bring the robot to a safe, controlled stop. The remaining terms capture measurement uncertainty, where C is an intrusion distance safety margin based on the expected human reach, $Z_R$ is the robot position uncertainty, and $Z_S$ is the operator position uncertainty [8].

Most of the literature implementing SSM, is focused on identifying and avoiding potential collisions (e.g. [6], [7]). Due to the non-linear nature of the human tracking issue, accurately forecasting the response time of a human-detection system is challenging. Presently, there exists no standardized approach for assessing the reaction time of a human-detecting sensor. Instead, it is typically regarded as a fixed value or buffer that the integrator is responsible for determining. However, a more accurate evaluation of the whole chain of latency, from the sensor trigger to the command to the robot to stop ($T_R$), is becoming more and more crucial as collaborative robotics expands and evolves. In such context, while safety remains paramount, there is the need for maximizing robot performance (productivity) while collaborating alongside human operators. In fact, poor estimation of $T_R$ can poses a substantial safety risk if the actual value is too large, or, in contrast, inefficiency in the human-robot collaboration and downtime if too small, regardless of the accuracy and precision of the reported data.

The $T_R$ parameter plays a crucial role in the equations governing SSM, effectively influencing the decision-making process related to the thresholds to set for the maximum speed and maximum separation. Few works have focused on some of the elements of the SSM equation, proposing ad-hoc methodologies for their assessment.

Marvel et al. [8] evaluate the reaction time for rail-mounted, 6 degree of freedom robot manipulator by using, a system (e.g., a pressure-sensitive mat) that monitors the boundary of the protected zone and a timer that is then stopped when the signal from the safety system is received. Szabo et al. [9] conduct experiments aimed at estimating reaction times of the robot by setting up a linear motion test in which the robot interrupted a laser beam connected to a safety relay. Rashid et al. [10] propose a method to concurrently determine the safety parameters of intrusion distance for sensors and the reaction time for robot controllers. To the best of the authors' knowledge, no prior work has proposed methods for evaluating the parameter $T_R$ within a typical industrial use case, while implementing SSM.

This work presents an approach to the assessment of latency as a critical factor in industrial network that adopt safe communication standards between nodes of elements of a collaborative robotic system. Beyond physical safety considerations, we incorporate the dimension of psychological safety to underscore the significance of a holistic safety approach in HRI. Furthermore, we introduce productivity as a third element, emphasizing the imperative to limit downtime of collaborative robots for enhanced overall efficiency in their operational environments.
This work is structured as follows: Section II describes the experimental setup and methodology for the evaluation of the time parameter $T_R$. Section III discusses the results of our approach. Finally, Section IV and V respectively provide conclusions and discuss limitations.

## II. Methodology

To assess $T_R$ in a physical environment simulating the typical industrial network controlling a cobot, both hardware and software tools have been used. Below the equipment utilized, the experimental setup and the final assessment are described

### A. Equipment

The hardware and software components utilized to conduct the assessment of the time required for a robot system to respond to the presence of an operator ($T_R$) are the following:

*1) Hardware:*

- NDIVIA's Jetson Nano Developer kit (NVIDIA, Santa Clara, California, United States) [16]. This development platform is equipped with a 128-core Maxwell Architecture GPU and a CPU operating at a maximum frequency of 1.43 GHz. The Jetson Nano provides the computational power necessary for training neural networks and executing multiple neural networks simultaneously;
- Safety remote I/O device based on Ixxat Safe T100 (HMS Networks, Halmstad, Sweden). This product, although not yet available on the market, serves as an essential component for implementing safety communication protocols;
- Arducam Time-of-Flight (ToF) camera (Arducam, Nanjing, China) [17]. Utilizing a Vertical-Cavity Surface-Emitting Laser in continuous-wave modulation mode, this camera measures the distance of an object (in this case a human) with respect to the sensor by emitting modulated light and evaluating the round-trip time for the light to be reflected back from the object into the sensor;
- GuardLogix Safety Programmable Logic Controller (PLC) 5380 from Rockwell Automation (Rockwell Automation, Milwaukee, Wisconsin, United States) [18].

This safety programmable logic controller ensures the execution of safety functions within the system;
- Universal Robot UR16e (Universal Robots, Odense, Denmark) [19];
- SICK WL9-3P2232 Infrared sensor (SICK Sensor Intelligence, Waldkirch, Germany) [20]. A through-beam photoelectric sensor with a response time of less than 0.5 ms and a switching frequency of 1000 Hz, used for detecting the presence of the operator;
- Tektronix TDS-3032C Digital oscilloscope (Beaverton, Oregon, United States) [21]. It features a sample rate of up to 5 GS/s and a time base accuracy of $\pm 20$ ppm over any 1 ms time interval.

*2) Software:*

- Wireshark v4.0.10. Open-source packet analyzer employed for network analysis;
- Studio5000 v35. This software is utilized for programming Allen-Bradley controllers;
- Ubuntu v18.04. An open-source operating system based on the Linux kernel, serving as the default operating system for the NVIDIA platform.

### *B. Participants and Ethics Statement*

A total of 23 subjects (15 male and 8 female) were recruited for the data collection, with age ranges from 20-60 years. Before commencing the trial, a comprehensive briefing of the nature of the study was given, followed by the opportunity to confirm consent. No information that can directly identify participants was included in the data collection, in accordance with the General Data Protection Regulation 2018 of the EU. Ethics authorization from the University College Cork Ethics Committee was secured before starting the data acquisition, as per the law in force.

### *C. Experimental Setup*

To evaluate the time parameter $T_R$ within the SSM framework, it is important to understand the system down to component level. The experimental setup, as depicted in Fig. 1, is used to perform this analysis.

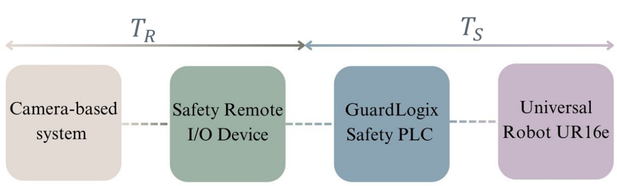


Fig. 1: The illustration depicts the experimental setup employed in this study, providing insight into the essential components and the operational definitions of $T_R$ and $T_S$ within the context of the analyzed configuration.

Below is a concise overview of the functionalities of the different blocks depicted in Fig. 1, along with insights into their interconnections.

The camera-based system is responsible for detecting the operator and determining their distance in relation to the robot. This system comprises the Jetson Nano Developer kit and the Arducam ToF camera mounted on it. Human detection is achieved through the utilization of the YOLO v8n model, developed by Ultralytics [11] , to ensure robustness and stability in object recognition processes. Distance calculation relies on data obtained from the ToF Camera and processed via Python environment.

The safety remote device implements the CIP safety communication protocols. One of the general-purpose input/outputs (GPIO) pin of the Jetson Nano board is connected to the input of the safety remote device (via voltage step-up to bring the 3.3V to 24V) and configured to switch state when the operator approaches within a distance of $1.2\text{m}$ from the robot (arbitrary distance that consider a safety margin respect to the maximum reach of the robot arm). In turn, the activation of the safety remote device input triggers the Safety PLC through ladder code, thereby regulating the speed of the UR16e universal robot.

In this configuration, the total time parameter, $T_R$, is determined as the sum of the processing time of the camera-based system and the safety remote I/O device (Fig. 1). Latency analysis for the camera-based system is conducted employing the infrared sensor and the digital oscilloscope. Similarly, for the safety remote device, latency assessment is carried out using the open-source packet analyzer Wireshark v4.0.10.

### *D. $T_R$ Assessment*

*1) Safety Remote I/O device:* Performance analysis of industrial networks and the automation systems that employ them is conducted either through hardware tools [12], [13] or via software [14], [15].

In this paper, for latency assessment of the safety remote I/O device, the examination of the exchanged messages between the Safety PLC and the Ixxat device is conducted, specifically focusing on the analysis of CIP safety messages. This type of analysis is selected to assess the device's latency with only the input connected, representing the scenario employed in the designated setup. Fig. 2 illustrates the timeline between the activation of the input of the safety remote I/O device and the subsequent received CIP Safety message.

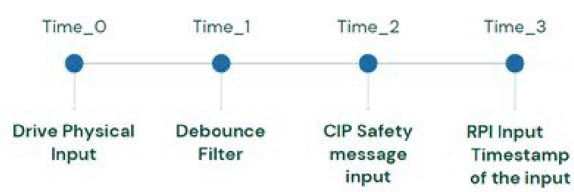


Fig. 2: Timeline when only the input of the remote IO device is activated.

In order to make this analysis, Wireshark v4.0.10 is chosen as software tool and a square wave signal with a 24 V amplitude serves as the input to the device (Fig. 3).

The initial step involves collecting messages and their corresponding timestamps from Wireshark, utilizing suitable

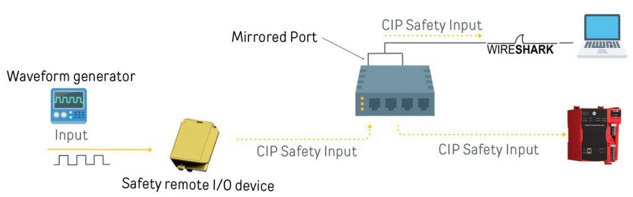


Fig. 3: Schematic diagram of the setup used.

filters. Following this, the device frequency is calculated in MATLAB using these data, achieved by identifying the total number of peaks and dividing them by the overall period. This methodology is replicated for different input Requested Packet Intervals (RPIs) (5ms, 10ms, and 20ms). This approach allows for a comparison between the input frequency of the theoretical square wave and the frequency of the safety remote I/O device and thus the computation of the corresponding latency.

*2) Camera-based System:* To evaluate the contribution of the camera-based system in assessing $T_R$, an external infrared sensor is employed. The infrared sensor and its reflector are positioned at a distance of $1.2\mathrm{m}$ from the camera. When the camera detects that the subject is closer to $1.2\mathrm{m}$, the state of the GPIO of the Jetson Nano is switched and consequently the input of the safety remote device is changed to $24\mathrm{V}$. This approach enables the estimation of the time required for the camera-based system to detect the presence of a person, estimating their distance, and activate the safety remote device input if the person gets closer than $1.2\mathrm{m}$ . For this evaluation, the output of the infrared sensor and the input of the safety remote device are connected via probes to the oscilloscope for activation time comparison. Both the infrared sensor and the ToF system are triggered upon the passage of a subject at the $1.2\mathrm{m}$ mark from the camera. Such setup, represented in Fig. 4, facilitates the assessment of the delay between the activation of the sensor, indicating the presence of a person within range, and the subsequent activation of the safety remote device input by the camera-based system.

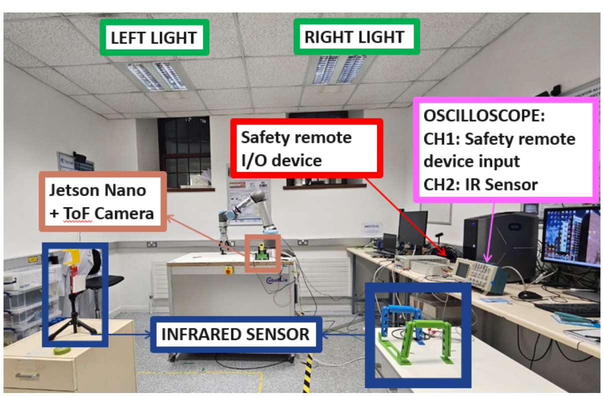


Fig. 4: $T_R$ assessment setup.

The testing procedure is structured as follows: Four distinct conditions of typical indoor neon lighting are defined:

1) Condition 1: Both lights turned on
2) Condition 2: Left light turned on (refer to Fig. 4)
3) Condition 3: Right light turned on
4) Condition 4: Both lights turned off

For each participant, the maximum distance from which the camera could effectively recognize the person is determined under each of the four lighting conditions. Subsequently, participants are instructed to take walk back and forth 20 times across the $1.2\mathrm{m}$ range mark ( Fig. 5). This process ensures that both the signal coming from the infrared sensor output and the signal fed into the input to the safety remote device generated by the Jetson Nano change state when the individual crosses the predetermined range.

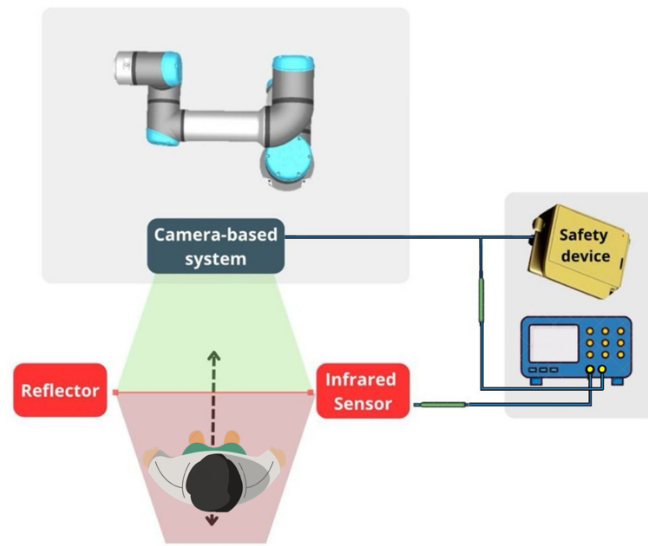


Fig. 5: $T_R$ assessment setup - Top view.

By employing this method, the latency between the activation of the individual's presence and the activation of the safety remote device input could be evaluated using an oscilloscope. This process is repeated for each of the four lighting conditions.

## III. Results and Discussion

*1) Safety remote I/O device:*

The results indicate the safety remote I/O device has a cutoff frequency, which is contingent on factors such as the input RPI, input filtering (e.g., debounce filter), and the number of safety inputs utilized, consistent with the specification. Specifically, the percentage of received signal at the variation of input frequency over three different RPI, keeping one single safe input of the safety remote I/O device and the debounce filter set to its minimum value of $1.2\mathrm{ms}$, are shown in Fig. 6.

According to the different RPI, once such cutoff frequency is surpassed, the device's ability to accurately track the input diminishes, resulting in a noticeable drop in performance. Consequently, latency $T_{\text{safety device}}$ can be calculated as:

$$T_{\text{safety device}} = \frac{1}{f_{\text{limit}}} \tag{1}$$

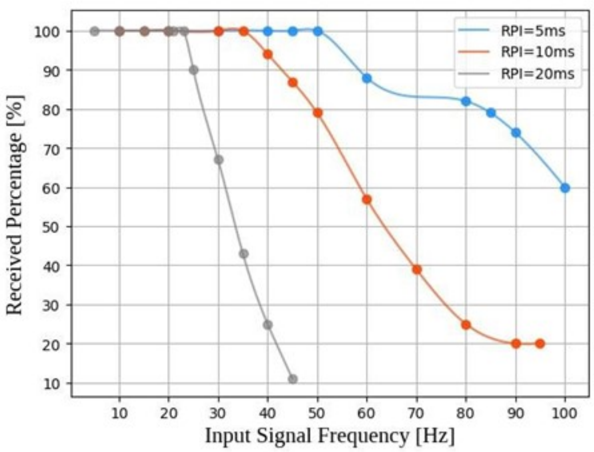


Fig. 6: Overall performance of the safety remote I/O device for different $RPI_{input}$. The x-axis represents the input frequency and the y-axis denotes ratio between the frequency of the safety remote I/O device and the input frequency in percentage.

For instance, when the input RPI is set to $5\text{ms}$, the debounce filter is configured at $1.2\text{ms}$, and only one input is active, the calculated latency amounts to $20.3\text{ms} \pm 1.7\text{ms}$.

*2) Camera-based system:*

Fig. 7 presents the latency analysis conducted on the camera-based system. Specifically, the mean latency and corresponding standard deviation are reported for male and female subjects across various light conditions. Notably, a discernible disparity in values based on gender is observed. This variance could predominantly stems from the dataset used for model training, which is known to exhibit a pronounced skew towards male subjects [22] .

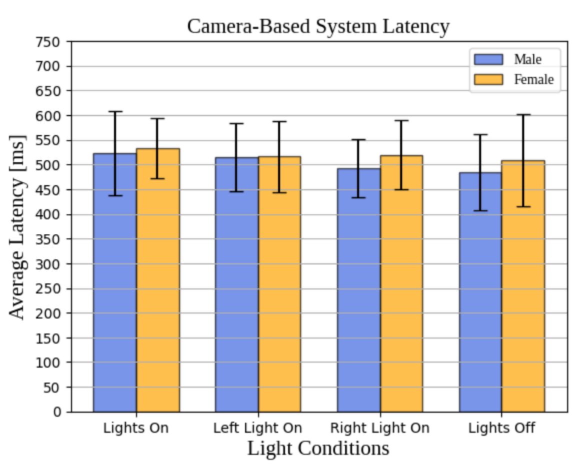


Fig. 7: Obtained Latency Results for camera-based system.

Moreover, the outcomes reveal that the longest latency occurs when both lights are illuminated, resulting in heightened brightness. In such instances, the maximum latency value recorded is $533.3\text{ms} \pm 60.1\text{ms}$. It is evident that artificial illumination acts as a noise factor in the distance processing phase within the utilized setup. This observation aligns with the operational principle of ToF cameras, where ambient light can have a significant impact on the Signal-to-Noise Ratio of reflected signals, particularly in environments with excessive ambient light [23]. This inference is further substantiated by the data presented in Fig. 8, illustrating the mean and standard deviation of the maximum distance at which the system can detect individuals across different light conditions, with higher values observed in the absence of artificial light.

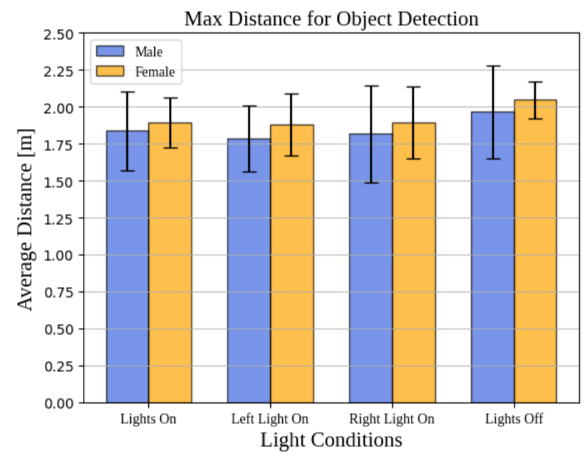


Fig. 8: Max distance results.

It should be noted that the results obtained are also affected by the oscilloscope cursor resolution, which, with the employed configuration, stands at $\pm 4\text{ms}$. Remarkably, this accounts for less than one percent of the overall results obtained. To gain deeper insights into the primary factors influencing such latency, the cumulative pre-processing, inference, and post-processing time incurred by the model is considered. Such time period is determined to be $188.5\text{ms} \pm 1.9\text{ms}$ with the utilized setup (Jetson Nano timestamp). Moreover, such image processing duration inherently constrains the number of frames per second pulled from the ToF camera to 5. In our specific context, the low fps value does not significantly impact our results due to several factors. Firstly, participants were executing steps at a moderate pace within the sensor range to activate the camera-based system. Moreover, the camera-based system triggers when individuals enter a specified range rather than requiring precise distance measurements.

## IV. Conclusions

This work delves into the assessment of latency as a critical factor in optimizing the SSM standard in collaborative robotics. Beyond physical safety considerations, we incorporate the dimension of psychological safety to underscore the significance of a holistic safety approach in HRI. Furthermore, we introduce productivity as a third element, emphasizing the imperative to limit downtime of collaborative robots for enhanced overall efficiency in their operational environments. As technology continues to advance, particularly with the integration of sensing technologies for enhanced self-awareness and autonomy in cobots, it becomes imperative for safety standards to evolve in parallel.

We presented an ad-hoc methodology for assessing the critical yet unexplored aspect of the time required for a robot system to respond to the presence of an operator ($T_R$). By focusing on a collaborative robotics network featuring a camera-based human tracking and distance calculation device (ToF camera module and Jetson Nano board), a PLC controlling a UR16e, and a safety I/O remote device implementing CIP safety, we have evaluated $T_R$ with a high degree of precision. Through software-based methodologies and comparative analysis with a retro-reflective sensor, we determined, for the worst-case performance, a $T_R$ of $553.3\text{ms} \pm 61.7\text{ms}$.

This estimation of response time is a substantial improvement in determining the appropriate robot speed to prevent collisions with operators, which is otherwise obtained by considering high estimated tolerances. Moreover, our proposed methodology can be applied to various network configurations, thereby offering insights to better set the SSM parameters. By providing a more accurate assessment of the overall reaction time of the system, our methodology not only enhances safety but could also minimize robot underperformance and downtime.

## V. Limitations and Future Works

While our study has provided an insight into the evaluation of the $T_R$ parameter within the SSM framework, it is important to note that the focus of this work is not on the sensing technology part, including improving the performance of the model for object recognition, but rather finding a methodology to evaluate latency within a typical industrial context. Nevertheless, few limitations have been identified, suggesting venues for future research. What affects latency the most is the performance of the YOLO v8n model for object detection, that is heavily influenced by the hardware on which it operates. Variability in hardware specifications can result in significant fluctuations in the model real-time processing capabilities, compounded by the challenge of low frames per second. Addressing this limitation requires further investigation into optimizing the model performance across different hardware configurations to ensure consistent and reliable object detection service. Additionally, another hardware limitation is the use of a low resolution ToF camera, which may impact the system's capabilities and overall performance. In subsequent phases, our focus will shift towards the integration of dual-camera setups, either for stereo imaging or using one high resolution camera for object detection and one ToF camera to assess distances. Furthermore, as part of our future work, we aim to compute the speeds of both the robot and the operator. This data will be instrumental in implementing dynamic SSM using the system, thereby ensuring adaptive and responsive safety protocols in dynamic environments.

## Acknowledgement

We would like to acknowledge the precious help of Simone Innocente during the preparation of the testing stage of the proposed assessing system.

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