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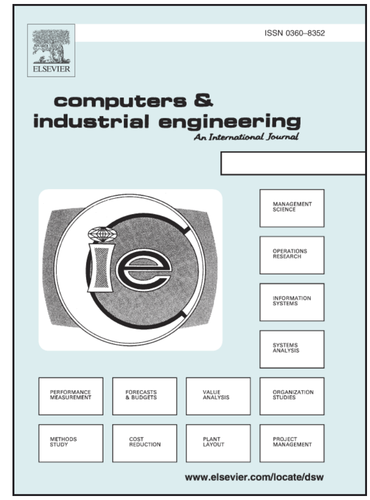

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Dynamic Risk Assessment and Active Response Strategy for Industrial Human-Robot Collaboration

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Dynamic Risk Assessment and Active Response Strategy for Industrial Human-Robot Collaboration

To enhance flexibility and sustainability, human-robot collaboration is becoming a major feature of next-generation robots. The safety assessment strategy is the first and crucial issue that needs to be considered due to the removal of the safety barrier. This paper determined the set of safety indicators and established an assessment model based on the latest safety-related ISO standards and manufacturing conditions. A dynamic modified SSM (speed and separation monitoring) method is presented for ensuring the safety of human-robot collaboration while maintaining productivity as high as possible. A prototype system including dynamic risk assessment and safe motion control is developed based on the virtual model of the robot and human skeleton point data from the vision sensor. The real-time risk status of the working robot can be known and the risk field around the robot which is visualized in an augmented reality environment so as to ensure safe human-robot collaboration. This system is experimentally validated on a human-robot collaboration cell using an industrial robot with six degrees of freedom.

Keywords: human-robot collaboration; dynamic risk assessment; risk visualization; active response strategy; augmented reality

1 Introduction

Industrial robots have evolved from the replacement of labour, the use of precise repetitive work and large loads to industrial collaborative robots with multi-modal sensing capabilities, proactive decision-making capabilities and friendly collaboration interfaces (Q. Liu et al., 2019). At the same time, the traditional workspace of industrial robots with safety fences has also been replaced by unstructured collaboration environment. Human-robot collaboration is going to be the essential feature of the next-generation robots, and industrial collaborative robots will become the foundation of robotic manufacturing (Fu, Wu, & Zhao, 2017).

In the context of the rapid development of industrial collaborative robot applications, safety becomes the primary problem and the necessary mandatory constraint in actual production (Lasota, Fong, & Shah, 2017). Collaborative tasks can only be carried out when the safety of personnel is ensured. In this regard, a series of industrial robot safety standards for collaborative scenarios have also been developed internationally. The Collaborative robot safety specification ISO/TS 15066 (ISO, 2016) describes the concepts, terminology and detailed requirements of human-robot collaboration and complements the traditional industrial robot safety standard ISO 10218 (ISO, 2011). Four collaboration modes are defined in ISO 10218: safety level monitoring stop, manual guidance, speed and separation monitoring (SSM), power and force limits. ISO/TS 15066 describes and supplements functional details, implementations, mode switching, and more.

The development and introduction of safe collaboration standards provide standardized terminology and level of collaboration for the safety of industrial human-robot collaboration (Bdiwi, Pfeifer, & Sterzing, 2017; Rosenstrauch & Krüger, 2017). However, such qualitative descriptions have little significance for the assessment of safety risks and the implementation of risk responses. Therefore, a quantitative description of the risk level is in need. Zanchettin et al. (Zanchettin, Ceriani, Rocco, Ding, & Matthias, 2016) proposed a safety metric strategy based on the speed of each joint and related control strategies, which is similar to the speed and distance monitoring defined in ISO 10218. Gustavsson et al. (Gustavsson, Syberfeldt, Brewster, & Wang, 2017) and Liu et al. (H. Liu & Wang, 2017) introduced a methodology to predict the human motion. Grahn et al. (Grahn, Johansen, & Eriksson, 2017) introduced a safety assessment model includes various safety issues and consideration of cost-effectiveness. Lacevic et al. (Lacevic & Rocco, 2010) defined a safety risk assessment method called a danger field and based on this, a series of studies were carried out. Real-time assessment of the safety risks of industrial collaborative robots and the quantification and visualization of risk is of great significance to the implementation of safety strategies and the implementation of collaborative tasks. Factors affecting the safety of industrial integrators are diverse, such as the material of the robot, the own weight, tool type, operating speed, response rate, etc. These safety-related factors are described in ISO 15066. But in a complex environment, the biggest impact on safety is undoubtedly the speed of industrial robots, which is the most important cause of injury to people. Therefore, a unified model for assessing the safety risk of industrial human-robot collaboration is of great necessity, considering both the impact of various safety indicators and the real-time application requirements. In addition, the visualization technology is suggested to present the dynamic risk assessment results in three dimensions, enabling the collaborators to control the dangerous areas of the shared workspace in real-time during the task execution, providing an immersive experience and increasing the sense of safety.

The remainder of this paper is structured as follows. In Section 2, the related work about industrial robot risk assessment methods and collision avoidance strategy is introduced and discussed. Section 3 proposes a risk assessment model for an industrial robot and a dynamic risk assessment method based on modified SSM is introduced. Section 4 describes the obstacle avoidance strategy of industrial collaborative robots and the obstacle avoidance path planning based on a dynamic risk index. Section 5 conducts the experimental verification and analysis of the proposed method. Finally, the conclusion about the proposed research is discussed in Section 6. Variable Definitions are listed in Table 1.

Table 1. Variable Definitions

Variable	Definition
δ_i	Assessment result of each indicator
δ	Assessment result of inherent indicators
w_i	Weight of each indicator
k, μ, λ	Correction, scaling and normalization factors

$\boldsymbol{p}_A$, $\boldsymbol{p}_B$	Joint position of point A and B
R_{AB}	Coordinate transformation matrix from B to A
α, β, θ	Rotation angles of axis x, y, and z
Δx, Δy, Δz	Coordinate value of the origin point of B in A
T_p	The threshold of the standard SSM
r_H, r_R	Reserved distance of the human and the robot system
$\boldsymbol{a}_{R,\max}$	Max acceleration of the robot
$\boldsymbol{v}_H$	Supposed max speed of the human
$\boldsymbol{v}_R$	Speed of the robot' TCP
t	System's detection and reaction time
$\boldsymbol{p}_t$, $\boldsymbol{p}_o$	Coordinate value of robot's TCP and human's hand
$\boldsymbol{v}_{tcp}$, $\boldsymbol{v}_{hand}$	The velocity of the robot's TCP and the human's hand
T_b	Breaking time
D_0	Reserved distance represents the uncertainty of sensors and errors in system reaction
$\boldsymbol{v}_s$, $\boldsymbol{v}_t$	Velocity at the two ends of one link
$\boldsymbol{p}_m$, $\boldsymbol{v}_m$	Any point on one link and its velocity
D_{t-h}, D_{l-h}	Risk threshold of "TCP to hand" and "link to hand"
$t_b(i)_{\max}$	Maximum of the braking time
s_{index}	The risk index at one position
v_d	Robot running speed to be controlled
s_{slow}, s_{danger}	Two risk index thresholds of the collaboration state regionalization
v_0, v_c	Running speed in maser task and slave task
$\boldsymbol{s}$, Δs	Gradient direction of the risk index and the step value of

	gradient descent

2 Related Work

2.1 Risk Assessment of Industrial Robots

Research on the risk assessment of industrial collaborative robot and human-robot collaboration has been a hot issue in international research and has gained a lot of research results after the release of the international collaborative robot safety standards. Pedrocchi et al. (Pedrocchi, Vicentini, Matteo, & Tosatti, 2013) studied the international safety specification and proposed a safe state machine method for workspace safety partitioning to ensure the collision avoidance strategy in the robot workspace. An on-line control strategy is implemented to complete motion re-plan using early prediction of human motion by (Mainprice & Berenson, 2013). The author of (Lee, Yu, Choi, & Han, 2011) proposes a quantitative safety assessment approach that uses workers and the work environment as assessment targets, assesses the risk factors that can lead to various accidents, and assesses operational risk by considering the time workers are exposed to high-risk work environments. Bdiwi et al. (Bdiwi et al., 2017) studied the parameters of industrial robots for safety risk assessment under various collaboration levels and proposed a workspace monitoring algorithm. Sadrfaridpour et al. (Sadrfaridpour & Wang, 2018) proposed a robotic combination control method that enables robots to take active actions based on human motion prediction in human-robot collaboration to ensure efficient execution of collaborative tasks. Geravand et al. (Geravand, Shahriari, De Luca, & Peer, 2016) designed an energy monitoring and control system based on the energy flow between different subsystems in human-robot collaboration and adjusted the selected safety measures to improve safety. Alonso-Mora et al. (Alonso-Mora, Beardsley, & Siegwart, 2018) proposed a collaborative strategy for partitioned computing safety speed and proposed a collision-free path calculation method based on the relative speed between the robot and the obstacle. Bogue (Bogue, 2017) conducted a study on safety collaboration standards and conducted a detailed analysis of safety standards and specifications. In the human-robot collaboration grading proposed in ISO 10218 and ISO/TS15066, the first three methods are to achieve safe human-robot collaboration through robot motion planning and safety strategies. And the realization of workspace sharing and meeting the production efficiency requirements of the collaborative manufacturing occasion is the third mode of cooperation, namely speed and separation monitoring (SSM).

2.2 Speed and Separation Monitoring and Safety-related Field

As the name implies, SSM is a method for real-time detection and control of the distance between the operator and the robot. It combines the robot and human position, speed and external contour to evaluate the current dangerous condition. Based on the concept proposed in the collaborative safety standard, Marvel (Marvel, 2013) conducted a Tri-Modal SSM with quantified the safety index and carried out a series of experimental verifications to prove that the proposed method is effective. Vicentini et al. (Vicentini, Giussani, & Tosatti, 2014) proposed a dynamic SSM that relies on a trajectory to establish a minimum safe area. However, the method is still a passive response of the robot triggered by the movement of the person and workspace risk has not been quantified.

The safety-related field is a quantitative method proposed by Polverini et al. (Polverini, Zanchettin, & Rocco, 2014) to evaluate the current pose and velocity of an industrial robot to the danger of objects in the workspace. This method can calculate the dangerous field value of any given point in the robot workspace. Based on this idea, Lacevic and Polverini et al. (Lacevic, Rocco, & Zanchettin, 2013; Polverini, Zanchettin, & Rocco, 2017) conducted further research to extend the object generated by the danger field and proposed a closed-loop calculation method for real-time dynamic demand. The human-robot collaboration safety measurement method proposed by Zanchettin et al. (Zanchettin et al., 2016) is the same as the dangerous field method. Based on the minimum separation distance standard, this method deduces a set of simple constraints on the robot speed, and also considers the constraints on production efficiency. However, the safety of industrial robot is not only related to the speed and separation of the robots, but also to the external equipment such as the tools used in the production environment and the parts being machined.

Shortcomings exist for both SSM and safety-related field. For example, under the same external condition, the hazard of the tool has an impact on the safety risks of industrial robots. Therefore, static factors such as workspace and environment need to be evaluated before the dynamic safety assessment of industrial robots. Marvel et al. (Marvel, Falco, & Marstio, 2015) proposed a risk assessment method for offline evaluation of the safety of collaborative robot systems before the start of the task from the perspective of manufacturing tasks. Mansfeld et al. (Mansfeld, Hamad, Becker, Marin, & Haddadin, 2018) proposed a safety map to evaluate the extent to which robots cause harm to the human body.

2.3 Sensor Technologies and Safety-related Strategy

The premise of dynamic safety risk assessment is the real-time perception (Shackleford, Cheok, Hong, Saidi, & Shneier, 2016). Vision-based perception technology has a wide range of applications in industrial integrator robot safety risk assessment. Safeea et al. (Safeea & Neto, 2019) used laser ranging technology to calculate the minimum distance between human and robot. Flacco et al. (Flacco, Kroeger, De Luca, & Khatib, 2015; Flacco, Kröger, De Luca, & Khatib, 2012) proposed a method for calculating the distance between the robot and human using depth visual perception and proposed a robot obstacle avoidance control method based on depth visual perception. Furthermore, the author of literature (Fabrizio & De Luca, 2017) proposes to perceive the distance between the person and the robot through a plurality of depth cameras and uses the distance to generate a repulsion vector for real-time motion control of the robot when performing the task. Lihui Wang (Wang, 2015) used the binocular depth vision system to perceive the human-robot integration production environment in real-time and proposed a safety risk assessment and dynamic control method based on perceived data. Ragaglia et al. (Ragaglia, Zanchettin, & Rocco, 2018) proposed a human-robot collaborative trajectory control algorithm based on multi-depth camera fusion perception.

Human-robot collaboration safety-related strategy can be divided into two major directions of collision detection and collision avoidance (Villani, Pini, Leali, & Secchi, 2018). The former mainly uses the torque sensor to accurately detect the occurrence of collision or contact, so as to respond after the collision occurs. The latter uses some means of sensing to monitor the workspace in real-time and respond before collisions to avoid collisions. In the workspace of the industrial robot, the perception of robots and human workers needs to ensure real-time performance. Choi et al. (Choi, Chang, Wang, Kim, & Elber, 2009) proposed a moving ellipsoid continuous collision detection algorithm, which can solve the Cartesian space bounding ball collision detection problem. Collision avoidance needs to follow the principle of "minimum safety distance" in collaborative tasks, that is, the robot must maintain a certain safe distance between people. Otherwise, the collision avoidance response may not be completed due to the limitation of braking time and response speed. Ragaglia et al. and Ricardez et al. (Garcia Ricardez, Yamaguchi, Takamatsu, & Ogasawara, 2015; Ragaglia, Zanchettin, Bascetta, & Rocco, 2016) utilized this principle. The former proposed a speed control strategy for asymmetric speed regulation, the latter to ensure minimum safety distance through joint torque admittance control. Pereira et al. (Pereira & Althoff, 2015) proposed a safety index method similar to the minimum safety distance. Taking the risk index as a constraint, an online iterative collision-free trajectory planning method was proposed in a finite time range. Dietrich et al. (Dietrich, Wimbock, Albu-Schaffer, & Hirzinger, 2012; Dietrich, Wimböck, Täubig, Albu-Schäffer, & Hirzinger, 2011) proposed a responsive collision avoidance algorithm based on virtual potential field, which is mainly used to avoid robot self-collision. Literature (Raiola, Cardenas, Tadele, De Vries, & Stramigioli, 2018) proposed an impedance control method to ensure the safety of personnel in the human-robot collaborative scenario, and achieve safe human-robot collaboration through energy and power constraints. Mohammed et al. (Mohammed, Schmidt, & Wang, 2017) proposed a multi-collaboration strategy for human-robot collaboration, using the real-time perception between operators and robot to dynamically switch collaboration modes. Lacevic et al. (Lacevic et al., 2013) gave a responsive dynamic obstacle avoidance method based on the proposed danger field, using a danger field-based control strategy to enable the robot to perform tasks while minimizing the risk. Ceriani et al. (Ceriani, Zanchettin, Rocco, Stolt, & Robertsson, 2015) proposed an interactive system design method that integrates safety assurance and manufacturing tasks into a robot controller. Zanchettin et al. (Zanchettin & Rocco, 2017) proposed a robot motion normalization and robust robot response control method, which combines traditional trajectory planning strategy and optimization control strategy, and designs a unified framework for motion planning and safety control.

In summary, new concepts and methods for safe human-robot collaboration emerge in an endless stream. The collision avoidance strategy based on danger field and risk index can meet the needs of unstructured human-robot integration environment. However, the real-time performance of collision avoidance planning still needs experimental verification. The advantages of collaboration between collaborators and industrial robots still need to be combined with task execution efficiency.

3 Dynamic Risk Assessment

In this paper, a collaborative scenario of one human with one industrial robot is constructed for the research of safety risk assessment. Concretely, the assessment consists of the assessment model and the assessment method.

3.1 ISO/TS 15066 Oriented Dynamic Risk Assessment Model

In the practical scenario, the assessment model should be designed according to the requirements of collaborative tasks. For instance, the safety risk index will be much higher than common tasks when a welding torch is installed on the industrial robot. Safety risk-related indicators vary when the task changes. More importantly, the assessing process should be of real-time and dynamic capabilities towards changeable human-robot collaboration.

3.1.1 Indicators and Principles

Risk-related indicators and principles are the basis of the risk assessment model and method. Based on ISO/TS 15066 standard and former researches (ISO, 2016), we first summarized the principles for the establishment of the risk assessment paradigm in the industrial human-robot collaborative cell.

(1) The scientificity principle: the establishment of the risk assessment model should have theoretical support.

(2) The independent principle: indicators should be independent of each other and not repeated.

(3) The completeness principle: all significant indicators affecting the risk factors in the human-robot collaborative cell should be contained in the assessment model.

(4) The conciseness principle: the developed risk assessment model should be as simple as possible to facilitate the implementation of risk assessment methods.

(5) The classification principle: the assessment indicators should be classified to meet the needs of dynamic real-time risk assessment.

In ISO/TS 15066, indicators for the risk assessment are divided into three aspects, that are robot-related hazards, hazards related to the robot system, and application-related hazards. This kind of classification is defined according to the source of every risk indicator which is more selectable in the predesign phase of the robot system and applications. However, in the execution phase of a human-robot collaborative manufacturing task, all those indicators need to be assessed in real-time. This is because the dynamics of moving robots and human works result in changes of velocity and acceleration which affect the indicators dramatically. Towards this problem, risk-related indicators are further classified into inherent and dynamic ones.

An updated classification for the risk assessment in human-robot collaboration is shown in Table 2.

Table 2. Indicators for Risk Assessment (Cordero, Carbone, Ceccarelli, Echávarri, & Muñoz, 2014; ISO, 2016)

Indicator set	Indicators	Property
Robot-related hazards	Robot characteristics	Dynamic
	Location of installation	Inherent
	Quasi-static contact conditions	Inherent
Hazards related to the robot system	End-effector and workpiece hazards	Inherent
	Manually controlled robot guiding device	Inherent
	Influence and effects of surroundings	Inherent
Application-related hazards	Operator's motion and location	Dynamic
	Process-specific hazards	Inherent
	Deficiency in ergonomic design	Inherent

For risks-related indicators with inherent property, such as the end-effector and workpiece hazards, offline assessment based on experts' knowledge and experience is adopted. Concretely, every indicator has a certain weight, which is taken as the scaling factor of the dynamic real-time assessment after normalization. In collaborative tasks, dynamic indicators that have a direct impact on safety, such as robot speed, are processed by the dynamic risk assessment method. The risk assessment matrix in Table 3 (Marvel et al., 2015) belongs to the Z10 standard issued by ANSI is adopted as the assessment standard. The risk matrix is based on the combination of the expected severity of the damage in the worst case and the possibility of the damage in the assessment of the risk priority.

Table 3. Risk Matrix for Risk Assessment of Inherent Indicators (Marvel et al., 2015)

		Potential severity			
		catastrophic	Severe	Moderate	minor
Likelihood of occurrence	Frequent (likely to occur repeatedly)	High(4)	High(4)	Serious(3)	Medium(2)
	Probable (likely to occur multiple)	High(4)	High(4)	Serious(3)	Medium(2)
	Occasional (likely to occur sometime)	High(4)	Serious(3)	Medium(2)	Low(1)
	Remote (possible, but not likely to occur)	Serious(3)	Medium(2)	Medium(2)	Low(1)
	Improbable (very unlikely)	Medium(2)	Low(1)	Low(1)	Low(1)

Using the principle in the risk matrix, each qualitative indicator can be quantified with specific values. It lays a foundation for the subsequent normalization of indicators and the implementation of assessment methods.

3.1.2 Paradigm and Formulation

Due to the classification of inherent indicators and dynamic indicators, a hierarchical risk assessment model is adopted. Before the launch of one collaborative task, inherent indicators will be assessed offline. On the other hand, during the processing of one collaborative task, dynamic indicators should be assessed driven by real-time data from the collaborative workspace.

For the assessment of inherent indicators, the addition operation and multiplication operation are utilized to transform different indicators into one integrated value (Du, Cao, Liu, Yan, & Li, 2011). The addition operation is a kind of linear weighting mathematical model. It uses $\delta = \sum_{i=1}^{n} w_i \delta_i$ to synthesize indicators. Concretely, $0 \le w_i \le 1 (i = 1, 2, \ldots, n), \sum_{i=1}^{n} w_i = 1$. Multiplication operation is a kind of non-linear weighting mathematical model. It uses $\delta = \sum_{i=1}^{n} \delta_i^{w_i}$ to synthesize indicators.

Through the definition of these two mathematical models, it is not difficult to see that each mathematical model has advantages and disadvantages. For the linear addition operation, indicators of large value may cover other indicators with a lower value. In the multiplication model, as it is a multiplication synthesis, as long as there are indicators with small values, the overall result must be very close to zero, which is not conducive to the differentiation between the values of various assessment schemes. In the risk assessment scenario of this paper, since each indicator is independent of each other and each has a certain weight, the linear weighting model is selected. The weight of each indicator is determined by the decision method of quantifying the qualitative analysis problem subjectively and manually, and the weight is determined according to the influence of each indicator on the risk.

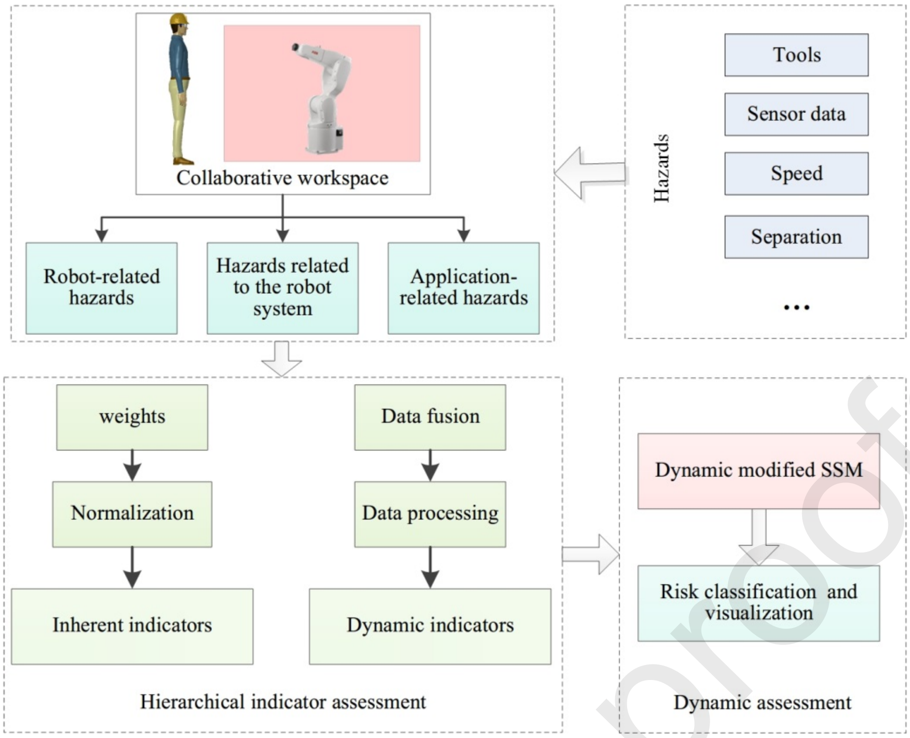

Figure 1. The dynamic risk assessment paradigm.

The risk assessment paradigm proposed is shown in Figure 1. Combining the assessment result of inherent indicators and the dynamic data from the perception system as the input for the modified SSM (speed and separation monitoring), the result of dynamic assessment can be obtained. Moreover, dynamic assessment result is further visualized in the collaborative workspace which lays a foundation for collaborative tasks. Concretely, the assessment can be formulated by (1).

$$\delta = k\sum_{i=1}^{n}\delta_i w_i \tag{1}$$

3.2 Dynamic Safety Risk Assessment Method

On the foundation of the risk assessment model, a dynamic risk assessment is proposed based on modified SSM. Risk-related indicators are assessed with the principles in the dynamic risk assessment model discussed above. Results of assessment are shown by visualization as well as the risk during the collaborative task is marked.

3.2.1 Data Fusion and Processing

To assess the risk caused by dynamic indicators, the running state of the industrial robot and the real-time state of human are requisite. For the later one, perception methods that are mostly adopted are:

- Using depth vision system such as RGBD cameras to get the motion and position of moving human.
- Using wearable motion capturing sensors.

Among all visual perception solutions, depth vision system has advantages in efficiency, accuracy and price (Schmidt & Wang, 2014). In this paper, a depth vision sensing system based on dual RGBD cameras is proposed. The deployment is shown in Figure 2.

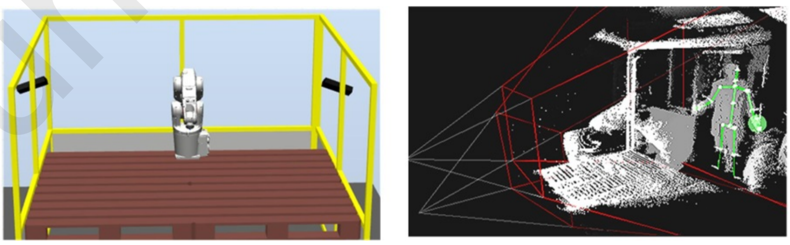

Figure 2. The deployment of the depth vision system.

In figure 2, Two Microsoft Kinect V2 depth cameras are installed at the rear of the collaborative workspace. After camera calibration, the coordinates of the depth visual space can be fused with the robot coordinate system, so that the position and the relative distance between the operator and the robot can be monitored in real-time. The specific fusion method is as follows.

Suppose the coordinate system of one of the Kinect cameras is A and the other is B. the essence of vision data fusion is unifying the coordinate systems of each RGBD sensor into one. A simple way is to transform data in B to A. for instance, suppose a joint in A is $\boldsymbol{p}_A\left(x_A, y_A, z_A\right)$ and the same point in B is $\boldsymbol{p}_B\left(x_B, y_B, z_B\right)$. So the relationship between these two coordinate systems can be formulated by (2) and (3).

$$\mu \times R_{AB} \times \begin{bmatrix} x_B \\ y_B \\ z_B \end{bmatrix} = \begin{bmatrix} x_A - \Delta x \\ y_A - \Delta y \\ z_A - \Delta z \end{bmatrix} \tag{2}$$

$$R_{AB} = \begin{bmatrix} c\beta c\theta & c\beta s\theta & -s\beta \\ -c\alpha s\theta + s\alpha s\beta c\theta & c\alpha c\theta + s\alpha s\beta s\theta & s\alpha c\beta \\ s\alpha s\theta + c\alpha s\beta c\theta & -s\alpha c\beta + c\alpha s\beta s\theta & c\alpha c\beta \end{bmatrix} \tag{3}$$

In (2) and (3), $s\theta$ and $c\theta$ are respectively $\sin\theta$ and $\cos\theta$. All these hyper-parameters can be measured before deployment. Logistic graph of data fusion is shown in Figure 3.

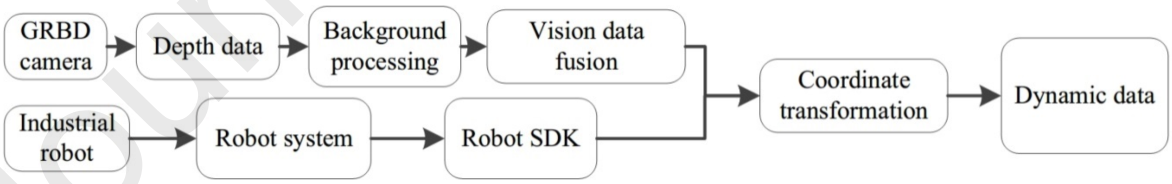

Figure 3. The logistic graph of data fusion.

The RGBD camera obtains the depth image of the environment. Firstly, the background of the workspace is filtered and the skeleton of human is extracted by the Microsoft Kinect SDK. After vision data fusion, the kinematic parameters of moving industrial robot will be transmitted to the coordinate transformation module. Finally, dynamic data for real-time risk assessment is ready.

3.2.2 Modified SSM based Dynamic Safety Risk Assessment

In this section, we modified the standard SSM aiming the calculation of safety separation as well as the integration of risk assessment model proposed above. On the basis of ensuring dynamic real-time performance, it is more closely combined with the actual collaborative environment. Specific improvement and method principle are as follows.

According to the definition of ISO/TS 15066, when the robot and the operator move in the collaborative workspace, the separation between human and robot should always beyond the safety threshold to avoid a collision. The robot system should react to keep the safe separation. Once the distance between human and robot approaches the safety threshold, the robot system should respond. Otherwise, when the distance is greater than the safety threshold, the robot should resume its work. And the value of the safety threshold will change dynamically with the change of robot motion state.

Marvel et al. (Marvel, 2013) put up with a standard SSM:

$$T_p = \boldsymbol{v}_H \left(\frac{\boldsymbol{v}_R}{\boldsymbol{a}_{R,\max}} + t \right) + \boldsymbol{v}_R t + \frac{\boldsymbol{v}_R^{\ 2}}{2\boldsymbol{a}_{R,\max}} + \left(r_R + r_H \right) \tag{4}$$

The definition of (4) is totally safety oriented. Human's safety can be guaranteed if the separation between human and robot is over the threshold. However, the maximization of safety may lead to negative effects on production efficiency. For instance, if the robot always halts when reaches the threshold, interrupts will frequently occur during collaboration. Indeed, the velocity of both human and robot maybe not always at a maximized value. Besides, the standard SSM did not take influence caused by the collaborative environment and tasks into consideration. For example, even in similar condition, risk will be clearly higher in cutting tasks than carrying ones. When cutting, the cutter on a robot will boost the risk sharply to human compared with carrying tasks. The heavy of loads when carrying also means different levels of risk to humans. Therefore, in this paper, we modified the standard SSM on the basis of the risk assessment model.

Toward this modified SSM, we firstly represented the relationship in human-robot collaboration to the velocity vector relationship between two particles in Cartesian space (Figure 4).

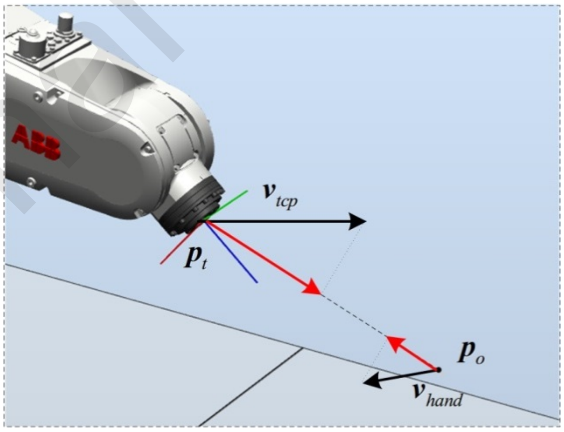

Figure 4. The velocity vector relationship.

The representations and definition are as follows. At any time step t_0, the coordinate value of the tool central point (TCP) of a robot in the global coordinate system is $\boldsymbol{p}_t(x_t, y_t, z_t)$, the velocity is $\boldsymbol{v}_{tcp}$ and the time for braking is T_b. If the coordinate value of human's hand is $\boldsymbol{p}_o\left(x_o, y_o, z_o\right)$ and the corresponding velocity is $\boldsymbol{v}_{hand}$, the risk threshold can be defined with (5), which is also the minimized separation between human and robot.

$$D_{t-h} = \delta \int_{t_0}^{t_0+t_b} \left(\boldsymbol{v}_{hand} + \boldsymbol{v}_{tcp}\right) \frac{\boldsymbol{p}_o - \boldsymbol{p}_{\mathrm{t}}}{\left|\boldsymbol{p}_o - \boldsymbol{p}_{\mathrm{t}}\right|} dt + D_0 \tag{5}$$

To keep safe, (6) should be guaranteed by movement in the next time step.

$$\left|\boldsymbol{p}_o - \boldsymbol{p}_{\mathrm{t}}\right| > D_{t-h} \tag{6}$$

The equation (5) defines a hazard zone in the collaborative workspace. When nobody is in this hazard zone, the robot can run with maximum power. It is obvious that D_{t-h} changes over the speed of the robot. While in the standard SSM, the deceleration is regarded as a uniformly one.

In the collaborative workspace, not only the movement of TCP should be considered, but also all other joints and links. Based on the risk threshold of TCP mentioned above, an accumulated risk threshold can be conducted.

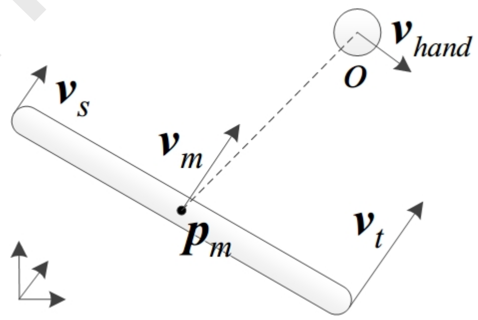

Figure 5. The robot joints and moving obstacles in the global coordinate system.

In Figure 5, the velocity on any point $\boldsymbol{p}_m$ can be formulated by (7).

$$\boldsymbol{v}_m = \boldsymbol{v}_s + m\left(\boldsymbol{v}_t - \boldsymbol{v}_s\right), m \in [0,1] \tag{7}$$

Combined with the definition of the TCP risk threshold in (5), the accumulated risk threshold can be conducted by (8).

$$D_{l-h}=\delta\int_{t_0}^{t_0+t_b(i)_{\max}}\left(\boldsymbol{v}_{hand}+\boldsymbol{v}_m(i)\right)\frac{\boldsymbol{p}_o-\boldsymbol{p}_{\mathrm{t}}}{\left|\boldsymbol{p}_o-\boldsymbol{p}_{\mathrm{t}}\right|}dt+D_0,\forall m\in[0,1] \tag{8}$$

From (6), the same determination can be promoted to multiply links on one robot. For an industrial with n links, the minimum separation should satisfy (9).

$$\min\left|\boldsymbol{p}_o-\boldsymbol{p}_m\right|\geq D_{l-h},\forall i\in\mathbb{N}>0 \tag{9}$$

Up to now, the risk assessment can be conducted and numerically analysed. Due to the volume of the industrial robot cannot be ignored in practice, it should also be contained. Other conditions being the same, the range of risk threshold of industrial robots at different speeds is shown in Figure 6.

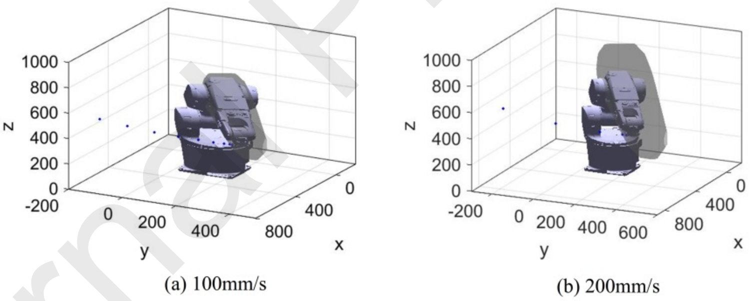

Figure 6. The hazard zones of industrial robots at different speeds.

In the same way, the definition of risk threshold can be extended by the proposed dynamic SSM to calculate the risk index of the entire workspace. According to the definitions above, the risk index at the position o in the collaborative workspace is (10).

$$s_{index}=\lambda\left[\mathrm{T_b}+\frac{\min\left|\boldsymbol{p}_o-\boldsymbol{p}_m\right|-D_{l-h}(o)}{\left(\boldsymbol{v}_{hand}+\boldsymbol{v}_m\right)\cdot\left(\boldsymbol{p}_o-\boldsymbol{p}_{\mathrm{t}}\right)}\left|\boldsymbol{p}_o-\boldsymbol{p}_{\mathrm{t}}\right|\right],\forall\mathrm{i}\in\mathbb{N}>0 \tag{10}$$

The minimum value of the risk index is 0. With the risk index of each part of the collaboration workspace and the risk threshold corresponding to a specific risk index, the safety risk of the robot can be dynamically quantified and evaluated in real-time. It also provides instructions for people to make task decisions in collaborative tasks and incentives for robot safety response strategies.

4 Active Response Strategy in Human-Robot Collaboration

Based on the dynamic assessment of the risk of industrial robots, the corresponding response strategies can be selected according to the risk assessment results to avoid collisions. This chapter proposes an active response strategy based on dynamic safety risk assessment, which enables industrial robots to make decisions and ensure the safety of human.

4.1 Foundation

4.1.1 Bounding Box for Human Body

The dual RGBD cameras system designed in this paper can realize the perception of the human body. Because the human body structure is complex and can not be regarded as particle processing in close collaboration tasks, the human collision bounding box is utilized. The bounding box technology is widely used in rigid body collision detection. Commonly used bounding box types include bounding sphere, AABB bounding box, OBB bounding box and k-DOPs bounding box.

Combined with the human perception system and application environment designed in this paper, the human bounding box in the collaborative model adopts the hybrid bounding box construction method of the bounding sphere and the OBB bounding box, and the human collision bounding box constructed is shown in Figure 7.

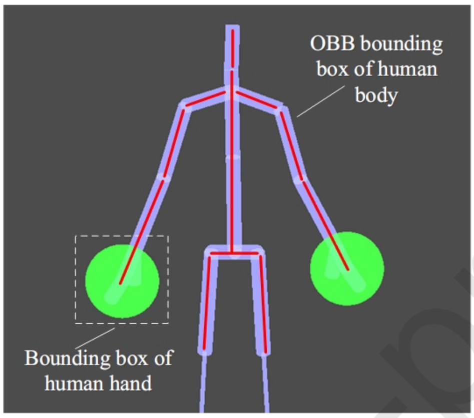

Figure 7. The human collision bounding box construction.

Figure 7 shows the human body bounding box constructed with a hybrid bounding box. The specific processing method is as follows: the hand of the acquired human skeleton data is processed by the bounding sphere to increase the safety factor of the person. The other part is processed by the OBB bounding box to reduce the complexity of the processing. With the human bounding box model, when risk analysis is performed on the human body, only the risk of the bounding box is analyzed, and the complexity caused by the different data structures of various parts of the human body is avoided, which is beneficial to the dynamic real-time of risk assessment, and provides a convenient source of human data for collaborative model research.

4.1.2 *Collaborative Workspace Regionalization*

In the manufacturing process, the interaction state between the human and the robot may not occur frequently, and continuous adjustment of the running speed of the robot may also affect the execution efficiency of the task. Aiming at the human-robot collaboration in this context, this paper proposes a collaborative strategy of workspace regionalization and a multi-task control method for the robot. The collaboration regionalization mechanism in human-robot collaboration is shown in Figure 8.

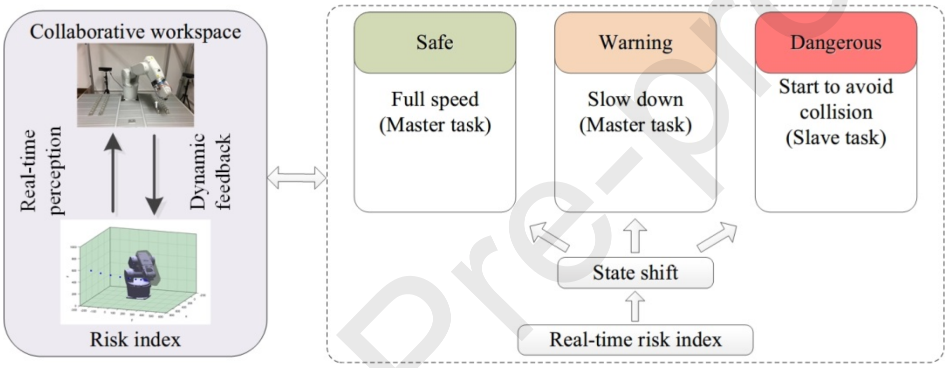

Figure 8. Collaboration regionalization mechanism

In the execution of the collaborative task, the industrial robot task space is first decomposed. The specific manufacture tasks, the completion of the manufacturing target-related motion planning and control are defined as the master tasks. Relevant motion planning and control to ensure human safety, risk avoidance, and reduction of risk assessment index values are defined as slave tasks. Then the risk assessment system completes the real-time perception and dynamic risk assessment of the shared workspace, and dynamically feedbacks the operation mode of the industrial robot based on the evaluation results. The specific rules are:

(1) **No danger**: The human is in a safe area or no human is detected, that is, the dynamic risk index is less than the deceleration threshold. In this state, the industrial tri-co robot performs the master task at the maximum speed.

(2) **Warning**: The human approaches the dangerous area, that is, the dynamic risk index is greater than the deceleration threshold (a threshold defined to slow the robot down) but less than the risk threshold. In this state, the industrial robot will decelerate to perform the master task.

(3) **In danger**: The human is in a dangerous area, that is, when the dynamic risk index is greater than the risk threshold, it is a dangerous state. In this state, the industrial robot will enter the slave task state of avoiding risk.

The master-slave task is switched based on the dynamic risk assessment, and the quantified assessed result can determine the change of the task state according to whether the threshold is reached. When the risk index passes the collision avoidance response below the risk threshold, the robot can be restored to the master task to ensure the task execution efficiency. The risk threshold adopts the same as in the dynamic risk assessment method, and the deceleration threshold is where the distance between human and robot is close that collision may occur in the shared workspace, which needs to be determined according to the specific task to keep task efficiency. Based on the knowledge and experience of experts and our experiment scenario, the collaboration regionalization threshold can be determined as shown in Table 4.

Table 4. Risk Index Threshold

	Risk Index	Robot state
No danger	<0.4	master task (normal)
Warning	0.4~0.62	master task (deceleration)
In danger	>0.62	slave task (collision avoidance)

In the safety state (no danger), the industrial robot runs at the normal task execution speed. In the warning state, the robot speed needs to be decelerated, and the speed is reduced until the dynamic risk index is lower than the deceleration threshold. In the dangerous state, the industrial robot switches into the task of avoiding collisions to reduce the risk index. When humans are in the early warning state, the industrial robot still maintains the original task execution state to ensure work efficiency. In this state, the robot running speed will change according to the change of the risk index. The following is a study on the robot speed control under the condition of early warning.

The control of the robot running speed v_d according to the risk index can be expressed as:

$$v_d = \begin{cases} v_0 & , s_d < s_{slow} \\ v_0 \cdot f\left(s_{danger} - s_{slow}\right) & , s_{slow} < s_d < s_{danger} \\ v_c & , s_d > s_{danger} \end{cases} \tag{11}$$

Where $f\left(s_{danger} - s_{slow}\right)$ represents the relationship between the risk index and the speed of the robot in equations (8) to (10).

4.2 Active Response Strategy Minimizing the Risk Index

According to the definition of the safe collaboration model and the collaborative workspace regionalization, when the dynamic risk index is greater than the risk threshold, the industrial robot needs to enter the collision avoidance mode to avoid injury to human collaborator. In the collision avoidance mode, the robot will adopt the gradient risk index minimization method to reduce the risk index. The collision avoidance is made by the robot according to the risk index, which is more efficient and intelligent than the emergency stop triggered by human motion. Lacevic et al. (Lacevic et al., 2013) proposed a virtual thrust collision avoidance method based on danger field. This paper improves it and proposes a gradient risk index minimization method based on dynamic risk assessment method to complete collision avoidance. The gradient risk index minimization method is studied below. To avoid the robot colliding with the position, robots need to evade the direction in which the risk index decreases the fastest as shown in Figure 9.

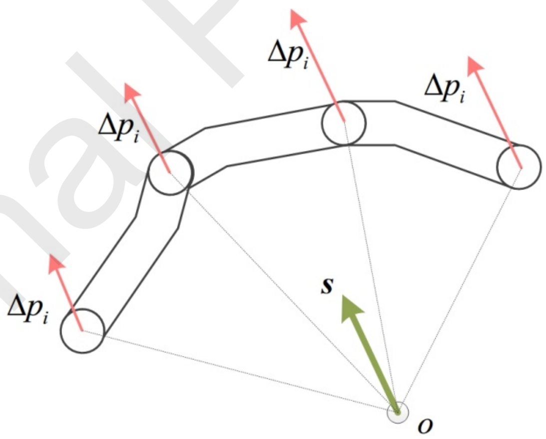

Figure 9. The gradient risk index minimization

In Figure 9, the point o is the position of the obstacle that needs to be avoided. Then the displacement that the mechanical arm joint needs to evade in Figure 9 can be expressed as:

$$\Delta p_i = D_{l-h} - f\left(\Delta s\right)^{-1} \tag{12}$$

Wherein, $f(\Delta S)^{-1}$ is the function of the risk index and the distance which is conducted by the inverse function of expression (10). Due to the structure of the industrial robot, each joint has an intrinsic correlation and different speeds. The avoiding direction of each joint is the gradient of the risk index but the displacement size is different, which is related to the specific joint, and the joint displacement is mapped to the joint angle. The change is easy for the robot to control and the shutdown limit detection can be conveniently performed.

In the collision avoidance state, the industrial robot no longer moves along the mission path and avoids the collision according to the avoidance displacement generated by the gradient risk index minimization method. When the dynamic risk index is less than the risk threshold, the robot completes the collision avoidance, and the robot will decide to run the task according to the state of the human. If the human remains stationary, he will be regarded as a static obstacle, and the minimum risk index path planning task is performed in the presence of the obstacle. A collision-free path with the smallest safety index is planned between the current position and the original target point. When the human makes an interactive gesture, the robot enters the human-robot interaction state, and various interactive tasks can be completed through real-time perception and gesture recognition according to the task requirements. If the human is free to move, the next move is determined according to the dynamic risk index. The flow chart of the safe collaboration strategy for the industrial collaborative robot is shown in Figure 10.

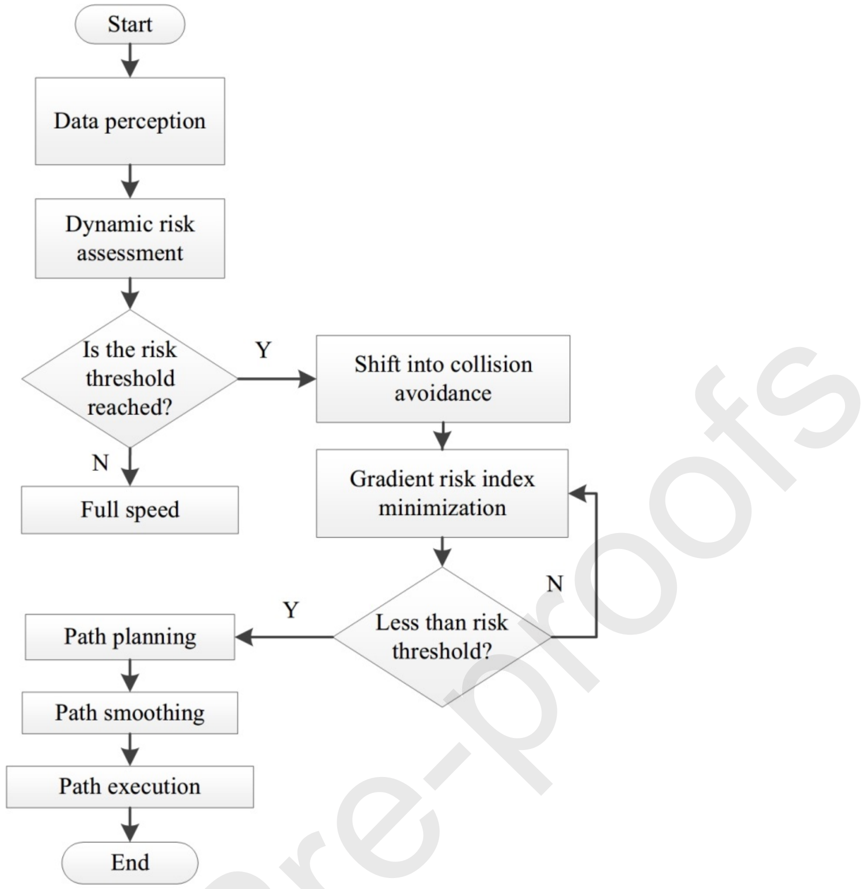

Figure 10. The flow chart of the safe collaboration strategy for the industrial collaborative robot.

5 Validation and Discussion

5.1 Results of Dynamic Risk Assessment

In this section, the proposed dynamic risk assessment is validated with simulation. The collaborative workspace is designed as Figure 11. The runtime data and vision data is obtained from the computer linked to the robot controller. Human in the collaborative workspace is arranged in the left area in the shared space.

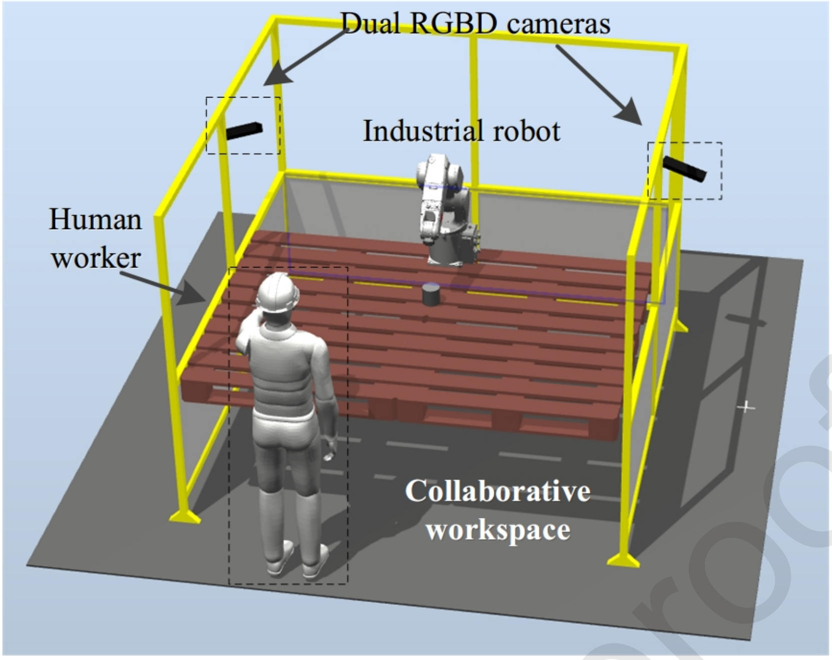

Figure 11. The human-robot collaborative workspace.

According to the collaborative workspace in Figure 11 and related tasks, inherent indicators towards the risk assessment are listed below.

- Risk of robot-related hazards: X_1 (robot characteristics), X_2 (location of installation), X_3 (quasi-static contact conditions).
- Risk of hazards related to the robot system: X_4 (end-effector and workpiece hazards), X_5 (risk of tools installation), X_6 (manually controlled robot guiding device), X_7 (other related hazards).
- Risk of application-related hazards: X_8 (process-specific hazards), X_9 (deficiency in ergonomic design).

Utilizing the assessment model proposed in this paper, the offline assessment of inherent indicator was conducted with step 1~2.

Step 1: using the risk matrix in Table 3, the risk of each inherent indicator in the collaboration workspace was quantitatively evaluated.

Step 2: the weights of indicators of each inherent risk were determined, and the quantitative assessment results and indicators weights obtained by the subjective weight determination method were shown in Table 5.

Step 3: using (4), the assessment indicators in Table 5 are processed according to the normalized weight. The result $\delta = 1.25$ is obtained for the inherent assessment.

Step 4: deploying inherent assessment result in dynamic assessment, dynamic assessment for human-robot collaboration safety is given in a simulation environment.

Table 5. The assessment of inherent indicators.

	Robot-related hazards			Hazards related to the robot system				Application-related hazards	
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
Assessment	M(2)	L(1)	L(1)	M(2)	L(1)	L(1)	L(1)	L(1)	L(1)
Weight	0.05	0.05	0.05	0.2	0.1	0.1	0.17	0.16	0.12

The proposed dynamic assessment method is simulated and analysed. The simulation data source is the robot data recorded in the simulated manufacturing task experiment and the data of the visual perception system. The tool for simulation and data processing is Matlab. The specific process of the task is as follows: (1) the robot moves the workpiece back and forth between the raw material storage area and the processing area; (2) the robot carries out preliminary processing of the workpiece; (3)

the robot carries the initially processed workpiece to the working area of the worker; (4) the robot carries the workpiece processed by the worker to the finished product area.

With the dynamic risk assessment, the industrial robot will adjust its running speed according to the change of risk index which is shown in Figure 12. To guarantee the safety of the human worker, when the separation between human and robot is closing to the risk threshold, the industrial robot will slow down. When the separation is leaving away the risk threshold, the robot will recover the speed. Figure 13 shows the dynamic risk index after normalization. From (10), the risk index is calculated as 0.623. Combining Figure 12 and Figure 13 we can see that when the risk index is near the risk threshold, the robot will try to decrease the risk index to keep the human worker safe.

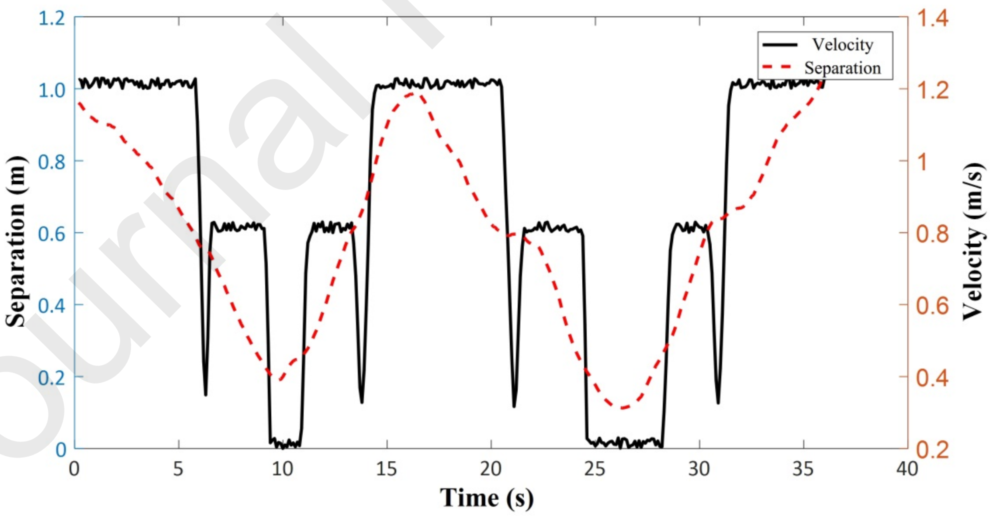

Figure 12. The measured velocity of the robot's TCP and the relative separation distance of the TCP.

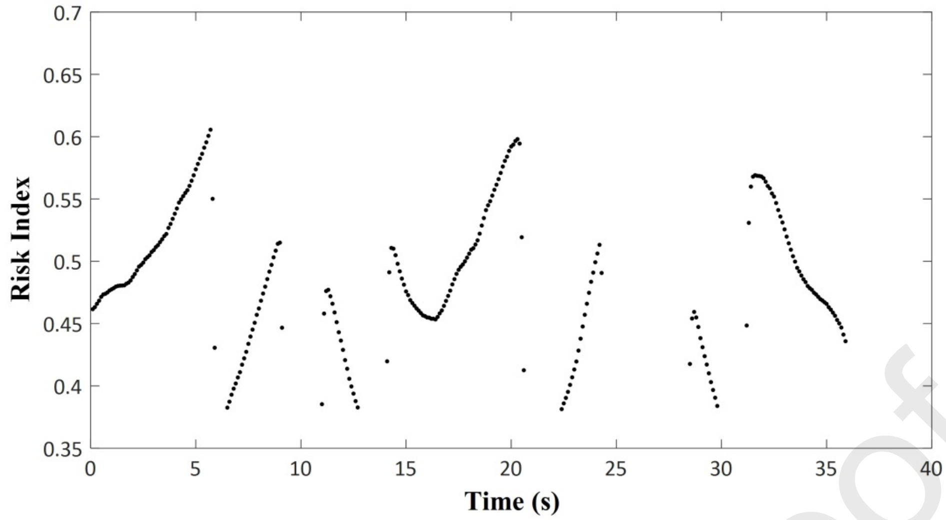

Figure 13. The dynamic risk index of the robot implementation over time.

By using (10) to assess the risk index inside a collaborative workspace, a dynamic risk field can be generated in Figure 14. Areas in the workspace where the risk index is below the risk threshold are considered safe and where the human worker can perform tasks. On the other hand, areas with a risk index greater than the risk threshold are at risk of collision and should be avoided to human workers.

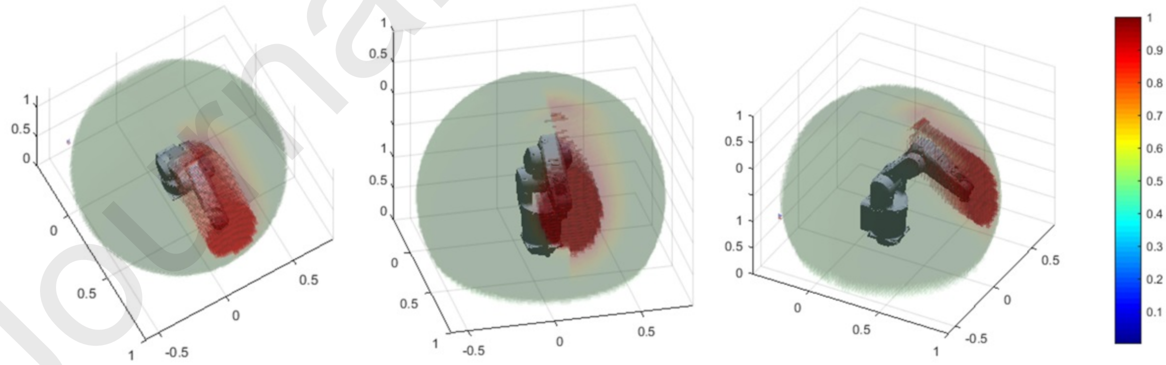

Figure 14. The dynamic risk index of a collaborative workspace with risk assessment.

5.2 Results of Active Response Strategy

To validate the efficiency and availability of the active response strategy, a simulation was conducted. ABB Robotstudio and Matlab were utilized in this phase.

An industrial model was first imported into the simulation software as well as a pre-defined task path (the yellow one in Figure 15). Risk threshold and index were calculated and analyzed in Matlab.

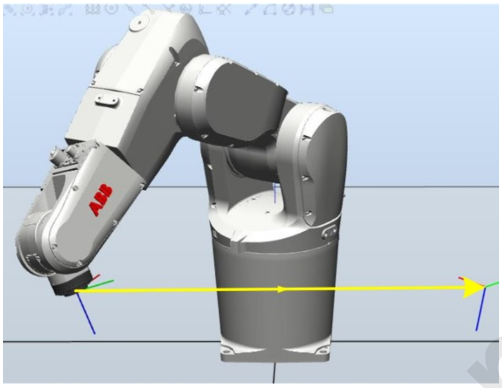

Figure 15. The simulation and pre-defined path without obstacles.

Finishing the pre-defined path is the main task for the industrial robot. Without obstacle in the workspace, the robot should run alongside the pre-defined path. In this experiment, the regular speed of the robot is v_{normal} and the start point of the pre-defined path is $q_s = [527.15, -300, 300]$. Three experiments were conducted as follows.

Experiment 1:

In the workspace without obstacles, the industrial robot runs in a uniform linear motion at the speed of $v_{normal} = 200mm/s$.

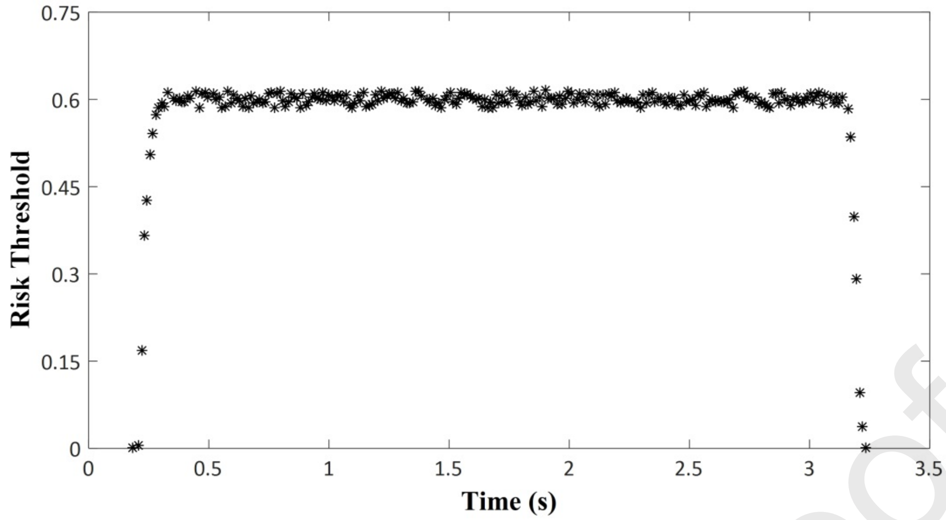

Figure 16. The risk threshold in a uniform linear motion.

This experiment shows that the risk threshold is tightly associated with the real-time speed of the industrial robot.

Experiment 2:

A globular obstacle was added into the scenario in experiment 1 with the radius of 150mm. This obstacle was located at $q_o = [500, 0, 400]$ and the modified scenario is shown in Figure 17.

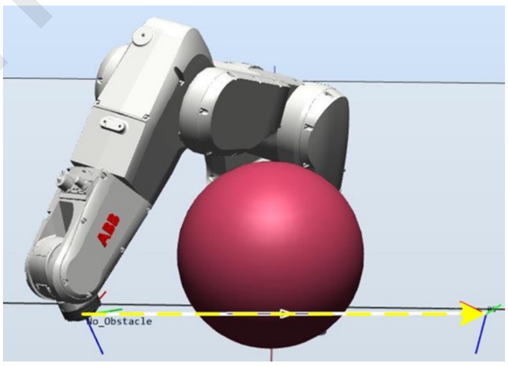

Figure 17. The simulation scenario with obstacles.

In Figure 17, if there are no collision avoidance strategies, a collision will be inevitable. This experiment firstly invalidated the calculation of risk index in the collision which is shown in Figure 18.

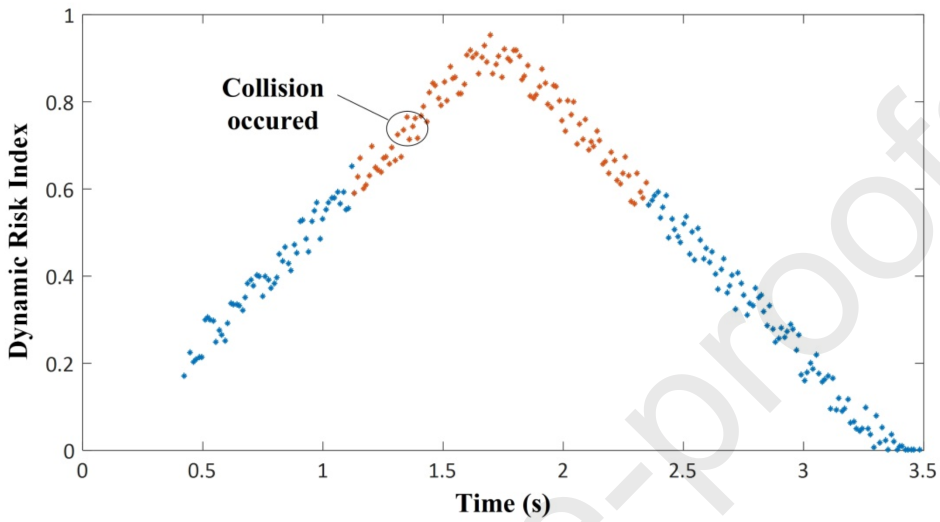

Figure 18. The risk index in the collision.

In Figure 18 we can see that the risk index exceeded the risk threshold (nearly 0.6 in Figure 16) at the time stamp of 1.1s. The highlighted dots in Figure 18 are corresponding to the collision phase.

Then, the active response strategy was deployed for validation. When the risk index reached the risk threshold, the industrial robot would shift to collision avoidance mode. Results are shown in Figure 19.

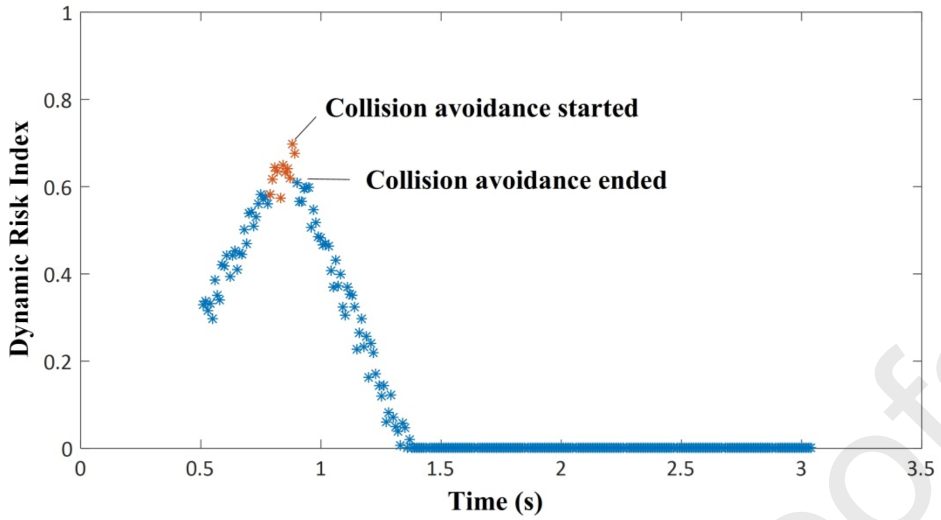

Figure 19. The risk index during collision avoidance.

From the illustration we can summarize that when the risk index reached the risk threshold, the robot could avoid the collision. Because there was no task arranged to the robot after collision avoidance, the robot runs decreasing the risk index after the collision was eliminated. Compared with Figure 18, results show that our proposed methods can effectively reduce the risk index and escape away from the collision.

Experiment 3:

When the obstacle still exists in the workspace, the robot needs to re-plan the path after collision avoidance. The path re-plan is also based on the principle of minimizing the risk index. In this experiment, discrete points were firstly selected, then interpolation was utilized for path smoothing (Figure 20).

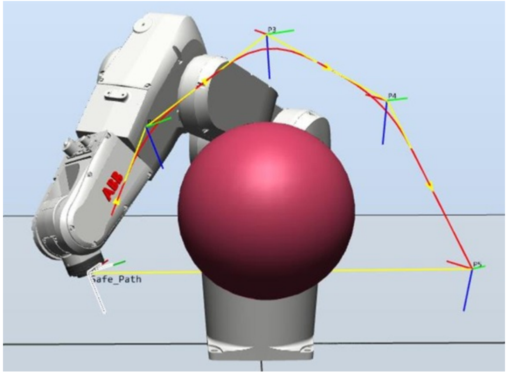

Figure 20. The smooth path during collision avoidance.

During the path smoothing in collision avoidance, we can see the risk index in Figure 21 that there are only a few dots above the risk threshold. In the simulation, the collision was not detected by the software. The time cost is higher than it in a scenario without obstacle but the safety of both human and robot can be guaranteed in the collaborative workspace.

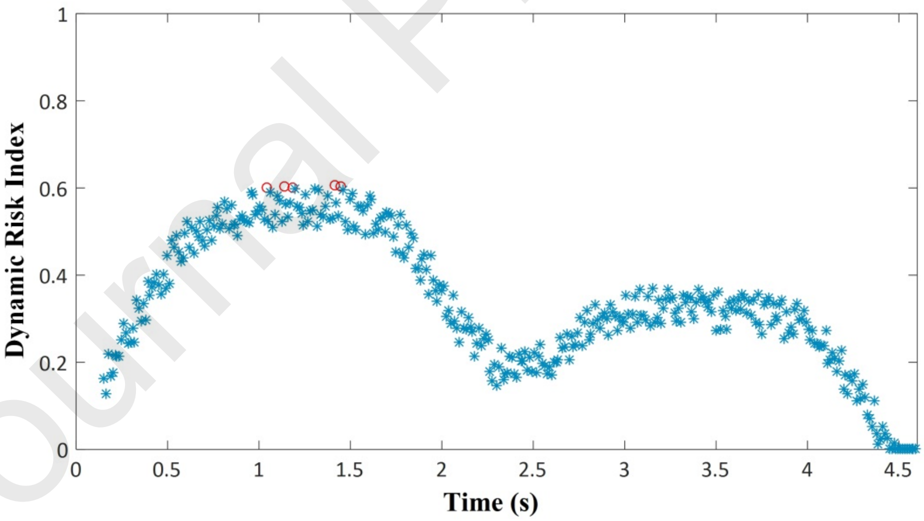

Figure 21. The risk index in collision avoidance with a smooth path.

5.3 Comparison and Discussion

To discuss the advantages of the proposed modified SSM, a comparison with the conventional SSM in ISO/TS 15066 and Tri-Modal SSM in (Marvel, 2013) is conducted. Figure 22 and Figure 23 are respectively the results from the conventional SSM in ISO/TS 15066 and the Tri-Modal SSM.

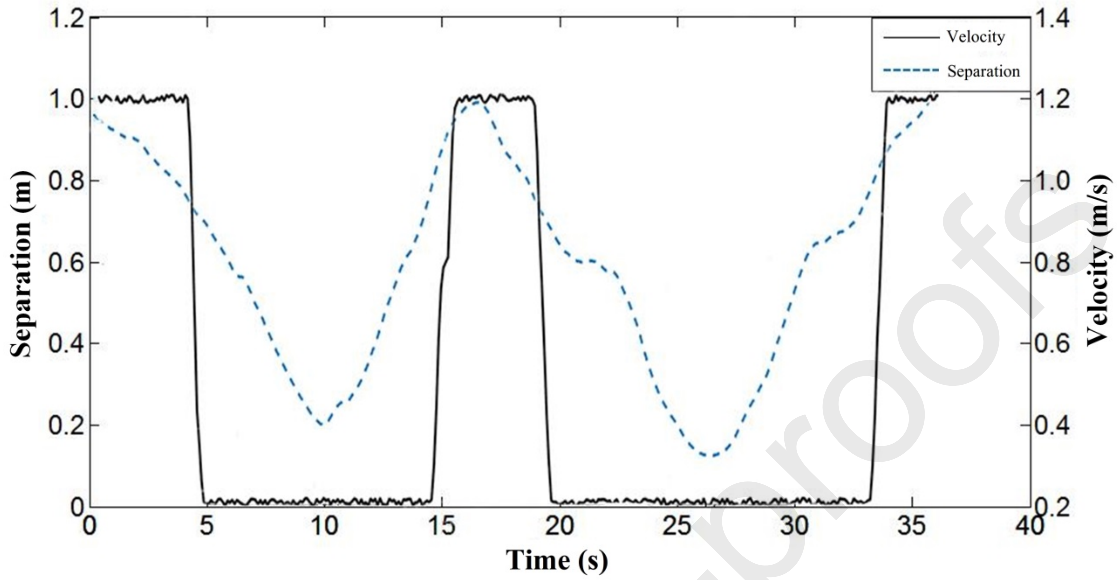

Figure 22. The result from the conventional SSM.

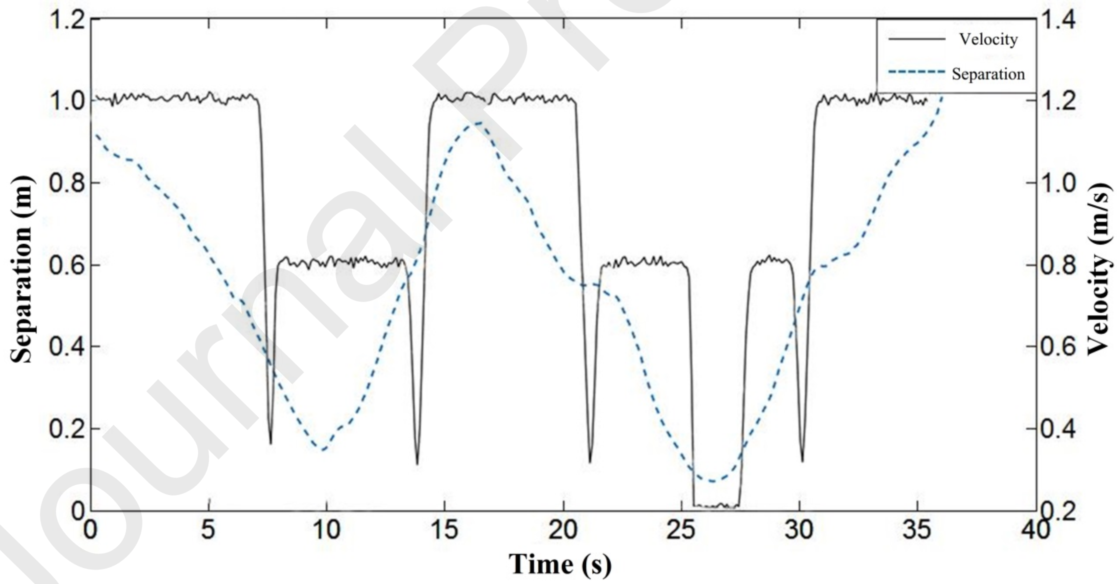

Figure 23. The result from the Tri-Modal SSM.

From Figure 12, 22, and 23, in terms of the effectiveness of risk assessment, the dynamic assessment method proposed in this paper and the tri-modal SSM can realize the dynamic assessment of risk and adjust the robot speed according to the assessment results to ensure the safety of manufacturing tasks. However, the conventional SSM is excessively conservative in the calculation of the risk threshold, and the robot is in a state of risk-avoiding for a long time, resulting in low efficiency. The assessment method proposed in this paper considers the risk of the inherent indicators of the workspace, and not only takes the robot speed as an indicator to assess the risk but also makes the assessment more comprehensive. Table 6 shows the time taken by the three methods at the same running speed, and the average value of recorded results are taken. As can be seen from the data in the table, the time efficiency of the three methods is not significantly different, which can meet the requirements of ISO/TS 15066 in terms of numerical value.

Table 6. The time cost of three risk assessment methods.

Method	Average time cost（ms）
Conventional SSM	147
Tri-Modal SSM	162
Dynamic modified SSM (our method)	159

The dynamic risk index proposed in this paper quantifies the real-time risk, comprehensively evaluated the environmental risk offline according to different task scenarios, and realizes the responsive safety decision-making and control based on the dynamic risk index. Both the conventional SSM and Tri-Modal SSM are based on the distance between human and industrial robots and the running speed of robots to trigger deceleration or emergency stop. Regardless of the environmental factors of specific task scenes, they are essentially passive safety trigger mechanisms.

The average reaction time of three methods is illustrated in Figure 24. From it we can conclude that the conventional SSM has the shortest reaction time because the reaction strategy of it is an emergency brake. The reaction time of the Tri-Model SSM and the proposed dynamic modified SSM are approximately equal and both satisfy the international standard.

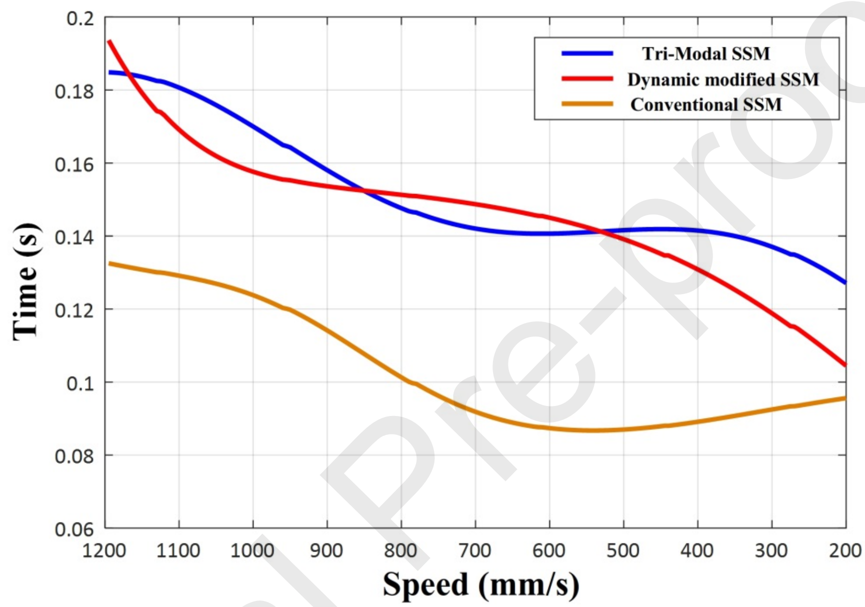

Figure 24. The average reaction time of three SSM methods.

Moreover, robot speed can be dynamically adjusted based on the dynamic risk index which benefits the execution efficiency of the robot system. On this point, the conventional SSM always breaks when the risk occurs. Besides, the Tri-Model can only keep efficiency when the robot slows down.

The efficiency of the industrial robot is represented by the speed during collaborative tasks. Influence on robot speed by these three SSM methods is illustrated in Figure 25.

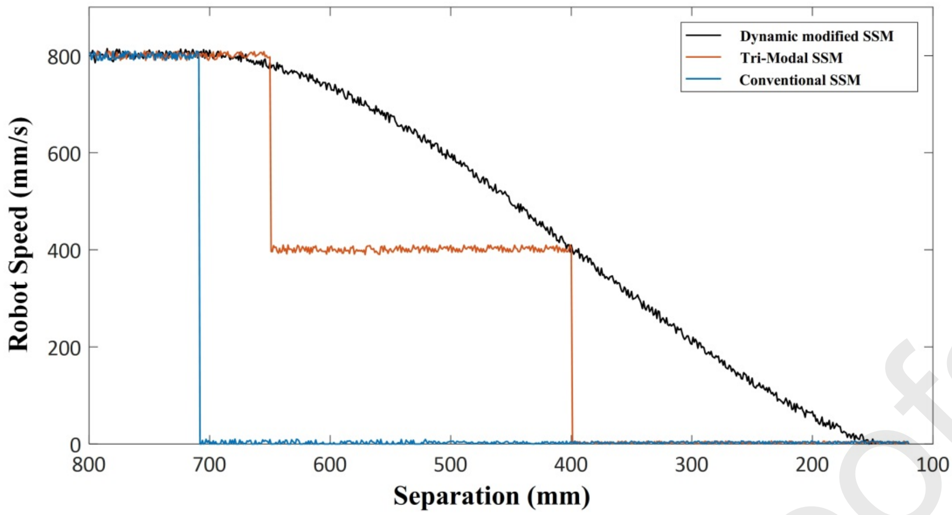

Figure 25. The impact on robot speed by these three SSM methods.

5.4 System Integration and Risk Visualization

To validate the efficiency of the proposed method in a more practical condition, a human-robot collaborative system was constructed. An ABB IRB1200 industrial robot and two Microsoft Kinect sensors were deployed. Besides, an augmented reality helmet (Microsoft Hololens v1) was attached to the human for a better human-robot interface. Figure 26 shows the hierarchical architecture of the proposed human-robot collaborative system.

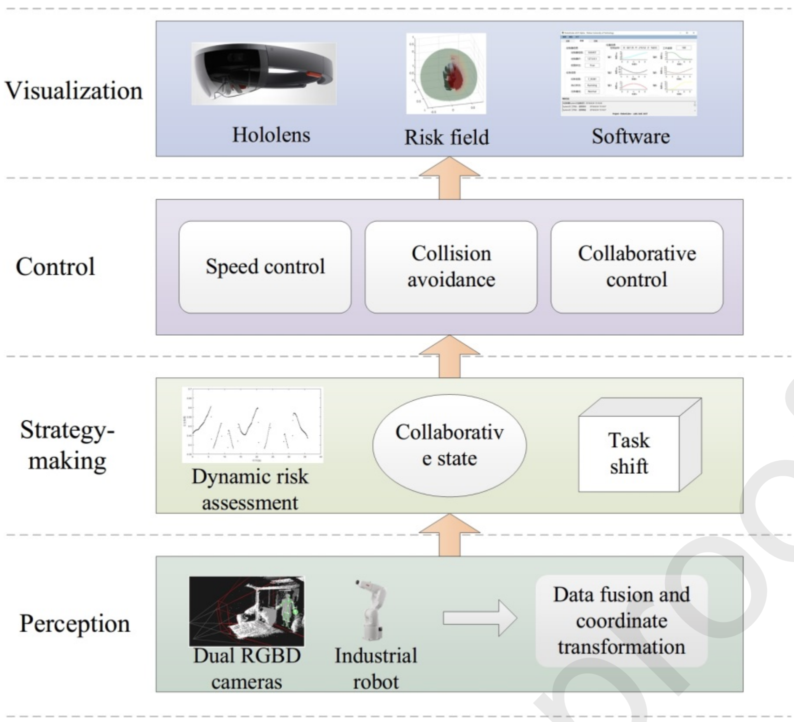

Figure 26. The architecture of the human-robot collaborative system.

Figure 27 is a diagram of the collision avoidance process. The human hand was located on the left front of the end-effector of the robot. When the hand moved to the right, the industrial robot avoided to the right rear.

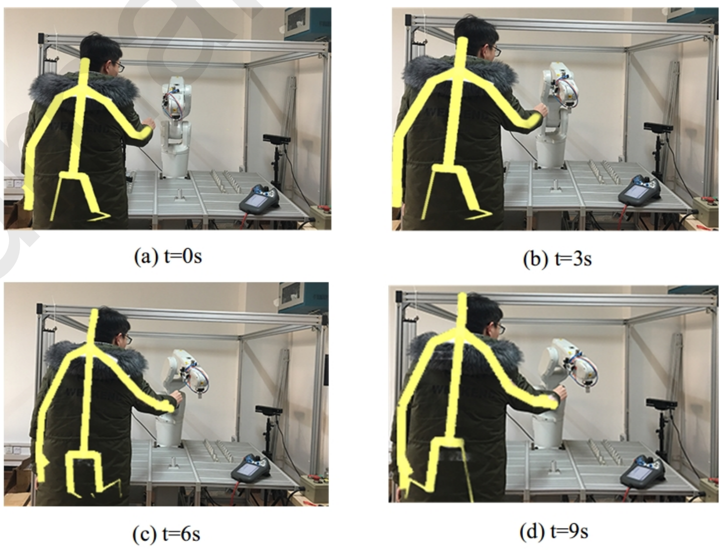

Figure 27. The process of collision avoidance in human-robot collaboration.

Risk visualization was realized on the Microsoft Hololens, an AR helmet. Figure 28 shows the AR images overlaying onto the physical industrial robot. Inside this AR image, a virtual industrial robot which was same as the physical one and the risk field was plotted. In this risk field, risk index in the red zone was higher than it in the green zone. By wearing the AR helmet, the human can interact with the industrial robot only in the green zones. When human entered the red zone, the collision avoidance state will be activated.

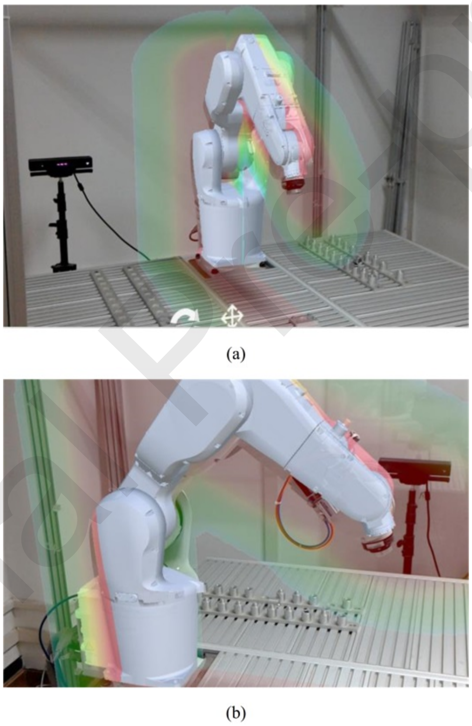

Figure 28. The risk visualization based on augmented reality.

6 Conclusion

Safety as the top priority of human-robot collaboration has attracted more and more attention. The proposal of new ISO standards for collaborative robots indicates that dynamic risk assessment and active response capability of industrial robots are of significant importance in industrial human-robot collaboration. This paper firstly established the risk assessment model based on the direction of ISO/TS 15066 as well as the dynamic assessing method using data fusion. Indicators inspired by related publications were contained and classified considering the inherent and dynamic properties in the modified SSM model. This method takes the inherent properties of the industrial robot as the weight factor and realizes the quantitative risk assessment of the dynamic operation data in the joint space. Dynamic visual risk zones are also designed. Moreover, an active response strategy based on the proposed risk index and the threshold was also designed. Risk index minimization using gradient descent was utilized to get the direction of collision avoidance. Besides, augmented reality was integrated with system integration and risk visualization.

Results of the validation show that our method is effective in the dynamic human-robot collaboration. Specifically, the proposed dynamic modified SSM take the influence on the production efficiency into consideration. Compared with the conventional SSM and the Tri-Model SSM, our method has less impact on production efficiency. The combination of SSM and visual risk field in augmented reality brought a new collaborative interface for industrial human-robot collaboration.

Future works may contain the optimization of the weight of risk-related indicators, the deeper use of robot joints redundancy, the improvement of time delay, and more practical application developments.

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Appendix

The running speed and response time of the experimental robot

Figure A1(a) is a graph showing the change in the running speed of the robot when it is in a warning state and the risk index is gradually increased. Due to the robot programming control limitation, the robot speed cannot be linearly controlled. Therefore, multiple intervals are set for the deceleration response based on the risk index. The smaller the interval division, the more frequent the robot deceleration trigger, and accordingly, the smoothness of the robot motion is reduced. The simulation system shown in the figure is divided once every 200mm/s, that is, the acceleration of the robot triggered by the risk index to 200mm/s will trigger a deceleration response of the actual robot. Figure A1(b) shows the response time of the motion state change at various speeds of the robot in the experiment. In practical applications, it is necessary to examine the various speed indicators of the robot to select the appropriate deceleration interval size to improve the smoothness of the robot movement while ensuring safety.

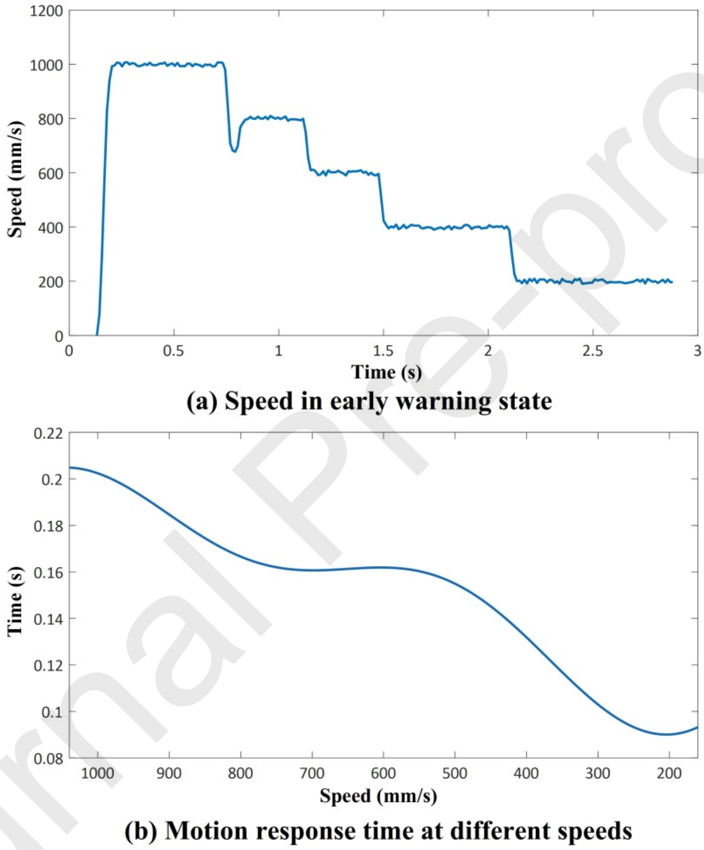

Figure A1. The running speed and response time.

Highlights

- Dynamic risk assessment and active response capability is of great significance in human-robot collaboration
- Classification and pre-define of risk-related indicators are meaningful for the risk assessment
- The modified SSM in this paper trades off the risk and production efficiency
- Weights of indicators and thresholds of collaboration states are designed to be flexible under different scenarios
- Risk field using augmented reality brings a new interface for human-robot collaboration