CIRCULARITY: A Metric for Region Template Selection in Airborne Vision Navigation

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Abstract: Reliability template is a key factor of airborne vision navigation system. This paper proposes a new metric for region template selection. Firstly, a measurement model for uncertainty and inaccuracy of edge feature is given in detail. Furthermore, the influence of spatial distribution of edge features of correct recognition probability is analyzed in statistical probability theory. Then an "ideal" spatial distribution of region template which is the most easy to be recognized is proved by extreme-case analysis. Finally, a new metric is proposed by calculating the shape distance from this "ideal" spatial distribution, called CIRCULARITY, which can be deemed as "geometry self-similarity" to one target. The validity of new metric is experimentally demonstrated by using real ground targets. The results show that the new metric can meet the requirements of matching area selection and generating template.

1. Introduction
As one of the key techniques in computer vision, template matching has been used in robotic control, remote precision guidance and other vision navigation system for three decades. Both theory and practice show that sufficient information about target in predefined template is one of the most important factors, which determines to success or failure in recognition. Now edge information is most frequently used in region template. We focus on the spatial distribution of edge template for the presence of position uncertainty by imaging mechanism, natural illumination, imaging geometry and weather condition, and try to develop a measure method of assessing the quality of edge template.

Evaluating the quality of template has been extensively investigated for many years. Most of them widely used are divided into three kinds: image information based metric, shape information based metric and statistical computing based metric. The first are those that rely on some parameters to measure the information on template, which represent image complexity, such as repeat mode [1], correlation coefficient [2], independent pixel [3] and other similar parameters. Some criteria of suitable matching area selection are addressed by experience. The second kind is based on shape information of template, such as shape eccentricity ratio [4], shape compactness [5], shape convexity [6] and shape complexity [7]. The third kind is based on statistical probability theory, such as object
pose estimation [8], partial occlusion match [9] and background clutter interference [10]. However, these metrics are difficult to use in real scene because application conditions are not easy to obtain.

Inspired by [11], the quantitative relationship between spatial distribution of edge template and recognition performance is studied in this article, which is used for region template selection. First, we adopt a measurement model [12] that selects a random region around edge feature of uncertainty and inaccuracy. Moreover, an "ideal" spatial distribution is derived based on a "hypothesis and test" analysis theory, independent of matching method. Furthermore, a computable method that is called CIRCULARITY is proposed for comparing shape similarity to "ideal" spatial distribution. This new metric can measure the quality of edge template.

2. A new metric for edge template selection

2.1. A general probabilistic framework for recognition

A typical recognition procedure is composed of a feature extracting stage and a template matching stage. Feature extracting stage is difficult to model for many factors, such as weather conditions, sensor uncertainty and edge detector. In [13], a measurement model is present for the distortion of edge feature. This model addresses some important issues representing the uncertainty and inaccuracy measurement on edge feature of object boundary. The actual location of feature is perturbed randomly according to a statistical probability density, which is associating with an error boundary. In this paper, we assume that this error boundary is according to uniform distribution density.

For example, there are a set of independent edge feature measurements with positional error \( r \), \( M = \{ x_1, x_2, \ldots, x_m \} \) are made on the boundary of an object \( O_T \). Thus, all the measurements are located inside:

\[
O_T^r = \{ x \mid \exists v \in O_T, s.t. \|v - x\| < r \}
\]

We refer \( O_T^r \) as "measurement boundary ".

At template matching stage, a template is represented by the locations of 2D edge features. Without lost of generality, we use the vote-based matching criterion in [14]. Let \( O_h \) be a hypothesis of object \( O_t \) of position \( P \). The probability of a template-hypothesis similarity can be simply defined as a normalized area:

\[
\gamma = \frac{A(O_h \cap O_t)}{A(O_t)}
\]

Where \( A(R) \) is the area of region \( R \).

In the procedure of searching an object, some hypotheses are picked based on the number of correspondence features that exceed the threshold of votes \( V \). Let \( H_{pick} \) be a set of picked hypotheses. Then we define some hypotheses of \( H_{pick} \) that satisfying the location accuracy as \( H_{correct} \). We measure the performance of recognition by calculating the percentage of correct hypotheses \( H_{correct} \) to all picked hypotheses \( H_{pick} \). Consequently, the question is how to compute the probability of correct recognition (PCR), which is defined as follows:

\[
PCR(T_{target}, H_{picked}) = \Pr(\exists H \in (H_{pick} - H_{correct}), \exists H \in H_{correct}, V(\tilde{H}, T_{target}) > V(H, T_{target})]
\]

If the threshold of votes is set \( M \), then the probability of one incorrect hypothesis can be estimated as:

\[
PIR(T_{target}, H) = \text{prob}(H \in H_{pick} \& \& H \notin H_{correct}) \leq \left[ \gamma \right]^M
\]

Where \( \gamma \) is described in (2).
For more than one hypothesis, the calculation of the PCR of one recognition becomes extremely complicated. From (2), we defined
\[ \gamma_{\text{max}} = \max_{H \in \mathcal{H}_{\text{max}}} \gamma^n_H \]
for calculating PCR, which can be deemed as “geometry self-similarity” parameter. Then PCR is defined as:
\[ \text{PCR} = 1 - \sum_{i=1}^{n} \text{PIR}(T_{\text{arg} H}, H_i) \geq 1 - \sum_{i=1}^{n} \left[ \gamma^n_H \right]^m \geq 1 - \sum_{i=1}^{n} \left[ \gamma_{\text{max}} \right]^m \]  

(5)

2.2. “Ideal” spatial distribution model

We assume that the boundary of an object is a regular polygon with n orientations and use \( T_{\text{EN}} \) to denote it. Before depriving, we assume the followings:

1. The number of features is the same to each object, which is denoted as R;
2. There is a one-to-one correspondence between similar features in hypothesis and template.
3. The data measurement model is considered.

So the number of edge features according to one orientation is the same. It can be defined as:
\[ L_i = \frac{R}{n}, i \in [1, n] \]

Let \( \varepsilon \) be localization precision for a correct recognition. We refer \( R_{\text{radius}} \) as measurement error. Let \( S \) denotes all incorrect hypotheses. It can be noted that the range of feature correspondence for incorrect hypotheses in one orientation is written as:
\[ [L_i - \varepsilon, L_i - \varepsilon - s], i \in [1, n] \]

From (2), the range of template-hypothesis similarity is estimated:
\[ \frac{A(L_i - \varepsilon)}{A(S)} \geq \gamma \geq \frac{A(L_i - \varepsilon - s)}{A(S)}, i \in [1, n] \]

(6)

We obtain the value of self-similarity \( \gamma_{\text{max}} \) as:
\[ \gamma_{\text{max}} = \frac{A(L_i - \varepsilon)}{A(S)} \]

(7)

Then another object with \( n+1 \) orientations is denoted as \( T'_{\text{EN}} \). We also obtain:
\[ \gamma'_{\text{max}} = \frac{A(L_i' - \varepsilon)}{A(S)} \]

(8)

Clearly \( \gamma'_{\text{max}} < \gamma_{\text{max}} \), because \( L_i' < L_i \).

Finally, the inequality implies:
\[ \text{PCR} (T'_{\text{EN}}) = 1 - \sum_{i=1}^{n} \left[ \gamma'_{\text{max}} \right]^m \geq \text{PCR} (T_{\text{EN}}) = 1 - \sum_{i=1}^{n} \left[ \gamma_{\text{max}} \right]^m \]

(10)

To circular shape means \( n \to \infty \), we taking the limit to (6):
\[ \gamma_{\text{max}} = \lim_{n \to \infty} \frac{A(L_i - \varepsilon - s)}{A(S)} = 0 \]

(11)

From (5), then
\[ \text{PCR}(T_{\text{circle}}) = 1 \]

(12)

This equality indicates that circular shape is an "ideal" spatial contribution to recognition because \( \text{PCR}(T_{\text{circle}}) \) is equal to 1. More commonly, we consider one polygon is more easily to be recognized if it is more similar to circular shape. We call this shape similarity as "CIRCULARITY" metric.
2.3. Calculating CIRCLURITY metric

We use the value of circularity measuring (CM) to represent this shape similarity, which is defined as:

\[ C = \frac{CM_{\text{polygon}}}{CM_{\text{circle}}} = \frac{P^2}{A_{\text{polygon}}} = \frac{A_{\text{polygon}}}{A_{\text{circle}}} \]  

(13)

Where \( C \) is the value of CIRCULARITY metric, \( A \) is the shape area and \( P \) is the shape perimeter.

The CIRCULARITY metric means that an edge template is the more similar to circular shape, the more likely to be recognized. Then we choose some simple polygons to illustrate the effectiveness of the new metric. As demonstrated in Figure 3, regular polygons are shown in the first row with increasing number of sides, and irregular polygons are shown which both have the same sides in the second row. The values below the polygons are obtained by CIRCULARITY metric. Then the simulation of measurement on the boundary of the polygons is done. We use these measured polygons as input to recognition algorithm. Without loss of generality, we do experiment with our recognition algorithms: man square differences (MSD), mutual information (MI), sum of absolute transformed difference (SATD), hausdorff distance (Hausdorff). We use \( R_{\text{Nghmax}} \) to evaluate the recognition performance. A Monte Carlo approach is used to these polygons. Specifically, the means are evaluated over 100 different Mont Carlo runs for finding the location of one polygon.

![Polygon set](image)

Figure 1. Polygon set (a) regular polygons (b) irregular polygons

Figure 2 shows the results obtained by using four recognition algorithms. As can be seen, the \( R_{\text{Nghmax}} \) increases monotonically while CIRCULARITY increases. Firstly, let us focus on the polygons of the first row, as the sides of them increasing, the \( R_{\text{Nghmax}} \) monotonically increasing. Moreover, the value of \( R_{\text{Nghmax}} \) is significant difference to the four algorithms. The hausdorff method has a minimum \( R_{\text{Nghmax}} \) is about 0.3 with respect to other algorithms. The facts show that there has a big variation compared to different recognition criteria. And the \( R_{\text{Nghmax}} \) does not increase linearly as the CIRCULARITY is increased.
3. Experimental results

In this section, validation experiment is carried out by choosing four typical ground buildings in real scene, which are denoted by Target A, Target B, Target C and Target D. The templates for these targets are generated based on orthographic projection visible satellite image beforehand. (See Figure 3) In application, predefined template is transformed into forward-looking sensor image plane by airborne vision system. We choose a series of infrared aerial image sets in the pose for verification. The detail information is shown in Table 1. Correspondingly, one hundred frames of each image set are picked for performance statistics. The resolution of each frame is 512×256. Edge map is built by using canny operator. Hausdorff algorithm is chosen for matching. As can be seen, it is clear that the results are generally good for that $R_{\text{NgbR}}$ is decreasing when CIRCULARITY is increasing. The match performance of target B is much better than those of other targets as the value of $R_{\text{NgbR}}$ is the lowest. Certainly for all targets, the highest CIRCULARITY results in the best value of $R_{\text{NgbR}}$. However, we also note that the change range of $R_{\text{NgbR}}$ between target B with target D is not obviously like the variation on CIRCULARITY. The reason for this situation seems likely to be due to the disturbance of clutter of background. This topic is beyond the scope of the paper, but one which we intend to pursue in the future.

![Figure 3. Four ground-buildings for validation experiment](image1)

(a) Target A; (b) Target B; (c) Target C; (d) Target D.

| Target | scene | edge map | template | circularity |
|--------|-------|----------|----------|-------------|
| A      | ![](image2) | ![](image3) | ![](image4) | 0.339       |
Furthermore, a set of experiments are carried out to show the relationship between CIRCULARITY metric and precision of pose angle. Some angle transformation on the template of true position to simulate the different pose precision. The precision range of aspect angle and depression angle are both from -7 degrees to 7 degrees. The sampling interval is one degree.

![Graphs showing PCR as a function of pose angle precision](image)

Figure 4. The graphs show PCR as a function of pose angle precision
(a) Aspect angle; (b) Depression angle.

Figure 4 shows the PCR as a function of pose angle precision. Obviously, the value of PCR is the same high with high pose angle precision to four targets. No matter the value of CIRCULARITY is high or low, the performance effect is not obvious with high-precision angle measurements. Then value of PCR is varied when precision is reduced. Especially, the value of PCR varied significantly in depression angle. It means that precision of depression angle influences recognition system than that of aspect angle easily. This fact shows that the new metric is more suitable to be used in situation of somewhat low pose angle precision.

4. Conclusion
In this paper, a reasonable method of revealing the relationship between the spatial distribution of edge features and recognition performance is present. It is the first approach that derives an "ideal" spatial distribution model as standard for template assessment. Moreover, a new computable metric is proposed to measure the difficulty of an object to be recognized by its boundary. There are few relevant researches in this area. Validation is done by a number of experimental data from real scene. All experimental results show the potential effectiveness of the proposed metric. In conclusion, the work presented in this paper lays a conceptual foundation, which is very valuable in the making high reliable template.
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