Vision-Based Safety System for Barrierless Human-Robot Collaboration

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Abstract—Human safety has always been the main priority when working near an industrial robot. With the rise of Human-Robot Collaborative environments, physical barriers to avoiding collisions have been disappearing, increasing the risk of accidents and the need for solutions that ensure a safe Human-Robot Collaboration. This paper proposes a safety system that implements Speed and Separation Monitoring (SSM) type of operation. For this, safety zones are defined in the robot’s workspace following current standards for industrial collaborative robots. A deep learning-based computer vision system detects, tracks, and estimates the 3D position of operators close to the robot. The robot's control system uses this information to lower the robot's speed or to stop the robot, depending on the operator's location. Other operation modes are also implemented, which vary how the human and the robot interact.

The novelties of the safety system presented in this paper are:

1) A deep learning strategy to detect and track humans in industrial human-robot collaboration environments.
2) Three different operation modes: An SSM-based operation mode that follows the ISO/TS 15066; a dynamic safety zones mode, where the reaction of the robot depends on its euclidean distance to the operator; and an obstacle evasion mode, where the robot modifies its trajectory to avoid contact with any operator that is on its way.
3) Additionally, we include the 3D representation of the workspace using ROS (Robot Operating System) and MoveIt!, which allow a direct interaction/communication between the control and the perception systems and give the control system re-planning and collision avoidance capabilities.

The paper is structured as follows. Section II introduces the problem statement and the risk assessment. Section III describes the barrierless safety system, which includes the definition of the safety zones, the vision system and the operation modes. Section IV presents the experiments and results that the performance of the safety system. Lastly, Section V presents the conclusions and future work.
II. PROBLEM STATEMENT
The system was developed for a scenario where a robotic manipulator performs a pick-and-place routine on a table while operators move around it. A Kinect camera was located at the height of 3.45 m facing downwards, reaching an area of 4.2 m x 3.1 m of the scene of interest. Fig. 1 shows the system’s setup. The left side shows the UR3 robotic arm used in the study with a Robotiq 2F-85 gripper. The right side shows an example of what the camera captures when an operator enters the robot’s workspace.

![Fig. 1. Barrierless scenario. UR3 performing a pick-and-place routine (left). The robot and operator are sharing the workspace (right). A camera facing downwards monitors the robot-operator interaction.]

A. Risk Assessment
A risk assessment for the UR3 was carried out based on [8] and following the guidelines of the ISO 10218 and ISO 13849 standards to determine the reliability requirements for risk reduction measures, based on assessing the basic properties of hazard defined in Table I.

| Property of hazard | Possible values                          |
|--------------------|-----------------------------------------|
| S - Severity of injury | S1 - slight, normally reversible injuries |
|                     | S2 - severe, normally irreversible injuries |
| F - Frequency of exposure to hazard | F1 - rare |
|                     | F2 - frequent, constant |
| P - Possibility of avoiding hazard or limiting harm | P1 - possible under certain conditions |
|                     | P2 - scarcely possible |

From the selection of the properties of hazard, the required safety Performance Level (PL) is obtained and ranked on a scale of increasing degree of risk reduction from PLa to PLe.

For a collaborative robot like the UR3, the PL is PLe (Fig. 2). It is a medium level, one level less than the required one for standard industrial robots (PLd). A PLe implies that a medium-level risk reduction measure must be taken using an external safety system. The result is consistent since collaborative robots are designed to interact with humans. They should represent a lower risk than a standard industrial robot. However, as there is a higher frequency of exposure to hazards, other safety measures must be implemented to reduce the risk of injury. Because of this, we propose a vision-based safety system to achieve the required PLe level.

III. BARRIERLESS SAFETY SYSTEM
The system was planned under the Speed and Separation Monitoring (SSM) type of operation, in which the robot’s speed depends on the constant evaluation of the horizontal distance of the operator relative to the robot [7]. The distance analysis is performed by a vision system that communicates with the UR3 control system to vary its speed.

Fig. 3 presents the architecture of the proposed safety system. The left side describes the vision system where a convolutional neural network (CNN) is used for the detection of the operators nearby the robot, and a tracking algorithm is used to follow them while on scene (see Section III-B). The operators’ 3D position and height are estimated in real-time and are used to identify the safety zones and the risk of collision (determined by the human-robot distance).

The right side of Fig. 3 describes the robot’s control system. It receives the 3D position and height of the operators and the risk zone where they are detected. This data is then used to generate 3D figures in a simulated space, representing the operators as collision objects to the robot with the color of their respective safety zone. The 3D position is also used to find the human-robot distance and change the robot’s speed based on their closeness to avoid a collision. The robot performs a programmed routine that adapts to the speed changes. The robot’s routine and other capabilities, like collision avoidance, were possible by taking advantage of the integration of the control system with ROS and MoveIt [20], [21].

A. Definition of Safety Zones
The safety zones around the robot were defined based on the technical specification ISO/TS 15066: 2016 and studies carried out in [11], [12]. These studies suggest that it is possible to limit the problem of the minimum separation distance (MSD) between the robot and an operator to a 1D-problem, where the MSD $S_a$ is calculated as follows.

$$S_a = S_h + S_r + S_s + C + Z_d + Z_r$$  \hspace{1cm} (1)

$S_a$ is expressed as the sum of contributions from:
- The operator’s movement: human distance $S_h$.
- The robot’s movement: reaction distance $S_r$ and stop distance $S_s$. 

![Fig. 2. Risk graph for a collaborative robot (ISO 13849) [9]]
The sensors’ attributes used for distance measurement: intrusion distance \( C \), uncertainties from the robot’s position \( Z_{d} \), and the operator’s position \( Z_{r} \).

\( C \) can be discarded as it is an attribute for devices installed parallel to the robot’s z-axis, which is not the case. Likewise, position uncertainties are not included since additional information is necessary for evaluating these measures, and their contribution is negligible for the calculation [11].

Distances can be written in terms of speed and time as:

\[
S_{a} = v_{h}(T_{r} + T_{s}) + v_{r}T_{r} + \frac{v_{r}T_{s}}{2} \quad (2)
\]

\( v_{h} \) is the speed at which a human walks towards the robot, defined as 1600 mm/s in the ISO 13855 standard. \( v_{r} \) is the robot’s speed, taken as 500 mm/s from the UR3 technical specification sheet [13] as 50% of its nominal speed (i.e., the speed of the robot before it stops). \( T_{r} \) is the robot’s reaction time when in the presence of an operator. The latter was determined experimentally using the vision system integrated with the robot’s control system, obtaining an average of 28.3 ms. Finally, \( T_{s} \) is the stop time of the robot, taken as 400 ms from the UR3 user manual [14]. Therefore, replacing the values above in Eq. (2), the minimum separation distance is \( S_{a} \approx 800 \) mm.

The result means that if the distance \( S \) between the base of the robot and an operator is less than or equal to the MSD, the robot must stop. The result is consistent, considering that the maximum reach of the robot is 500 mm. Although Eq.1 does not consider the robot using an end effector, the maximum reach, including the Robotiq 2F-85, is 662.8 mm. This length is still within the protection zone, with a margin \( \Delta_{s} = 137.2 \) mm between the end effector and the MSD.

Assuming the worst-case scenario, where the robot is at its maximum reach (including its end effector) and an operator is crossing the line of the MSD in a straight line toward the end effector; the estimated collision time between the operator and the end effector is obtained using Eq. 3.

\[
t_{\text{collision}} = \frac{\Delta_{s}}{v_{h}} = \frac{137.2 \text{ mm}}{1600 \text{ mm/s}} = 0.0858 \text{ s} = 85.8 \text{ ms} \quad (3)
\]

As can be seen, \( t_{\text{collision}} > T_{r} \). It indicates that the robot would react to the detection of an operator even in the worst-case scenario. However, during the routine that the robot performs, it never extends to its maximum reach.

| Zone               | Color | Boundaries                   |
|--------------------|-------|------------------------------|
| High-risk zone     | Red   | \( S \leq S_{a} \)           |
|                    |       | \( S \leq 800 \text{ mm} \)  |
| Low-risk zone      | Yellow| \( S_{a} < S \leq S_{b} \)   |
|                    |       | \( 800 \text{ mm} < S \leq 1550 \text{ mm} \) |
| Safe zone          | Green | \( S > S_{b} \)              |
|                    |       | \( S > 1550 \text{ mm} \)    |

The boundaries of the safety zones are summarized in Table II. The high-risk zone includes the area from the robot’s base to \( S_{a} \). The low-risk zone was defined using the technical specification ISO / TS 15066. It indicates that there must be a clearance of at least 500 mm of distance. For better visualization of the traffic within that area, a 750 mm distance was assumed. Therefore, the outer limit of the low-risk zone is defined as \( S_{b} = S_{a} + 750 \text{ mm} = 1550 \text{ mm} \). The remaining area is the safe zone, where no safety actions are taken as there is not possibility of collision. This zone is described as any distance \( S \) greater than \( S_{b} \).

Fig. 4 shows the dimensions of the zones defined in Table II with the robot in the scene.
B. Vision System

The vision system handles three processes: operator detection, tracking, and 3D position estimation. The Tensorbox object detection framework [16] was used to detect people from above. This framework was further trained using 21,222 images with similar characteristics. The data was split 50% for training, 30% for validation, and 20% for testing. The algorithm showed an accuracy of 92% with the test dataset [15]. The CNN-based detector works in parallel with a tracking algorithm. Therefore, for every frame, the coordinates of the bounding box of the detected heads are sent to the tracker. The tracker uses the received data to predict the operator’s position when the detector fails. The Simple Online and Real-time Tracking algorithm (SORT) [17] was used. When tested, it showed a higher accuracy and a higher and steadier tracking speed.

The safety system requires the operator’s position relative to the robot’s base and his/her height. This data was estimated by using the intrinsic camera parameters (Kinect [19]), the camera extrinsic parameters (found by calibration), and the camera’s depth sensor. The details of the vision system are presented in [15].

C. Operation Modes

Knowing which zone the operator is in allows the control system to modify the robot’s behavior. Three operation modes for the safety system are proposed, which can be used depending on the needs. For all modes, if there is more than one operator on the scene, the speed will change according to the safety zone of the closest operator.

a) SSM with static zones: This mode aims to change the robot’s speed according to the operator’s relative distance. If operators are detected in the safe zone, the robot moves at 100% of its nominal speed, at 50% speed if operators are detected in the low-risk zone, and it stops its movement if operators are detected in the high-risk zone. The robot performs a category two protection stop as indicated in the ISO 10218-1:2011 standard. It is a controlled stop in which the robot continues to be powered [14] so it can resume its routine when the operator has left this area.

b) SSM dynamic zone: Compared to the previous mode, the robot does not stop its movement if the operator enters the high-risk zone. Instead, an additional analysis is performed to stop the robot only when it is strictly necessary to ensure the operator’s safety and greater efficiency in the robot’s task. To achieve this, dynamic safety zones are created around those critical joints of the robot that can cause a collision with the operator. Fig. 5 shows the new safety zones created around the wrist and elbow joints. Those joints were chosen since they are the ones that move along the Cartesian plane.

By inspecting the surroundings of these joints as the robot moves, it is possible to have a closer human-robot interaction and to stop the robot only if the operator is close enough to collide with the robot. The MSD between the operator and any of the two joints was established equal to 200 mm as shown in Fig. 5, considering the collision time calculated in Eq. 3 and covering all moving parts of the robot.

Since the protection zones change their position as the robot moves, this operation mode offers a freer human-robot interaction, maintaining a minimum safety distance between them. Table III presents the boundaries of the dynamic safety zones. The robot only stops if the horizontal distance between the detected operator and the robot’s wrist or elbow is less than or equal to 200 mm. Like in the previous mode, a category 2 protection stop is performed, so that the robot can resume its routine when the operator walks away from it.

c) Obstacle avoidance: This operation mode seeks to replace the robot’s protection stop with an obstacle avoidance algorithm, such that the robot does not stop its routine at all, and the operator’s safety is still ensured. In this mode, the robot performs a controlled stop in which the robot continues to be powered [14] so it can resume its routine when the operator has left this area.

| Zone                  | Speed                  | Robot's reference speed |
|-----------------------|------------------------|-------------------------|
| Dynamic zones         | €200 mm                | 0 mm/s                  |
| High-risk zone        | 800 mm > 200 mm        | 250 mm/s                |
| Low-risk zone         | 800 mm < 2 ≤ 1550 mm   | 500 mm/s                |
| Safe zone             | > 1550 mm              | 1000 mm/s               |

Fig. 5. Safety zones around wrist and elbow joints. By controlling these zones, the robot will stop only when required, ensuring safety and efficiency.

IV. Experiments and Results

Three experiments were carried out (all in the SSM operation mode with static zones) to evaluate the performance of the safety system and how it is affected by the number of people on the scene. The first experiment evaluates the system’s ability to classify the detected people on the scene correctly. The second and third experiments evaluate the robot’s reaction and stop time when the operator moves from...
one safety zone to another and when he/she enters the high-risk zone. Videos are available in

### A. Risk Zone Identification

This experiment determines how accurate the vision system classifies the zone where the operator is detected compared with the actual zone. A video (900 frames) where operators walked around the scene was recorded, and the operators’ heads were manually labeled to obtain ground truth data. Table IV shows the different performance measurements calculated per zone.

| Measure | Green zone | Yellow zone | Red zone |
|---------|------------|-------------|---------|
| Accuracy | 85.6 % | 91.9 % | 97.9 % |
| Precision | 97.7 % | 99.4 % | 99.5 % |
| Recall | 57.4 % | 81.9 % | 91.5 % |
| F-score | 72.3 % | 89.8 % | 95.3 % |

The accuracy and precision of the zone classifier were greater than 85 % and 97 % respectively for each of the three zones. Overall, the system correctly classifies the safety zone where the operator was located. A low recall percentage was obtained for the green zone, indicating that only 57.4 % of the cases were detected correctly. Most false negatives are caused by the absence of detections and not by a wrong classification. The latter can be attributed to the Kinect’s disparity effect, which reduces the usable field of view (no depth data on the borders of the image). Therefore, the number of correct detections in the green zone is reduced, and the recall score decreases.

### B. Reaction time

This experiment calculates the time it takes for the robot to change its speed from when the system sends the information that an operator has moved from the safe zone to the low-risk zone or vice versa. The average reaction time is calculated after running the system for 1 minute in real-time while operators were walking between both zones. The results are compared with the reference reaction time ($T_r$) calculated in Section III-A.

Table V shows the average reaction time for two tests carried out with one and two people in the scene. For each case, 20 zone changes were made, in which the operators switched from the safe zone to the low-risk zone or vice versa. Fig. 7 shows an example of the experiment. The image on the left shows the results of the vision system. The image on the right shows how the operators are perceived as obstacles by the robot when they are represented as 3D figures.

| # People in the scene | Average $t_r$ (ms) |
|-----------------------|-------------------|
| Test 1 | Test 2 | Average |
| 1 | 38.3 | 32.8 | 35.6 |
| 2 | 54.5 | 52.5 | 53.5 |

Results registered in Table V show that by increasing the number of people in the scene from one to two, $t_r$ increased by an average of 17.9 ms. This increment is coherent because more 3D figures must be created in the simulation environment, and more calculations are required to find the closest operator to the robot. Nevertheless, the found values do not represent a risk to people passing through the scene. If we consider that the time it takes an operator to cross the entire low-risk zone in a straight line (750 mm) at an average speed of 1600 mm/s (Section III-A) is about 469 ms, the different $t_r$ found in Table V are sufficient for the robot to change its speed, even when multiple operators are on the scene.

On the other hand, the values in Table V are greater than the reference $T_r$ calculated in Section III-A ($T_r = 28.3$ ms). This increment occurs because $T_r$ was estimated without considering the system’s underlying calculations, such as zone classification and generation of 3D collision objects in the simulated environment.

### C. Stop time

This experiment calculates the time it takes for the robot to stop its movement from the moment the system sends the information of the operator detected in the high-risk zone. The average $t_s$ is calculated after running the system for 1

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1 Videos of the safety system https://youtube.com/playlist?list=PLgYA51rB9xXw1RwwL0Udv1lKwel168HY5y
minute in real-time while operators were entering the high-risk zone. The results are compared with the reference $T_s$ ($T_s = 400 \text{ ms}$) discussed in Section III-A, and the estimated $t_{\text{collision}}$ calculated in Eq. 3.

Table VI shows the averages of $t_s$ for two tests carried out with one and two people in the scene. For each case, 20 zone changes were made, in which the operators walked from the low-risk zone to the high-risk zone.

| # People in the scene | Test 1 | Test 2 | Average |
|-----------------------|--------|--------|---------|
| 1                     | 67.1   | 60.2   | 63.7    |
| 2                     | 76.9   | 75.5   | 76.2    |

Similar to the previous test, when the number of people in the scene increases, $t_s$ increases too, due to the extra computational cost of having two operators in the scene.

The times obtained in these tests are smaller than the reference $T_s$ of the UR3. This difference is because $T_s$ was estimated considering that the robot is stopped through the immediate disconnection of its power. While for our safety system, a control loop is started to maintain the robot in the last position [14]. This action requires less time to stop the robot than waiting for it to be entirely powered off.

It is also observed that the different $t_s$ found are lower than the calculated $t_{\text{collision}}$ ($t_{\text{collision}} = 85.8 \text{ ms}$) in the worst-case scenario presented in Section III-A Therefore, it can be guaranteed that the robot will stop in time, and there will be no collision between the operator and the robot.

V. CONCLUSIONS AND FUTURE WORK

This paper presented a safety system for an industrial manipulator, combining Speed and Separation Monitoring (SSM) operation with computer vision and deep learning techniques. The results from the experiments demonstrated that the system’s performance ensures the operator’s safety within the robot’s workspace. People were classified in the high-risk zone with an accuracy of 97.9\% and a precision of 99.5\%. In the second and third experiments, the average $t_r$ and $t_s$ were 53.5 ms and 76.2 ms for two operators in the scene. Both values, when compared to the ones found for the definition of the safety zones, validated that the robot reacts and stops within the time limits when the operator enters the high-risk zone. The three operation modes proposed in the paper introduced distinct types of human–robot interaction. The results confirmed that it is feasible to eliminate physical barriers around an industrial robot while keeping the operator’s safety. Future improvements are guided to include kinematic and dynamic models of the robot and its operator in the safety system to anticipate their behavior and execute more complex actions.

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