Image Matching Method Based on Laplacian Feature Constrained Coupling Variance Measure

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Abstract. In order to overcome the current image matching algorithms, which mainly use the distance information between pixels to achieve feature matching, ignoring the variance information between images, resulting in more false matching in the matching results, this paper designs an image matching method based on Laplacian feature constrained coupling variance measure. Firstly, Harris operator is introduced to extract image features roughly. On the basis of rough extraction, Laplacian feature of pixels is used to optimize the extracted image features to obtain more accurate image features. Then, the gradient feature of the image is used to calculate the direction information of the image. Based on the gradient feature, the neighborhood of the feature points is established, and the Haar wavelet value in the neighborhood is obtained to obtain the feature vector. Finally, the regional variance model is used to measure the variance information of the image, and it is introduced into the process of image feature matching. The variance information is added on the basis of Euclidean distance measurement of feature points to achieve image feature matching more accurately. RANSAC method is used to purify the results of feature matching, eliminate mismatching and complete image matching. The experimental results show that compared with the existing matching algorithms, the proposed algorithm has better matching performance and higher accuracy, which accuracy maintained above 90%.

Keywords: Image matching, Harris operator, Laplace feature, Gradient feature, Direction information, Regional variance, RANSAC algorithm

1. Introduction
In order to achieve better image matching, many image matching methods have been developed [1-4]. For example, fan et al. [5] introduced sparse representation into the process of image matching, described the image features locally through the image strength and geometric information, and completed the feature matching based on sparse representation. Because the sparse representation method does not consider the variance characteristics of the image, the matching accuracy of the method is poor. Fernando et al. Simulated the intersection of the round spider web by the sampling
points associated with the feature points to form the spider local image feature descriptor, and then applied it to the process of feature distance measurement to complete the image matching. Because the process of feature matching only depends on the distance measurement, and ignores the variance feature of the image, there are many mismatches in the matching results. Su et al [6] proposed a method to find the best scale. Through the training of the sample image, a zoom factor is obtained and used in the process of image feature matching. The voting mechanism of the generalized Hough transform is introduced to find the rotation and scaling of the image, locate the position of the template image in the scene, so as to eliminate the mismatches completely. Because it is difficult to build a complete dictionary when training the zoom ratio, the accuracy of the matching results is not high. Song Jiaqian et al. [7] use edge detection method to improve the Gauss difference feature extraction operator, use the gradient feature of image to describe the feature, and use the Euclidean distance measurement method to complete the feature matching. Because this method only relies on Euclidean distance measurement to complete feature matching, and ignores the variance feature of the image, the accuracy of the matching results is reduced.

2. Image Matching Algorithm in this Paper

In this paper, the image matching algorithm is mainly composed of four parts: the acquisition of image features, the formation of feature vectors, the acquisition of matching feature points and the optimization of matching feature points:

1) acquire image features. The operator is used to realize the first extraction of image features. On this basis, the Laplacian feature of image is used to optimize the first extraction results of the operator and remove the pseudo image features.

2) form feature vector. Using the gradient information of image, the main direction of image feature is calculated. On this basis, the neighborhood of the feature points is established, and the wavelet information of the image is calculated in this neighborhood to obtain the robust feature vector.

3) get matching feature points. The regional variance model of image is introduced to measure the variance information of image. And the variance information and Euclidean distance information between feature points will be combined to accurately obtain matching feature points.

4) optimization of matching feature points. In order to find out the wrong matching points and refine the image matching results, the algorithm is used to test the matching correctness of matching feature points.

2.1 Image Feature Acquisition

Compared with the existing image feature extraction operators, Harris operator has the advantage of high detection accuracy. When Harris operator extracts image features, it first constructs neighborhood I (x, y) of pixel point P. after moving it according to coordinates (A, B), the generated gray level change information G(A, B) is [8-9]:

\[ G(A,B) = \sum_{x,y \in I} S[I(x+A,y+B)-I(x,y)]^2 \]  

(1)

In the formula, \( \sum \) represents weighted operation; s is Gaussian function, whose function is:

\[ S = e^{-|x|^2/\sigma^2} \]  

(2)

Equation (1) is transformed into an approximate representation of quadratic terms, and its function is as follows:

\[ G(A,B) = [A \ B] W [A \ B] \]  

(3)

Where W is the real symmetric matrix:
\[ W = \sum S \left[ \begin{array}{cc} \left( \frac{\partial^2}{\partial x^2} \right)^2 & \left( \frac{\partial^2}{\partial x \partial y} \right) \\ \left( \frac{\partial^2}{\partial x \partial y} \right) & \left( \frac{\partial^2}{\partial y^2} \right)^2 \end{array} \right] \]  

(4)

Then, using the determinant \( \text{DET}(W) \) and trace \( \text{TR}(W) \) of \( W \), the feature extraction function \( H \) [10, 11] can be obtained:

\[ H = \frac{\text{DET}(W)}{\text{TR}(W) + \alpha} \]

(5)

Where, \( \alpha \) is an arbitrary constant to prevent the denominator of \( H \) from being 0.

Then set the extraction threshold \( RH \), and compare it with the \( H \) value of the calculated pixel point \( P \) in equation (5). If \( H \geq RH \), the pixel point \( P \) can be regarded as a candidate feature point.

In order to remove the false feature points in the image feature points extracted by Harris operator and optimize the image feature extraction results. In order to optimize the feature points, Laplace operator is used to calculate the Laplacian features of candidate feature points and their neighbors.

Firstly, the Laplace operator \( \nabla^2 p(x, y) \) corresponding to the four neighborhood points of the candidate feature point \( P \) (x, y) is calculated:

\[ \nabla^2 p(x, y) = \frac{\partial^2 p(x, y)}{\partial x^2} + \frac{\partial^2 p(x, y)}{\partial y^2} \]

(6)

Where, \( \frac{\partial^2 p(x, y)}{\partial x^2} \) and \( \frac{\partial^2 p(x, y)}{\partial y^2} \) respectively represent the pixel difference between the candidate feature point \( P \) and its horizontal and vertical neighborhood points, and their calculation functions are as follows:

\[ \frac{\partial^2 p(x, y)}{\partial x^2} = p(x+1, y) - 2p(x, y) + p(x-1, y) \]

(7)

\[ \frac{\partial^2 p(x, y)}{\partial y^2} = p(x, y+1) - 2p(x, y) + p(x, y-1) \]

(8)

In the Bresenham circle [12] of the candidate feature point \( p \) shown in FIG. 1, the Laplacian feature \( \nabla p \) of the candidate feature point \( p \) and the Laplace feature \( \nabla p_i (i = 1, 2, 3, \cdots 16) \) of its 16 neighboring points are calculated using Equation (6). Then compare the magnitudes of \( \nabla p \) and \( \nabla p_i (i = 1, 2, 3, \cdots 16) \). If \( \nabla p \) is smaller or larger than \( \nabla p_i (i = 1, 2, 3, \cdots 16) \), \( p \) is regarded as a feature point, otherwise \( p \) is regarded as a pseudo feature point and eliminated.

![Figure 1 The circle of Bresenham](image)
2.2 Formation of Feature Vectors

After the image features are obtained, their feature vectors will be obtained for feature matching. In order to improve the robustness of the algorithm, this paper combines the gradient magnitude and gradient direction of the feature points to obtain the main direction of the image features. Then, a circular neighborhood of feature points is established to adapt to transformations such as rotation. Then, the Haar wavelet information of the image is calculated in the neighborhood to obtain a more robust feature vector.

The gradient amplitude $M(x, y)$ and gradient direction $\theta(x, y)$ of the feature point $p(x, y)$ are [13]:

$$M(x, y) = \sqrt{(p(x+1,y) - p(x-1,y))^2 + (p(x,y+1) - p(x,y-1))^2}$$

(9)

$$\theta(x, y) = \arctan \frac{p(x, y+1) - p(x, y-1)}{p(x+1, y) - p(x-1, y)}$$

(10)

Among them, $\arctan$ is the arctangent operation.

Calculate $M(x, y)$ and $\theta(x, y)$ of pixels in the neighborhood of $p(x, y)$ according to equations (9) and (10), and use this to form a gradient histogram with a range of $[0, 360^\circ]$. The histogram was then divided into 10 parts, and the peak size of each part was compared. Consider the direction at the peak of the histogram as the main direction $\phi$ [14].

As shown in FIG. 2, a concentric circle neighborhood of $p(x, y)$ is established with $\phi$ as the starting direction, and it is equally divided into $45^\circ$ steps. Haar wavelets with a size of $4\sigma$ (where $\sigma$ is the scale factor corresponding to $p(x, y)$) are used to calculate the Haar wavelet responses $dx$, $dy$ on the $x$ and $y$ axes of each molecular domain. Thus, combining the sub-domains $dx$, $dy$ and $|dx|$ and $|dy|$, a four-element vector $D$ can be formed.

$$D = \left[\sum d_x, \sum d_y, \sum |d_x|, \sum |d_y|\right]$$

(11)

Finally, the vector $D$ of 8 subdomains is synthesized to obtain a feature vector $C$ with 32 elements.

![Figure 2](image.png)

Figure 2 Division of concentric circles

2.3 Get Matching Feature Points

Using Euclidean distance to complete image feature matching is a widely used method. However, this method does not consider the relationship between the feature points and the surrounding pixels, which is prone to mismatching. For this, this paper introduces the regional variance model of the image, and obtains the variance information with the feature point as the center area. And it is combined with Euclidean distance information between feature points to accurately obtain matching feature points to improve the correctness of the algorithm.

Let two different feature points be $e$ and $v$, then the Euclidean distance $D_i(e, v)$ between them is
calculated as [15]:

\[ Di(e, v) = \sqrt{\sum_{i=1}^{32} \left( C_i^e - C_i^v \right)^2} \]  \hspace{1cm} (12)

In the formula, \( C_i^x(x = e, v) \) is the i-th element in point x.

For the neighborhood of the feature point e of size \( M \times N \), the corresponding area variance Fe is calculated as [16]:

\[
F_e = \frac{\sum_{m=-(M-1)/2}^{(M-1)/2} \sum_{n=-(N-1)/2}^{(N-1)/2} \left[ \epsilon(x+m, y+n) \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \epsilon(x_i, y_j)}{M \times N} \right]^2}{M \times N}
\]  \hspace{1cm} (13)

Use equation (13) to calculate the variance information Fe and Fv of the feature points e and v, and calculate the difference DF (e, v):

\[ DF(e, v) = |F_e - F_v| \]  \hspace{1cm} (14)

Finally, the formulas (12) and (14) are combined to find the matching point of the feature point e:

\[ v = (arm \ min \ Di(e, v)) \ & \ (arm \ min \ DF(e, v)) \]  \hspace{1cm} (15)

In the formula, && represents an AND operation symbol.

It can be seen from formula (15) that only the feature point v with the smallest Euclidean distance from the feature point e and the smallest variance information difference can become the matching point of the feature point e.

2.4 Optimization of Matching Feature Points

The RANSAC algorithm uses the geometric relationship between the feature points to achieve the correctness of the matching calculation [17]. Let the feature points d1 and d2 whose coordinates are \( (x_1, y_1) \) and \( (x_2, y_2) \) be a pair of matching points, then their geometric relationship can be expressed as [17]:

\[
[\xi x_1 \ 
\xi y_1 \ 
\xi] 
= [h_1 \ h_2 \ h_3 \ 
    h_4 \ h_5 \ h_6 \ 
    h_7 \ h_8 \ h_9] 
[x_2 \ 
y_2] \]  \hspace{1cm} (16)

make:

\[
J = \begin{bmatrix}
-x_1 & y_1 & 1 & 0 & 0 & 0 & -x_2 & x_1 & -x_2 & y_1 \\
0 & 0 & 0 & x_1 & y_1 & 1 & -y_1 & x_1 & -y_2 & y_1 \\
\end{bmatrix}
\]

\[
K = \begin{bmatrix}
x_2 & y_2 \\
\end{bmatrix}^T \\
\xi 
\]

\[
H = [h_1, h_2, h_3, h_4, h_5, h_6, h_7, h_8, h_9] 
\]  \hspace{1cm} (17)

According to equation (17), equation (16) can be transformed into the following form:
Based on equation (18), the value of \( h_i (i = 1, 2, 3, \cdots, 8) \) can be obtained by the least square method [18]. Then judge the correctness of the matching of \( d_1 \) and \( d_2 \). The detailed RANSAC algorithm is described in [17].

3. Conclusions

This paper uses MATLAB 7.0 software to test the algorithm in this paper on a computer with Intel I3 and 500G hard disk. In the experiments, the algorithms in [19] and [20] were used as the control group, and the control group algorithm and the algorithm in this paper were used to match a variety of images, and the results of each algorithm were compared to analyze the effectiveness of the matching.

Based on Harris operator, this paper designs an image matching algorithm based on Laplacian feature coupling variance measure. On the image features extracted by Harris operator, the Laplacian features of the image are used to optimize them to obtain the image features. Using the image gradient and Haar wavelet information, the feature vector of image features is obtained. The variance information of the image was measured by the regional variance model, and the information was combined with the Euclidean distance information to accurately match the image features. Through the RANSAC algorithm, the geometric relationship between the matching points is used to determine the correctness of the matching, and the feature matching results are optimized. By observing the matching results of the algorithm in this paper on brightness, scaling and rotating images, it can be seen that the algorithm in this paper has better matching performance.

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