Thinning/Thickening and Difference Sub-template Matching
-For Robust Recognition of Strongly Deteriorated Signboard Images-

1. Introduction
The amount of visual information being present in the real world is clearly immense. Signboards are good examples that have rich information contents. It has become a challenging and important research area to recognize signboards under bad conditions and deteriorations, especially road sign recognition in Intelligent Transport Systems (ITS). However, the recognition of road signs presents a number of difficulties, in terms of both the image formation process and the environment in which the signboard is found. In the former, effects such as sensor noise and motion blur may be present in the image. In the latter, difficulties can be divided into the following groups: (i) the physical condition may make recognition difficult (such as the effect of deteriorating paint quality over time, damaged, incorrectly placed, the presence of graffiti or just general deterioration of the signboard), (ii) partial occlusions due to both of static and dynamic nature, (iii) lighting conditions such as reflections, shadows and low-light conditions may also have a severe influence.

Although many algorithms were developed to solve these problems, the recognition for deteriorated images is a difficult task that has not been adequately addressed and presents an opportunity for our present research. When color images are used, segmentation is usually performed through color thresholding, region detection and shape analysis. Recognition can be accomplished by a number of approaches including template matching technique that can be combined with other methods for higher performance. Although template matching is a classical approach to the problems of locating and recognizing of objects, it has versatile applications. Several methods have used Normalized Cross Correlation (NCC) and square root of Sum of Square Differences (SSD) as measures of similarity. Moreover, other template matching techniques such as Sum of Absolute Differences (SAD) and Sequential Similarity Detection Algorithm (SSDA) have been adopted in many applications. Adaptive skipping using inner sub-templates’ distances was also discussed. S. Kunimitsu et al. proposed template matching using partial and whole template to detect the objects with standard shape under outdoor environments.

Most of existing methods suffered from extremely deteriorated images under bad conditions. This fact is our main concern which we will explore and investigate in this paper. To overcome these difficulties, we propose a new framework for template matching with two types of sub-templates. Images under partial occlusion, specular highlights, and severe illumination changes are considered in our proposed system. In this aspect, we have employed the Main Peak (MP) finding algorithm for...
Occlusion and Reflection (O/R) removal. Here it is supposed that an input image has been normalized after segmented. The main contributions of this paper are:

* The novelty of two newly developed sub-templates outperform the existing template matching methods especially dealing with difficulties remain even after various preprocessing techniques such as occlusion removal, refinement of intensities changes, etc.

* The adoption of Modified STandard Deviation (MSTD) has made a major advance as the optimal Matching Criterion (MC) where the conventional MC, for example, NCC and STD are no longer valid.

This paper is organized as follows. In section 2, we present some preliminaries concerning with Uniform Color Regions (UCRs), MP finding algorithm\(^{12}\) for O/R removal\(^{13}\), and robust Matching Criterion (MC). In section 3, we introduce a new matching method which uses two types of sub-templates: Thinning/Thickening (T/T) and Difference (D). Some experimental results are shown in section 4. Finally, we give the concluding remarks in section 5.

2. Preliminaries

In order to realize our new template matching, we introduce some preliminaries on UCRs, MP finding, and MC. Here, we focus on planar objects which are composed of UCRs. Some examples of these objects are road signs, billboards, logos, and so on.

2.1 Extraction of Uniform Color Regions (UCRs)

The concept of UCRs is a key component in our method of recognizing and locating objects. To describe an extracting procedure of UCRs, we first define \( U_j \) as \( j^{th} \) UCR of an object \( O \) and \( N \) as a region formed by the border regions and all non-UCRs. Illustirical examples are shown in Fig.1 (a). So the object \( O \) can be represented by (1). Here it is supposed that UCRs have been already extracted, for example, using MP finding. For each extracted UCR \( U_j \), the corresponding template \( T_j \) is obtained after thinning by one pixel from the original \( U_j \), i.e. \( T_j = \text{thinning}(U_j) \).

\[
O = \left( \bigcup_j U_j \right) \cup N, \\
U_j \cap N = \emptyset, \forall j, \\
U_j \cap U_k = \emptyset, \text{for } j \neq k, \\
|O|, |N|.
\]

where \( \emptyset \) is an empty set, \( |O| \) and \( |N| \) represent the total number of pixels in \( O \) and \( N \), respectively.

2.2 Main Peak (MP)

We introduce the MP finding algorithm based on each component on HSV color space. Hue component is mainly used here. Examples of Hue histograms of objects without and with occlusion are illustrated in Fig.1 (b). The MP finding algorithm is composed of five steps:

(i) Compute the Hue histogram of template region for the target object,

(ii) Smooth the histogram by moving average,

(iii) Find the maximum of the moving average values, and let the corresponding position be \( P_1 \),

(iv) Calculate the standard deviation (STD) of the histogram within \( P \pm q \) moving \( P \) from \( P_1 - q \) to \( P_1 + q \), where \( q \) is experimentally-decided as 16,

(v) Search the smallest value of the calculated STDs.

Let us denote the corresponding position by \( P_2 \), and the STDs at \( P_1 \) and \( P_2 \) by \( \delta_1 \) and \( \delta_2 \), respec-
tively. The aspects of parameters \( q, P_1, P_2, \delta_1 \), and \( \delta_2 \) are shown in Fig.1 (c), and the result is not so sensitive to the value of \( q \).

When the smoothed histogram is symmetric, \( P_1 \) and \( P_2 \) are equal. In the non-symmetrical case, the painted regions on the right side in Fig.1 (c) mean the regions which are within \( 2\delta_k \) from \( P_k \) (\( K=1, 2 \)). From this figure, it should be noticed that the extracted region using \( P_2 \) consists of more uniform color pixels than that of \( P_1 \), that is, the advantage of \( P_2 \) over \( P_1 \). MP is found at \( P_1 \), and MP finding algorithm results in \( P_2 \). Then the system recognizes the outside as O/R regions. We cannot use the fixed values of \( P_2 \) and \( \delta_2 \) because they differ under changing of illumination conditions, even if the same signboard is used. By using adaptive \( P_2 \) and \( \delta_2 \) like this, UCRs are robustly extracted and O/R regions can be removed.

2.3 Optimum Matching Criterion (MC)

We now consider about MC for recognition of extremely deteriorated images taken under a great variety of bad conditions. Under such situations, conventional matching criteria NCC and STD (used for SSD) are no longer useful for template matching. Here, we adopt the MSTD which is used as a measure of similarity, since it has been experimentally confirmed to be the optimum MC.

Let \( Z_1 \) and \( Z_2 \) be the whole region of the object and the corresponding region to each sub-template, respectively. Generally speaking, whenever STD \( s_1 \) of \( Z_1 \) is larger (smaller), the STD \( s_2 \) of \( Z_2 \) is also larger (smaller). Our previous work\(^4\) showed that optimal matching result could not be achieved by using conventional STD under various bad conditions. In order to get the stable parameters, we adopt MSTD \( s_2 / s_1 \) instead of STD \( s_2 \), since STD is too sensitive to illumination changing. It has been found that under bad conditions, MSTD showed the best performance among three MCs (NCC, STD, and MSTD). So, MSTD is used as the MC here. The matching value of a template \( T \) and an input image \( I \) is denoted by \( MC(T) \) which is a function of HSV values. Here, we define \( MC(T) \) as a linear combination as follows:

\[
MC(T) = \left[ \alpha MC_H(T) + \beta MC_S(T) + \gamma MC_V(T) \right] / (\alpha + \beta + \gamma) \tag{2}
\]

where \( \alpha, \beta, \gamma \) are weights and \( MC_H(T) \), \( MC_S(T) \), \( MC_V(T) \) are MSTDs using hue, saturation and intensity of HSV, respectively. We have decided empirically that \( (\alpha, \beta, \gamma) = (1, 0, 4) \) in chromatic region and \( (\alpha, \beta, \gamma) = (0, 0, 1) \) in achromatic region to give the optimal matching value.

We search the best matching within \( \pm 2 \) pixels along \( x \) and \( y \) axes.

3. Proposed method

We now define two types of sub-templates: T/T and D. They are related to each other. The formulation of D sub-template is based on the similar morphological operations used for T/T sub-templates. Here, we should take Occlusion/Reflection (O/R) regions into account, so it is supposed that the removal of O/R regions has been already done before applying sub-templates matching. This can be done by using our algorithm described in Section 2. After the removal of O/R regions sub-templates matching is to be carried out. The step by step procedures are described in the followings.

3.1 Thinning and Thickening (T/T) sub-templates

To obtain T/T sub-templates automatically from \( T \), we carry out morphological operations of dilation and erosion for thinning and thickening by (3) and the illustration is shown in Fig.2 (a).

\[
TT^{(k)}_i(T) = \begin{cases} 
k \text{ time thinning of } T_i, & k < 0, \\
T_i, & k = 0, \\
k \text{ time thickening of } T_i, & k > 0.
\end{cases} \tag{3}
\]

The special characteristics of T/T sub-templates matching are illustrated in Fig.2 (b) for one input image \( I_1 \) and in Fig.2 (c) for two input images, \( I_1 \) and \( I_2 \). If the matching region includes only one UCR, then the MC(T) is very small. Otherwise, it is very large. Illustration of T/T sub-templates matching for an object image under strong deterioration is shown in Fig.2 (d). It can be seen from (3) that the MC(T) of T/T sub-templates are very small for \( k<0 \) and the MC(T) is may be suddenly increased or non-decreased for \( k>0 \). Using these characteristics, our system can decide whether or not the input image matches with the template. This fact leads to two matching conditions Cond.1 and Cond.2 shown in (4) and (5). That is, if the following two conditions are satisfied, the system concludes that the template matches with the input image.

\[ \text{[Cond.1] For an integer } a, \text{ the } MC(TT^{(k)}_i(T)) - a \leq k \leq -1 \text{ of the T/T sub-templates are relatively small and do not change significantly.} \]

\[
MC(TT^{(k)}_i(T)) < Th_1, \quad -a \leq k \leq -1, \quad (4)
\]

\[
MC(TT^{(k)}_i(T)) - MC(TT^{(k-1)}_i(T)) < Th_2, \quad -a+1 \leq k \leq -1. \quad (5)
\]

3.2 Reflection (O/R) sub-templates

We now define two types of sub-templates: T/T and D. They are related to each other. The formulation of D sub-template is based on the similar morphological operations used for T/T sub-templates. Here, we should take Occlusion/Reflection (O/R) regions into account, so it is supposed that the removal of O/R regions has been already done before applying sub-templates matching. This can be done by using our algorithm described in Section 2. After the removal of O/R regions sub-templates matching is to be carried out. The step by step procedures are described in the followings.

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\[ \text{[Cond.1] For an integer } a, \text{ the } MC(TT^{(k)}_i(T)) - a \leq k \leq -1 \text{ of the T/T sub-templates are relatively small and do not change significantly.} \]

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MC(TT^{(k)}_i(T)) < Th_1, \quad -a \leq k \leq -1, \quad (4)
\]

\[
MC(TT^{(k)}_i(T)) - MC(TT^{(k-1)}_i(T)) < Th_2, \quad -a+1 \leq k \leq -1. \quad (5)
\]
plates becomes suddenly increased, because the corresponding regions exceed the original one so that they may contain other color regions.

\[
\left| \text{MC}(TT_i^{(a)}) - \text{MC}(TT_i^{(0)}) \right| < \text{Th}_1, \\
\left| \text{MC}(TT_i^{(i-1)}) - \text{MC}(TT_i^{(i-a)}) \right|, \\
\text{(5)}
\]

where \(\text{Th}_1, \text{Th}_2, \text{Th}_3\) are predetermined thresholds. It should be pointed that the two matching conditions, Con.1 and Con.2 are valid for any integer value of \(a\). However, the value of \(a\) can be assigned depending on the size of template used. For example, the value of \(a=3\) can be used for the template size 64x64 and seven sub-templates are used here. In this case, two matching conditions are obtained by substituting \(a=3\) in (4) and (5). Here, \(\text{Th}_1=0.85, \text{Th}_2=0.1\) and \(\text{Th}_3=3\) are optimal according to pre-experiments.

3.2 Difference (D) sub-templates

In this section, D sub-templates are defined by (6) as another type of sub-templates.

\[
D_i^{(k)} = TT_i^{(k+\Delta)} - TT_i^{(k-\Delta)}. \\
\text{(6)}
\]

For the sake of discussion, we consider D sub-templates \(D_i^{(k)}, -3 \leq k \leq 3\) and \(\Delta=1\). It can be seen that \(D_i^{(0)} \subset T_i\) for \(-3 \leq k \leq -2\) resulting the value of \(\text{MC}(D_i^{(k)})\) is very small. On the other hand, this value becomes large for \(-1 \leq k \leq 0\) since \(D_i^{(k)} \subset T_i\). For \(k \geq 1\), the region \(D_i^{(k)}\) may be included in another UCR so that the values of \(\text{MC}(D_i^{(k)})\) become small again. But these values are unstable for \(k \geq 1\) since they depend on each object patterns. The illustrations of D sub-templates are shown in Fig.3 (a).

The aspect of template matching using \(TT_i^{(k)}\) and \(D_i^{(k)}\) is shown in Fig.3 (b). Although T/T and D sub-templates are applicable at the same time, from here onwards we will use T/T sub-templates only since we observe that 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. An example of their matching using a real road sign image is shown in Fig.4.

4. Experimental results and discussions

Experiments were conducted to evaluate the performance of the proposed method. 200 images were taken by various types of digital cameras in outdoor scenes under a great variety of bad conditions and cluttered backgrounds. All of the images were segmented and normalized into 64x64 beforehand. Some examples of reference
objects and templates are shown in Fig.5 (a-i), (a-ii). Examples of images $I_k$, $k=1,...,6$ are shown in Fig.5 (b). Temp$^1$, Temp$^2$ and Temp$^3$ look simple in shape but it is not easy to distinguish each other because of their close similarity such as $I_1$, $I_2$ and $I_3$ and existence of occlusion such as $I_1$, $I_5$ and $I_6$. For such cases, it is difficult to recognize using the conventional matching methods, but our T/T sub-templates matching method can overcome. Moreover, the results of other extremely deteriorated images such as $I_4$, $I_5$ and $I_6$ under low resolution and O/R show the robustness of our method. After O/R removal, the results of T/T sub-templates matching are summarized in Table 1.

To explain in more detail, we take an example of road sign image affected by both specular highlight and partial occlusion for practical use. The O/R regions in the input image are removed and the results are shown in Fig.6 (a). These results show that the two templates satisfy both Cond.1 and Cond.2 (Fig.6 (b)) so that the system gives the correct recognition result. To evaluate the performance, 200 images are examined under a great variety of bad conditions. Some images used in experiments are shown in Fig.7 and both T/T and D sub-templates are tested. It was found that our proposed method worked well especially for extremely deteriorated images under partial occlusion and severe illumination changes. Only a few failure cases were detected for the images like the last two inside of the dotted rectangle in Fig.7, since they were severely occluded or deteriorated so that the system couldn’t find significant UCRs at all. The proposed method gave 96% precision rate under a great variety of bad conditions including nighttime, foggy day and rainy day.

5. Conclusions

This paper has addressed the signboard recognition problems arising due to bad conditions in the environment. Especially, we developed a robust object recognition method which can detect and recognize the sign-
boards even they are strongly deteriorated and blurred. This method is also capable of reducing computational time required to process the whole image sequence, making this framework suited for real-time applications. Moreover, future research efforts should look at an application of sub-templates matching to cluster a large number of online images by forming classification in pre-defined templates. Such kinds of problems remain to be investigated in future research work.

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