Virtual Fence Approach for Safety Monitoring of CNC Machine Tool with Dual Regions of Interest

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***Abstract*—This study is about machine vision-based virtual fence technology for CNC machine tools. The proposed smart system is composed of cameras and industrial personal computers, and the object of concern is the safety door. First, the operation mode of the camera is in real-time, and the industrial personal computer is responsible for image storage, analysis, and decision-making. In the total field of view, key regions of interest are predefined by experts, including the safety door and the work area, which represent the behavior of the workers and the operating status of the machine, respectively. However, since the contrast between the door opening and closing is significant, a background subtraction method is employed to monitor the status of the safety door. Then, the work area adjacent to the safety door has the ability to detect foreign intrusion. Its properties are different from the safety door in contrast, and the frame difference learning method is more suitable for solving this problem. The experimental results show that the proposed method can accurately detect the state of the safety door and the intrusion of foreign objects. Furthermore, the proposed method still has reliable performance within tolerable error after reducing the detection frequency, which also confirms that the trade-off problem of computational cost and accuracy can be taken into account at the current stage of this study. Future research will focus on determining regions of interest and keyframes, as well as performance testing for object detection and semantic segmentation.**

***Index Terms*—Virtual Fence, Condition Monitoring System, Occupational Safety, CNC Machine Tool.**

I. Introduction

THE Fourth Industrial Revolution has brought an impact on the traditional factory in the way of thinking and operation. Factory managers have formulated countermeasures to respond to external pressures, such as through the update of software and hardware equipment and operating models, making factories gradually move towards automation and intelligence. However, the digital transformation of factories is a lengthy and costly process. Therefore, many factories are still unable to realize the advanced manufacturing mode with intelligent automation as the core. The current state of the factory is based on many people performing their duties to drive production activities. The workers on the factory site have different professional backgrounds and practical experience, which leads to the gap between work efficiency and quality, and even is related to the probability of accidents. The issue of occupational safety is long-standing and difficult to prevent completely, which also promotes the vigorous development of safety protection technology. However, livestock farms are vast and often understaffed, placing a huge need for automated management. Therefore, the related technology of Virtual/Electronic Fence (VF/EF) [1]-[11] was developed very early, specifically considering the way of audio or electric shock. Its value is to replace the traditional physical fence facilities and achieve better results. This concept can be mapped to safety monitoring in other fields such as circuit design [12], homeland security [13], ecological protection [14], water rescue [15], agriculture [16], and Unmanned Aerial Vehicles (UAV) [17] and nuclear power plants [18]. This is the same as livestock farms are to use non-traditional methods to solve existing problems. In addition, the security defense related to people in the workplace has grown significantly in recent years, from process improvement, and installation of protective equipment to signal-based security monitoring, such as Ultra-wideband (UWB) [19, 20], Bluetooth Low-Energy (BLE) [21], Global Navigation Satellite System-Radio Frequency (GNSS-RF) [22, 23]. The approach is to predefine high-risk areas, and then use different communication devices to detect the relative positions of people. It is known from the field test results that the system operates successfully. However, since the wireless signal is susceptible to environmental interference or shielding, the signal strength has uncertainties, so it needs to be evaluated and tested very carefully. On the factory side, Zhou [24] et al. used multiple signals based on environmental information to protect the health and safety of personnel, including dust concentration, temperature and smoke concentration. Lee [25] et al. proposed a Process Model-based Human-robot Collaboration (PM-HRC) system to ensure the safety of people in human-robot collaboration mode, so safety is the most important prerequisite. However, the design of the machine tool without a sheet metal shell made accidents frequent in the early years, and then this pain point was taken seriously and improved. For machine tools, software or hardware protection are common options for operational safety. The targets of security defense include machinery and personnel in factories, and monitoring methods are usually based on signals or images received by sensors. Karabagli [26] et al. and Racz [27] et al. focus on improving the safety of machine tools, using machine vision to monitor and analyze the production process, and using the Analytic Hierarchy Process (AHP) to monitor the health of the machine. Finally, this study proposes a machine vision-based virtual fence method, and it is used for the safety monitoring of CNC machine tools during operation. It is a safety mechanism after the physical protection device fails due to natural or human intervention. The performance of the technology is required to have real-time detection to ensure the safety of personnel. The specific methods are in the subsequent sections of this paper.

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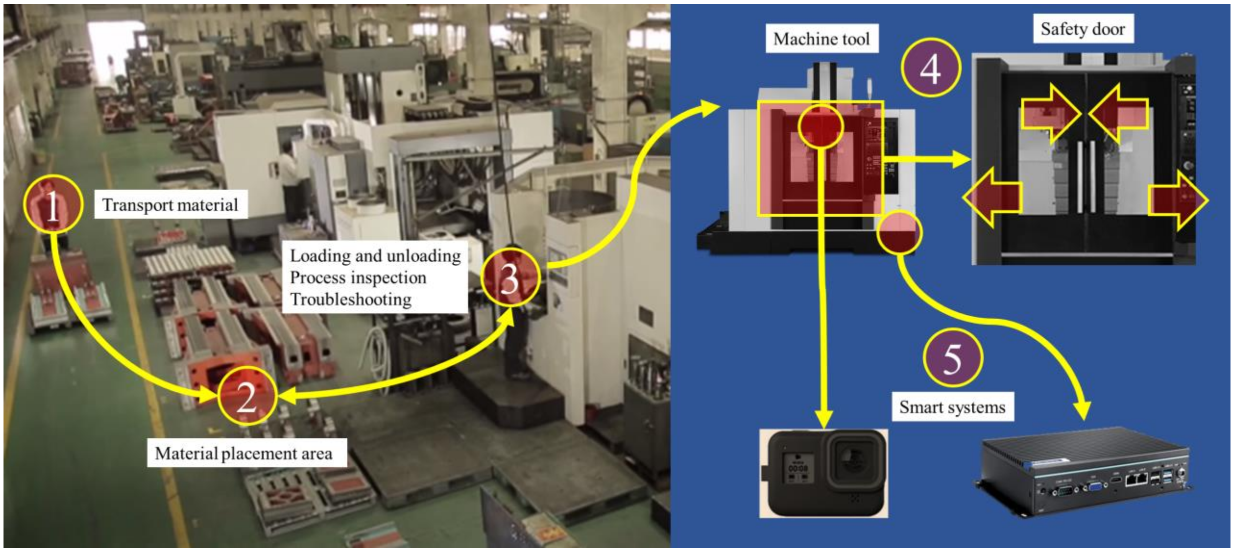


Fig. 1. The view of the manufacturing plants and the smart systems.

II. Manufacturing Plants and Smart Systems

This research was carried out in a smart factory mainly composed of CNC machine tools as shown in Fig. 1. The manufacturer partner provided the machines and equipment on the production line as a research resource for this article. The definition of the problem and the description of the solution are given in the following sections.

A. Definition Problem

CNC machine tool is a complex manufacturing system composed of a large number of components. In order to make it run smoothly on the production line, safety guards are configured for subsystems, key components and workers. This article focuses on worker safety issues. According to expert experience shared by manufacturer partners, there is a high correlation between worker safety hazards and personal habits and work experience. Specifically, the problem is again focused on the safety door of the CNC machine tool. The guidelines and situations for the use of safety door are as follows.

1) *Loading and Unloading*
First, the material is transported to the designated production station according to the production plan on the work order. The worker performs the loading procedure to place the material in the machine. When the processing program ends, the worker executes the unloading program to remove the material from the machine. Workers open and close safety doors during the process. Since the status of the machine is “Not Started” and “Finished”, it means that the work safety is high.

2) *Process Inspection*
In order to ensure the stability of quality during processing, workers often actively check the status of the workpiece. This makes the opening/closing of the safety door more frequent, which in turn causes the protective device of the safety door to be deliberately disassembled by workers, so as to open the safety door to inspect the workpiece during the operation of the machine. But this behavior is one of the causes of disastrous consequences, so it is the subject of this article. Since the status of the machine is “Running”, it means that the work safety is low.

3) *Troubleshooting*
The causes of equipment failure are related to human or non-human factors. The corresponding solutions include time-based, preventive and even predictive maintenance. In short, it means that the machine status is “Offline”, which means that the work safety is high.

B. Smart Systems

The smart systems is built on a CNC machine tool, and the main elements are cameras and an Industrial Personal Computer (IPC). Alert events triggered by VF technology are presented to workers on a built-in dashboard, as shown in Fig. 2.

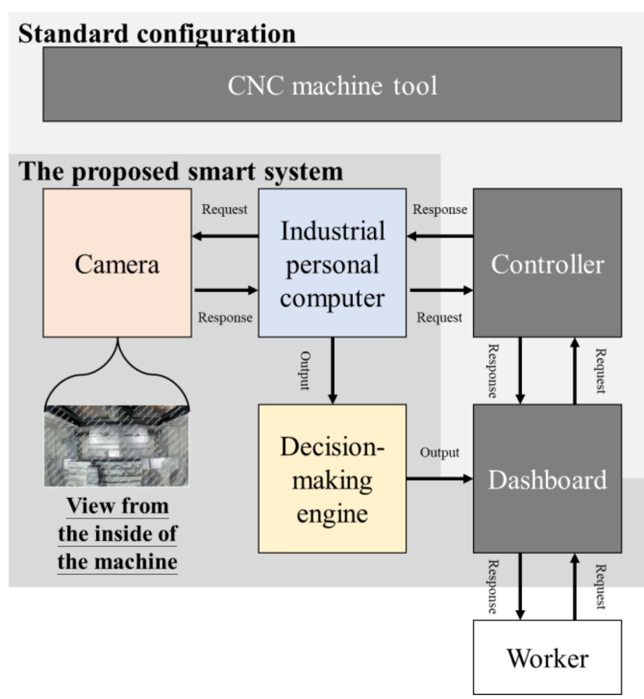


Fig. 2. The architecture of the smart systems.

1) *Hardware*

The VF technology is based on machine vision in this paper. Therefore, a camera is necessary, and an IPC is an auxiliary device for analysis. In the selection of camera specifications, the main considerations include price, wide angle, resolution and waterproof. In addition, since this is an application in a factory, the computer specifications must meet the industrial level, and hardware cost is still one of the factors that need to be considered under the premise that the computing performance meets the requirements.

2) *Software*

This article uses Python (Rev. 3) and MATLAB (Rev. R2022a) software for research and development work. However, machine vision-based VF rely heavily on image processing, statistics and machine learning algorithms. Furthermore, the technology involves work safety issues, so a lightweight algorithm is a prerequisite for real-time monitoring. Finally, this study is one of the few special and real situations where vision is embedded in CNC machine tools. The details are described in the next section.

III. The Proposed Method

The proposed method is a machine vision-based safety defense technology and reduces the risk to workers during the work process. In fact, an image processing method based on the concept of time series analysis is adopted. The flowchart is shown in Fig. 3, and detailed techniques are presented in subsections.

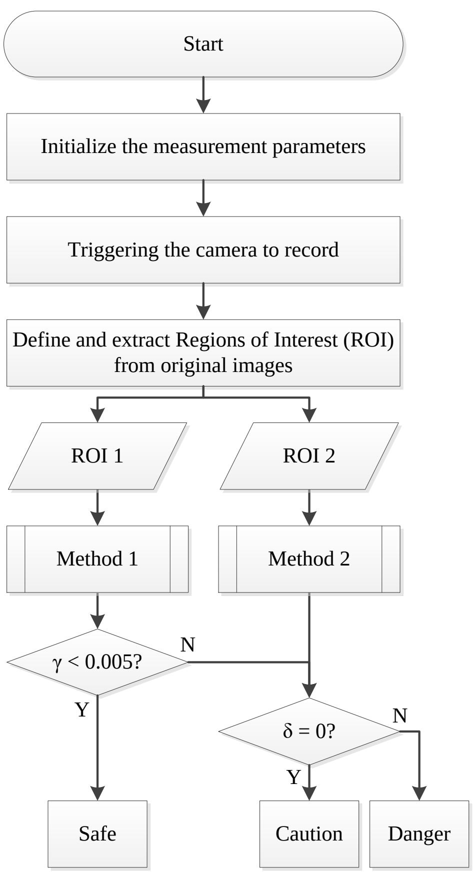


Fig. 3. Flowchart of the proposed method.

A. Image Processing

The machine vision equipment inside the machine provides the original image for the research work, which covers the main field of view. A balance is obtained between resolution and computational cost, and the image size is 1280x720, as shown in Eq. (1). However, image processing and analysis methods are important and indispensable for original images.

$$X=\begin{bmatrix} x_{1,1} & x_{1,2} & x_{1,3} & \cdots & x_{1,j} & \cdots & x_{1,n} \\ x_{2,1} & x_{2,2} & x_{2,3} & \cdots & x_{2,j} & \cdots & x_{2,n} \\ x_{3,1} & x_{3,2} & x_{3,3} & \cdots & x_{3,j} & \cdots & x_{3,n} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & x_{i,2} & x_{i,3} & \cdots & x_{i,j} & \cdots & x_{i,n} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m,1} & x_{m,2} & x_{m,3} & \cdots & x_{m,j} & \cdots & x_{m,n} \end{bmatrix} \quad (1)$$

1) *Regions of Interest*

In most object detection research, Region of Interest (ROI) is an indispensable step for image processing, which can effectively improve the performance of the algorithm. In this paper, two ROIs are designed to realize the function of VF, named ROI 1 and 2 respectively, as shown in Eq. (2).

$$X_{roi}=\begin{bmatrix} x_{i,j} & \cdots & x_{i+\alpha,j} \\ \vdots & \ddots & \vdots \\ x_{i,j+\beta} & \cdots & x_{i+\alpha,j+\beta} \end{bmatrix} \quad (2)$$

Furthermore, the two are simply defined as disjoint sets, called $X_{roi1} \cap X_{roi2} = \varnothing$. Specifically, ROI 1 is used to detect the action of the safety door; ROI 2 is used to detect the status of the work area. The boundaries given in this study are shown in Table I. The ROI is a part of the original image, meaning the area that is more relevant for the study, as shown in Fig. 4.

Table I
Boundary Limits for Regions of Interest

ROI	Lower bound *i*	*j*	Upper bound *α*	*β*
1	680	100	1000	160
2	680	170	1000	210

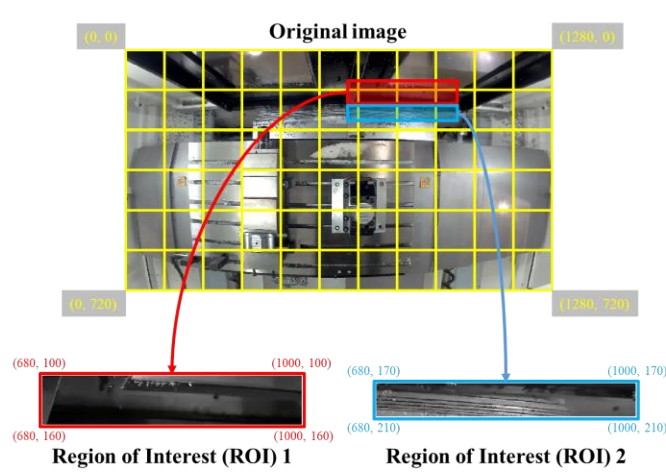


Fig. 4. Location of ROI 1 and 2 in the original image.

2) Color Space Conversion

The National Television System Committee (NTSC) defines three primary colors for raw images, including Red (R), Green (G), and Blue (B). Since all color information needs to be considered in this study, and the load on the algorithm from the amount of data must be reduced, the original image is converted to grayscale using Eq. (3), as shown in Fig. 5. However, the image still needs to go through the steps of processing and analysis, the details are shown below.

$$Gray = 0.299R + 0.587G + 0.114B \tag{3}$$

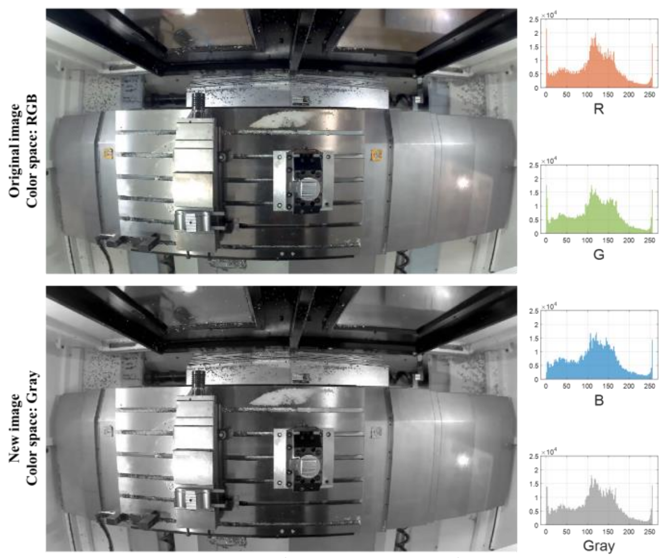


Fig. 5. Convert the color space of the original image from RGB to Gray.

3) Noise Reduction

The image is processed by lightweight noise reduction methods such as thresholding and filtering. Since the tone of ROI 1 is a dark color close to black, the gray image is simplified by the binarization inversion method, as shown in Eq. (4). In addition, the tone of ROI 2 is close to the light color of white, so the gray image is reduced by the binarization method, as shown in Eq. (5). Then, the residual noise is cleaned up by filters, including averaging and Gaussian filters, as shown in Fig. 6.

$$Binarization = \begin{cases} 1 & ,if\ X_{roi} > Threshold \\ 0 & ,otherwise \end{cases} \tag{4}$$

$$Binarization\ Inversion = \begin{cases} 0 & ,if\ X_{roi} > Threshold \\ max(X_{roi}) & ,otherwise \end{cases} \tag{5}$$

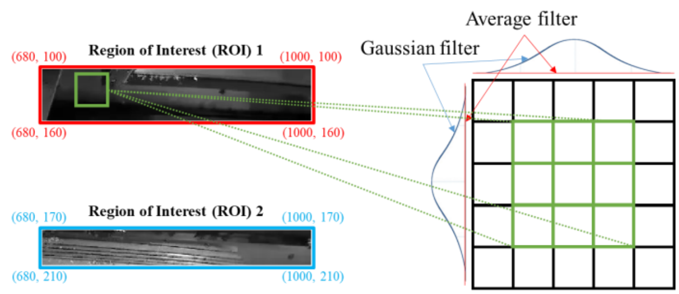


Fig. 6. Schematic of averaging and Gaussian filters.

B. Image Analysis

For the part of image analysis, image alignment was used to evaluate the events during the video process in ROI 1 and 2, respectively, as shown in Fig. 7.

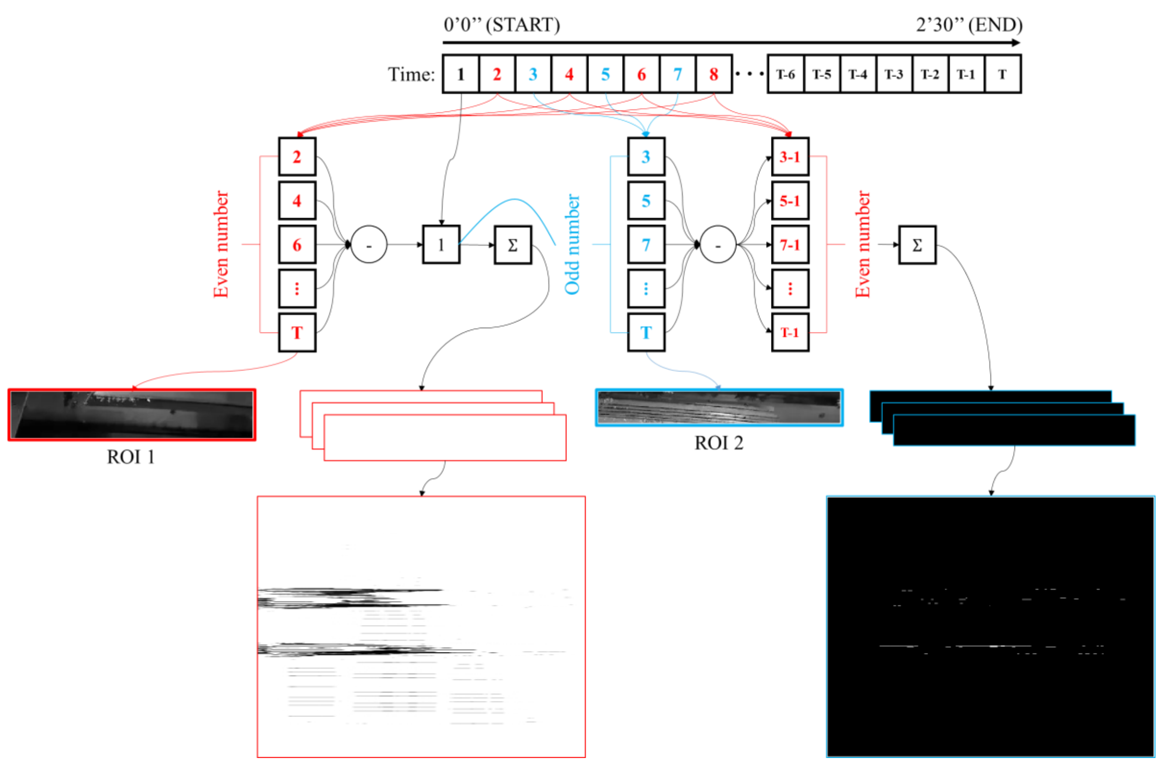


Fig. 7. Flowchart of ROI and its analysis method.

1) *Background Subtraction Method*

The Background Subtraction (BS) method is a classic method for dynamic object detection. The first frame is usually used as the base image for the background, and the objects to be compared are new images over time. In order to reduce the computational cost of the algorithm and realize the real-time detection, the image acquisition cycle of ROI 1 and 2 is one frame every two seconds, e.g., $X_{ROI1}(nt)$-$X_{ROI1}(t)$, where t is one second, n is a constant, and its value is even, as shown in Fig. 7. Then, the image is processed according to the plan in Fig. 8, including color space conversion and noise reduction, respectively. The purpose is to reduce the sensitivity and interference to decision-making from noise. Finally, the black pixel ratio (γ) of the image is calculated, and it becomes the basis for judging the state of the safety door.

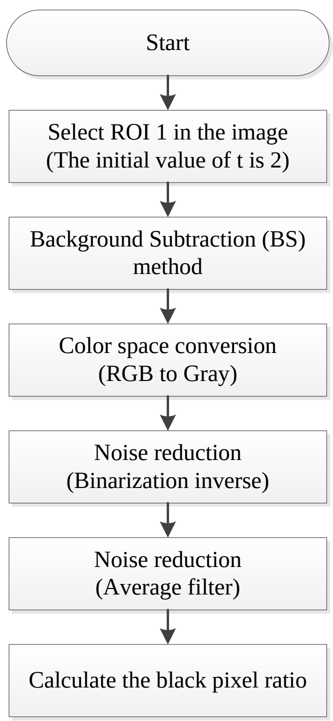


Fig. 8. Flow chart of safety door detection method.

2) *Frame Difference Method*

The Frame Difference (FD) method and BS method are both classic methods of dynamic object detection. The method is similar to the Dynamic Programming (DP) method and the Monte Carlo (MC) method. However, the single-step update makes it perform better and meets the constraints of detection immediacy, but the magnitude of the object change affects its performance. Therefore, the sampling period of the FD method is a challenging problem. In this study, ROI 2 is defined as $X_{ROI2}(t)$-$X_{ROI2}(t-1)$, where t is the time constant and its value is odd, as shown in Fig. 7. In addition, Fig. 9 shows the method and steps of image processing, including color space conversion and noise reduction. The purpose is to suppress the influence of noise on the output. Finally, the white pixel ratio (δ) of the image is calculated, and it becomes the basis for judging the status of the work area.

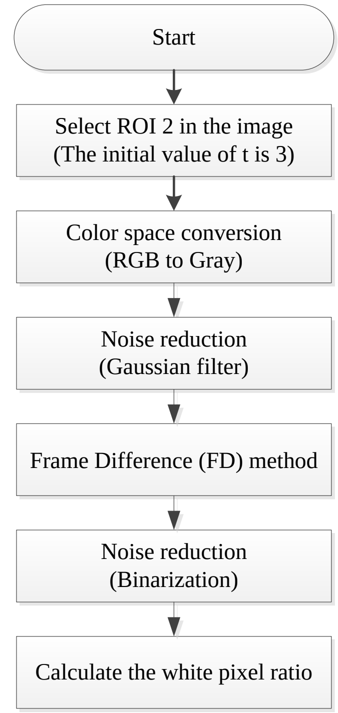


Fig. 9. Flow chart of work area detection method.

3) *Inference Mode*

For ROI 1 and 2, characteristic indicators such as black pixel ratio and white pixel ratio are obtained by the BS method and FD method, respectively. On the other hand, Fig. 3 clearly describes the decision-making rule, that is, ROI 1 detects the state of the safety door, and ROI 2 detects the state of the work area. Finally, the key thresholds are obtained from the experiments as shown in Table II, where γ is based on the purpose of anti-noise, including shaking caused by closing the door, cutting fluid, and iron filings. The active reminder mechanism of the safety fence includes two stages, namely the status of the safety door and the status of the work area. If γ is less than 0.005, it means that the state of the safety door is "Close", so the safety level is "Safe"; if γ is greater than 0.005 and δ is 0, the state of the safety door is "Open" and the state of the work area is "Normal", so the safety level is "Caution"; if γ is greater than 0.005 and δ is greater than 0, the state of the safety door is "Open" and the state of the work area is "Abnormal", so the safety level is "Danger".

Table II
PREDEFINED THRESHOLDS FOR SAFETY FENCES

Safety level	ROI 1 (Safety door)		ROI 2 (Work area)	
	Open	Close	Abnormal	Normal
Safe	-	$\gamma < 0.005$	-	-
Caution	$\gamma \geqq 0.005$	-	-	$\delta = 0$
Danger	$\gamma \geqq 0.005$	-	$\delta > 0$	-

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The research team and partners from the industry have jointly established a database for the research and development of the technology, as shown in Table III. The experiment used a camera to record the process of workers performing production work with machines. There are three events during the two minutes and thirty seconds, including safe, caution, and danger.

Table III
EXPERIMENTAL DATABASE FOR THIS STUDY

Date	Filename	Video length	Frame rate	Resolution		Image number	Safety level		
				Width	High		Safe	Caution	Danger
2021/2/3	WIN_20210203_10_03_16_Pro_2.mp4	2′30″	30	1,280	720	4,500	✓	✓	✓

The proposed method uses frame frequency adjustment for dual ROIs, so the total number of frames is reduced by half from 4,500 (150 sec multiplied by 30 frames) to 2,250. Fig. 10 shows ROIs 1 and 2 extracted from the original image, respectively. Specifically, the composition is based on the dimensions shown in Table I multiplied by 2,250 frames. Since the door is closed most of the time in ROI 1, the color is black (value 255); the work area of ROI 2 is in the normal state most of the time, so the color is white (value 0). Then, the color features of the dual ROIs are converted into the black pixel ratio and the white pixel ratio, respectively, as shown in Fig. 11. In addition, in order to reduce the load of the method and make it have a real-time performance during monitoring, the frequency adjustment of the frame is an important task. The results show that the performance of event detection can still be guaranteed after reducing the computational cost by half the frames. Table IV shows the results of the quantification. The difference of ROI 1 under the frequency adjustment of the frame is approximately 0, which is related to the salient features when the door is open. On the other hand, the variation of the work area is unique and random, which makes the performance of ROI 2 error-prone, with an error rate of 2.38 % in both normal and abnormal.

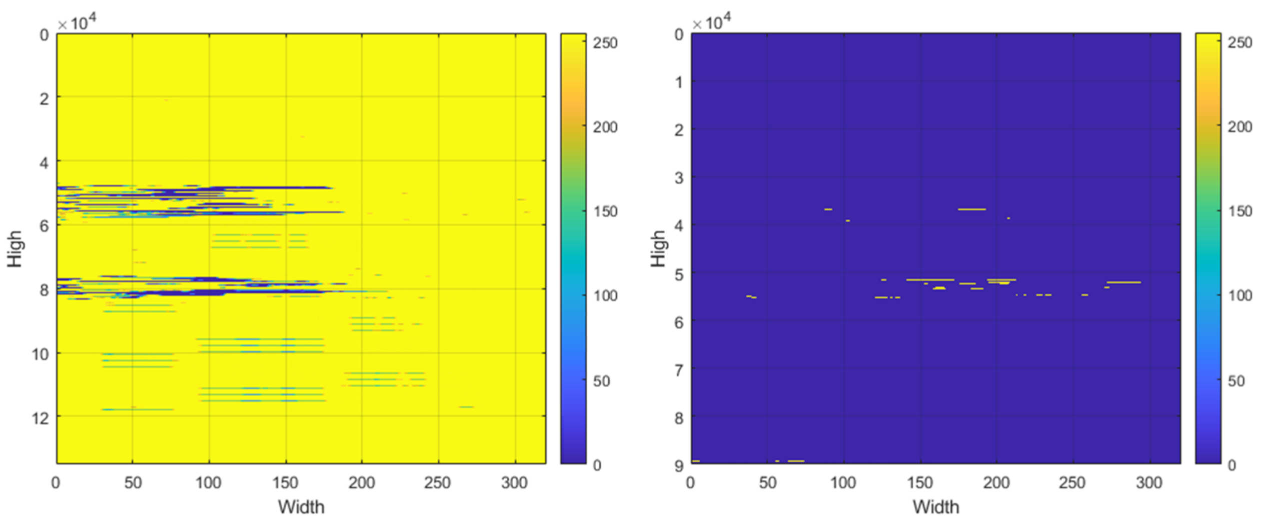
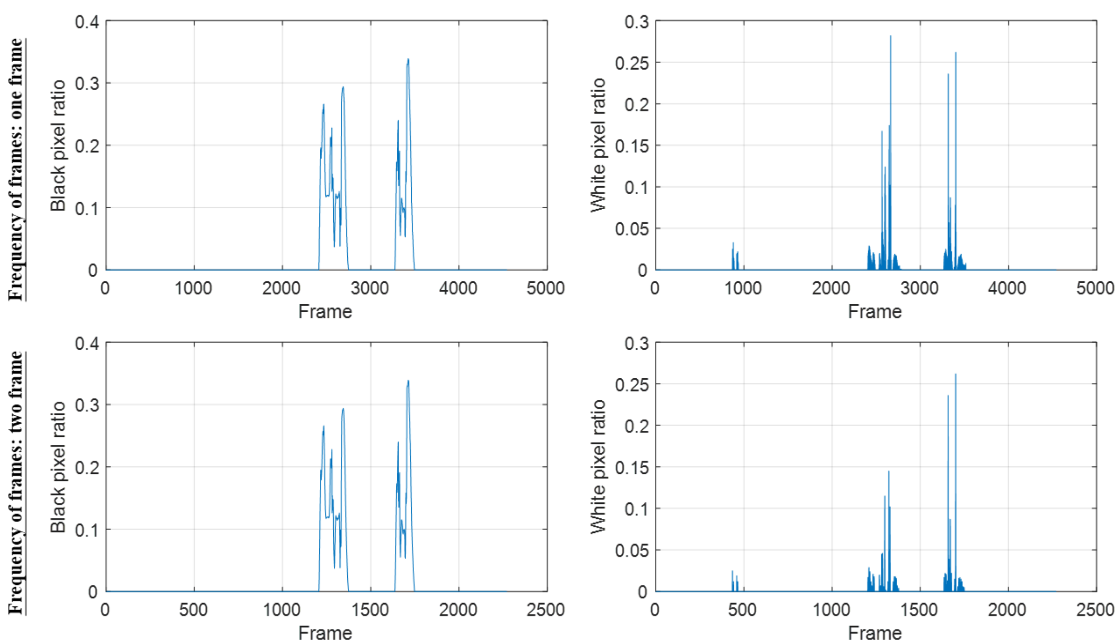


Fig. 10. Feature models of the proposed method: (a) safety door (ROI 1) and (b) work area (ROI 2).



(a) Black pixel ratio for ROI 1
(b) White pixel ratio for ROI 2

Fig. 11. Compare the image features under frequency adjustment of frames.

Table IV
EVALUATE THE PERFORMANCE OF IMAGE FEATURES UNDER FREQUENCY ADJUSTMENT OF FRAMES

ROI	Frame	Max.	Min.	Avg.	Std.	Sum.	Normal (ROI 1: $\gamma < 0.005$), (ROI 2: $\delta = 0$)			Abnormal (ROI 1: $\gamma \geqq 0.005$), (ROI 2: $\delta \geqq 0$)		
							Frame	Percentage (%)	Error (%)	Frame	Percentage (%)	Error (%)
1	One	0.3390	0	0.0183	0.0567	82.2460	3,950	87.78	0	550	12.22	0
	Two	0.3390	0	0.0183	0.0568	41.1850	1,975	87.78		275	12.22	
2	One	0.2820	0	0.0014	0.0103	6.2720	4,233	94.07	2.38	267	5.93	2.38
	Two	0.2620	0	0.0010	0.0100	2.3490	2,170	96.44		80	3.56	

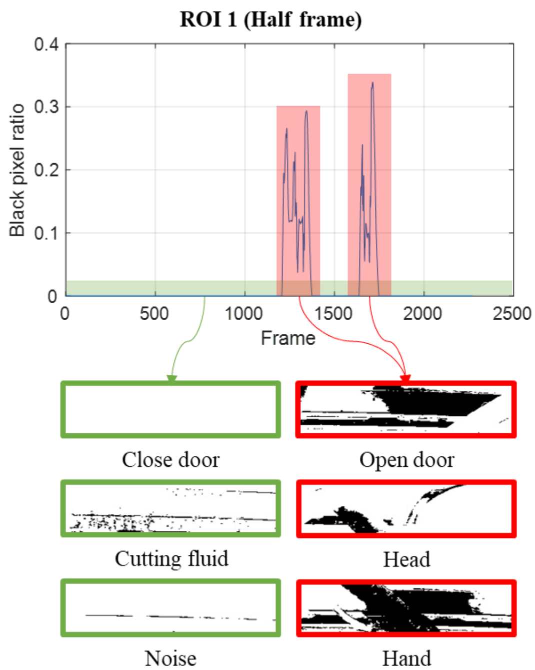


Fig. 12. Visualization of events for safety door (ROI 1) and work area (ROI 2).

Further, the significance of the experimental results is explained, as shown in Fig. 12. The first is the two scenarios for ROI 1, which has a clean white when the door is closed. Interference sources during machining include cutting fluid and noise, but they are still close to white. In addition, ROI 2 also has two scenarios, with clean black when the door is open. If a worker's limb approaches or enters the machine, its color reacts violently. It was even confirmed again from the results of the black/white pixel ratio. However, the thresholds given in Table II become the inference engine for the black/white pixel ratio, and the analysis results are shown in Fig. 13. The definitions are as follows:

- **IF** the “Door is Closed” **AND** “Work Area is Not Running”, **THEN** the safety level is “Safe” and the color is “Green”.
- **IF** the “Door is Closed” **AND** “Work Area is Running”, **THEN** the safety level is “Safe” and the color is “White”.
- **IF** the “Door is Open” **AND** “Work Area is Normal”, **THEN** the safety level is “Caution” and the color is “Yellow”.
- **IF** the “Door is Open” **AND** “Work Area is Abnormal”, **THEN** the safety level is “Danger” and the color is “Red”.

Table V shows that there are 1,975 (87.78 %) frames whose status is “Safe” according to ROI 1, while the remaining 275 (12.22 %) frames are determined by ROI 2. In ROI 2, 80 (3.56 %) frames belong to the “Danger” state, and after subtracting them from the remaining unknown frames in ROI 1, the proportion of “Caution” frames is obtained, and the number is 195 (8.67 %).

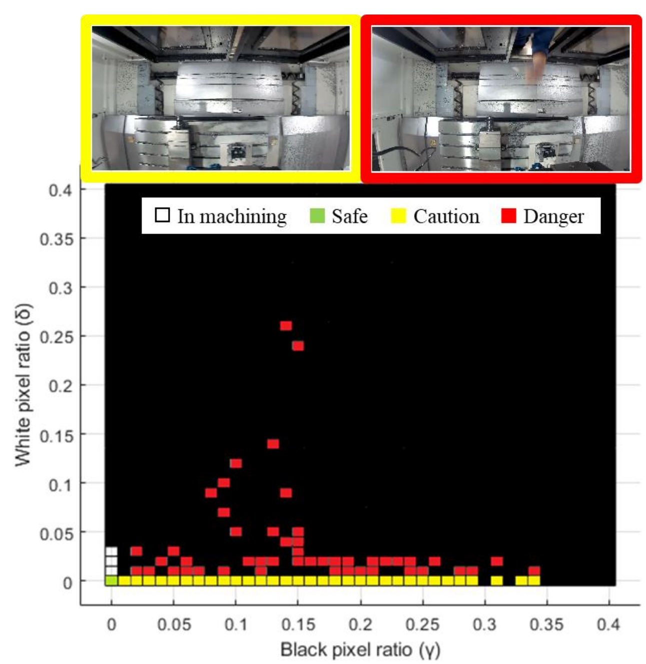


Fig. 13. Visualization of security levels and events based on dual ROIs.

Table V
STATISTICS OF SAFETY LEVELS AND EVENTS BASED ON DUAL ROI

ROI	Safe ($\gamma < 0.005$)	Caution ($\gamma \geqq 0.005$, $\delta = 0$)	Danger ($\gamma \geqq 0.005$, $\delta > 0$)
1	1,975 (87.78 %)	275 (12.22 %)	
2	-	2,170 (96.44 %)	80 (3.56 %)

Table VI
EVALUATE THE ACCURACY OF CLASSIFICATION FOR THE SAFETY LEVEL

Item	Safe ($\gamma < 0.005$)	Caution ($\gamma \geqq 0.005$ & $\delta = 0$)	Danger ($\gamma \geqq 0.005$ & $\delta > 0$)	Total
(G)round truth	1,967 (87.42 %)	178 (7.91 %)	105 (4.67 %)	2,250 (100 %)
(R)OI 1 & 2	1,975 (87.78 %)	131 (5.82 %)	144 (6.40 %)	2,250 (100 %)
|Error| = |(G) - (R)|	8 (0.41 %)	47 (26.40 %)	39 (37.14 %)	94 (4.17 %)
Accuracy (%)	99.59 %	73.60 %	62.86 %	95.82 %

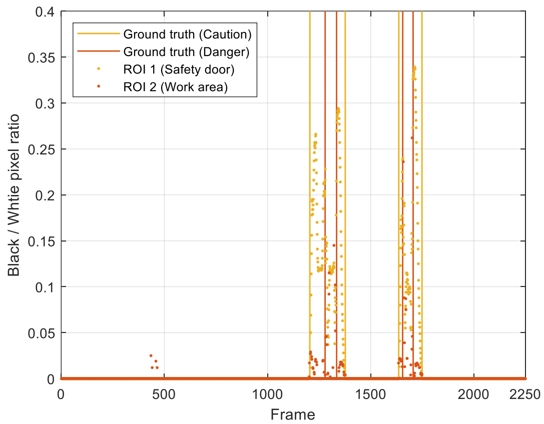


Fig. 14. Distribution of black/white pixel ratio between ground truth and dual ROIs.

Prediction result \ Ground truth	Safe	Caution	Danger
Safe	**1967 (100 %)**	8 (4.49 %)	0 (0.00 %)
Caution	0 (0.00 %)	**131 (73.60 %)**	0 (0.00 %)
Danger	0 (0.00 %)	39 (21.91 %)	**105 (100 %)**

Fig. 15. Confusion matrix for safety levels based on dual ROIs.

From Table VI, the performance of the proposed method is validated. The state is "Safe" with 99.59 % accuracy and 0.41 % error or 8 frames. In addition, the accuracies for the status of "Caution" and "Danger" were 73.60 % and 62.86 %, respectively. The overall mean accuracy under cumulative error is 95.82 %. The ground truth of each frame in Fig. 14 is carefully labeled by experts and also contains the results of the proposed method. The yellow line here is "Caution", and there is also a red line inside it for "Danger". Further, interpret the characteristics of the algorithm from the confusion matrix of both (ROI 1 & 2), as shown in Fig. 15. The "Safe" and "Danger" are clearly distinguished, and the "Caution" sandwiched in between is not easy to define. Based on this, the accuracy is 100 % for "Safe", 73.60 % for "Caution", and 100 % for "Danger". The number of frames where "Caution" is classified as "Safe" is 8, which equals 0.26 seconds. The number of frames where "Caution" is classified as "Danger" is 39, which equals 1.3 seconds. Important factors to be addressed in the future are as follows:

- Labels: Over-precise labels make a small change in "Safe" classified as "Caution", but the algorithm does not consider it to be "Caution". Likewise, there is a blurry line between "Danger" and "Caution".
- Interference: The camera is mounted above the safety door, and the movement of the safety door temporarily disables the ROI. Therefore, the installation location will be re-emphasized in the future.
- Threshold: The design of the anti-interference threshold will affect the inference performance of the algorithm.

V. CONCLUSION

This study proposes a VF approach based on dual ROI, which is applied to worker safety protection of CNC machine tools. Firstly, the working process was recorded using machine vision, and the images were calculated using an IPC. Then, two ROIs were predefined to focus on key locations, including safety door and work areas. The BS method and FD method are used for the processing and calculation of ROI 1 and 2. Furthermore, the frequency adjustment of frames is utilized to reduce the load on the proposed method. From the experimental results, the computational cost is reduced by half and the performance is good, with an error of only 2.38 %. Further comparing with the ground truth, the respective detection accuracies of the three safety levels (safe, caution and danger) are 100 %, 73.60 % and 100 %, respectively. The overall average accuracy is 97.91 %. Since the proposed method outputs an inference result every two frames, it has the performance of instant response. In future research, proof-of-concept work will be performed in the field of partner companies, and its reliability and accuracy will continue to be enhanced.

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