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Dynamic Decision Threshold Fire Warning Based on Neyman-Pearson Criterion

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Abstract

In the problem of selecting the fire warning device discrimination threshold, we designed a dynamic judgment threshold fire warning device combining the YOLO human flow statistical monitoring system and the Neyman-Pearson criterion. The traditional fire early warning device is to make a choice between the leakage alarm rate and the false alarm rate, sacrificing the performance of one party in exchange for the better performance of the other party. After the threshold selection, the dynamic change cannot be realized according to the demand situation. However, most fire events are caused by human factors. Therefore, we combined with the YOLO target tracking and monitoring system to dynamically adjust the judgment threshold of the fire early warning device by monitoring the flow of people. In the period of large flow of people, the judgment threshold of fire warning is reduced, and the minimum leakage alarm rate is selected. In the period of small flow of people, the judgment threshold of fire warning device is improved and the minimum false alarm rate is selected. And use the Neyman-Pearson criterion to achieve the ideal lowest leakage alarm rate and false alarm rate under the demand condition, and improve the accuracy of fire prevention. Through this improvement, the problem of too rigid threshold of fire warning device is solved, better adapted to the practical application needs, and provides a more optimized solution for balancing the protection of the safety of people's lives and property and reducing the waste of human and material resources.

Keywords

YOLO, Neyman-Pearson criterion, fire warning device, leakage alarm rate, false alarm rate.

1. INTRODUCTION

Among all kinds of disasters, fire is one of the major disasters that most commonly threaten public safety and social development. With the advancement of the high-quality development of emergency management, emergency management pays more attention to prevention and focuses on source prevention and control, so fire monitoring and prevention has become particularly important. The traditional fire early warning mechanism is to choose between false negative and false positive, and in some scenarios, the fire false negative rate caused by the choice is high, which is easy to threaten the safety of people's lives and property; In other scenarios, the false positive rate of fire caused by selection is high, which is easy to lead to the waste of human and material resources, and cannot make the false negative rate and false positive rate reach a low ideal value, and the false negative rate and false positive rate are determined by the response threshold to a certain extent. In order to solve the above problems, we designed a dynamic judgment threshold fire early warning device combined with the YOLO

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people flow statistics monitoring system, which adjusts the judgment threshold in real time by monitoring the flow of people, so as to achieve the ideal minimum of the false negative rate and false positive rate under the demand conditions, and improve the accuracy of fire prevention.

2. NEYMAN-PEARSON CRITERION

In order to obtain the minimum false negative rate under different false positive rates, this paper uses the Neyman-Pearson criterion to determine the initial threshold of detection verdict on the basis of the semi-Gaussian model for both non-fire events H_0 and fire events H_1 [1]. Under the constraint conditions $P(H_1/H_0)=\alpha$, the criterion maximizes the probability of correct judgment $P(H_1/H_1)$, that is, it is equivalent to minimizing the false negative rate $P(H_0/H_1)$. Construct the objective function using the Lagrange multiplier $\mu(\mu \ge 0)$:

$$J = P(H_0/H_1) + \mu\left[P(H_1/H_0) - \alpha\right] \tag{1}$$

Under the constraints of $P(H_1/H_0)=\alpha$, to minimize the probability of false judgment $P(H_0/H_1)$, that is, to find the minimum value of the objective function J, and convert equation (1) into an integral operation, we can obtain:

$$J = \int_{R_0} P(\mathrm{x}/H_1)dx + \mu \int_{R_0} P(\mathrm{x}/H_0)dx - \alpha \tag{2}$$

Transform the integration field:

$$\int_{R_1} P(x/H_0)dx = 1 - \int_{R_0} P(x/H_0)dx \tag{3}$$

Substituting equation (2) yields:

$$J = \mu(1-\alpha) + \int_{R_0}\left[P(x/H_1) - \mu P(x/H_0)\right]dx \tag{4}$$

In the equation, $\mu(1-\alpha)$ is not negative, and in order to make J achieve a minimum, the integrand should take a negative value. In this case, the resulting decision expression is as follows:

$$\lambda(x) = \frac{P(x/H_1)}{P(x/H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \mu \tag{5}$$

Where $\lambda(x)$ is the likelihood ratio, and the decision threshold μ can be obtained from the constraints:

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$$P\left(H_1/H_0\right)=\int_{R_1} P\left(x/H_0\right)dx=\int_{\mu}^{+\infty} P\left(\lambda/H_0\right)d\lambda=\alpha \tag{6}$$

In the same way, the minimum false positive rate and the corresponding judgment threshold can be obtained under different false negative rates.

The criterion determines the optimal threshold through theoretical derivation, and obtains the minimum false negative rate $P\left(H_0/H_1\right)$ and the minimum false positive rate $P\left(H_1/H_0\right)$ in different situations, which provides support for the dynamic adjustment of the optimal judgment threshold of the multi-sensor fusion fire detector. Figure 1 and Figure 2 show the threshold results of the minimum false alarm rate and minimum false alarm rate.

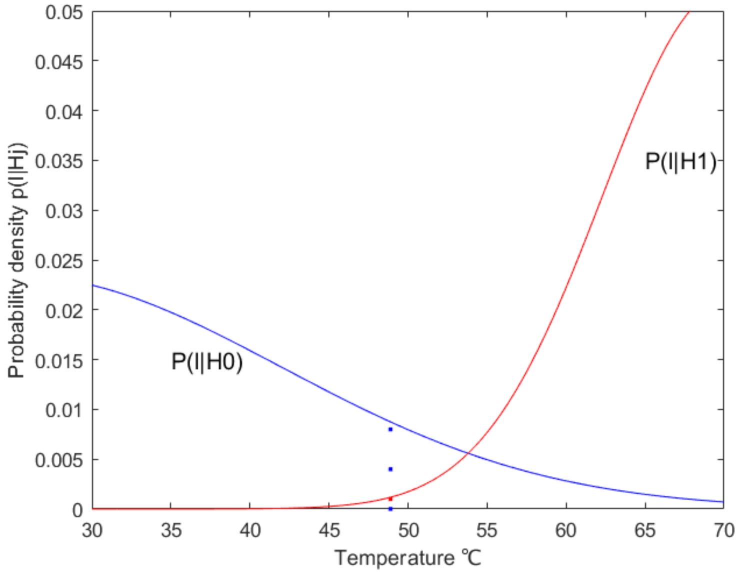

Figure 1. The false positive rate is 8%, and the minimum false negative rate under the constraint is 8%.

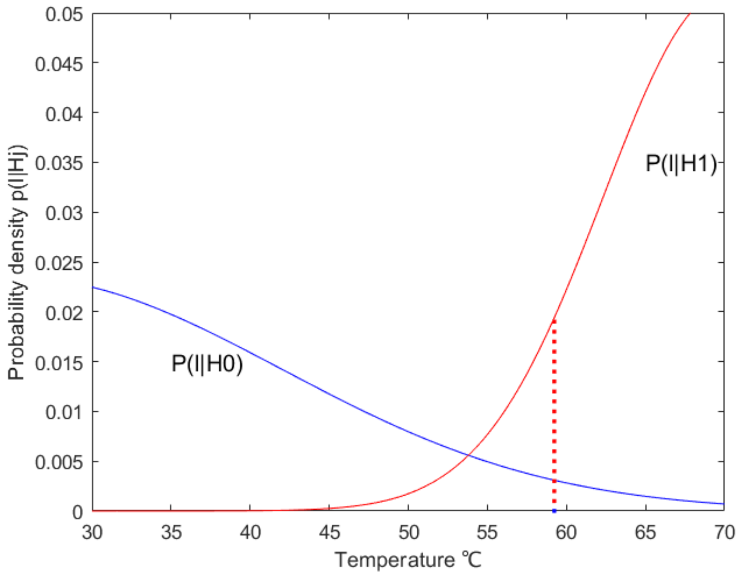

Figure 2. The false negative rate is 8%, and the minimum false positive rate under the constraint is 8%.

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Table 1 and Table 2 show the minimum false negative rate, false positive rate, and corresponding decision thresholds under different constraints.

Table 1. The false positive rate is the minimum false negative rate under the α constraint

$P(H_1/H_0)$	3%	5%	8%
$P(H_0/H_1)$	4.5%	1.3%	0.3%
Judgment threshold $\mu/°C$	57.0	53.0	48.9

Table 2. False positive rate is the minimum false negative rate under β constraint

$P(H_0/H_1)$	8%	5%	3%
$P(H_1/H_0)$	2.2%	2.9%	3.8%
Judgment threshold $\mu_1/°C$	59.2	57.4	55.6

3. YOLO PEOPLE FLOW STATISTICS MONITORING SYSTEM

After obtaining the minimum false negative rate and false positive rate under different constraints, it is necessary to associate these threshold data with the corresponding environment. Therefore, the YOLO statistical monitoring system is used to statistically monitor the flow of people in different time periods, and the hierarchical flow data segments corresponding to different time periods are obtained, that is, the required threshold application environment. The implementation of YOLO people statistics monitoring system is divided into the following two steps:

3.1. Deepsort Target Tracking

DeepSORT (Deep Learning + SORT) is a multi-target tracking algorithm based on deep learning and trajectory sorting, the core of which is the Kalman filter algorithm and the Hungarian algorithm, which tracks objects through prediction and association matching. Based on the Simple Online and Realtime Tracking (SORT) algorithm, DeepSORT introduces a convolutional neural network (CNN) to extract target features and achieve more accurate target associations [2].

After obtaining the original video frame, the object detector is used to detect the target in the video frame, extract the features in the target detection frame, which includes the apparent feature and the motion feature, calculate the matching degree between the two frames before and after the target [3], and assign an ID to each tracked target. Since the SORT algorithm is a coarser tracking algorithm, the ID of the object is particularly easy to be lost when it is occluded, so the DeepSORT algorithm adds Matching Cascade and Confirmed of new trajectories [4] to solve this problem.

Detections is the object detection box, and Tracks is the trajectory information. Tracks are divided into confirmed state and non-confirmed state, and the newly generated tracks are non-confirmed. Unconfirmed tracks must be matched with Detections a certain number of times (3 by default) before they can be converted into a confirmed state. The workflow is shown in Figure 3:

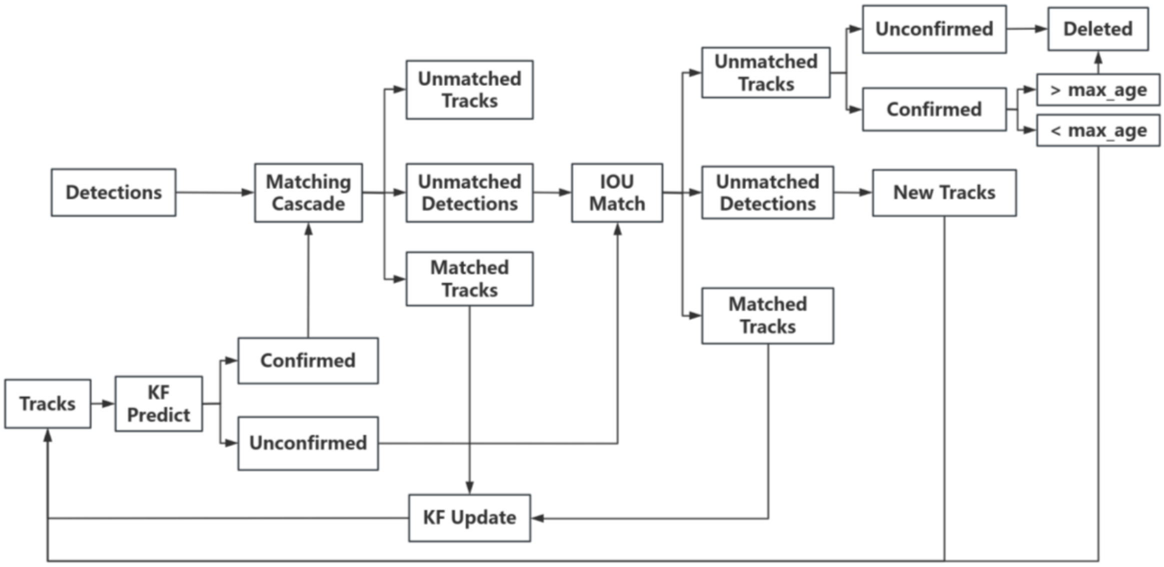

Figure 3. Workflow diagram of the DeepSORT algorithm

The workflow of the entire algorithm is as follows:

(1) The corresponding tracks are created by the first frame detection result, and the corresponding boxes are predicted by the Kalman filter, and the tracks are in an uncertain state. The IOU is matched between the object detection frame of the second frame and the frame predicted by Tracks in the previous frame, and then the cost matrix is calculated from the results of IOU matching [5].

(2) The obtained cost matrix is used as the input of the Hungarian algorithm to obtain a linear matching result, and after the detection box and the prediction box are successfully paired, the corresponding Detections are updated to the corresponding Tracks variable through the Kalman filter. Cycle through the above steps until the end of the tracks or video frame in the acknowledgment state.

(3) The Kalman filter is used to predict the boxes corresponding to the confirmed and unconfirmed tracks. Cascade matching of the boxes and Detections of the confirmed state tracks. After the tracks are successfully matched, the corresponding tracks variable is updated by the Kalman filter. Repeat the loop until the end of the video frame.

3.2. Human traffic data statistics

After the target is tracked by the tracking algorithm, it will obtain a unique identification ID and its corresponding motion trajectory. Using these two data, we can set counting logic to perform counting:

(1) Define Counting Lines: Define two virtual lines in the video frame, the uplink collision line and the downlink collision line, as the counting reference. When the target crosses these two lines, the counting logic is triggered.

(2) Detection of intersection: Determine whether the target has effectively crossed the line by analyzing the intersection point between the tracking trajectory and the counting line. Only when the target completely crosses the line (rather than just touching the line), it is counted towards the total.

4. DYNAMIC DECISION THRESHOLD

Through the advanced YOLO target tracking and monitoring system, deep learning technology is used to accurately identify and calculate past personnel, and real-time statistics

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of the number of people flowing during different time periods. Based on the collected data, it is divided into six levels and combined with the optimal temperature decision threshold under different constraint conditions obtained from previous research to obtain the corresponding demand environment and the appropriate minimum false negative rate (minimum false positive rate) correspondence.

According to research, most fire incidents are caused by improper employee operation or other human factors. Therefore, during periods of high pedestrian traffic, the probability of fire incidents occurring is much higher than in situations with few or no people present. Therefore, during periods of high pedestrian traffic, the judgment threshold of fire warning devices should be lowered and the minimum false negative rate should be selected for application. During periods with low foot traffic, the probability of fire incidents occurring is lower due to environmental factors, and the waste of human and material resources caused by false positive during these times is even greater. So during periods of low pedestrian traffic, the judgment threshold of fire warning devices should be raised and the minimum false positive rate should be selected for application.

The corresponding relationship between the dynamic judgment threshold temperature fire warning device for a factory with 150 employees is shown in Table 3:

Table 3. Table of Corresponding Judgment Thresholds for Pedestrian Flow and Dynamic Threshold Temperature Fire Warning Devices

Time period	Human traffic	Judgment threshold $\mu/°C$	$P(H_0/H_1)$	$P(H_1/H_0)$
0:00—8：00	54	59.2	8%	2.2%
8：00—10：00	276	57.0	4.5%	3%
10：00—13：00	322	48.9	0.3%	8%
13：00—16：00	225	55.6	3%	3.8%
16：00—19：00	284	53.0	1.3%	5%
19：00—23：00	73	57.4	5%	2.9％

5. CONCLUSION

This study designed a dynamic decision threshold fire warning device by combining the YOLO pedestrian flow statistical monitoring system and the Neyman Pearson criterion, achieving an improvement in the accuracy of fire warning. By using the Neyman Pearson criterion to determine the initial threshold for detection judgment [6], the minimum false negative rate and minimum false positive rate under different conditions are obtained, providing support for dynamically adjusting the optimal judgment threshold for fire detectors. Then, through the YOLO target tracking and monitoring system, the pedestrian flow data segment is combined with the previously obtained judgment threshold to obtain the corresponding demand environment and the appropriate minimum false negative rate (minimum false positive rate) correspondence, achieving a dynamic judgment threshold. Greatly improving the accuracy of fire prevention.

In practical applications, the system can dynamically adjust the judgment threshold of the fire warning device based on changes in pedestrian flow at different time periods, making it more suitable for practical environmental needs. Especially for periods with high pedestrian traffic, a strategy of reducing the judgment threshold is adopted to minimize the false negative rate and improve the sensitivity and accuracy of fire warning. For periods with low pedestrian traffic, a strategy of increasing the judgment threshold is adopted to minimize false positive rates, avoid resource waste and unnecessary social panic. In the future, the algorithm and

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technology of the system can be further improved to enhance its adaptability and accuracy in different scenarios, promoting the high-quality development of emergency management.

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REFERENCES

[1] SONG Shanshan, ZHAI Xuping: Improved Infrared Anomaly Target Detection Algorithm.

[2] GU Xun LlJiang-tao, et al. Design and implementation of people counting based on deep learning, Journal of Guiyang University(Natural Sciences), Vol. 18(2023)No. 4 p48-53.

[3] GOU Lingtaom, SONG Huansheng, et al. Real-Time Cross-Camera Vehicle Tracking Method for Tunnel Scenes by Fusing Spatiotemporal Features, Computer Engineering and Applications, Vol. 59(2023)No. 24, p89-97.

[4] ZHOU Xiongfeng: Automatic Acquisition Method of Multi-target Vehicle Trajectory Based on Deep Learning, Transportation Science & Technology, (2021)No. 04, p135-140, 144.

[5] FU Yonggao: Research on Vehicle Speed Recognition in Traffic Scene Based on Machine Vision, Urban Roads Bridges & Flood Control, (2023)No. 08, p253-255.

[6] FAN Ziyi, WANG Hongsheng, Yao Qinjian: Detection of Pedestrian and Motor Vehicle Running Red Light Based on Yolov5, Changjiang Information & Communications, Vol. 35(2022)No.3, p51-53.

[7] XIA Shuang zhi, LlU Bingqi, ZHOU Wan xing: Relationships among Quantization Bits of Sensors under N-P Criterion, Journal of Detection & Control,Vol. 31(2009)No. 01, p15-18,22.