Digital core image registration based on SIFT features

Yuxue Wang, Xue Zhang
School of Mathematics and Statistics, Northeast Petroleum University, Daqing 163000, China
2521279664@qq.com

Abstract. In this paper, SIFT features and FLANN matching are applied to digital core image registration to achieve the purpose of fast digital core image registration. In this paper, three groups of digital core images data are used to carry out experiments from different aspects of rotation, brightness, translation and the combination of the three. The experimental results show that the method in this paper can effectively perform digital core image registration.

1. Introduction
The purpose of digital core image registration is to locate small core from large core. In digital core image registration, the resolution of digital core image obtained by CT scanning is different, because of the different scales between large core and small core. Direct image registration cannot accurately determine the position of the small core in the large core.

For this problem, a method must be found that can accurately perform image registration under different image resolutions, and accurately determine the position of the small core in the large core. The SIFT feature is invariant when an image undergoes a series of changes in scale, rotation, translation, brightness, and so on. It is also stable to a certain extent for angle change, affine transformation and noise[1]. These characteristics are just needed for the study of digital core image registration. But the speed of SIFT feature extraction is slow. This paper selects FLANN matching to solve the problem of image registration efficiency. Three groups of experiments are used in this paper to show that the combination of SIFT features and FLANN matching can achieve digital core image registration with different resolutions.

2. SIFT Feature Extraction
SIFT feature extraction is an algorithm to extract image local feature points. The extracted feature points contain scale, position, direction and other information.

2.1. Establish Scale Space to Detect Extreme Points
The scale space of image is defined by convolution of the original image of an image and Gaussian function[2-3]:

\[ L(x, y, \sigma) = G(x, y, \sigma) \ast I(x, y) \]  (1)

Where: \( L(x, y, \sigma) \) represents the scale space, \( \sigma \) represents the scale space factor, \( \ast \) represents convolution operation, \( I(x, y) \) represents the input image matrix, \( G(x, y, \sigma) \) represents Gaussian function, and its expression is shown in formula(2):

\[ G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}} \]  (2)
The difference of Gaussian pyramid (DOG) is often used to build the scale space of SIFT features in practical application. The calculation formula is as follows:

\[ D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma) \]  

(3)

After the construction of the DOG pyramid is completed, the next step is to detect the extremum points. In extreme point detection, the extreme point to be detected must not only be compared with the points in the same layer neighborhood, but also with the adjacent points on the upper and lower layers. Only when the extreme point to be detected is larger than or smaller than all adjacent points at the same time can be recognized as an extreme point. And the detected extreme point is a feature point.

2.2. Feature Points Location

DOG is performed in a discrete space. The extreme points in the discrete space cannot completely replace the extreme points in the continuous space. Usually, the sub-pixel interpolation method is used for the extreme points in the discrete space to obtain the extreme points in the continuous space. Taylor expansion of the DOG function is:

\[ D(x) = D + \frac{\partial D}{\partial x} x + \frac{1}{2} x^T \frac{\partial^2 D}{\partial x^2} x \]  

(4)

Take the derivative of the above formula and substitute the derivative of 0. The offset of the extreme point can be obtained \( \hat{x} \):

\[ \hat{x} = -\frac{\partial^2 D^{-1}}{\partial x^2} \frac{\partial D}{\partial x} \]  

(5)

Substituting \( \hat{x} \) into the above Taylor expansion, there are:

\[ D(\hat{x}) = D + \frac{1}{2} \frac{\partial D}{\partial x} \hat{x} \]  

(6)

Noise can interfere with points with very low contrast. In order to eliminate the noise interference, it is necessary to set a threshold. When the threshold is less than or equal to \( |D(\hat{x})| \), the feature points are considered to meet the requirements. Otherwise, they are not satisfied and should be removed. In addition, noise will also interfere with unstable boundary points. The eigenvalues of the Hessian matrix \( H \) are proportional to the principal curvature of \( D \). Therefore, the principal curvature can be obtained through the Hessian matrix. The formula is as follows:

\[ H = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix} \]  

(7)

\( D \) can be obtained by the neighborhood difference approximation of the extreme point.

When the ratio of the maximum eigenvalue to the minimum eigenvalue of the Hessian matrix exceeds a threshold \( R \), i.e. the following formula is true. Then the extreme point of this detection is an unstable boundary response point, which should be eliminate.

\[ \frac{\text{Tr}(H)^2}{\text{Det}(H)} < \frac{(R + 1)^2}{R} \]  

(8)

2.3. Direction Estimation of Feature Points

The main direction is determined by calculating the gradient distribution of the four pixels around the feature point. The calculation formula of the gradient weight of the feature point is as follows[4]:

\[ m(x, y) = \sqrt{(L(x + 1, y) - L(x - 1, y))^2 + (L(x, y + 1) - L(x, y - 1))^2} \]  

(9)

The calculation formula of the gradient direction is as follows:
\[ \theta(x, y) = \tan^{-1}\left(\frac{(L(x, y + 1) - L(x, y - 1))}{L(x + 1, y) - L(x - 1, y)}\right) \]  

The gradient direction and size represented by each pixel are different. The direction is superimposed on the eight directions of adjacent points, i.e. upper, lower, left, right, upper left, upper right, lower left and lower right. The histogram statistic of these eight directions show that which direction has the largest cumulative value of gradient points is the main direction of the feature point.

After determining the main direction, the original image should be rotated to the same direction as the main direction. And the coordinate system should be reset. Count the directions of all points in the new coordinate system, and combine them with the previously determined main directions to determine the description vector of the SIFT feature.

### 2.4. Define the Feature Descriptor of the Surrounding Area

Take these feature points obtained above as the center to sample the image area where the feature points are located, and then generate feature descriptor.

Generally, 16*16 sampling windows are selected. Then each sampling window is divided into 4*4 sub-sampling windows. In each sub-sampling window, there are total 4*4 points. Each point corresponds to a specific gradient direction. Summarize all these gradient directions into the eight directions mentioned above. Then each sub-sampling window will generate eight vectors in different directions. Finally, all the sub-sampling windows are combined, which is the feature descriptor of SIFT for this feature point. The SIFT feature points descriptor with brightness invariance can be obtained by normalizing the feature vector.

After the above four steps, the SIFT feature points that are invariant to scale, rotation, and brightness can be extracted.

### 3. FLANN Matching

FLANN matching is a combination of basic image registration and accelerated search algorithms to achieve the purpose of acceleration. The main idea of basic image registration is to find the feature point to be registered that is closest to the registered feature point by calculating the Euclidean distance. The general steps as follows:

1. Select a feature point in the registration image, then calculate the Euclidean distance between it and all feature points to be registered.
2. Find the closest distance and the next closest distance among these distances.
3. If the ratio of the closest distance to the next closest distance is less than the set threshold (usually between 0.5 and 0.8), the registration is considered successful.
4. By repeating the above three steps for all the feature points, the registration of the two images can be completed.

This paper uses random K-d tree algorithm to accelerate. Firstly, need to build multiple K-d trees. Secondly, randomly select some dimensions from the N-d dimension with the highest variance. Then divide the data into several parts using these dimensions[5]. Finally, the general steps of image registration are performed on each part.

### 4. Experiment

Use three groups of different digital core images to conduct experiments from three aspects of rotation, translation, brightness and the combinations of the three. The feasibility of digital core image registration with the combination of SIFT feature extraction and FLANN matching is verified respectively.

#### 4.1. Rotation and Brightness Change Experiment

The first group of experiments first rotates the small core and then performs a CT scan to obtain the digital core image. Then change the brightness of the small core. Respectively register with the large core image. The results are as follows.
The green line in Fig.1 is the line of good registration feature points. The square line represents the position of the small core in the large core. It can be seen from Fig.1 that the position of the small core in the large core is inclined. It shows that although the small core is rotated, the method in this paper can still accurately perform image registration. In addition, this paper defines the registration rate to further evaluate the registration results. The calculation formula is as follows:

\[
\text{ratio} = \left( \frac{p_1}{p_2} \right) \times 100\%
\]  

(11)

Among them, \( p_1 \) represents the number of good registration feature points, \( p_2 \) represents the total number of registration feature points.

In the above experiment, there are 58 good registration feature points. The total registration feature points are 110. The registration rate is 52.7%. Although the ratio is not particularly high, it is acceptable because it exceeds 50%. Compared with image registration by human eye observation, this method can effectively improve the speed of image registration.

It can be seen from Fig.2 that when the rotation and brightness of the small core image change simultaneously, the method in this paper can still be used for image registration. In this experiment, there are 54 good registration feature points. The total registration feature points are 98. The registration rate is 55.1%. The registration rate has little change in the two experiments. This shows that the method in this paper is effective when the rotation and brightness of the digital core image change simultaneously.

4.2. Brightness and Rotation Change Experiment

The second group of experiments directly performs a CT scan on the small core to obtain the digital core image. Then process the brightness and rotation of the small core image to carry out experiments. The results are as follows.
The brightness and rotation change simultaneously 237 432 62.5%

Fig.3 is the image registration of the small core image without any change. Fig.4 is the image registration only by changing the brightness of the small core image. Figure 5 is the image registration by first changing the brightness of the small core image and then rotating it. Table 1 shows the number of feature points and the registration rate of image registration in these three cases. It can be seen from the table that the registration rate is generally above 60%. And it can be as high as 90% when the small core image is not changed. The second group of experimental results show that the method in this paper is still effective when the brightness and rotation of digital core image change simultaneously.

4.3. Translation, Rotation and Brightness Change Experiment

In the second group of experiments, the small core is drilled in the edge of the large core. So only part of the small core image is contained in the large core image, i.e. the small core has a translation change. In this group of experiments, change the brightness and rotation of the large core image. Then respectively register with the small core images after translation changes. The results are as follows.
Fig. 6 is the image registration of the large core image without any processing. Fig. 7 is the image registration after changing the brightness of the large core image. Fig. 8 is the image registration by first changing the brightness of the large core image and then rotating it. It can be seen from the green line and square line in the figures that the method in this paper can determine the position of the small core registration part in the large core. Since the small core has its own unique feature points, the registration rate at this time cannot accurately explain the registration relationship between the small core and the large core feature points, so this paper does not evaluate the registration rate for this group of experiments. The third group of experimental results show that the method in this paper is still effective when the translation, brightness and rotation of the core change simultaneously.

5. Conclusion
In this paper, SIFT features and FLANN matching are applied to digital core image registration to achieve the purpose of fast digital core image registration. In this paper, three groups of different digital core images are used for experiments. In the first group of experiments, the small core is rotated to obtain a digital core image, and change the brightness of the small core. The second group of experiments process the small core image with rotation and brightness change. In the third group of experiments, translation change translation is performed for small core, and rotation and brightness changes are performed for large core. In each group of experiments, respectively register the images of the small core and the large core before and after the change. The three groups of experimental results all show that the position of the small core in the large core can be determined, which shows that the method in this paper can effectively perform digital core image registration.

This paper is the registration of two-dimensional digital core images, and can further study the registration of three-dimensional digital core images. Three-dimensional image registration will be more widely used in practice.

References
[1] Yang Yan, Research on image feature analysis and matching methods of complex scenes[D]. Dalian: Dalian University of Technology, 2019:18. (in Chinese)
[2] Bala A, Kaur T. Local texton XOR patterns: A new feature descriptor for content-based image retrieval[J]. Engineering Science & Technology An International Journal, 2016, 19(1):101-112.
[3] Xiao Z, Yu L, Qin Z, etal. A point matching algorithm for brain CT images based on SIFT and gray feature[C]. Proceedings of the IEEE International Conference on Signal Processing. Chengdu, 2017:1-6.
[4] Chen Min, Tang Xiaoan. Comparative study on the application of SIFT and SURF feature extraction algorithms in image matching[J]. Modern Electronic Technology, 2018, 41(7): 41-44. (in Chinese)
[5] Wang Jinlong, Zhou Zhifeng. Research on image feature extraction and FLANN matching algorithm based on SIFT[J]. Computer Measurement and Control, 2018, 26(12): 175-178. (in Chinese)