A Video Image Processing Method for Continuous Object Detection

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2023 8th International Conference on Computer and Communication Systems (ICCCS) | 978-1-6654-5612-8/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICCCS57501.2023.10151187

***Abstract*—Post-processing of video images is essential to the whole video image detection, especially for continuous objects. Continuous objects refer to objects with continuity, integrity, and consistency at the level of physical media or data application, including tracks, cables, lane lines, chain structures, etc. Usually, objects are composed of a series of small homogeneous units, such as a piece of track, a piece of cable, a color ring, etc. The rapid development of artificial intelligence technology and 5G communication technology has driven the gradual maturity of deep learning and autonomous driving technology. At the same time, the standard for the detection of continuous objects is growing higher and higher. Therefore, how to detect objects in different business scenarios and scene-based optimization have become a top priority. The existing problems include: (1) Small units of multiple continuous objects in complex scenes interfere with each other, hindering recognition; (2) Various negative factors (insufficient brightness, steam, smoke occlusion, etc.) cause poor image quality. Consequently, the recognition performance is negatively influenced, and the model cannot adjust parameters adaptively; (3) The skew and distortion of image lower the object recognition performance. Aiming at these problems, this paper proposes a video image post-processing optimization algorithm for object detection of continuous objects, including an object integration search algorithm, threshold adaptive adjustment algorithm, rotation perspective correction algorithm, etc. Prior knowledge is utilized to improve the accuracy and efficiency of detection.**

Keywords*—*image processing, object detection, prior knowledge, artificial intelligence

I. Introduction

Object detection (OD) technology usually refers to detecting the location and corresponding category of objects in an image. Further, the object detection of continuous objects includes detecting the positions of a series of objects in an image and their corresponding categories and corresponding attributions, which emphasizes the integrity of the detected objects. Traditional object detection algorithms mainly detect discrete independent objects, such as animal, human, vehicle, etc. However, with the rapid development of artificial intelligence technology and 5G communication technology, technologies such as autonomous driving, intelligent transportation, and intelligent warehousing are also evolving. These scenarios put forward higher and higher requirements for continuous object detection. Optimizing object detection results for objects in different business scenarios has become a top priority. Continuous objects refer to objects that have continuity at the physical medium level or data application level, including tracks, cables, lane lines, and chain structures. As shown in Figure 1, taking the lane line as an example, the object detection method is generally selected in units of pigment blocks [1]. A continuous lane line contains a lot of prior knowledge. More specifically, the color of the front and rear color blocks are the same, the distance between adjacent color blocks is the same and meets a certain threshold, the angle change speed between adjacent color blocks also meets a certain ratio threshold.

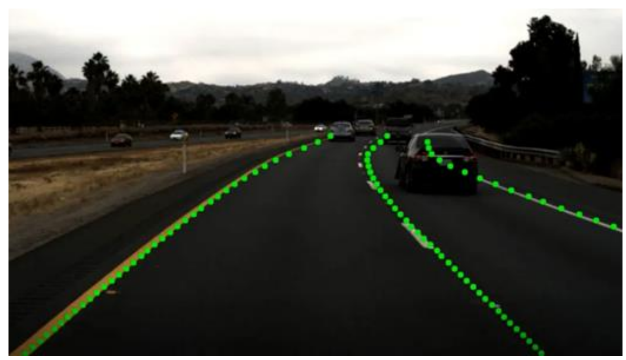

Fig. 1. Lane object detection.

Due to many factors, including mutual interference, environmental noise, overlapping and interlacing, etc., object detection results cannot be directly output as required [2]. Specific post-processing is needed to convert the obtained result to helpful information that can be directly used. Using this prior knowledge, we can post-process the results of video image object detection, thereby improving the detection accuracy and detection rate.

II. Related Works

A. Object Detection

Object detection is an important computer vision task and has recently received considerable attention. Viola and Jones presented one of the earliest successful real-time object detection algorithms in 2001 [3]. It adopts a sliding window approach by partitioning the image into patches (repeated for different scales) and then performing binary classification on each patch to determine whether a face is present in that region.

With advances in deep learning research and state-of-the-art performance in image classification, performing object detection with deep learning was a natural next step [4-9]. One

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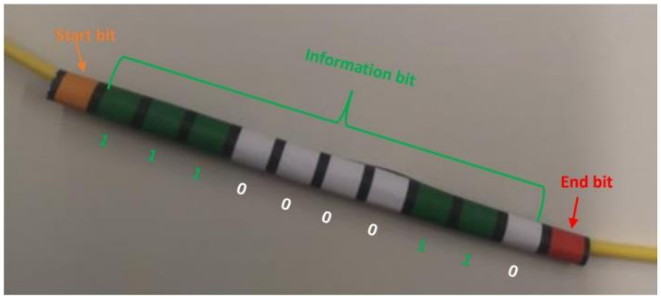

Fig. 2. Design drawing of color ring. Orange marks the start bit, green and white marks the information bits, and red marks the end bit.

line of research focuses on two-stage solid object detectors [4-7], which first generate a sparse set of RoIs with a Region Proposal Network (RPN) [5] and then perform classification and bounding box regression. Another line of research develops fast single-stage object detectors [8-9]. SSD [9] (Single Shot MultiBox Detector) discretizes the output space of bounding boxes into a set of default boxes over different aspect ratios and scales per feature map location. The network generates scores for the presence of each object category in each default box and produces adjustments to the box to better match the object shape. Additionally, the network combines predictions from multiple feature maps with different resolutions to naturally handle objects of various sizes. SSD is relative to methods because it eliminates proposal generation and subsequent pixel or feature resampling stages and encapsulates all computation in a single network.

In addition to the general framework object detection methods, there are also some methods for small target detection [10], fine-grained detection [11], hyperspectral image detection [12], SAR image detection [13], where the object involves people [14], buildings [15], traffic signs [16] and so on.

B. *Color-ring Resistors Recognition*

Printed circuit board (PCB) is the essential component of electronic products, which consists of various electronic components to achieve specific functions. Color-ring resistors are the most common type in PCB. They are distinguished by sequential color rings and may be wrongly assembled in PCB due to similar visual appearance.

However, manual inspection of color-ring resistors has low efficiency and a high false detection rate. Traditional image-based methods have limitations in solving the locating problem of color-ring resistors and color rings in PCB images under various illuminations, imaging distances, and views, resulting in difficulty detecting and measuring the color-ring resistors.

The automatic detection and measuring method for PCB color-ring resistors [17] were proposed based on a convolution neural network. The color PCB images in different complex scenes are used to verify the proposed method. According to features of PCB images, an automatic detection and segmentation method for color-ring resistors in PCB images was proposed based on the encoder-decoder convolution neural network. The cross-entropy loss function with weights was used to train the network to reduce the influence of training data imbalance. Then, the optimal model was established by comparing the segmentation accuracy in different parameters.

The color ring is a label used to mark the occupancy of the ports of the optical branching device (OBD). The specific form is shown in Figure 2. It consists of 1 start bit, 10 information bits, and 1 end bit, using color blocks to convey information.

III. METHODS

The post-processing optimization algorithms described in this paper include an object integration search algorithm, an adaptive threshold adjustment algorithm, and a rotational perspective correction algorithm. Among them, the object integration search algorithm uses the continuity and consistency of the object, including a priori information such as angle, size, intersection ratio, head and tail information, etc. to classify and integrate the object; the threshold adaptive adjustment algorithm uses the integrity and continuity of the object, the confidence threshold is gradually reduced within a specific range, and the adaptability of the object detection algorithm to environmental changes is realized; the rotation correction algorithm is aimed at non-rectangular objects because the existing object detection methods are not suitable for non-rectangular objects. For existing OD algorithms, the detection frame contains much invalid information, producing inferior performance. Re-detection after rotation correction of such objects can improve the detection accuracy and detection rate.

A. *Object Integration Search Algorithm*

The object integration search algorithm utilizes objects' continuity, integrity, and consistency, including angle, size, intersection over union (IoU), head and tail information, number of units, and other prior information, to classify and integrate objects. First, the head and tail information is used to determine the start or end position of a series of objects, and the size and confidence of the head and tail objects are obtained. Secondly, according to the obtained size, the object whose size ratio near the start bit is within a specific threshold range is searched. If the intersection ratio of the object is less than a certain threshold, it will be added to the series as a new object. At the same time, according to the angle between the new object and the center point of the previous object, the angle reference of this series is obtained. In the subsequent search, the new object must simultaneously meet the size ratio, angle reference, and IoU to meet the corresponding threshold requirements. If no qualified object is found, a missing value is marked in the area where the object should be predicted to appear. Repeat the above operations until the end bit is reached, and stop the search. We illustrate this algorithm by taking the integrated search for a string of color-ring labels as an example. Preliminary object detection methods detect each small color patch, requiring an object integration search algorithm to combine these color patches into color rings that can express information.

In addition, for scene-based detection objects, endpoint detection algorithm and reverse lookup algorithm are also proposed in this paper, and objected optimization is carried out by using the characteristics of color ring labels.

Algorithm 1: Object Integration Search Algorithm

Input: Object Detection result set $\{\boldsymbol{R}, \boldsymbol{Y}, \boldsymbol{B}\}$, color ring length $\boldsymbol{L}$.
Output: Object Integration results set $\boldsymbol{Q}$.

for Start Point $\boldsymbol{Y_i}$ **do**:
  $\boldsymbol{S} = \boldsymbol{Y_i}$; add $\boldsymbol{S}$ to $\boldsymbol{Q}$;
  while $\boldsymbol{k < L - 1}$ **do**:
    Find the nearest $\boldsymbol{B_k}$ to $\boldsymbol{S}$ in set $\boldsymbol{B}$;
    Calculate the angle $\boldsymbol{\alpha_k}$ and distance $\boldsymbol{\delta_k}$ of $\{\boldsymbol{B_k}, \boldsymbol{S}\}$;
    Calculate the area $\boldsymbol{\beta_k}$ of $\boldsymbol{B_k}$ and the area $\boldsymbol{\beta_S}$ of $\boldsymbol{S}$;
    if $|\boldsymbol{\alpha_k} - \boldsymbol{\alpha_{k-1}}| < \boldsymbol{\theta_1}$ and $|\boldsymbol{\delta_k} - \boldsymbol{\delta_{k-1}}| < \boldsymbol{\theta_2}$ **do**:
      if $|\boldsymbol{\beta_k} - \boldsymbol{\beta_S}| / \boldsymbol{min}(\boldsymbol{\beta_k}, \boldsymbol{\beta_S}) < \boldsymbol{\theta_3}$ **do**:
        Update $\boldsymbol{B_k}$ as an adjacent point of $\boldsymbol{S}$, i.e., add $\boldsymbol{B_k}$ to $\boldsymbol{Q}$;
    Delete $\boldsymbol{B_j}$ from $\boldsymbol{B}$; $\boldsymbol{S} = \boldsymbol{B_j}$;
  end while
end for

B. Adaptive Threshold Adjustment Algorithm

We propose an adaptive threshold adjustment algorithm to solve the missing value problem. Among them, the threshold adaptive adjustment algorithm utilizes the integrity and continuity of the object. It gradually reduces the confidence threshold within a specific range, realizing the adaptiveness of the object detection algorithm in the face of environmental changes. Specifically, for the position of missing values in the search algorithm, a local confidence threshold of a specific step size is gradually reduced until a sufficient number of objects are detected. The algorithm is to solve the problem of the decrease of the confidence of the prediction frame in some local areas due to environmental changes.

Currently, in practical industrial Internet scenarios, many complex situations occur, such as insufficient brightness, steam, smoke occlusion, etc. Therefore, in the actual detection process, the quality of the detection image is inevitably affected. For example, when the quality of image to be detected is poor (inclined, dimly lit, blurred, etc.), the classification probability score of the detected object will be very low. The threshold value will be adaptively adjusted when many detected objects are missing. In the post-processing method, if the complete color ring cannot be detected (that is, the color ring containing the missing value N in the detection result), the relevant threshold of the search algorithm is reduced by a specific step size. Then, the search is performed repeatedly, until a complete color ring is detected. Among them, we innovatively propose a method of locally adjusting the threshold. The global adjustment threshold is severely affected by the local noise, which leads to the decrease of the accuracy of some detection boxes. However, the local threshold adjustment solves this problem, and only the threshold adjustment is made for the part of the detection box area where the detection result is missing. Similarly, taking color ring label detection as an example, the algorithm steps for adaptive local adjustment of the threshold are as follows Algorithm 2.

For the detection frame information that has been corrected and merged based on the object integration search algorithm, we perform local detection frame prediction before the missing value to make it meet the object integration search algorithm: the area of adjacent labels on the image is close; the angle of label deflection is consistent; the separation distance of adjacent labels is the same.

Next, perform a local threshold reduction step size reduction in the area where the detection frame is predicted to appear. If a color ring that meets the current threshold standard is detected, record it; if it is not detected within the expected area, continue to reduce the threshold until it is detected (returns the patch value) or reaches 0.1 (returns patch missing). If there are still missing values in the color ring (12 bits in total, including head and tail), go back to the first step to predict before the next missing value color ring according to the detection result of the prediction box; otherwise, return the color ring information.

Algorithm 2: Adaptive Threshold Adjustment Algorithm

Input: Object Integration results set $\boldsymbol{Q}$, color ring length $\boldsymbol{L}$.
Output: Adaptive Threshold Adjustment results set $\boldsymbol{Q_{New}}$.

for Point $\boldsymbol{Q_k} = \boldsymbol{N}$ **do**:
  Calculate the angle $\boldsymbol{\alpha_k}$ and distance $\boldsymbol{\delta_k}$ of $\{\boldsymbol{Q_{k-1}}, \boldsymbol{Q_{k+1}}\}$
  Calculate the area $\boldsymbol{\beta_{k-1}}$ of $\boldsymbol{Q_{k-1}}$ and the area $\boldsymbol{\beta_{k+1}}$ of $\boldsymbol{Q_{k+1}}$
  Predict the local detection box area $\mathbf{Q_{New_{\it i}}}$, **which satisfies**:
  $|\boldsymbol{\alpha_k} - \boldsymbol{\alpha_{New}}| < \boldsymbol{\theta_1}$ and $|\boldsymbol{\delta_k} - \boldsymbol{\delta_{New}}| < \boldsymbol{\theta_2}$ and
  $|\boldsymbol{\beta_{k-1}} - \boldsymbol{\beta_{New}}| / \boldsymbol{min}(\boldsymbol{\beta_{k-1}}, \boldsymbol{\beta_{New}}) < \boldsymbol{\theta_3}$ and $|\boldsymbol{\beta_{k+1}} - \boldsymbol{\beta_{New}}| / \boldsymbol{min}(\boldsymbol{\beta_{k+1}}, \boldsymbol{\beta_{New}}) < \boldsymbol{\theta_3}$
end for
while det > 0.1 and len($\mathbf{Q_{New}}$)< L , **do** :
  det=det-0.05
  find $\boldsymbol{Q_i}$ in the local detection box area, and add $\boldsymbol{Q_i}$ to $\mathbf{Q_{New}}$.
end while

C. Rotation Correction Algorithm

The rotation correction algorithm solves the problem of missing detection caused by object rotation and distortion. For some non-rectangular objects, since the existing object detection methods have a poor effect on non-rectangular objects, the detection frame will contain much invalid information. Re-detection after rotation correction of such objects can improve the detection accuracy and detection rate. In this paper, the angle information obtained by the object integration search algorithm is used to rotate and correct the tilt deflection of the object, improve the detection of tilted and rotating objects, and ensure the robustness of the model.

Further, when the image is seriously deflected and distorted, the ordinary rotation correction method cannot improve the detection effect. This paper introduces the perspective transformation method to solve this problem. Perspective transformation is the projection of an image onto a new viewing plane, also known as projection mapping. The purpose of perspective transformation is to transform objects that are straight lines in reality, which may appear as oblique lines in the picture, and convert them into straight lines through perspective transformation. The method of perspective correction in this paper is to write the equation by analyzing the relationship between the wrong interpolation parameters and the correct interpolation parameters. Then solve the equation to get the correct interpolation parameters.

Among them, starting from the world coordinates, the triangle is rasterized and rendered to the screen space. Assuming that the three points of the triangle (homogeneous coordinates) are P_0, P_1 and P_2 respectively, the three points are used as column vectors to form a 4x3 matrix:

$$P = [p_0\ p_1\ p_2] \tag{1}$$

The matrix from of world coordinates to screen space is written as:

$$M = M_{viewpoint} M_{proj} M_{view} \tag{2}$$

Note that no perspective division (by the w component) is executed here. The w components are stored separately into the matrix W:

$$W = \begin{bmatrix} w_0 & 0 & 0 \\ 0 & w_1 & 0 \\ 0 & 0 & w_2 \end{bmatrix} \tag{3}$$

where w_0, w_1, and w_2 are the w components of M_{p_0}, M_{p_1} and M_{p_2}, respectively. During rasterization, the attributes of the points inside the triangle are calculated by interpolating screen coordinates. We denote the screen space interpolation parameters (barycentric coordinates) as:

$$T_s = \begin{bmatrix} \alpha \\ \beta \\ \gamma \end{bmatrix} \tag{4}$$

The correct interpolation parameter should be an interpolation parameter T_w in world coordinates:

$$T_w = \begin{bmatrix} \alpha_w \\ \beta_w \\ \gamma_w \end{bmatrix} \tag{5}$$

Therefore, T_w exists because the projection transformation maps lines to lines and surfaces to surfaces. In this paper, the point after T_w interpolation in world coordinates is called the T_w interpolation point. Name its w component w (* can be any number):

$$PT_w = \begin{bmatrix} * \\ * \\ * \\ w \end{bmatrix} \tag{6}$$

With these definitions, we can write the interpolation equation for the interior points of the triangle:

$$MPW^{-1}T_s = M(PT_w)w^{-1} \tag{7}$$

Simply put, any T_s interpolation point in screen space has a corresponding world coordinate interpolation point T_w. The T_w interpolation point is transformed into the screen space and becomes the T_s interpolation point. Solving for T_w with this equation, we can interpolate to get the correct u, v value:

$$\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} u_0 & u_1 & u_2 \\ v_0 & v_1 & v_2 \end{bmatrix} T_w \tag{8}$$

Among them, u_i and v_i are the u and v attributes of point P_i. According to mathematical derivation, the interpolation parameters of perspective transformation are $T_w = W^{-1}T_s/w^{-1}$.

All the values required in this formula can be obtained through the object integration search algorithm to filter the adjacent detection area ratio, distance ratio, and other parameters calculated in screening the detection frame. Using this interpolation parameter, the original image can be transformed with perspective correction, thereby improving the detection accuracy.

IV. Experiments and Results

A. Endpoint Search Algorithm

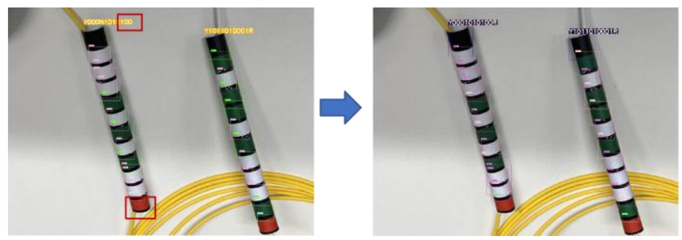

Fig. 3. The endpoint search algorithm uses before-and-after maps.

For the specific scene of color ring label recognition, we limit the end bits and the number of bits of the object detection result according to the characteristics of the color ring label. Figure 3 shows the optimized endpoint search algorithm. It can be found that the end bit of the first color ring of the graph is misidentified. After using the optimized endpoint search algorithm, the end bit is fixed to the value R, and the combined result is corrected.

B. Reverse Search Algorithm

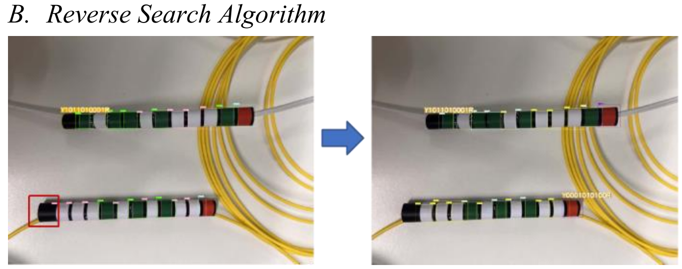

Fig. 4. The endpoint search algorithm uses before-and-after maps.

The object integration search algorithm is based on finding the start bits of a series of objects. If the object detection result is not good enough, the first round of object integration search algorithm does not find the start bit object that meets the threshold range and may miss detection. Given this situation, we consider using the end bit as the start point of a series of objects to perform a reverse search, which effectively solves this problem and improves accuracy. It can be seen in Figure 4 that the starting position of the color ring at the bottom of the left picture is not recognized due to the threshold and consequently, the entire color ring is not detected. The reverse search algorithm is added in the right picture, and both color rings are correctly identified.

C. *Threshold Adaptive Adjustment Algorithm*

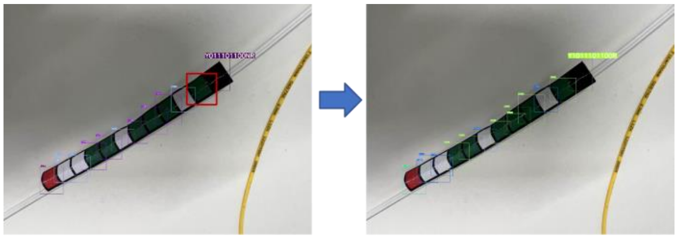

Fig. 5. The threshold adaptive adjustment algorithm uses before-and-after maps.

In Figure 5, there is insufficient light in some part of the object to be detected, which affects the confidence of the object detection result, causing the missing value of the color ring in the left picture during recognition, which affects the overall information expression. In response to this situation, we use the threshold adaptive adjustment algorithm to gradually reduce the confidence range with a step size of 0.05. When the range is reduced to 0.4, the complete color ring is recognized, effectively improving detection accuracy.

D. *Rotation Perspective Correction Algorithm*

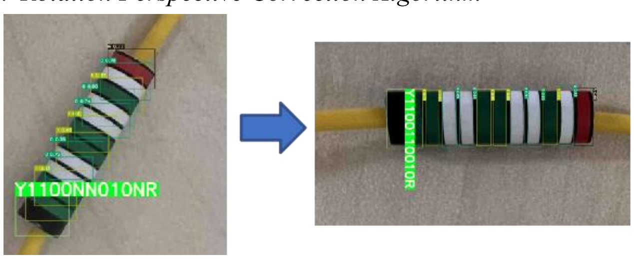

Fig. 6. The rotation perspective correction algorithm uses before-and-after maps.

The classic object detection networks can only generate positive rectangular box predictions, which is suitable for natural objects such as cats and dogs. However, they usually cannot effectively detect oblique quadrilaterals. For tilted color rings, to completely frame the color ring, it will inevitably contain some irrelevant information (noise). This is especially obvious on small-sized color ring objects, and more than 60% of the area is invalid. It can be seen in Figure 6 that the color ring label in the left picture is inclined, so the effect of object detection is inferior, i.e., many wrong and missing detections occur, and the overall recognition effect is not good. After the rotation perspective correction algorithm, the image is corrected. The effective information in the corresponding detection box is increased, and the detection effect is obviously improved.

E. *Results*

After integrating all the previous algorithms and processing the 200 images in the test set, the changes of the model's accuracy and false positive rate are shown in Table 1. Under the premise that the consumption time does not increase much, the overall prediction effect has been greatly improved.

TABLE I. COMPARISON BEFORE AND AFTER PROCESSING

Processing	Recognition accuracy	False positive rate(FPR）
Before	64%	15%
After	97%	1%

V. CONCLUSIONE

Post-processing of video images is essential to the whole video image detection, especially for continuous objects; excellent post-processing algorithms can significantly improve detection accuracy. This paper proposes a video image processing method for continuous objects, including an object integration search algorithm based on a priori information such as angle, size, intersection over union (IoU), head and tail information, etc., which can take advantage of the consistency of these parameters. The continuity of the control object ensures the integrity of continuous object detection; it includes a post-processing algorithm for rotation correction, which can use the angle, size, and other information to rotate the perspective to correct the tilt deflection of the object and improve the tilt, rotation, and distortion of the object. The detection situation, to a certain extent, solves the problem of poor object detection for non-rectangular object detection, improves the accuracy and detection rate of image detection through the integrity and continuity of the object, and ensures the robustness of the model; it also includes A post-processing algorithm with adaptive threshold adjustment is proposed. This algorithm enables the model to adaptively adjust the confidence threshold when the environment changes, as long as specific head and tail information can be provided and the integrity of the continuous object is used to achieve the generality of the object detection method for different environments.

The method proposed in this paper is applicable to most of the existing object detection techniques. With the rapid development of 5G technologies and the widespread popularization of AI technology, object detection technology is used in a large number of AI quality inspection and AI monitoring scenarios. The video image processing method proposed in this paper can greatly improve the accuracy of object detection and detection. In summary, we believe that this innovative algorithm can make contribution in a wide range of scenarios and create promising commercial value.

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