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A FAST AUTOMATED VISION SYSTEM FOR CONTAINER CORNER CASTING RECOGNITION

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Key words: computer vision, histograms of oriented gradients, support vector machine, corner casting, container port, port automation.

ABSTRACT

With the development of container port automation, the automated vision systems for containers have been widely used in automated ports. This paper presents a rapid automated vision system for container corner casting recognition. The histograms of oriented gradients (HOG) descriptors are used to preprocess the image of the container and the vectors of HOG are then built. A trained support vector machine (SVM) classifier is applied to recognize the right corner casting of the container. At last, through symmetry, a flipping mirror algorithm is used for quick left corner casting recognition. The experimental results show this algorithm scans and detect the two corner castings of the container almost twice as fast as the traditional algorithms.

I. INTRODUCTION

In recent years, automated container ports have become the focus in port construction all over the world. Port cranes, as major engineering machines, began to require full automation and intelligence. In most early automated container ports, such as the Shanghai International Port in China (Xie, 2005), the cranes can be guided automatically by encoder positioning, which is not flexible and inefficient. Unlike the cranes in container ports that were built more than 10 years ago, the latest cranes should be intelligent and unmanned. The cranes should be flexible and efficient. More and more researchers and engineers have developed many different ways to achieve automated and flexible guidance for port cranes.

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The vision systems are the most popular ways to guide the port cranes to load and unload containers automatically. Laser vision systems were applied to port automation in the early stages. Yan (2006) started to use a laser measurement system (LMS) as the key vision measurement system for an automated ship loader in Luojing Bulk Port in Shanghai (Yan, 2006). Mi et al. (2013, 2015a) studied the point cloud images generated by LMS for ships, then developed fast algorithms that could recognize and position the ship cargo holds. Shanghai Zhenhua Heavy Industries Co. Ltd, which is the biggest port crane manufacturer in the world, has also developed an automated container position system that is mainly based on laser vision (Zheng, 2012). It also applied laser vision systems for container positioning at the Xiamen Ocean Gate Container Terminal, which was the first fully automated container port in China. However, although laser vision systems are highly accurate and easy to process, they have some disadvantages, which may cause them to be inefficient. The laser vision systems can scan only one plane of the target during a scanning cycle. Therefore, most laser vision systems should be connected with servo mechanisms in order to implement multi-plane scanning (Zheng, 2012). If a laser vision system must scan the whole target, it may be inefficient, because the servo mechanism requires much time.

With the development of computer hardware, an icreasing number of researchers and engineers have started to use image vision systems to position and recognize targets. Image vision systems were first used to recognize the symbols on containers. Wu and some researchers started to use image vision to recognize the container codes (Wu, 2012, 2015; Kumano, 2004). As image vision systems were beginning to be applied at container ports, more and more researchers and engineers used image vision solutions to meet different requirements of automated ports. Mi and some researchers solved the port personnel safety problems using image processing (Mi, 2014; Mi, 2015b). Yang and some researchers used image vision systems to improve the operation for cranes (Shapira, 2008; Yang, 2012). Peng (2012) studied the improvement of cranes' operation based on image vision. These image vision systems were used to track and evaluate the cranes' operations. Many researchers are focusing on the auxiliary functionalities of cranes, such as personnel safety and operation tracking, while other researchers focus on crane automation. Kim and some

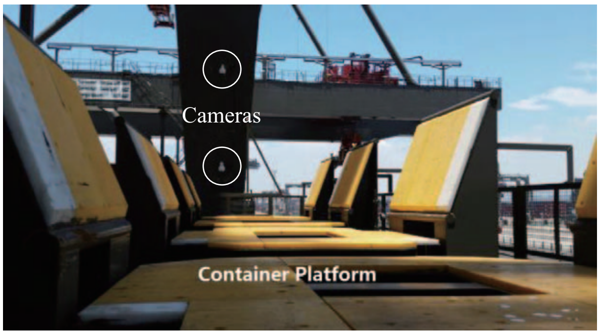

Fig. 1 Cameras for container checking in the automated crane.

Fig. 2 The lower two corner castings of front container image.

researchers developed an anti-sway control method using image vision (Kim, 2003; Sano, 2010). Park (2006) implemented an automated landing system for container cranes based on image processing. These image vision systems track big targets, such as container trucks and spreaders. However, the problem of quick tracking and positioning the small and key targets is still difficult to be implemented using vision systems. Yoon (2010) tracked and positioned the hanging holes of containers using image vision. In Yoon's method, the edges of container should be recognized first, and the holes at the corners can be then positioned. Therefore, this method cannot directly recognize and position small hanging holes. For automated container ports, the recognition of accessory devices of containers is very important for automated cranes. However, little research has been conducted for that purpose.

As shown in Fig. 1, at present, through the cameras, the container checking task in automated crane should be finished using remote manual operation. Due to the lack of the recognition technology for the accessory devices of containers, the checking takes much time. This paper presents a method to recognize the corner castings of containers, which are the important accessory devices of containers. Based on the accurate positions of corner castings of containers, the container checking systems can calculate the positions of other key accessory devices and check them automatically. Compared to early algorithms, this method can directly and quickly recognize the targets without requiring any edge detection or other image preprocessing.

II. CORNER CASTING DETECTION ALGORITHM

The corner casting detection is made up of four phases: feature extraction, classifier training, right corner casting multi-scale detection, and the left corner casting detection via mirror transformation.

1. HOG Feature Extraction Algorithm

The corner casting feature of a container is described by the HOG feature in this paper (Dalal & Triggs, 2005). Compared to other features, there are many reasons to use HOG features in this paper:

1) The edge structural features of corner casting are significantly different from the other structures in container images, so the HOG feature can clearly describe the local shape information and contour features of the corner castings of containers.
2) In fact, the target container usually has a certain degree of translation and rotation in its camera frame. The influence of this can be suppressed by the HOG feature.
3) Light levels change greatly in the port environment. The HOG feature can maintain great invariance to the optical features of corner casting of containers because it operates at the local cell level of images.

The HOG feature was first used for human detection in Dalal and Triggs (2005). However, the traditional training for human detection can only gain a little useful specific features because the HOG feature is based on edge shape and all kinds of human postures and shapes will lead to different complex edge shapes. In this paper, only the lower two corner castings need to be detected in an image of the front of the container. As shown in Fig. 2, the lower two corners of a container are similar and symmetrical. Compared to the complex features of human bodies, the lower two corner casting features are more obvious, and a higher detection rate can be theoretically obtained. According to Dalal and Triggs (2005), the HOG feature is extracted by computing the statistical data of the local gradient direction of an image. A detailed description of each of these steps follows.

1) Standardization of Color Space

Image noise is proportional to the square root of the light intensity in the strong light environment of a port, which can be suppressed by a square root compression gamma correction operation. The standardized pixel values of three channels, $R_{x,y}$, $G_{x,y}$, and $B_{x,y}$ can be calculated using Eq. (1):

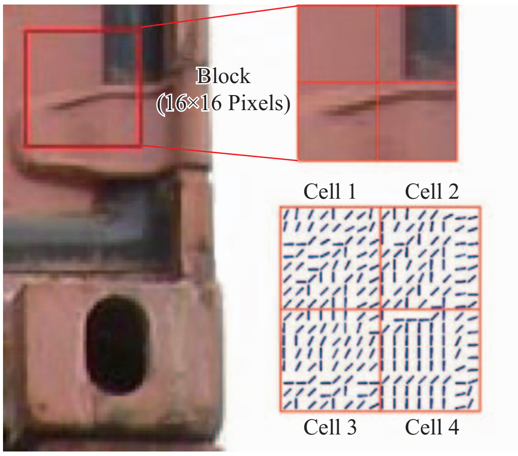

Fig. 3 Shematic illustration of the HOG descriptor.

$$R_{x,y} = \sqrt{r_{x,y}}$$

$$G_{x,y} = \sqrt{g_{x,y}}$$

$$B_{x,y} = \sqrt{b_{x,y}} \quad (1)$$

Where, $r_{x,y}$, $g_{x,y}$, and $b_{x,y}$ are the original pixel values of the red, green, and blue channels, respectively, and the subscript x, y represents the pixel coordinates.

2) Computation of Image Gradient

In this paper, the image gradient will be calculated using a one dimensional discrete differential template according to Eq. (2) and Eq. (3):

$$\nabla f_{x,y} = \sqrt{G_x^{\,2}(x,y) + G_y^{\,2}(x,y)} \quad (2)$$

$$\theta_{x,y} = tan^{-1}(G_y(x,y)/G_x(x,y)) \quad (3)$$

$\nabla f_{x,y}$ and $\theta_{x,y}$ are the gradient magnitude and gradient direction of pixel points x and y, respectively. $G_x(x, y)$, $G_y(x, y)$ indicate the component of the gradient magnitudes of pixel points in the x and y axis, which can be calculated by Eq. (4):

$$G_x(x,y) = f_{x+1,y} - f_{x-1,y}$$

$$G_y(x,y) = f_{x,y+1} - f_{x,y-1} \quad (4)$$

Where, $f_{x,y}$ is the value of pixel point x, y.

3) Block HOG Feature Extraction

As shown in Fig. 3, the whole image is scanned by a 16 × 16 pixels block, which is divided into four 8 × 8 pixels cells. The gradient direction is divided into 9 parts called bins. The gradient direction of each point in a cell is discretized into these bins in order to extract the cell HOG feature vector using a tri-linear interpolation method. A 36 (= 4 × 9)-dimensional HOG feature vector can be extracted from each block.

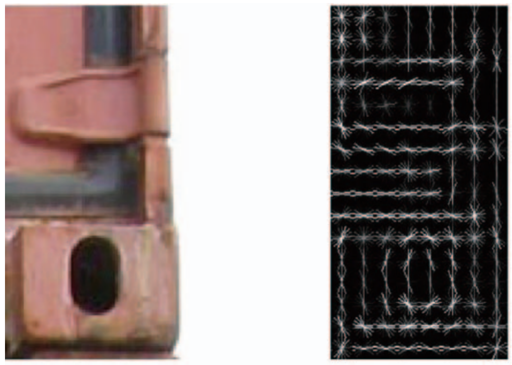

Fig. 4 HOG features of a corner casting.

4) Contrast Normalization

In order to further reduce the effect of the background illumination and edge mutation, the HOG feature of each block needs to be normalized by L2-Norm function using Eq. (5).

$$v \leftarrow \frac{v}{\sqrt{\|v\|_2^2 + \varepsilon^2}} \quad (5)$$

Where, ε is a very small number used to avoid division by zero.

5) Image HOG Feature Extraction

Finally, all block HOG feature vectors of the whole image are saved and connected to form a 3780-dimensional feature vector. After the steps above are complete, the HOG feature vector of the corner casting of container is obtained, as shown in Fig. 4.

2. SVM Classifier Training

SVM is used to detect the container corner casting due to its ability for machine learning and classification. Cortes and Vapnik (1995) first proposed SVM in 1995. It has obvious advantages in solving small data sets and nonlinear and high dimensional pattern recognition problems.

In detecting corner casting, an SVM classifier aims to find a hyper-plane in the 3780-dimensional feature space, which is able to classify positive and negative samples correctly and maximize the geometrical margin of classification. As shown in Fig. 5, the plane H_1 and H_2 is parallel to hyper-plane H, which passed through the sample points closest to hyper-plane H. The distance between plane H_1 and plane H_2 is called the maximum margin, and the features of the sample points on planes H_1 and H_2 are support vectors. The equation of the hyper-plane can be formulated with Eq. (6).

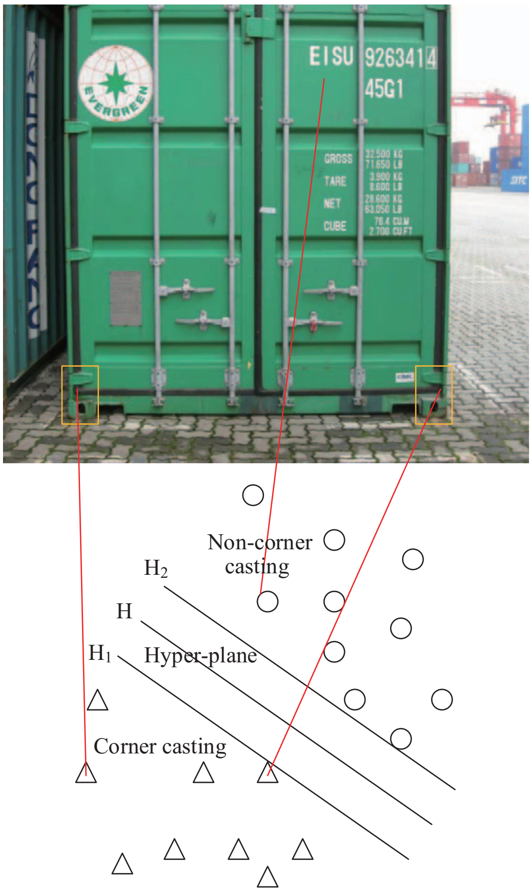

Fig. 5 Shematic illustration of SVM classifier.

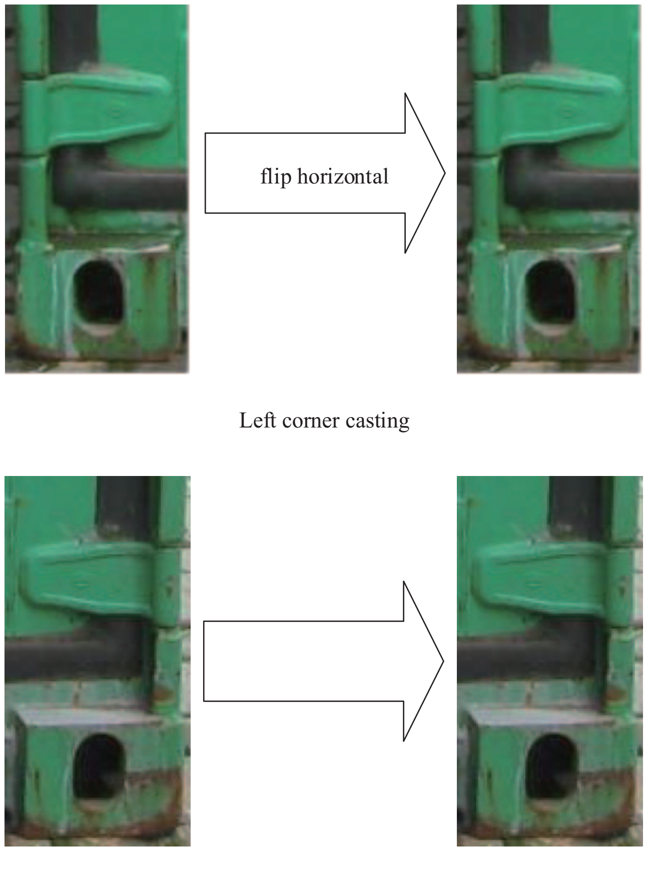

Fig. 6 The unity of the two corner castings.

$$w^T x + b = 0 \tag{6}$$

During the container handling process at a port, the lower corner castings need to be detected. As shown in Fig. 6, the left corner castings must be horizontal flipped to become the type of the right corner casting. Otherwise, the two types of positive samples may result in inaccurate detection.

The sample sets are collected in the container handling area in Taicang port. The SVM training process is as follows:

Step 1: Preprocessing of Samples.

According to the images captured in the handling area, the lower two corner castings are kept by a window size of 64 × 128 pixels, as positive samples. Of course, the left corner casting must flip horizontally, like in Fig. 5. Besides the corners, the other place of the container can be kept by the same size window, as negative samples. The HOG feature space of samples need to be mapped to a higher-dimensional feature by using a radial basis function (RBF), as shown in Eq. (7).

$$K(x, x_c) = e^{(-\|x-x_c\|^2/(2\sigma^2))} \tag{7}$$

Where, x is a feature vector in the feature space and x_c is the position of the center of kernel function. The width parameter σ of the function can control the radial scope of impact from the kernel function. The HOG feature space of samples can be linearly separated using this mapping.

Step 2: HOG Feature Extraction.

The positive samples will be labeled as $y_i = +1$, and the negative samples will be labeled as $y_i = -1$ Then the 3780-dimensional HOG features of each sample will be extracted.

Step 3: Initial SVM classifier training.

The HOG features extracted in Step 2 are used to obtain the initial SVM classifier. As shown in Fig. 5, the two hyper planes of the initial SVM classifier can be generated through objective functions and constraint functions, as shown in Eq. (8).

$$\begin{cases} \min \frac{1}{2}\|w\|^2 + c\sum_{i=1}^{l} \zeta_i \\ s.t: y_i \cdot (w^T x_i + b) - 1 \geq 0 \ (i = 1, 2, \ldots, l) \end{cases} \tag{8}$$

Where, c and ζ_i represent the punishment factor and slack variables, respectively, which can increase the fault tolerance of the SVM classifier. l is the number of samples, and y_i indicates the label value of $x_i \cdot w$ represents a combination of feature vectors, which can be calculated by Eq. (8):

$$w = \alpha_1 x_1 y_1 + \alpha_2 x_2 y_2 + \cdots + \alpha_n x_n y_n \tag{9}$$

Where, α are Lagrange multipliers, and n is the size of sample sets.

Step 4: Hard example.

Detecting corner casting in negative samples with the initial SVM classifier will lead to some erroneous results, which are called hard examples.

Step 5: Final SVM classifier training.

The HOG features of the hard examples will be extracted to combine the initial HOG features as the new HOG feature space. Then, the final SVM classifier can be trained by the new HOG feature space.

3. The Right Corner Casting Detection

After the completion of the classifier training, the SVM classifier can be used to detect the right corner casting. Each part of the whole image needs to be scanned at multi-scales in order to detect the right corner casting. However, it will take a lot of time to zoom in/out and scan all the positions of the image.

The camera takes the container images from the front angle; thus, the container is basically bilaterally symmetrical in the image. According to the vertical center line, the image can be divided into two parts in order to detect the right corner casting by the SVM classifier in the right part directly.

If the multi-scales detection is used for each corner casting, the detection efficiency must be maintained at a lower level. Therefore, a corner casting fast search algorithm is proposed in this paper in order to scan the image quickly and detect the left corner casting according to the symmetry of the container. This algorithm aims to find out the possible position range of the left corner casting in the original image, which can save a lot of time for the left corner casting detection.

III. CORNER CASTING FAST SEARCH ALGORITHM

Detecting the left corner casting in the same way is very time-wasting for two reasons:

1) The detection window is used to scan at multi-scales, which is repetitive and redundant during the second detection. Furthermore, multi-scale corner casting detection will take a lot of time.
2) It is also repetitive and time-consuming to intensively scan each part of the image twice.

Therefore, the fast search method proposed by this paper must be applied before the original detection algorithm in order to save time. The left and right corner castings are located in the left and right halves of the image, respectively, because the container is located in the middle of the image in actual scene. Hence, the left corner casting can be located by the right corner casting detection. The detailed description of each step follows.

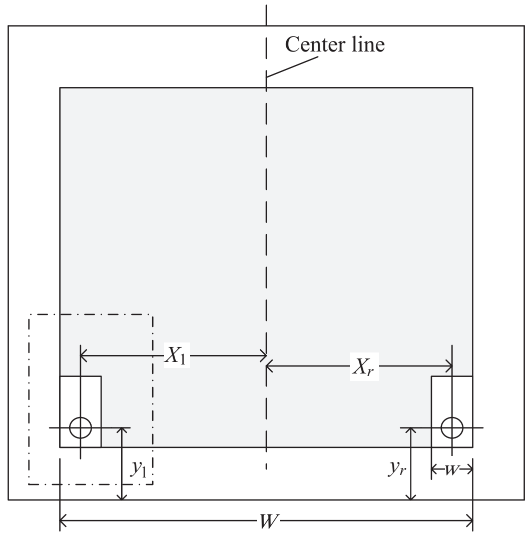

Fig. 7 Shematic illustration of corner casting fast search principle.

Step 1: At first, the actual width of the corner casting is w, as shown in Fig. 7. When the right corner casting is detected in a certain scale, the pixel width (n) of the corner casting can be obtained. The ratio factor (α) between n and w can be calculated by Eq. (10).

$$\alpha = \frac{w}{n} \tag{10}$$

Using the ratio factor (α), the pixel number can be converted into the actual length in the certain scale. Therefore, the horizontal distance (x_r) from the right corner to the center line can be calculated using Eq. (11), and the vertical distance (y_r) from the right corner to the bottom of the image can be calculated by Eq. (12).

$$x_r = \alpha n_{rx} \tag{11}$$

$$y_r = \alpha n_{yx} \tag{12}$$

Where, n_{rx} and n_{ry} represent the number of pixels from the right corner casting to center line and the bottom of the image.

Step 2: According to the standard width (W) of a container and the distance (x_r), as shown in Fig. 7, the horizontal distance (x_l) between the left corner casting and the center line can be obtained by Eq. (10), and the vertical distance (y_l) is equal to y_r.

$$x_l = W - x_r - w \tag{13}$$

Table 1 Experimental results.

Algorithm	Right corner casting detection	Left corner casting detection
Image number	500	500
TRUE	821	829
Undetected	5	3
FALSE	17	15
Accuracy	97.39%	97.87%
Time	254 ms	28 ms

Fig. 8 The experimental results of corner casting detection.

Step 3: The left corner casting position may be inaccurate due to the actual position of the camera. As we know, the corner casting can only be detected at a certain scale, so the position range of the left corner casting cannot exceed the scale factor λ, as shown in Eq. (14).

$$\begin{cases} x_l' \in (x_l / \lambda, \lambda x_l) \\ y_l' \in (y_l / \lambda, \lambda y_l) \end{cases} \tag{14}$$

Step 4: Finally, the left corner casting can be detected on the specified position of the maximum range. This corner casting fast search algorithm can improve the detection speed because of the large reduction of the scanning area in the image.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

At the container terminal of Taicang Port, the corner casting detection system has conducted some tests in an operation field. Fig. 8 shows the results of tests and the red rectangle blocks are the recognized corner castings.

According to the field test results, this algorithm performs well in terms of corner casting detection. About 500 images of the field scene were randomly selected to perform evaluations of the corner casting detection algorithm. The test results are shown in Table 1.

There might be several corner castings in an image, so the corner casting number is greater than the image number. According to the experimental results shown in Table 1, the detection accuracy is higher than 97%; therefore, it is able to meet the actual demands in a port. In terms of detection time, the right corner casting detection takes about 250 ms, and the left corner casting detection uses only 28 ms due to using the fast search algorithm before detecting. Thus, the corner casting fast search algorithm can save about 88% of the time comparing to the previous method.

The corner casting fast search method proposed in this paper has made a great improvement in detection efficiency.

V. CONCLUSIONS

This paper aimed at solving the problem of container positioning and presented a fast algorithm with which to recognize the lower corner castings of a container in an image. Compared to many other methods applied to automated container loading, this algorithm directly detects the right corner castings by using HOG features and an SVM classifier. Based on the mirror flipping character of the container image, the left corner castings can be recognized much more quickly than the typical multi-scales detection methods.

The experiment results show that the detection rate of the method is high enough to meet the requirement of automatic handling in a port. The fast search algorithm can save about 88% of the time required and meet the demands of real-time detection. Compared to detection without a fast search algorithm, this algorithm can improve the overall efficiency by about 44%.

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