Template Matching and Registration Based on Edge Feature

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ABSTRACT

In order to improve the performance of heterogeneous image matching and registration, the Weighted Voting Accumulation Measure (WVAM) based on the edge feature and image registration algorithm based on the steepest descent of the likelihood function are proposed. The WVAM is capable of resisting the interference of noise and the similarity region and can achieve matching location of template. On this basis, the likelihood function of edge sets registration is established on the basis of Gauss Mixture Model (GMM) of point sets. In order to achieve the registration between the template and matching area, and resolve the optimum transformation parameter by using the steepest descent method, the likelihood function is regarded as objective function and the affine transformation parameter is regarded as the optimization variance. The results of simulation experiments of this algorithm proved that the good performance of template and registration.

Key words: template matching; edge feature; WVAM; likelihood function

1 INTRODUCTION

Image matching aided navigation determines the geometric transformation between the template and real image according to matching and registration of them, and then determines the real-time position and attitude of vehicle accurately. During image matching, the preliminary geometric correction for real time image is completed firstly using the measurement parameters of vehicle unit. But there is some geometric distortion between the area to be matched in the real-time image and template image because of the measuring errors in parameters, and then the matching degree is demand to resist the geometric distortion. In addition, in order to correct the measuring parameters errors of vehicle unit, the accurate registration between the area to be matched and template image is demanded, and then can determine the geometric transformation between them accurately. Template matching and registration is the key link in image matching aided navigation.

Template matching and registration algorithm is consisted of (1) image feature extraction; (2) matching measure establishment; and (3) search matching. On the image feature extraction, the matching feature we choose must be invariance because of the template image and real-time image are obtained by different sensors under different environments. The feature points with invariance include edge points[1], corner points and virtual corner points[2], branching point[3], etc. Considering that the consistency of heterogeneous image feature and the real-time of algorithm,

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the edge is regarded as the feature of matching and registration, and then the Canny edge extract operators is used to achieve the edge feature extraction[4]. On the edge image matching measure establishment, the template matching measure is capable of resisting the interference of noise and the similarity region because of the non-homonymy exterior point will be product during the extracting the edge of real-time image and in the real-time edge image, there would be the region which similar to template image region due to the complex of the ground scene. Therefore, the template matching measure is capable of resisting the interference of noise and the similarity region. On the search matching, in order to improve the real-time performance, the fast matching acceleration mechanism is introduced into search matching[5].

According to the design requirements above, a novel edge template matching measure is proposed to achieve matching the template and real-time image based on the point set correlation, termed Weighted Voting Accumulation Measure (WVAM), and the likelihood function steepest descent of edge sets registration is established to achieve the accuracy registration between the template and matching area. The simulation results proved that the validity of proposed algorithm.

## 2 WVAM

In essence, if we regards the edge image as the 2D point sets, the problem of template edge image matching can be transformed into a the point sets matching. Suppose after preliminary geometric correction, the template edge image can be express as

$$\mathbf{Y} = \{ \mathbf{y}_n = (x_n, y_n)^T \mid n = 1, \cdots, N \}$$

where, \( \mathbf{y}_n \) is the coordinate of edge point in template image, the sub-image which has same size as real-time image is

$$\mathbf{X}^k = \{ \mathbf{x}_m = (x_m^k, y_m^k)^T \mid m = 1, \cdots, M_k \}$$

where \( \mathbf{x}_m^k \) is the coordinate of edge point in sub-image, \( k \) is the serial number. Let \( \mathbf{D}^k \) is 2D accumulator array and can be expressed as:

$$\mathbf{D}^k(p, q) = \sum_{n=1}^{N} \sum_{m=1}^{M} \delta(x_n - x_m^k - p, y_n - y_m^k - q)$$

where \( \delta(a, b) \) represents 2D delta function, only when \( a = 0 \) and \( b = 0 \), \( \delta(0, 0) = 1 \), else, \( \delta = 0 \).

In ideal condition, if \( \mathbf{Y} \) and \( \mathbf{X}^k_{opt} \) are complete registration, the \( \mathbf{D}^k_{opt} \) has the maximum value at \((0,0)\), \( \mathbf{D}^k_{opt}(p, q) \) will reduced obviously with the distance between \((p, q)\) and \((0,0)\) increases. Therefore, we can according this characteristic to construct the similarity measure function \( S^k \) between sub-image and template edge image, which can be written as:

$$S^k = \frac{\sum_p \sum_q \mathbf{D}^k(p, q)e^{-\sqrt{p^2 + q^2}}}{\max\{M, M_k\}}$$

We can see form formation process of \( \mathbf{D}^k(p, q) \) that every accumulation in accumulator equivalent to perform one voting for the coordinate difference between two points and then perform the distance weighted summation of total voting. Therefore, this measure is named as Weighted Voting Accumulation Measure (WVAM).
In the formula (1), the Gaussian kernel \( e^{-\sqrt{p^2+q^2}} \) weighted summation operation of accumulator array \( D^{k_{\text{opt}}} (p, q) \) in molecular is performed. The reason is that there is peak diffusion at the maximum value which should be appeared at \((0,0)\) in accumulator array \( D^{k_{\text{opt}}} (p, q) \) due to the residual geometric distortion between the area to be matched in the real-time edge image and template edge image, which cause that kernel weighted result in the similarity measure including the collection and processing of peak effusion. However, as shown in Fig.1, when only using the molecular of formula (1) as the similarity measure, the maximum value of similarity measure will form at the wrong matching region shown as Fig. (1). This is because that this region has similar edge with template and there are many stray points in internal, and the measure value is bigger than matching region due to the total point in these two point sets will participate accumulation. In order to resolve this problem, we increase factor \( \max\{M, M_\ell\} \) at denominator in formula (1), where \( \max\{\cdot, \cdot\} \) is used to calculate the maximum value. It is easy to see that this factor can suppress the similarity measure value in wrong matching region, decrease the disturbance of similarity measure introduce by stray points and similar region, and then can reflect the characteristics of matching region uniquely.

![Fig.1 The interference of the outliers and similar region to the similarity measure](image)

The location with the measure maximum is regarded as the matching region by performing template edge image scanning on real-time image and calculating the WVAM of the relative location.

### 3 Likelihood Function of Edge Sets Registration

The area to be matched and template edge image are need to registration due to there is some geometric distortion between them. Edge sets registration is regarded as the Maximum Likelihood (ML) estimation problem of transform parameters[6,7]. The various components center of Gauss Mixture Mode (GMM) characterized by the points in template point sets, and the data points in GMM distribution characterized by the points in matching region edge point sets. GMM posterior probability is the maximum in matching region edge point sets under the optimal affine case.

Probability density function of GMM in matching region edge point sets is written as:

\[
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\]
where

\[ p(x_m | n) = \frac{1}{2\pi\sigma^2} \exp \left( -\frac{||x_m - By_n - t||^2}{2\sigma^2} \right) \]

is Gaussian probability density function. We use the same isotropic covariance \( \sigma^2 \) and the same prior probability \( \pi_n = 1/N \). \( B_{2n2} \) is affine transformation matrix. \( t_{2d} \) is translation vector. Estimate the parameter \( \Theta = \{B, t, \sigma^2\} \) by minimizing negative logarithm likelihood function shown in the following formula:

\[
E(\Theta) = -\ln p(X | \Theta) = -\ln \prod_{m=1}^{M} \sum_{n=1}^{N} \pi_n p(x_m | n)
\]

(3)

4 POINT SETS REGISTRATION ALGORITHM OF THE LIKELIHOOD FUNCTION STEEPEST DESCENT

4.1 point sets normalization processing

In order to provide the better initial state, normalization of two point sets is processed firstly. Mean vector for point set \( \hat{X} = (x_1, \cdots, x_m, \cdots, x_M)^T \) can be express as:

\[
\bar{x} = \frac{\sum_{m=1}^{M} x_m}{M}
\]

The normalization point set is:

\[
X = \left( \frac{x_1 - \bar{x}}{l_x}, \cdots, \frac{x_m - \bar{x}}{l_x}, \cdots, \frac{x_M - \bar{x}}{l_x} \right)^T
\]

(4)

Where, \( l_x = \sqrt{\frac{\sum_{m=1}^{M} ||x_m - \bar{x}||^2}{M}} \) is scale factor of point set.

The same process is used to point set \( \hat{Y} = (y_1, \cdots, y_n, \cdots, y_N)^T \):

\[
Y = \left( \frac{y_1 - \bar{y}}{l_y}, \cdots, \frac{y_m - \bar{y}}{l_y}, \cdots, \frac{y_M - \bar{y}}{l_y} \right)^T
\]

(5)

where, \( l_y = \sqrt{\frac{\sum_{n=1}^{N} ||y_n - \bar{y}||^2}{N}} \)
4.2 Affine transformation parameter estimation based on linear search steepest descent

In order to obtain the affine transformation parameter when minimizing formula (3), this paper uses steepest descent unconstrained optimization method. Steepest descent method is a basic and important method with advantages of simple iterative calculation, lower memory demands and fast convergence at away from extreme point, etc.

When we solve the problem of unconstrained optimization
\[
\min_{x \in \mathbb{R}^n} f(x)
\]
the steepest descent method process iteration according to the basic iteration scheme
\[
x^{k+1} = x^k + \alpha \lambda d^k,
\]
namely, searching begins from point \(x^k\) and along negative gradient direction, where \(\lambda\) is iteration step length, in general case, \(0 < \lambda < 1\). \(\alpha\) is linear searching coefficient. Linear searching is mainly used to solve the non-convergent problem introduced by the step is too long in original steepest descent method when close to function extreme point. According to the basic principle of the steepest descent method, taking derivation of formula (3) with respect to \(B\), \(t\), \(\sigma\):

\[
\begin{align*}
P(B, t, \sigma) &= \frac{\partial E(\Theta)}{\partial B} = \sum_{m=1}^{M} \sum_{n=1}^{N} \pi_n \exp\left(-\frac{1}{2\sigma^2} \|x_m - By_n - t\|^2\right) \left[ t - \left(x_m - By_n\right) \right] y_n^r \\
Q(B, t, \sigma) &= \frac{\partial E(\Theta)}{\partial t} = \sum_{m=1}^{M} \sum_{n=1}^{N} \pi_n \exp\left(-\frac{1}{2\sigma^2} \|x_m - By_n - t\|^2\right) \left[ t - \left(x_m - By_n\right) \right] \\
w(B, t, \sigma) &= \frac{\partial E(\Theta)}{\partial \sigma} = \sum_{m=1}^{M} \sum_{n=1}^{N} \pi_n \exp\left(-\frac{1}{2\sigma^2} \|x_m - By_n - t\|^2\right) \left(2\sigma - \frac{\|x_m - By_n - t\|^2}{\sigma}\right)
\end{align*}
\]

With writing the partial derivative above as vector form, we can get the following gradient vector:

\[
\nabla F = [P_{11}, P_{12}, P_{21}, P_{22}, Q_{11}, Q_{21}, w]
\]

Then, the negative gradient direction is:

\[
\nabla \bar{F} = -\frac{\nabla F}{\|\nabla F\|^2}
\]

Furthermore, the steepest descent method can be express as:
\[ \mathbf{F}_{k+1} = \mathbf{F}_k + \alpha \lambda \cdot \nabla \mathbf{F}_k \]

And we can obtain:

\[
\mathbf{B}_{k+1} = \begin{bmatrix}
F_{k+1}(1) & F_{k+1}(2) \\
F_{k+1}(3) & F_{k+1}(4)
\end{bmatrix}
\]

(9)

\[
\mathbf{t}_{k+1} = \begin{bmatrix}
F_{k+1}(5) \\
F_{k+1}(6)
\end{bmatrix}
\]

(10)

\[
\sigma_{k+1} = F_{k+1}(7)
\]

(11)

5 SIMULATION EXPERIMENT AND ANALYSIS

5.1 Experiment of edge template matching algorithm

The real-time image after geometric correction, template image and the relatively edge image are shown in Fig.(1). The weighted voting accumulation Measure between sub-image in edge image and edge template image is shown in Fig.2 (a) (the blue region and template are not completely overlapped and set to zero because there is no calculated measure value). The matching location of template in real-time is shown in Fig.2 (b). We can see that the measure value at matching points is the global maximum and have better contrast than neighborhood.

The Hausdorff Distance(HD)[8] is the most widely used measure in point sets registration and the Least Trimmed Square Hausdorff Distance (LTS-HD) is the improved HD with better performance at present[9]. Use images above to process registration experiment based on LTS-HD, we also can achieve the correct matching. However, in order to compare the performance difference in matching between the two kinds of images, two evaluation indexes are introduced to represent the global single peak characteristic and local gradient characteristic of measure respectively: global measure SNRM and local gradient characteristic, and they can expressed as:

Fig.2 real-time image and template image used in simulation
Where $M_{opt}$ is the measure value at matching point, $B_M$ is the mean value of measure, $\sigma_M$ is the standard deviation of measure. LSNRM and SNRM are similar except the calculation is performed in neighborhood matching points.

The comparison result of the global and local measure SNR of VWAM and LTS-HD is shown in Table 1. We can see that the VWAM have better single peak characteristic and local gradient characteristic.

<table>
<thead>
<tr>
<th></th>
<th>SNR&lt;sub&gt;M&lt;/sub&gt;</th>
<th>LSNR&lt;sub&gt;M&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>VWAM</td>
<td>8.0198</td>
<td>2.9322</td>
</tr>
<tr>
<td>LTS-HD</td>
<td>4.8715</td>
<td>2.1678</td>
</tr>
</tbody>
</table>

5.2 Experiment of edge template registration algorithm

The matching region obtained by template matching and the corresponding edge image are illustrate in Fig.3, where “blue O” represents edge template and “red *” represents matching region. We can see that they are misalignment because the geometric distortion between them.

Fig. 4 shows the matching result of SIFT characteristic between Fig.3 (a) and Fig.3 (b). The results illustrate that the SIFT characteristic of template and real-time image cannot match due to the difference of imaging properties between them and there is serious fault in homonymy points extraction. We can see that the performance of the registration algorithm by using these characteristic are limited.
The process of iteration registration at iteration parameter $\lambda = 0.2$ is shown in Fig.5. We can see that achieve the registration process only need 15 times iteration, and the registration parameters we can obtain are $B = \begin{bmatrix} 0.9101 & -0.0991 \\ 0.1023 & 0.8319 \end{bmatrix}$, $t = \begin{bmatrix} 15.9977 \\ 24.6890 \end{bmatrix}$.

In order to solve the problem of heterogeneous image matching and registration, the Weighted Voting Accumulation Measure (WVAM) and edge point sets registration likelihood function are proposed. The WVAM is capable of resisting the interference of noise and the similarity region. The registration algorithm based on the steepest descent of the likelihood function need not solve the corresponding relation between the edge points and has better robust performance of global registration. The valuate of algorithm is proved by measured image data.

**6 INCLUSIONS**
REFERENCES


