Fast and Reliable Template Matching Based on Effective Pixel Selection Using Color and Intensity Information

Rina Tagami, Hiroki Kobayashi, Shuichi Akizuki and Manabu Hashimoto
Graduate School of Engineering, Chukyo University, Nagoya, Japan

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Abstract: We propose a fast and reliable method for object detection using color and intensity information. The probability of hue and pixel values (gray level intensity values) in two-pixel pairs occurring in a template image is calculated, and only those pixel pairs with extremely low probability are carefully selected for matching. Since these pixels are highly distinctive, reliable matching is not affected by surrounding disturbances, and since only a very small number of pixels is used, the matching speed is high. Moreover, the use of the two measures enables reliable matching regardless of an object's color. In a real image experiment, we achieved a recognition rate of 98% and a processing time of 80 msec using only 5% (684 pixels) of the template image. When only 0.5% (68 pixels) of the template image was used, the recognition rate was 80% and the processing time was 5.9 msec.

1 INTRODUCTION

In recent years, image processing technology and robot vision systems have become increasingly popular in various fields in Japan against the backdrop of a shrinking production workforce and unmanned production sites due to the effects of the COVID-19 pandemic. However, there are strong constraints on the computing resources available on real production lines, and if the method is not understandable to the user, it is difficult to use. Therefore, keypoint matching (KPM) and template matching (TM), which combine simplicity, practicality, and versatility, are frequently used.

The SIFT(Lowe, 1999) method is one of the well-known methods for KPM, and its high cost for generating DoG (Difference-of-Gaussian) images and calculating gradient information has led to improvements for higher speed and accuracy, and various methods have been proposed. AKAZE(Alcantarilla and Solutions, 2011) is one of these methods. It is often used because it is rotation-invariant, robust to scaling, and fast due to the application of a nonlinear diffusion filter. However, since features are extracted each time an image is input, although it is fast, it takes a certain amount of processing time.

In TM, which is a more basic algorithm than KPM, typical matching methods include SAD (Sum of Absolute Differences), SSD (Sum of Squared Differences), and NCC (Normalized Cross-sectional Correlation). However, since matching is performed using all the pixels in the template image, the process is time-consuming and sensitive to small changes in illumination and deformation. Therefore, methods to reduce the number of pixels used, to narrow down the number of search candidates, or to convert pixels to features before matching are considered.

In previous research, there is a method(Dubuisson and Jain, 1994) that uses only edge pixels and calculates similarity based on the basis of Hausdorff distance. There is also a method for detecting edges that change little over time(Xiao and Wei, 2014), and a method that learns the edges and corners of an object and uses a segmented set of edges for flexible matching(Yu et al., 2017). Methods(Dubuisson and Jain, 1994)(Xiao and Wei, 2014)(Yu et al., 2017) are fast because they are edge matching, and methods(Xiao and Wei, 2014)(Yu et al., 2017) are robust to deformation and cluttered backgrounds, but can only be used when the object has sufficient edge information that can be extracted.

In addition to methods that use edge information, there is a method called BBS(Dekel et al., 2015) that measures the similarity of two sets of points by mapping the pixel values of a template image and an input image, and a method called DDIS(Talmi et al., 2017) that is faster than this method. BBS and DDIS are based on nearest neighbor search, and there is another method(Korman et al., 2018) that reduces the number of nearest neighbor searches and improves robustness

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against shielding by using a hashing scheme based on consensus set maximization. However, practical application of this method is difficult because it is not fast enough to enable real-time processing (less than 100 msec).

There is also a method that strategically reduces the number of pixels used to achieve high speed. A method(Korman et al., 2013) uses only pixels that depend on the smoothness of the image, enabling fast matching that is not affected by the size of the template image. A method(Hashimoto et al., 2010) called CPTM (Co-occurrence of Multiple Pixels in Template Matching) expresses the frequency of pixel value (gray level intensity value) pairs occurring as a co-occurrence histogram and uses only pixels with low frequency to achieve both high speed and high reliability. A method(Tagami et al., 2022) called CoP-TM (Color Co-occurrence of Multiple Pixels in Template Matching), which extends CPTM to color information, enables fast and reliable matching for color images. The practical use of co-occurrence histograms is attracting attention, such as in the use of this co-occurrence in similarity calculations(Kat et al., 2018) and as a filter in CNN(Shevlev and Avidan, 2019). However, method(Korman et al., 2013) is not very versatile because of its unreliability in matching high-frequency images, method(Hashimoto et al., 2010) in color images, and method(Tagami et al., 2022)(Kat et al., 2018) in grayscale images. Therefore, we propose a new method that is fast, reliable, and versatile, with matching accuracy that does not deteriorate depending on the image used.

Specifically, we merge the ideas of CPTM and CoP-TM and calculate the probability of occurrence on the basis of two measures: gray-scale information (pixel value) and color information (hue value), We then use only pixels with low probability for matching. The speedup is proportional to the pixel reduction rate, and the use of pixels with low probability of occurrence enables reliable matching because pixels are not used that are invalid for matching due to their high frequency of occurrence, such as background pixels. The advantages of this method are that it does not require the use of a high-end computer, as is the case with learning-based methods, and that it has a short online processing time.

2 CONVENTIONAL METHOD

In this section, we provide an overview of pixel-selective TM and explain the pixel selection methods of the CPTM and CoP-TM methods, which are the basis of the proposed method.

2.1 Overview of Pixel-Selective TM Method

First, in general TM, the template image containing the object to be found is successively matched with the input image by moving the template image onto the input image to determine the best similarity position, as shown in the upper row of Figure 1. In general methods, all pixels in the template image are used for matching with the input image. In contrast, the pixel-selection TM method, as shown in the lower part of Figure 1, expresses the distinctiveness of each pixel in the template image as a map representing the frequency of occurrence. Using this map as an index for pixel selection, only a small number of highly distinctive pixels are pre-selected from the template image and used for matching with the input image.

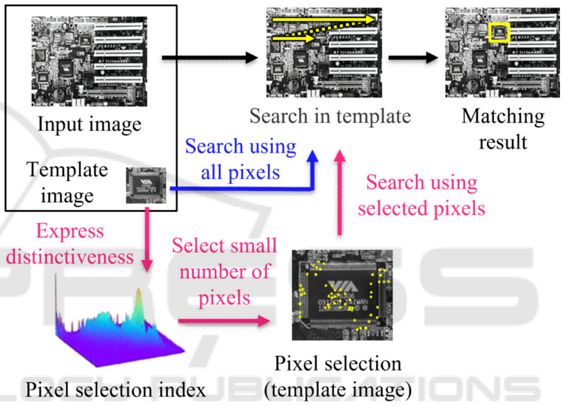
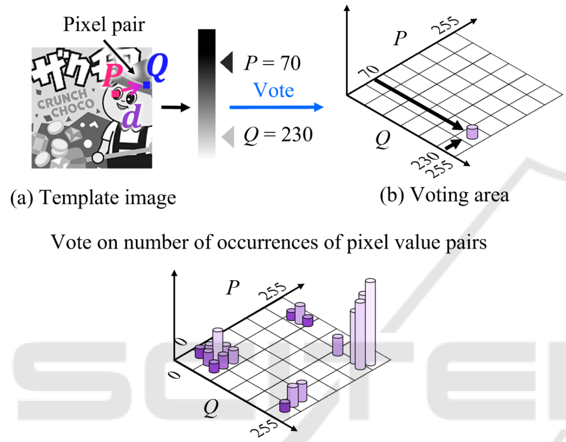


Figure 1: Process of selecting pixels.

2.2 CPTM Method (Based on Pixel Values)

The CPTM method uses a co-occurrence histogram as a measure of the distinctiveness of pixel pairs. In this study, we consider only two-point co-occurrences (pixel pairs) consisting of two pixels (starting pixel P and ending pixel Q) in a template image. First, the pixel pairs are fitted to all locations in the template image as shown in Figure 2 (a), and the number of occurrences is voted into the two-dimensional matrix shown in Figure 2 (b), indexed by pixel values p and q (usually 0 to 255) of P and Q, respectively. In the case of Figure 2, the pixel value p of the starting pixel is 70, and the pixel value q of the ending pixel is 230, which means that a pair is voted on at the coordinate position (70, 230) in the two-dimensional matrix (Figure 2 (b)). After all pixel pairs have been voted on, the pixel value co-occurrence histogram H_g is completed as shown in Figure 2 (c). There are multiple pixel distance patterns in the pixel arrangement (displacement vector $\boldsymbol{d}$) of the starting pixel P and the ending pixel Q. It can be assumed that multiple pixel value co-occurrence histograms are generated according to the pixel distance pattern. $H_g(p, q)$ corresponds to the frequency distribution of the occurrence of pixel pairs with starting pixel value p and ending pixel value q in the template image, and can be treated as a probability distribution. In other words, it can be judged that pixel pairs with large distributions are common, while those with small distributions are highly distinctive, i.e., distinctive pixel pairs. By selecting only such pixels and using them when searching in the input image, fast and reliable matching is possible.



(a) Template image (b) Voting area

(c) Pixel value co-occurrence histogram Hg

Figure 2: Pixel value co-occurrence histogram H_g.

2.3 CoP-TM Method (Based on Hue Values)

While the CPTM method introduced in **2.2** used two pixel values (usually 0-255) as an index to generate a hue value co-occurrence histogram, the CoP-TM method uses hue values, which can represent colors in a single channel, to reduce processing time, and it generates a hue value co-occurrence histogram H_c.

To use hue values in the CoP-TM method, the template RGB image shown in Figure 3 (a) is HSV converted, and 360 hue values from 0 to 359 are used. In the case of Figure 3, the starting pixel P is converted to a hue value of 50 because it is yellow, and the ending pixel Q is converted to a hue value of 320 because it is pink. However, even in the case of a color image, there are a few pixels that are not reliable as color information or cannot be converted to a hue value, so these pixels are assigned a hypothetical hue value of 360.

In other words, in terms of data processing, hue values are expressed in 361 steps from 0 to 360 (when the quantization number k is 360). In this section, the distance between pixel pairs, which was omitted in **2.2**, is explained in detail. First, let $v_P = (x_P, y_P)$ and $v_Q = (x_Q, y_Q)$ be the position vectors of P and Q, respectively, and $\boldsymbol{d} = (k, l)$ be the displacement vector of Q from P. Then, the hue value co-occurrence histogram $H_c(p, q)$ of a pixel pair consisting of these two pixels is defined by equations (1), (2), and (3). The displacement vector $\boldsymbol{d}$ is a vector from the starting pixel P to the ending pixel Q;thus, $x_Q = x_P + k$ and $y_Q = y_P + l$. The displacement vector $\boldsymbol{d}$ can have multiple patterns, and many positional relationships can be expressed by setting various $\boldsymbol{d}$. However, due to processing time and memory requirements, the CoP-TM method and the CPTM method are limited to two directions only, horizontal and vertical. The determination of the distance between two pixels corresponds to expressing the spatial frequency without changing the resolution of the image, and we consider five types of parameters: 1, 2, 4, 8 and 16. That is, $\boldsymbol{d}$ = (+1, 0), (+2, 0), (+4, 0), (+8, 0), (+16, 0), (0, +1), (0, +2), (0, +4), (0, +8), (0, +16) for a total of 10 pixel distance patterns.

$$H_c(p,q) = \sum_{v_P, v_Q \in R^2} \sum \delta(v_P, v_Q, p, q) \tag{1}$$

$$\delta = \begin{cases} 1 & if \quad \{f(v_P) = p\} \wedge \{f(v_Q) = q\} \\ 0 & otherwise \end{cases} \tag{2}$$

$$where, \quad v_Q = v_P + d \tag{3}$$

The hue values p and q (usually 0 to 359) of P and Q, respectively, are used as the vertical and horizontal indices, and the number of occurrences is voted on for one pair in the two-dimensional matrix shown in Figure 3 (b). In the example shown in Figure 3 (b), the starting pixel has a hue value p of 50, and the ending pixel has a hue value q of 320, which means that the pixel is voted on at the coordinate position (50, 320) in the two-dimensional matrix. After all pixel pairs have been voted on, a hue value co-occurrence histogram H_c is completed, as shown in Figure 3 (c). The values of H_c are normalized so that the sum of H_c equals 1, and the co-occurrence probability $P_c(p, q)$ is defined.

3 PROPOSED METHOD

This section describes the proposed method. Basically, it is an extension of the CPTM and CoP-TM methods described in the previous section.

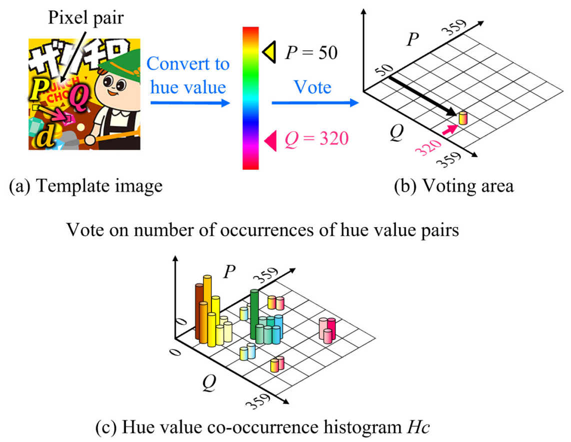


Figure 3: Hue value co-occurrence histogram H_c.

3.1 Pixel Selection

In this section, the pixel selection technique of the proposed method is explained using Figure 4. First, as shown in the upper part of Figure 4, an arbitrary number of pixels is selected using the CPTM and CoP-TM methods. Next, the pixels selected by the two methods are mapped as coordinate information as shown in Figure 4 (a), and the co-occurrence probability of the CPTM method or that of the CoP-TM method is compared for each pixel. The information of the method with the lower co-occurrence probability is labeled for the coordinates, and this process is repeated for an arbitrary number of pixels. In other words, if the CPTM method has a lower probability value, it is labeled 0, and if the CoP-TM method has a lower probability value, it is labeled 1, which is used in the matching described in **3.2**. The final result of pixel selection is shown in Figure 4 (c).

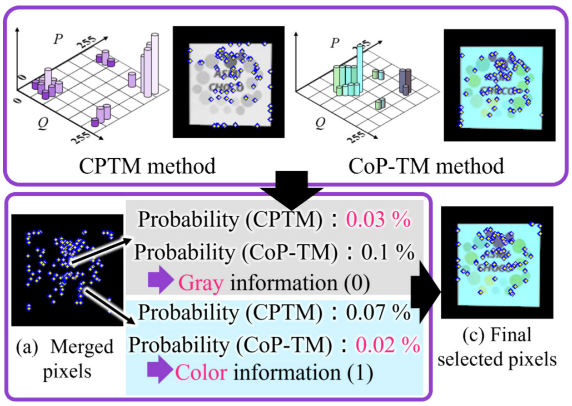


Figure 4: Overview of pixel selection for proposed method.

3.2 Matching Method

Since hue and pixel values are used for pixel selection in the proposed method, they are also used for matching. First, the RGB values of the input image are converted to pixel values and hue and pixel values quantized to 255 steps. Discrete pixels $f(n)$ selected using the co-occurrence probability are stored in a 1D array as $f_G(n)$ or $f_H(n)$, depending on the label $f_R(n)$ in **3.1**, either pixel value or hue value. The i-coordinate and j-coordinate of the selected pixel are also stored as $f_i(n)$ and $f_j(n)$ in a one-dimensional array. The S_{SSD} is calculated by the sum of the squares of the differences between the pixels of the template image displaced by (δ_x, δ_y) from the input image and superimposed on it, using Equations (4) and (5). The value of the input image is $g(i, j)$, and it switches between pixel value and hue value depending on the label $f_R(n)$ of the template image. The number of reference pixels is M. The SSDA method (Sequential Similarity Detection Algorithm), which uses SSD (Sum of Absolute Difference) as an index, speeds up the similarity calculation. The best match position is determined where the calculation results are lowest, i.e., where the similarity is highest. The differences are determined so as not to cause problems with the circular model of hue values.

$$S_{SSD} = \sum_{n=0}^{M-1} (g(f_i(n)+\delta_x, f_j(n)+\delta_y) - f(n))^2 \quad (4)$$

$$f(n) = \begin{cases} f_G(n) & if \quad f_R(n) = 0 \\ f_H(n) & if \quad f_R(n) = 1 \end{cases} \quad (5)$$

3.3 Robust Pixel Selection for Similar Objects

In this section, we expand on the proposed method and explain how to minimize misrecognition even when there are many similar objects around the object.

3.3.1 Basic Idea

Figure 5 shows the flow of this study, which consists of three steps from 1. to 3. 1. First, from the template image, the probability of pixel values and hue values in two-pixel pairs occurring is calculated using the CPTM method described in **2.2** and the CoP-TM method described in **2.3**, respectively, and the pixel with the lowest probability is selected and used as initial pixels. This is expected to reduce mismatches to a certain degree. 2. Next, the discriminative performance of the pixels selected from two sample images prepared in advance is evaluated: the target object images (positive sample) and the similar object images (negative sample). While evaluating the performance using Genetic Algorithms (GA), the pixels selected in 1. are further carefully selected, and the pixels with the maximum performance are used as the final pixels. 3. Finally, similarity is calculated using the matching method described in **3.2**, on the basis of pixels selected in 2. and the input images.

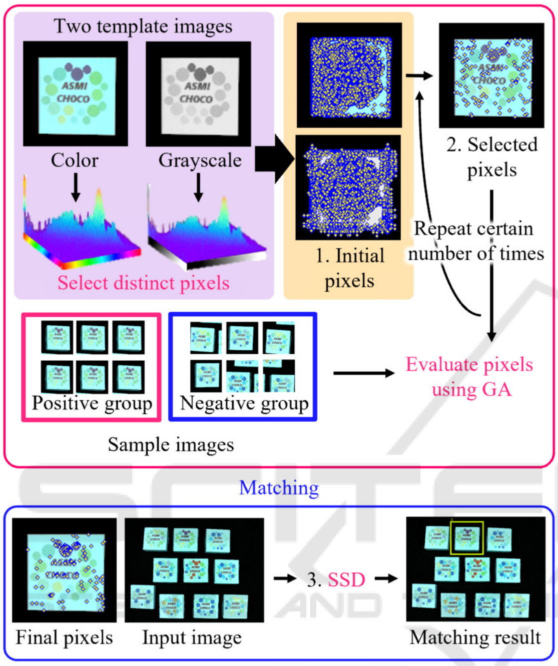


Figure 5: Proposed method robust to similar objects.

3.3.2 Evaluation of Pixel Discrimination Performance

In this study, the discriminative performance of pixels selected from the template image is evaluated using two pre-prepared image groups, as shown in Figure 6 (a). The right image in Figure 6 (a) shows images from which similar object regions are randomly cut out from input images that are assumed to have many similar objects including the target object (negative sample C_N), and the left image in Figure 6 (a) shows images from which target object regions are cut out (positive sample C_P). Specifically, one negative image and one positive image are cropped from a single image. If 200 sample images are prepared for each sample image, no two images will be exactly the same because they are cropped from 200 original images. Figure 6 (b) shows an example of the distribution when the similarity C_i between the selected pixels by 2. in **3.3.1** and these sample images is calculated and converted into the histogram. Using the two evaluation indices D and S calculated from the histogram, the discrimination performance of the selected pixels is evaluated using Equation (6).

$$F = w_1 \frac{1}{S+\varepsilon} + w_2 D \tag{6}$$

The larger the evaluation value F, the higher the discrimination performance, and the smaller the value of D and the larger the value of S, the better. Note that w_1 and w_2 are weight coefficients, and ε is a supplementary coefficient. The two evaluation indices are described in detail below. The first is the degree of class separation D. The class separation D of this method is defined as the difference between the mean values of the positive and negative similarity distributions. The purple line in Figure 6 (b) is the class separation, and the average similarity C_{pos} of the N_{pos} positive samples and the average similarity C_{neg} of the N_{neg} negative samples are calculated using Equations (7) and (8).

$$C_{pos} = \frac{1}{N_{pos}} \sum_{i \in C_P} C_i \tag{7}$$

$$C_{neg} = \frac{1}{N_{neg}} \sum_{i \in C_N} C_i \tag{8}$$

From the difference between C_{pos} and C_{neg}, the class separation D is calculated using Equation (9).

$$D = C_{pos} - C_{neg} \tag{9}$$

The larger D is, the further apart the distributions of the two sample groups are, and thus, the more stable the discrimination by the thresholding process is expected to be. The second is the duplicate area S, which is the duplicate area between the histograms of the two sample groups. The green area in Figure 6 (b) corresponds to the duplicate area, and the existence of this duplicate area indicates the misrecognition rate P_E. The misrecognition rate is the probability of misidentifying a similar object as a target object or a target object as a similar object. The misrecognition rate P_E of the positive sample group C_P and the negative sample group C_N is defined by Equation (10).

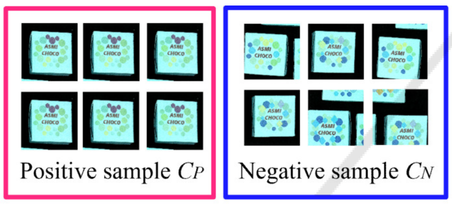
$$P_E = \frac{C_P \wedge C_N}{C_P \vee C_N} \tag{10}$$

$C_P \wedge C_N$ means the area S of the overlap between the positive and negative sample groups. $C_P \vee C_N$ means the total area of both classes minus the overlapped area. The pixels that minimize the misrecognition rate P_E are equivalent to the pixels that minimize S. The smaller this value is, the smaller the risk of misrecognition is considered to be. The area S of the overlapped area of both sample groups is calculated by Equations (11) and (12). The similarity C_i between each sample image and the template image is calculated, and the overlapped area S is calculated. p_{min} is the minimum similarity in the positive sample group.

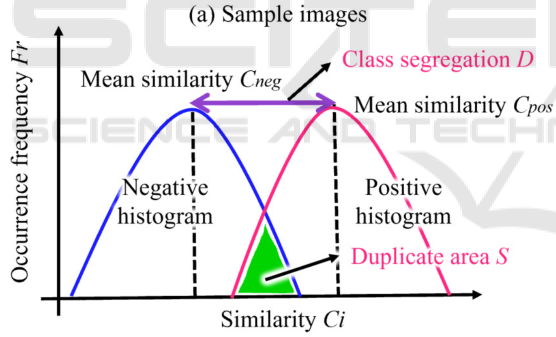
$$S = \sum_{i \in C_N} S_i \tag{11}$$

$$S_i = \begin{cases} 1 & if \quad C_i > p_{min} \\ 0 & otherwise \end{cases} \tag{12}$$

From the above, the pixel with the largest value of F in Equation (6) can be judged to be good. The proposed method generates groups of pixels one after another using GA and evaluates the goodness of the pixels using the above approach. Finally, pixels with a certain level of goodness from a practical standpoint are determined as an approximate solution.



(a) Sample images



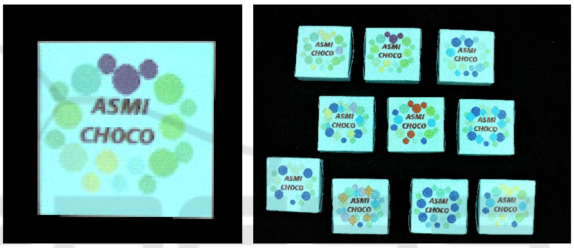
(b) Similarity histograms

Figure 6: Evaluation of discrimination performance.

4 EXPERIMENTS

4.1 Experimental Conditions

Two types of experiments were done: the first was an experiment to verify the pixels selected with the proposed method, and the second was to compare the performance of the proposed method with the base CPTM and CoP-TM methods in order to demonstrate the effectiveness of the proposed method. The objective was to show whether the proposed method can achieve more accurate matching than the conventional methods by using pixels selected by the proposed method. If the matching result was within ±4 of GT, the recognition was considered successful. As other comparison methods, we used the Canny edge detection method(Canny, 1986), the intensity gradient method, random matching, all-pixel matching, AKAZE(Alcantarilla and Solutions, 2011), YOLOv5(Jocher et al., 2020) and BBS(Dekel et al., 2015). Figure 7 (a) shows the template image used in the experiment. The size is 117×117 [pixel], and the target object simulated a box of chocolate candy. In the experiment, 0.1%, 0.2%, 0.5%, 1%, 2%, 4%, and 5% of the 117×117 [pixel] were used as the number of selected pixels. The input image size was 505×379 [pixel], and 100 patterns were prepared. Figure 7 (b) shows an example of an input image used in the experiment. 200 positive and 200 negative samples were used for each.



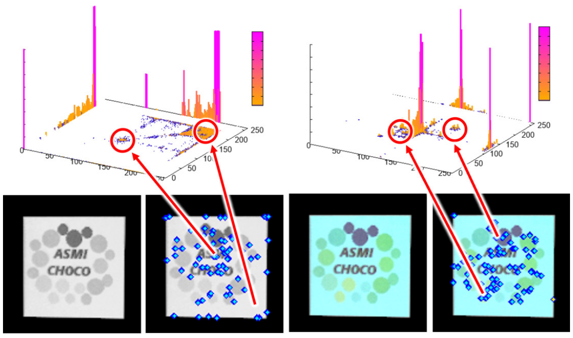
(a) Template image (b) Input image

Figure 7: Template image and input image.

4.2 Result of Selected Pixels

In this section, we show the co-occurrence histograms generated from the CPTM and CoP-TM methods, which are the base methods of the proposed method, and selected pixels (Figure 8). We confirmed that the co-occurrence histograms were correctly generated from the information of the pixels in the template image, and evaluated whether the selected pixels correspond to a distinctiveness distribution in the co-occurrence histograms.

The upper row of Figure 8 (a) shows the co-occurrence histogram generated by the CPTM method, the left side of the lower row shows the template image, and the right side shows the selected pixels. When the template image in Figure 7 (a) was grayscaled, the difference in the intensity of the pattern became less pronounced. Therefore, as shown on the left side of the lower row of Figure 8 (a), the only areas where the difference in intensity was clear were the areas corresponding to the characters and the purple pattern. The probability value of the co-occurrence histogram was high because light gray pixels (blue pixels in the color image) other than characters occupy a large percentage of the template image. The selected pixels were selected from the areas corresponding to characters and edges, and as can be seen from the co-occurrence histogram in the upper row of Figure 8 (a), they have low probability values and were confirmed to be pixels with high distinctiveness.



(a) CPTM method (b) CoP-TM method

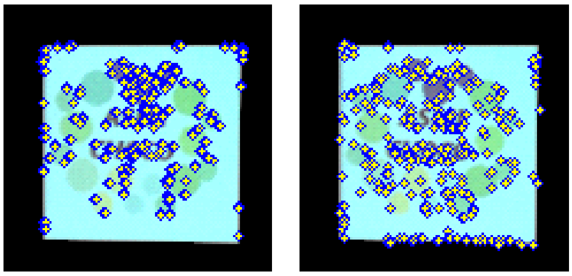
Figure 8: Co-occurrence histogram and selected pixels.

Figure 8 (b) upper row shows the co-occurrence histogram generated by the CoP-TM method, the left side of the lower row shows the template image, and the right side of the lower row shows the selected pixel pairs. The co-occurrence histogram in the upper row of Figure 8 (b) shows that the green and purple pixel pairs have a low probability value and low frequency of occurrence, indicating their distinctiveness. Another feature of this method is that pixels are not selected from the edges as often as the selected pixel by the CPTM method.

Figure 9 shows pixels selected by the proposed method. Proposed method 1 selected pixels using the method described in **3.1**, and proposed method 2 selected pixels using the method described in **3.3.2**. The pixels selected by proposed method 1 in Figure 9 (a) were selected in such a way that they covered both the pixels selected by the CPTM and CoP-TM methods in Figure 8. For example, edge pixels and purple pixels selected by the CPTM method and green pixels selected by the CoP-TM method fall into this category. In addition, the pixels selected by proposed method 2 (Figure 9 (b)) were selected for being robust to similar objects, not only on the basis of the distinctiveness of the template image.

4.3 Performance Evaluation

Figure 10 shows the recognition success rate for each number of selected pixels for the proposed method and the comparison method. Figure 11 shows the processing time when a Ryzen 5 5600X was used as the CPU for each number of selected pixels.



(a) Proposed Method 1 (b) Proposed Method 2

Figure 9: Pixels selected by proposed method.

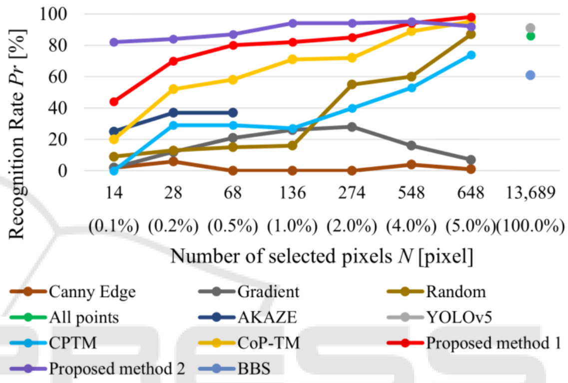


Figure 10: Recognition rate of each method.

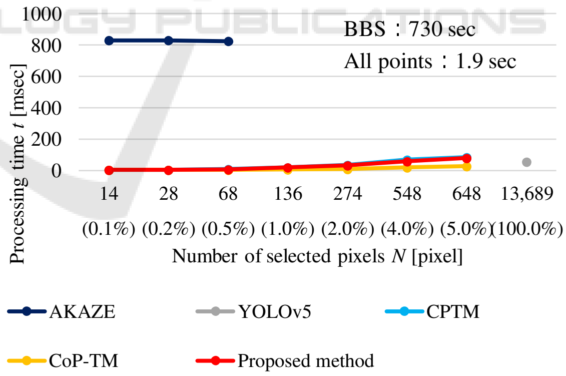


Figure 11: Processing time of each method.

The processing times for the Canny edge detection method, the intensity gradient method, and random matching were omitted because the CoP-TM method was used as the matching index. Since the number of keypoints in AKAZE and the number of pixels that can be judged as edges in the Canny edge detection method are limited, the recognition results are shown within the possible range. Proposed method 1 achieved a higher recognition rate than the compared methods for all conditions of the number of selected pixels. Figure 11 shows that proposed method 1 achieved reliable matching in almost the same processing time as the CPTM and CoPTM methods. Figure 10 and 11 show that proposed method 1 achieves the same performance as YOLOv5 despite its short off-line processing time (3 [sec]), with a processing time of 58 [msec] and a recognition success rate of 94%, while YOLOv5, a comparative learning-based method, had a processing time of 55 [msec] and a recognition success rate of 91%. The results of proposed method 2, shown in Figure 10, confirm that preferentially selecting pixels that are robust to similar objects is effective in improving the recognition rate.

5 CONCLUSIONS

In this study, we proposed fast image matching method that uses only effective pixels for matching on the basis of two measures from color and grayscale images. Experiments using 100 real images showed that when approximately 0.5% (68 pixels) of the 117×117 template image was used, the recognition success rate was 80% and the processing time was 5.9 msec. When 5.0% (648 pixels) was used, the success rate was 98% and the processing time was 80 msec, confirming that both high speed and high reliability are possible. The recognition rate of proposed method decreases in the presence of disturbances such as rotation, illumination change, and shading. We would like to improve the method by adding images that include highlights and illumination changes to the positive samples and by improving the pixel selection algorithm. In addition, since we used our own datasets for this experiment, we would like to experiment with public datasets(Wu et al., 2013) in the future.

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