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Electrical Engineering in Japan, Vol. 154, No. 4, 2006
Translated from Denki Gakkai Ronbunshi, Vol. 125-C, No. 1, January 2005, pp. 57–66

Detection of Object under Outdoor Environment by Matching with Partial and Whole Templates

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SUMMARY

This paper proposes the technique of augmented template matching that positions the object having a standard shape of two dimensions under the outdoor environment. The intensity of the object under the outdoor environment usually changes in various ways. The main reason is that the lighting condition changes, and the surface properties of the object change. It is difficult to apply the conventional template matching under the outdoor environment, because conventional template matching assumes the lighting condition does not change and the surface properties of the object do not change. Then, the partial template made by dividing the conventional template (the whole template) to increase information on the object to discriminate the object under the outdoor environment is introduced. The proposed technique is to calculate similarities with the partial and the whole templates, and to judge by the linear discriminant method. In this paper, the principle of the proposed technique and effectiveness based on the experimental result are shown. © 2006 Wiley Periodicals, Inc. Electr Eng Jpn, 154(4): 49–60, 2006; Published online in Wiley InterScience (www.interscience.wiley.com). DOI 10.1002/eej.20270

Key words: template matching; partial template; whole template; linear discriminant method; outdoor environment.

1. Introduction

Template matching is a method of searching for a similar area from an unknown image in each pixel to the object (template image) having a standard shape of two dimensions registered beforehand [1]. This method is very useful because it is used to position and to inspect parts of the production line of the factory [2].

Template matching is a technique for evaluating an unknown image on average based on the only criterion of similarity. However, it has the problem of receiving the influence of disturbance easily. The influence of disturbance does not become a problem under the indoor environment such as in factories, because environmental conditions such as lighting can be adjusted there. In contrast, it is difficult under the outdoor environment to adjust environmental conditions such as lighting in general. Moreover, there are various types of disturbance, including raindrops and dirt. As a result, there is no case that successfully applies the conventional template matching under the outdoor environment.

The authors had proposed the technique for matching an unknown edge image under the outdoor environment with the template of the binary edge image of the object [3]. The edge image is robust to changing the lighting. Therefore, it is thought to be a suitable image for template matching under the outdoor environment. However, when the edge image is matched, the misregistration of the profile line becomes a problem. Then, the edge image is made binary by an appropriate threshold. As a result, the profile line becomes a moderate thickness. Then, robustness improves to the misregistration of the profile line that is the problem of the edge image. However, evaluating an unknown image on average based only on the criterion of similarity is the same as conventional template matching and is inadequate from the standpoint of practical use.

On the other hand, Rumelhart introduced the finding of "recognition by partial and whole context" in cognitive science [6]. In summary, "the human race recognizes a complex object by interpreting the part and the whole at the same time." The authors thought that this finding might be effective in recognition of the object under the outdoor environment. That is, similarities of partial areas and the whole area are calculated for an unknown image. Then they are integrated and evaluated.

In this paper, the authors propose a technique for detecting the object under the outdoor environment that integrates template matching. First, a conventional template image is called a whole template. Next, some partial templates are made by dividing the whole template. And similarities of an unknown image are calculated with the partial templates and the whole template. Regarding those similarities, it is judged whether it is the object or not by the linear discriminant method [7].

The idea of matching using partial and whole templates has already been proposed for facial recognition [4]. However, this cannot be generalized because the structural elements of the eyes, nose, and mouth are set as partial templates based on human knowledge.

Moreover, the technique for judging the sum total of similarities of partial templates is proposed. The purpose is to reduce the influence of the shield [2]. This technique is different in that a whole template is not used and that the linear discriminant method is not applied to the synthesis of matching results.

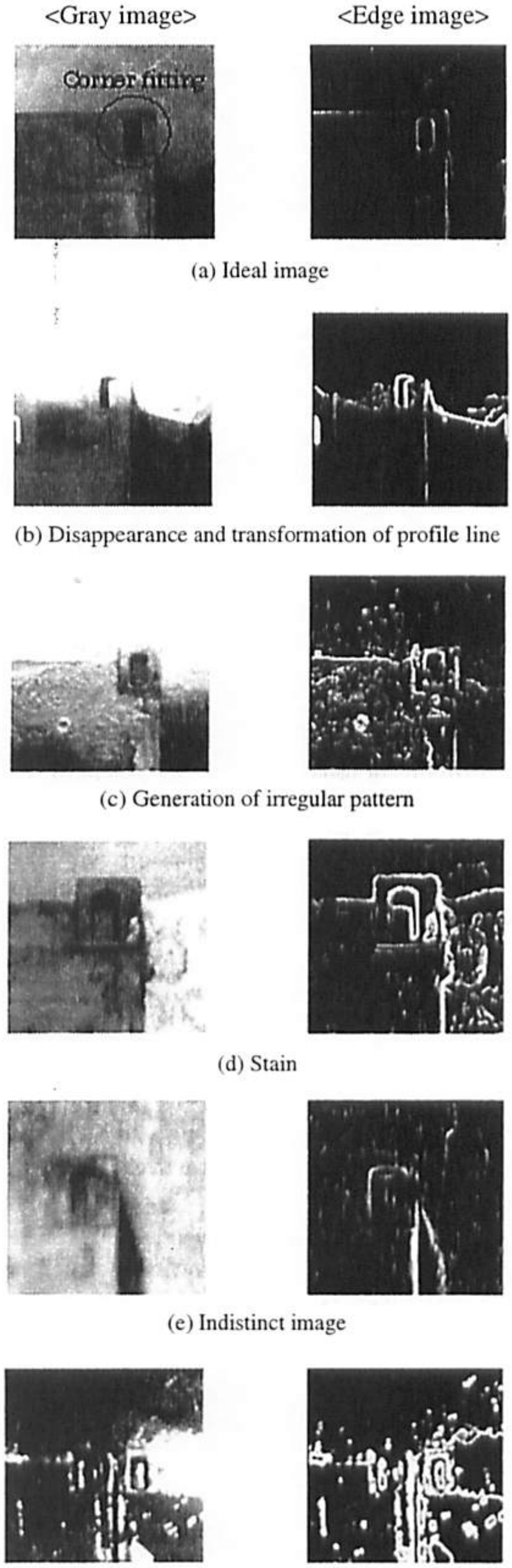
In addition, it differs in that it is not assumed to detect the object under the outdoor environment, unlike the other methods.

Below, the authors develop their argument using the corner fittings of a container as an example for the object under the outdoor environment. Section 2 summarizes the issues involved in matching under the outdoor environment. Section 3 explains the method for detecting the object using partial and whole templates as proposed in this paper. Section 4 demonstrates the effectiveness of the proposed method based on experimental results. Section 5 summarizes the paper and offers topics for the future.

2. Issues Involved in Matching under the Outdoor Environment

A major problem when using template matching under the outdoor environment is that the intensity distribution of the object changes depending on various factors as a result of changes in the lighting conditions and changes in the surface characteristics of the object. As a result, detecting the object is difficult because the similarity with the template images in general decreases.

Changes in the lighting conditions occur as a result of changes in the relative position of the sun and the object and changes in the distribution of clouds. Moreover, changes in the surface characteristics of the object occur due to changes resulting from ultraviolet light over the long term and from the adhesion of water and dirt due to rain in the short term. In particular, the fact that it is difficult to predict changes in the distribution of clouds and the devel-



(a) Ideal image

(b) Disappearance and transformation of profile line

(c) Generation of irregular pattern

(d) Stain

(e) Indistinct image

(f) Reflection light

Fig. 1. Image samples of corner fitting.

opment of stains makes using template matching under the outdoor environment problematic.

Figure 1 shows an example of monochrome images of the corner fittings on the container taken from above the container [5]. The left side of the figure shows the original images (grayscale images), and the right side shows the edge images resulting from differential processing of the original images using the Sobel operator [1]. The container fittings are almost rectilinear on the outside with holes running through the top and two sides. Standard shape of two dimensions can be confirmed when observing them from the upper side.

Figure 1(a) is an image taken under cloudy day time conditions with no effect from the position of the sun. The edge image of the corner fittings consists of the silhouette with elliptical holes. This image has almost no noise and is virtually ideal. Figure 1(b) is an example of the silhouette of the exterior of the container being lost due to sunlight and the silhouette of the holes in the corner fittings changing. Figure 1(c) is an example of the surface characteristics changing due to rain and an irregular pattern appearing on the container as a result of raindrop marks. Figure 1(d) is an example of stains on the surface of the corner fittings. In this image, the silhouette for the holes in the corner fittings has also changed. Figure 1(e) is an example of an indistinct image due to a lack of light at night. Figure 1(f) is an example of reflected light from lighting on the container surface during nighttime rain. Table 1 summarizes these phenomena and the factors involved.

Given the above, it can be confirmed that the intensity distribution of the object's image under the outdoor environment changes in various ways. Therefore, measures against various disturbances as seen in Fig. 1 and Table 1 are necessary to apply template matching under the outdoor environment.

Table 1. Phenomena of disturbance and the factors involved

Phenomena	Factors
Disappearance and transformation of profile line	Positional relation between the sun and the corner fitting
Generation of irregular pattern	Heavy rain
Adhesion of stain	Under the outdoor environment
Indistinct image	Illumination shortage
Reflection light	Rain and illumination

3. The Proposed Method

The authors are proposing a technique for integrating template matching to detect the object with standard shape of two dimensions under the outdoor environment into which the intensity distribution changes in various ways.

First, the basic concept of the proposed technique will be explained. This is the idea in cognitive science of "recognition by partial and whole context" [6]. Based on this idea, the human race recognizes a complex object by interpreting the part and the whole at the same time. The authors thought that this idea might be effective in the recognition of the object under the outdoor environment.

Below, the proposed technique is explained in concrete terms. The proposed technique follows a standard flow in pattern recognition [7]: (1) preprocessing; (2) feature extraction; (3) recognition. In (1) preprocessing, the size and orientation (rotation) of the object are revised and normalized using an affine transformation [1]. In (2) feature extraction, the whole template image and n partial template images of the object prepared beforehand for the preprocessed object image are used to calculate $n + 1$ features (similarities). In (3) recognition, the discriminant score is calculated by substituting the $n + 1$ features into the linear discriminant function prepared beforehand. Finally, whether or not the object image represents the object is determined using threshold processing of the discriminant score.

The above represents an outline of the proposing technique. Note that (1) preprocessing represents standard processing in template matching. Thus, (2) feature extraction and (3) recognition are explained in detail below.

In (2) feature extraction, one whole template and n partial templates are prepared beforehand for the object, and then the features representing the $n + 1$ similarities are calculated.

Conventional template matching is a method to determine whether or not an object represents the object image using one feature calculated using the whole template. This feature is a criterion which evaluates on average the object image overall. However, the intensity distribution of the object under the outdoor environment changes in various ways. As a result, the similarity deteriorates overall, and so detecting the object becomes difficult.

On the other hand, based on the idea of "recognition by partial and whole context," humans recognize a complex object by interpreting the part and the whole at the same time. According to this view, in the past an object image with a varying intensity distribution under the outdoor environment was evaluated using a feature calculated using only the whole template corresponding to an interpretation of the whole.

Thus, the authors conceived of the idea of using some partial templates in order to add the partial interpretation.

However, one major problem is how to create the partial interpretation with respect to the whole interpretation. For instance, one approach is to create the partial template using knowledge related to the object. However, here the authors decided to create n partial templates by dividing the whole equally in the horizontal and vertical directions in the consideration of generality. Figure 2 shows an example of a whole template and four partial templates ($n = 4$). $x_i (i = 1, \ldots, n, n + 1)$ refers to the feature calculated using each template.

The number of partial templates can be determined through learning with the training data. The details will be described later. The technique by interpreting the part and the whole at the same time is described in the section on recognition below.

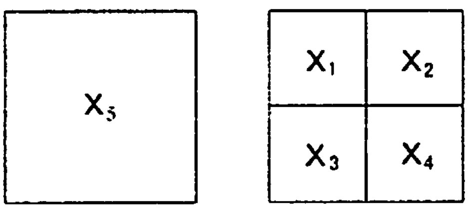
Calculation of the features uses the normal correlation coefficient [1] which is robust and widely used for uniform changes in intensity distribution. The normal correlation coefficient $x(u, v)$ is given as

$$x(u,v) = \frac{\sum_p^P \sum_q^Q (f(u+p,v+q)-\bar{f})(g(p,q)-\bar{g})}{\sqrt{\sum_p^P \sum_q^Q (f(u+p,v+q)-\bar{f})^2}\sqrt{\sum_p^P \sum_q^Q (g(p,q)-\bar{g})^2}} \tag{1}$$

Here, $f(u + p, v + q)$ represents an unknown image, $g(p, q)$ represents the template image, and $\bar{f}$, $\bar{g}$ represent the various average intensities.

In (3) recognition, whether or not the unknown image is the object is determined using the linear discriminant method, a statistical method, for the $n + 1$ features.

The authors decided to use the linear discriminant method as a technique to interpret the part and the whole at the same time. The linear discriminant method is a technique that finds the optimal one-dimensional axis for discriminating two classes from pattern distribution for two classes in $n + 1$ dimensional feature space. This method is explained below [7].



(a) Whole template (Partial templates)

Fig. 2. Example of a whole template and partial templates.

First, let a represent the $n + 1$ dimensional row vector which converts the pattern x in $n + 1$ dimensional feature space to the point z in the one-dimensional space (the discriminant score). Equation (2) is referred to as a linear discriminant function:

$$z = a'x \tag{2}$$

Next, the within-class covariance matrix Σ_W for the $n + 1$ dimensional feature space and the between-class covariance matrix Σ_B are given as

$$\Sigma_W = \sum_{i=1,2} P(\omega_i)\Sigma_i \tag{3}$$

$$\Sigma_B = \sum_{i=1,2} P(\omega_i)(m_i - m)(m_i - m)' \tag{4}$$

Here, $P(\omega_i)$ represents the a priori probability for the class ω_i, Σ_i represents the covariance matrix for the class ω_i, m_i represents the pattern average for the class ω_i, and m represents the overall pattern average.

Thus, using the $n + 1$ dimensional row vector a, the same $\tilde{\Sigma}_W$ and $\tilde{\Sigma}_B$ can be found in the converted one-dimensional space:

$$\tilde{\Sigma}_W = a'\Sigma_W a \tag{5}$$

$$\tilde{\Sigma}_B = a'\Sigma_B a \tag{6}$$

Here, $\tilde{\Sigma}_W$ and $\tilde{\Sigma}_B$ represent scalar quantities because a is a row vector. These quantities are referred to as the within-class variance and the between-class variance in the one-dimensional space after conversion. Because the space after conversion is useful for two-class discrimination, the within-class variance should be as small as possible, and the between-class variance should be as large as possible. Thus, the evaluation function that represents the degree of separation between classes in the space after conversion is set to J_Σ, and the ratio of the within-class variance to the between-class variance is defined. J_Σ can be expressed as a function of the row vector a:

$$J_\Sigma(a) = \frac{\tilde{\Sigma}_B}{\tilde{\Sigma}_W} = \frac{a'\Sigma_B a}{a'\Sigma_W a} \tag{7}$$

The row vector a which maximizes the evaluation function J_Σ can be found as an eigenvector corresponding to the maximum eigenvalue for

$$\Sigma_W^{-1}\Sigma_B$$

However, only the space (axis) is determined by the linear discriminant method. The boundary for discrimination is not decided. Setting up the boundary (threshold) on the axis is discussed in the section on verification experiments.

Separately, the calculation of the row vector a was performing using the training data. The training data consisted of the object and various images not of the object under the outdoor environment. These were normalized for size and rotation during (1) preprocessing. Next, during (2) feature extraction, the $n + 1$ features were calculated by specifying the number of partial templates. Then the row vector a, that is, the linear discriminant function in Eq. (2), was calculated using the procedure described in (3) recognition.

The optimal number of partial templates is that which maximizes the rate (discriminant hit ratio) at which the object is recognized as the object and everything else is not, this after finding the linear discriminant function as described above and evaluating the training data.

Note that the computational load for the $n + 1$ features is twice the number of pixels comprising the whole template, regardless of the number n (> 1) of partial templates. This is because the grand sum for the number of pixels in the partial templates equals data for the whole template. Therefore, there is no difference in the computational load resulting from the number of partial templates.

The proposed technique as described above applies the idea in cognitive science of "recognition by partial and whole context" to template matching. It has the following advantages compared to conventional approaches.

- $n + 1$ features are used as effective partial and whole information for recognizing the object.
- The linear discriminant method, a statistical method, is used to interpret $n + 1$ features at the same time.

4. Experiments

The authors discuss and evaluate the technique proposed in this paper using the results of verification experiments on a sample with the corner fitting on a container as the object under the outdoor environment.

4.1 Preparatory experiments

The authors selected the corner fitting of a container as the object under the outdoor environment. Figure 1 shows images taken near the corner fitting from above the container. Based on Fig. 1, the corner fitting is recognized as having a two-dimensional standard shape.

Figure 3 shows template images of the corner fitting [3]. Figure 3(a) represents a gray image template. Figure 3(b) represents an edge image template, which is created by differential processing of the gray image using the Sobel operator. Figure 3(c) represents a binary edge image template, and is created through binary processing of the edge image in Fig. 3(b). Here, the binary edge image in Fig. 3(c) is decided as the standard whole template. Its size is 45 pixels high by 41 pixels wide, with 1 pixel equivalent to roughly 4 mm.

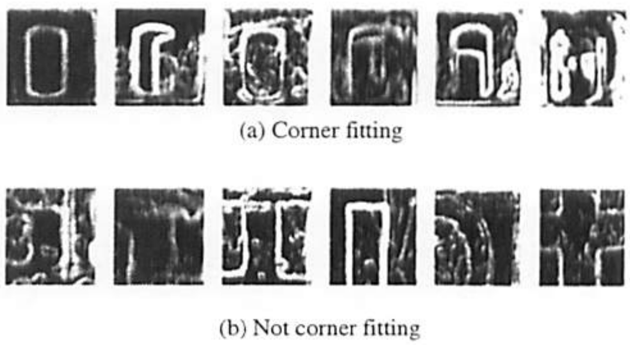
(a) Grey image (b) Edge image (c) Binary edge image

Fig. 3. Templates of corner fitting.

The training data consist of 910 edge images of the corner fitting and 695 edge images of something other than the corner fitting. Note that the edge images of something other than the corner fitting were created by matching the whole template to the images remaining after extracting the corner fitting from the real-world image and then selecting the regions with the highest normal correlation coefficient.

Figure 4 shows example of images for the training data. Based on these training data, the coefficient matrix a and the discriminant threshold for the linear discriminant function, as well as the number of partial templates, are determined.

In addition, 714 images including the corner fitting and separate from the training data were prepared as the test data to evaluate the proposed technique. Figure 1 presents an example. Note that the training data and the test data were both preprocessed and corrected for size. Size correction was necessary because of changes in the focal length with respect to the container due to the position of the camera on its crane. In concrete terms, the affine transformation was performed after converting the encoder value



(a) Corner fitting

(b) Not corner fitting

Fig. 4. Example of images for training data.

rate for the corner fittings and the number of partial templates for edge image templates.

In these figures, the number of partial templates on the horizontal axis being zero means that the conventional template matching is executed by using a whole template alone. The successful detection rate on the vertical axis represents the rate at which the detected region corresponds to the corner fitting and the discriminant score is greater than the threshold. Note that the proposed technique corresponds to (a), that is, the template images consist of partial and whole templates, and the recognition mean by using the linear discriminant method. Hereafter, the proposal technique is evaluated based on Figs. 7 and 8.

(1) Effect of the number of partial templates

Based on Figs. 7(a) and 8(a), the following can be confirmed.

1. The successful detection rate for the corner fittings varies depending on the number of partial templates and reaches a maximum when this is 16.

2. The successful detection rate is higher in all cases as compared to when the number of partial templates is zero.

Given the above, the proposed technique is effective for detecting the object under the outdoor environment when the number of partial templates is set appropriately. Moreover, for the corner fittings, the number of partial templates is optimal at 16. The reason that an optimal number exists for the number of partial templates is thought to be related to the fact that the balance of the number of features (amount of information) increases as the number of partial templates rises, and the value of the features decreases as the area of the template becomes small.

Note that the effect of the number of partial templates can be confirmed even in (c), that is, only a partial template is used and the recognition mean is the linear discriminant method. In contrast, when an accumulated value is used for recognition, as in (b) and (d), although there is some effect by using the partial template, it ultimately cannot be considered significant. In particular, when the edge image is

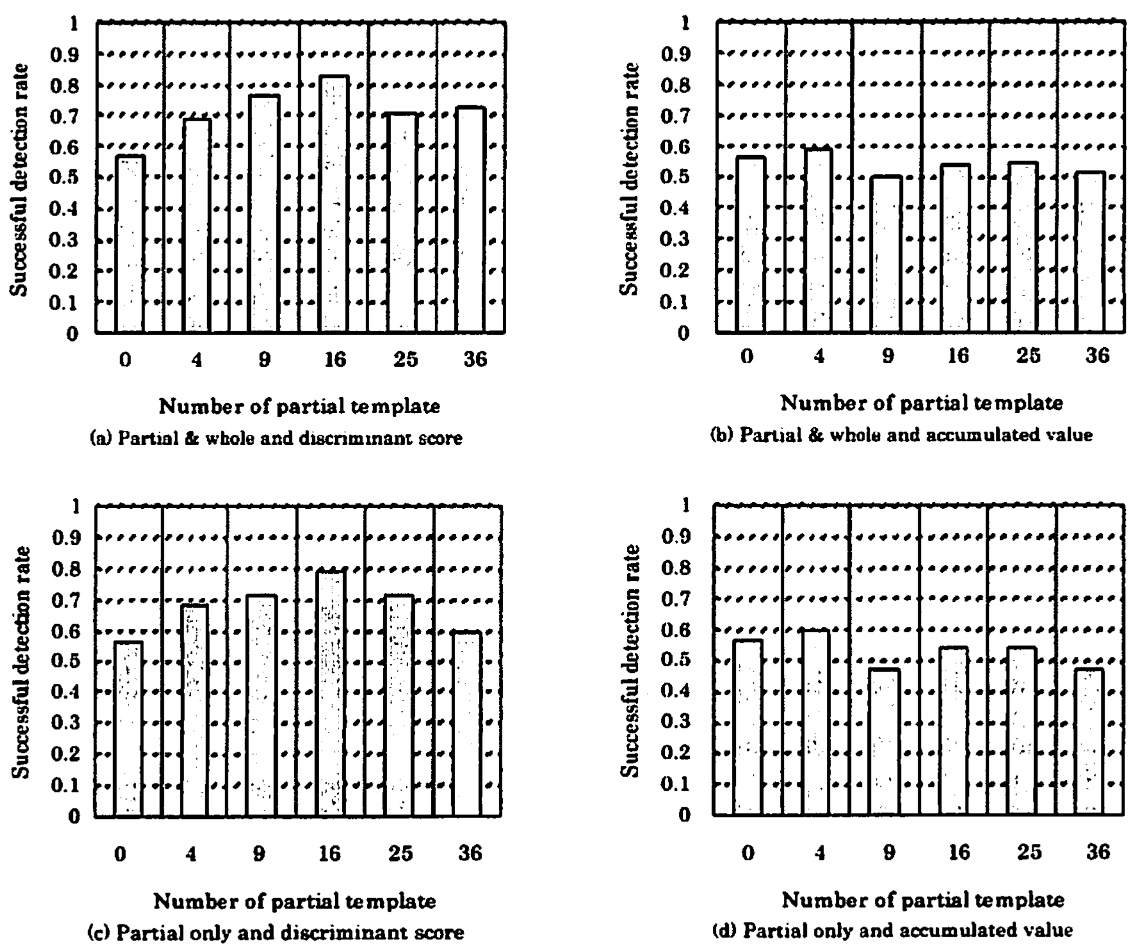


Fig. 8. Relationship between the number of partial templates and the successful detection rate (edge image).

used for the template image (Fig. 8), the effect cannot be considered adequate.

Given the above, the effect of the number of partial templates is significant in the linear discriminant method.

(2) Need for the whole template

The following can be confirmed by comparing (a) and (c) respectively in Figs. 7 and 8.

1. When the optimal number of partial templates (16) is used, the successful detection rate for the corner fittings is the highest when the partial and the whole templates are used.

2. In all other cases, a significant benefit is not seen for using the whole template.

Given the above, the necessity for the whole template can be confirmed under the condition in which the number of partial templates is set appropriately in the proposed technique. On the other hand, when recognition is executed by using an accumulated value as in (b) and (d), no effect is seen at all from the whole template. The reason for this is thought to be that the correlation between the accumulated value, the grand sum of the normal correlation coefficient calculated by using the partial templates, and the normal correlation coefficient calculated by using the whole template is high, as a result, the value of the normal correlation coefficient calculated by using the whole template is low as a feature.

(3) Effectiveness of the linear discriminant method in the recognition phase

The following can be confirmed by comparing (a) and (b) respectively in Figs. 7 and 8.

1. When a binary edge image is used as the template (Fig. 7), the linear discriminant method in (a) is about 5% higher for the successful detection rate of the corner fitting.

2. When an edge image is used as the template (Fig. 8), the linear discriminant method in (a) is more than 20% higher for the successful detection rate of the corner fitting.

Given the above, the linear discriminant method is effective as a recognition mean. Note that for the accumulated value, the number of partial templates for which the successful detection rate of the corner fitting is highest is 25 for a binary edge image and is 4 for an edge image. The reason for this is unknown.

(4) Effect of the type of template image

The following can be confirmed by comparing Figs. 7 and 8.

1. For (a) in Figs. 7 and 8, when the number of partial templates is 16, the successful detection rate of the corner fitting is highest.

2. The successful detection rate of the corner fitting for the binary edge image is higher than for the edge image. However, when the effectiveness of the proposed technique is compared in (b) and (d), the edge image is more remarkable.

Therefore, each template image of the binary edge image and the edge image is effective in the proposed technique. The effectiveness of the edge image is more remarkable than the binary edge image. The reason is that the binary edge image is originally effective in the detection of the object under the outdoor environment [3].

Block matching [2] referred to in Section 1 corresponds to Fig. 8(d). The successful detection rate of the corner fitting is 0.60. On the other hand, the binary edge image [Fig. 7(a)] is 0.89, and the edge image [Fig. 8(a)] is 0.83 at the successful detection rate of the corner fittings of the proposed technique. As a result, the effectiveness of the proposal technique can be confirmed.

4.4 Effects of noise under the outdoor environment

The result of the discrimination experiment of 714 test data was classified according to the type of disturbance, and the effectiveness of the proposal technique was confirmed.

Figure 9 shows the relationship between the template images and the successful detection rate for the corner fittings. The edge image and the binary edge image represent the conventional template matching with the whole

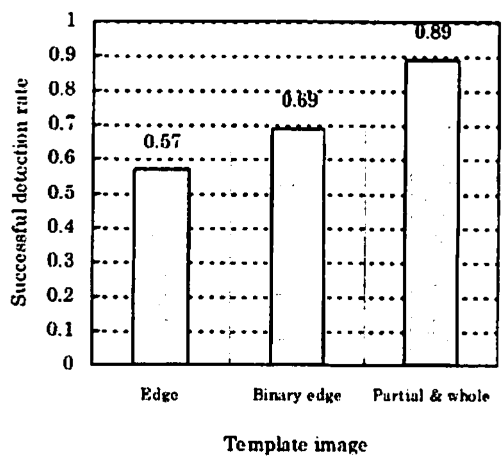


Fig. 9. Relationship between the template image and the successful detection rate for the corner fittings.

template alone, and "partial & whole" represents the proposed technique. From this figure, the successful detection rate of the corner fittings is 0.57 for the edge images, and 0.69 for the binary edge images. On the other hand, the successful detection rate of the proposed technique is 0.89. It has improved by 0.20 point or more versus the conventional technique. Therefore, the effectiveness of the proposed technique can be confirmed.

Figure 10 shows the results of classifying the content of Fig. 9 using noise categories. The horizontal axis in the figure represents the categories of noise, with (1) on the left representing an ideal image without any noise [210 images: Fig. 1(a)]; (2) representing disappearance or deformation of the silhouette [17 images: Fig. 1(b)]; (3) representing irregular patterns due to rain [123 images: Fig. 1(c)]; (4) representing shadows due to stains or holes [224 images: Fig. 1(d)]; (5) representing indistinct images [119 images: Fig. 1(e)]; and (6) representing reflected light [21 images: Fig. 1(f)].

Moreover, the three bars for each category represent the edge image, the binary edge image, and the proposed technique.

The proposed technique can confirm there is an effect of improving the detection performance for the whole disturbance under the outdoor environment from this figure.

The reason is that the proposed technique has decided the number of partial templates and the best axis of one

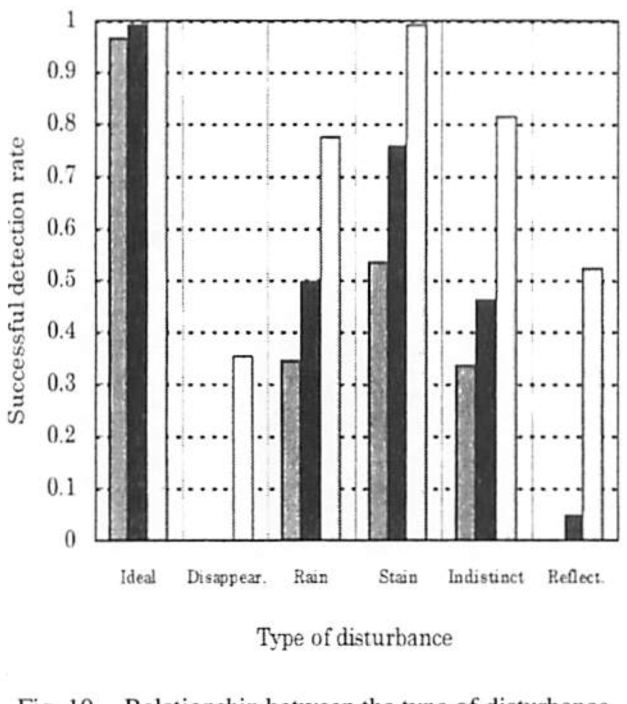


Fig. 10. Relationship between the type of disturbance and the successful detection rate for the corner fittings.

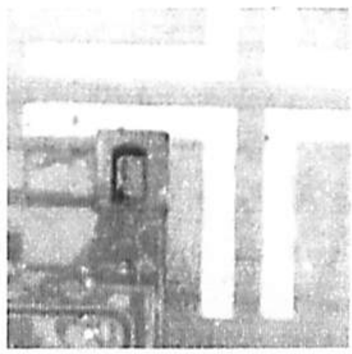


Fig. 11. Ground mark for positioning container.

dimension effective in discrimination by learning the training data by the linear discriminant method. On the other hand, it is necessary to prepare a lot of training data composed of images of both the object and other than the object under the outdoor environment so as to maintain the effectiveness of the proposed technique.

Figure 11 shows a photograph of the ground mark (white lines) used to position the container on the ground in the container terminal. At present, the authors are considering using the proposed method for detecting this ground mark.

5. Conclusion

This paper proposed a technique of augmented template matching for detecting the object having a standard shape of two dimensions under the outdoor environment. It applies the "recognition by partial and whole context" finding of cognitive science. That is, it is a technique for discriminating the feature calculated with the partial and the whole templates by the linear discriminant method. The corner fittings of the container were selected as an example of the object under the outdoor environment. The effectiveness of the proposed technique was confirmed based on the results of a detection experiment on the corner fittings.

Note that the corner fittings of a container are set up in four places symmetrically on the surface of a container. Therefore, the positional relationships between the four corner fittings and the sun all vary. If the position of two of the corner fittings can be detected geometrically, then the position of the container can be determined. In the results of the experiments, the successful detection rate for a single corner fitting was 0.89, making the probability that two or more corner fittings from among the four can be detected over 0.995. This is a number that can be used for practical applications of the proposed technique. As a result, the prospect of handling the container automatically was obtained.

Future topics include proving the generality of the proposed technique by applying it to objects other than corner fittings. In such cases, the need to prepare a lot of training data and test data will be an issue. One possibility is the ground mark (Fig. 11) used to position containers. We plan to study this in the future.

REFERENCES

1. Takagi M, Shimada H. Handbook of image analysis. University of Tokyo Press; 1991. (in Japanese)
2. Saitoh F. Robust image matching for occlusion using vote by block matching. Trans IEICE 2001;J84-D-II:2270–2279. (in Japanese)
3. Kunimitsu S, Asama H, Kawabata K, Mishima T. Detection of object under outdoor environment with binary edge image for template. IEEJ Trans IES 2004;124:480–488. (in Japanese)
4. Brunelli R, Poggio T. Face recognition: Features versus templates. IEEE Trans Pattern Anal Mach Intell 1993;15:1042–1052.
5. Kunimitsu S, Asama H, Kawabata K. Measurement of relative position of container with image processing for automatic container cranes. IEEJ Trans IES 2001;121:882–891. (in Japanese)
6. Rumelhart DE. Introduction to human information processing. John Wiley & Sons; 1977. (in Japanese)
7. Ishii K, Ueda H, Maeda F, Murase Y. Pattern recognition made easy. Ohm Publishing; 1998. p 14–18.

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