Novel Template Matching for Extremely Deteriorated Images
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Synopsis
Until now, template matching has been applied to many applications such as pattern recognition, object tracking, and image and video coding. In this paper, we propose a novel template matching method by two kinds of sub-templates: Thinning/Thickening (T/T) sub-templates and Difference (D) sub-templates. The robust matching criterion is also introduced in this paper. Special attention is paid to template matching for extremely blurred images. The performance of our proposed framework is confirmed through 200 images taken under a great variety of lighting changes in outdoor scenes.

KEYWORDS: template matching, T/T sub-template, D sub-template, blurred image, matching criterion

1. Introduction
Template matching has been a classical approach to the problems of locating and recognizing of an object in an image. Template matching technique, especially in two dimensional cases, has many applications in object tracking, image compression, stereo correspondence, and other computer vision applications. Even now, it is a fundamental technique to solve them. Among several matching methods, Normalized Cross Correlation (NCC) and square root of Sum of Square Differences (SSD) have been used as the measure for similarity. Moreover, many other template matching techniques such as Sum of Absolute Differences (SAD) and Sequential Similarity Detection Algorithm (SSDA) have been adopted in many applications for pattern recognition, video compression and so on. In addition, template matching has been widely used in various applications, for example, extraction of container identity codes, image segmentation, and so on.

Template matching algorithm with adaptive skipping using inner sub-templates' distances was discussed in [1]. Maximizing the normalized correlation between the template and the current image was used in [7,8]. S. Kunimitsu et al. proposed template matching using partial and whole template to detect the objects with the two-dimensional standard shape under outdoor environments. Most existing methods suffered from extremely deteriorated images under bad conditions, for example, illumination changes, specular highlights and occlusions. This fact is a major motivation to pursue this subject in this paper. To overcome these difficulties, we propose the new framework for the novel template matching with two kinds of sub-templates. Here, we discuss template matching of normalized images after segmentation.

This paper is organized as follows. In Section II, the proposed novel template matching method is presented and matching criterion (MC) for robust matching is discussed. The newly proposed sub-templates of T/T and D are also established. In Section III, the experimental results and the accuracy rates are described. Finally, the conclusion is summarized in Section IV.

2. Novel template matching
This method targets on planar objects which are composed of Uniform Color Regions (UCRs). Some examples are road signs, billboards, logos, and so on. The novel template matching method is proposed by two types of sub-templates of T/T and D. For template matching, criterion of some kind is necessary so that robust MC is also discussed in this section.

2.1 Uniform color region
The objects which are composed of UCRs such as visual signboards are mainly considered here. Some examples are shown in Fig.1(a). Each object O is composed of UCRs $U_j$ and border regions $N$ as expressed by Eq.(1). To use the color uniformity, each template $T_j$ is made from the corresponding UCR $U_j$ and it is a little thinner than its original size as shown in Eq.(2). For example, an object with UCRs is shown in Fig.1(b). In this figure, there are 4 templates and the rest region is their border region. The background regions are filled with black color.
Fig. 1. Objects with UCRs: (a) sample images and (b) an object with UCRs and its templates.

\[ O = \bigcup_{j} U_j \cup N, \tag{1} \]

\[ U_j \cap N = \phi, \forall j, \]

\[ U_j \cap U_k = \phi, \text{for } j \neq k, \]

\[ |O|, |N|, \]

where \( \phi \) is an empty set, and \(|O|\) and \(|N|\) mean the total number of pixels of \( O \) and \( N \), respectively. We can obtain the \( j \)th template \( T_j \) by thinning the \( j \)th UCR \( U_j \).

\[ T_j = \text{thinning}(U_j). \tag{2} \]

For simplicity, \( T_j \) is sometimes expressed as \( T \).

### 2.2 Matching criteria

The experiments are taken beforehand in several color spaces, for example, RGB, HSV, XYZ, L*a*b and L*c*h. The first two spaces produced relatively better results, and HSV was finally employed. In HSV color representation, Hue has the greatest discrimination power compared with the other components. Although Hue is the most useful attribute, it becomes meaningless when Saturation is very low. Then, the region is called ‘achromatic’. Here the achromatic region is defined by \( \mu_s < 30 \) and \( \delta_s < 8 \), where \( \mu_s \) and \( \delta_s \) represent the mean and standard deviation of a region in Saturation, respectively. Otherwise, it is called ‘chromatic’.

Here, MC for robust matching is discussed. The proposed method focuses on extremely deteriorated images and various illumination changes. In conventional NCC and SSD, the pixel colors \( T(i,j) \) of the template \( T \) have been used for calculating them. To get enough stability for changing illumination conditions, the mean value \( \mu \) of the related region of the input image \( I \) is used instead of \( T(i,j) \). In these situations, the criteria of SSD and SAD are no longer suitable for template matching. \( R_{NCC} \) and \( R_{SSD} \) are expressed in Eq.(3) and Eq.(4), respectively. According to Eq.(4), STD is defined as the minimum of \( R_{SSD} \), so the term STD is used instead of SSD from now. Here, Modified STandard Deviation (MSTD) is introduced as a more robust criterion than conventional matching criteria. In general, whenever STD \( S_1 \) of the whole object region is larger (smaller), the STD \( S_2 \) of the template region is also larger (smaller). In order to get the stable parameters, it is better to adopt MSTD \( S_2/S_1 \) instead of STD \( S_2 \).
\[
R_{\text{NCC}}(m,n) = \frac{\sum_{(i,j) \in T}(i,m,j+n)}{\sqrt{\sum_{(i,j) \in T} i^2(i,m,j+n)}}, \quad NCC = \max_{m,n} R_{\text{NCC}}(m,n).
\]

\[
R_{\text{SSD}}(m,n) = \frac{1}{N} \sum_{(i,j) \in T} (T(i,j) - I(i+m,j+n))^2 = \min_{m,n} R_{\text{SSD}}(m,n).
\]

\[
STD = \min_{m,n} R_{\text{SSD}}(m,n).
\]

For explanation, the template matching performance of NCC, SSD, and MSTD are compared using concrete examples shown in Fig.2. To decide whether or not the templates 'match' or 'un-match' with the input image, the thresholds are necessary to be decided beforehand. It must be noticed from Fig.2(b) that the threshold values can not be adjusted, so that they may fit for overall cases as far as only one fixed size template is used. There are two types of errors: Type1 (incorrect rejection of a true template), and Type2 (wrong acceptance of a false template). A trade-off between Type1 and Type2 are faced. The matching results NCC, STD, and MSTD are summarized in Table I by means of errors. There are seventy pairs using ten input images \(I_i (i = 1, \ldots, 10)\) and seven templates \(T_{\text{Templ}}, (j = 0, \ldots, 6)\) like as Fig.2(b). In this figure, the true and the false templates are represented by \(S\) and \(\bar{S}\), respectively. According to Table I, MSTD is the best among NCC, STD, and MSTD, but not perfect. According to these results, MSTD is adopted here as MC. The matching value of a template \(T\) and an input image \(I\) is expressed as \(MC(T)\). So, \(MC(T)\) is defined by Eq.(5) using \(MC_I(T), MC_H(T)\) and \(MC_S(T)\) corresponding to three components of HSV, respectively.

\[
MC(T) = \begin{cases} 
4 \times MC_I(T) + MC_H(T) / 5 & \text{for chromatic region,} \\
MC_I(T) & \text{for achromatic region.}
\end{cases}
\]

### 2.3 Thinning and thickening template matching

Here, the novel template matching is carried out by T/T sub-templates. T/T sub-templates are obtained automatically by morphological operations of dilation and erosion for thinning and thickening, as shown in Eq.(6).

\[
TT_{I^k} = \begin{cases} 
k \text{ time thinning of } T_i, & k < 0, \\
k \text{ time thickening of } T_i, & k > 0.
\end{cases}
\]

The special characteristics of T/T sub-templates are illustrated in Fig.3(b). If the matching region includes only one UCR, then the \(MC(T)\) will be very small. Otherwise, it will be very large. This aspect is also shown in Fig.3(c) with two input images. In the experiments, seven T/T sub-templates \(TT_{I^k}, -3 \leq k \leq 3\) are used. In this figure, the \(MC(T)\)s of the first four T/T sub-templates are very small since their template regions are included in only one UCR in both images. The \(MC(T)\)s of the last three T/T sub-templates for \(T_i\) are rapidly increasing, but those for \(T_2\) are not changed. Using these characteristics, the algorithm can decide 'whether or not' the input image matches with the template. When the following two conditions are satisfied, the system can decide whether or the template matches with the input image.
Fig. 2 Comparison of template matching criteria: (a) input images taken under illumination changing, and (b) matching values of NCC, STD and MSTD, respectively.
Table I  Type1 and Type2 errors.

<table>
<thead>
<tr>
<th></th>
<th>NCC</th>
<th>STD</th>
<th>MSTD</th>
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<tbody>
<tr>
<td>Type1</td>
<td>2 (2.86%)</td>
<td>2 (2.86%)</td>
<td>2 (2.86%)</td>
</tr>
<tr>
<td>Type2</td>
<td>13 (18.57%)</td>
<td>17 (24.29%)</td>
<td>1 (1.43%)</td>
</tr>
</tbody>
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Fig.3 Mutiple template matching: (a) T/T sub-templates, (b) characteristics of T/T sub-templates, (c) T/T template matching for two images, and (d) T/T and D template matching.

[Cond.1] The $MC(TT_i^{(k)})$, $-3 \leq k \leq -1$ of the T/T sub-templates are relatively small and do not change significantly.

$$MC(TT_i^{(k)}) < Th_1, \quad -3 \leq k \leq -1,$$

$$\left| MC(TT_i^{(k)}) - MC(TT_i^{(k-1)}) \right| < Th_2, \quad -2 \leq k \leq -1.$$
(Cond.2) After that, the $MC(\text{TT}_{i}^{(k)})$, $1 \leq k \leq 3$ of the T/T sub-templates becomes suddenly very large, because the corresponding regions exceed the original one so that they may contain other color regions.

$$\left| MC(\text{TT}_{i}^{(3)}) - MC(\text{TT}_{i}^{(0)}) \right| < \frac{3}{2} \left| MC(\text{TT}_{i}^{(3-1)}) - MC(\text{TT}_{i}^{(3-3)}) \right|. \quad (8)$$

Here, $T_{h_{1}} = 0.85$, $T_{h_{2}} = 0.1$ and $T_{h_{3}} = 3$ are decided according to pre-experiments.

### 2.4 Difference template matching

In this section, another type of template matching is carried out by D sub-templates that defined by Eq.(9).

$$D_{i}^{(k)} = \text{TT}_{i}^{(k+\Delta)} - \text{TT}_{i}^{(k-\Delta)}. \quad (9)$$

Here, seven D sub-templates $D_{i}^{(k)}$, $-3 \leq k \leq 3$ and $\Delta = 1$ are used. It is assumed that $MC(D_{i}^{(k)})$

- is very small at $-3 \leq k \leq -2$ because $D_{i}^{(k)} \subset T_{i}$,
- becomes large at $-1 \leq k \leq 0$ because $D_{i}^{(k)} \not\subset T_{i}$,
- may be small again when $k \geq 1$, because the region $D_{i}^{(k)}$ may be included in another UCR. But, $MC(D_{i}^{(k)}), k \geq 1$ are unstable because they depend on each object pattern.

The aspect of template matching using $\text{TT}_{i}^{(k)}$ and $D_{i}^{(k)}$ is shown in Fig.3(d). Although T/T and D sub-templates may be available at a time, the system use only T/T sub-templates afterwards as they can give satisfied recognition rate. Important thing is that the robust template matching can be achieved by size changing in either T/T or D sub-templates are used.

### 3. Experimental results

To evaluate the performance of the proposed framework, 200 images were taken by various types of digital cameras in outdoor scenes under a great variety of illumination changes and cluttered backgrounds. All of the images were segmented and normalized into 64*64 beforehand. One of the template matching results for one sample image by using T/T and D sub-templates are shown in Fig.4. To confirm the performances, ten types of various conditions were examined with different 20 images for each condition, altogether 200 images. Some are shown in Fig.5(a). The proposed template matching method can work well on extremely deteriorated images under bad illumination conditions and partial occlusion. But a few failure cases are left under large occluded regions, for example, the last two images in Fig.5(a). According to the experimental results, the proposed method gave 96% correct matching rate on an average even though under bad conditions such as nighttime, foggy, rainy day, and so on. In Fig.5(b), the graph describes the correct matching rate for each condition.

### 4. Conclusions

The novel template matching method using T/T and D sub-templates were proposed. The robustness of this system was confirmed through experimental results using 200 images taken under various illumination conditions. The method was very effective for outdoor scene images even though the image border region is ambiguous due to very low resolution. Furthermore, it can work very well on blurred and deteriorated images. But it may not do well when the occlusion occurs in the large part of the object region. For such a case, the system needs to develop a pre-process to remove such regions before template matching.
Fig. 4 Sample image and matching results: (a) input image and template and (b) template matching with T/T and D sub-templates.

Fig. 5 Experimental results: (a) some images used in experiments, (b) the matching rate under various conditions.

5. References