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# Registration of Brain Medical Images Based on SURF Algorithm and R-RANSAC Algorithm

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***Abstract***

*This paper proposes a matching method for medical image registration, which combined with SURF (Speeded up Robust Features) algorithm and the improved R-RANSAC (the Randomized of Random Sample Consensus) algorithm. Firstly, this algorithm extracts featured points with SURF algorithm from images and matches similar featured points with Euclidean distance. Secondly, the R-RANSAC algorithm is used to eliminate wrong matches and the SPRT (Sequential Probability Ratios Test) is used to minimize R-RANSAC runtime. Finally, the image registration process is accomplished by estimating space geometric varied parameters according to least square method. The algorithm combines robustness and high efficiency of SURF and high-accuracy of R-RANSAC algorithm. Experimental results show that in the condition of images with noise, non-uniform intensity and large scope of the initial misalignment, the proposed algorithm achieves better robustness and higher speed while maintaining good registration accuracy compared with the conventional area-based and feature-based registration methods.*

***Keywords***: *medical image registration, SURF, R-RANSAC, feature extraction*



## 1. Introduction

Medical image registration is to make two medical images feature of different time, at different observation points as well as in different models be completely consistent with each other on spatial location and anatomical structure by looking for some kind of space transformation [1]. According to image registration with different image information, there are two categories of image registration: the gray level-based matching approach [2] and the feature-based matching approach [3]. The feature-based matching approach is mainly to describe the image [4] by extracting the stable feature points and to match image according to the similarities of feature points. The method is fast, high efficient and widely applied to, but error matching often appears under the circumstances of varied image content. Therefore, the final registration results are affected. In order to avoid this problem, this paper studies and applies the implementation principle of SURF feature points detection, realizing the initial matching of the feature points by Euclidean distance, combing with the improved RANSAC algorithm to purify matching point, estimating space geometric varied parameters according to least square method, and finally image registration is realized by resampling and interpolating for the floating images.

### 2.1. SURF Algorithm

SURF (Speeded-Up Robust Features) algorithm mainly consists of feature point detection, feature points description, feature points matching [5]. It uses rapid Hessian matrix to detect feature points, and introduces integral image and box type filter in the calculation, improves the efficiency. The SURF has been applied by some scholars in image registration for it has strong robustness, good efficiency [6].

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**2.1.1. Feature Point Detection**

Feature point detection generally includes three steps, establish integral image firstly, and then, build scale space by box filter, positioning the characteristic points on the base of the scale space at last.

Detection object is to find the scale invariant point. SURF adopts Hessian matrix to test feature points. For *X=(x,y)* in the image, the Hessian matrix on the scale of sigma can be defined as follow.

$$H(X,\sigma)=\begin{bmatrix} L_{xx}(X,\sigma) & L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) & L_{yy}(X,\sigma) \end{bmatrix} \quad (1)$$

In the formula (1), $L_{xx}(X,\sigma)$ is the convolution of the Gaussian second order derivative $\frac{\partial^2 g(\sigma)}{\partial x^2}$ with the image in point x, and similarly for $L_{xy}(X,\sigma)$ and $L_{yy}(X,\sigma)$.

In order to reduce computation load, SURF algorithm use box-type filtering template and the original input image convolution $D_{xx}, D_{xy}, D_{yy}$ to replace $L_{xx}, L_{xy}, L_{yy}$ respectively, get Happrox that approximate Hessian matrix.

$$\det(H_{approx}) = D_{xx}D_{yy} - (0.9D_{xy})^2 \quad (2)$$

Use the maximum inhibition method, in a neighborhood, image feature points can be found under different scales. After finding out the maximum, use interpolation method for interpolating scales and image spaces, get positional value and dimension value of the feature points eventually.

**2.1.2. Feature Points Description**

Feature points description can divided inti two steps, get the major orientation of feature point first of all, to keep algorithm rotating invariably, and then, turn the neighborhood to the major orientation, describe this future point.

a) Determine the primary direction.In order to achieve rotation-invariant image, determine the primary direction of the extracted future point. The method is shown below. Used feature point as the center, take 6s (s means corresponding scale of the future point) as radius, find the Wavelet response values on x, y directions. Weight Gaussian function with center on feature points on Haar wavelet response value, adding higher weight coefficients on feature points that near the center and make more contribution. Useπ/3 fan window to traverse the entire circle area, sum all the Haar wavelet response vectors of feature points in each quadrant area, form different direction vectors, choose the direction with the maximum vector sum as the main direction at the last. This process is illustrated in Figure 1.

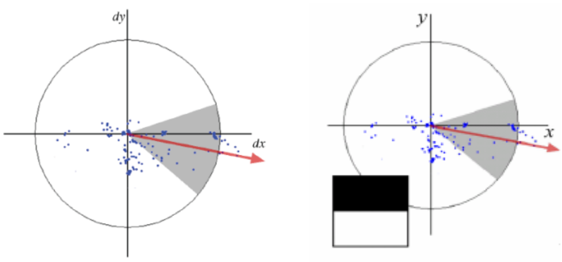



Figure 1. Determine the Primary Direction

b) Create vector. Select Rectangular region which is 20s on each side, center on the future point after determining the primary direction. Next, rotate main direction of the area in feature point. Divide the region into 16 sub-regions, each of 4×4, select 5×5 sampling sites in every sub-region, calculate corresponding Haar wavelet response dx and dy. Sum Haar wavelet response value and absolute value of 4 smaller sub-regions, get four-dimensional vector *v =(Σdx, Σdy,Σ|dx|,Σ|dy|)*,add vectors of the 16 sub-regions into eigenvectors separately, a 64 (4×16) dimensional feature vector descriptor can be received.

### 2.1.3. Feature Points Matching

Feature points matching can be regarded as catching the similarity between each feature descriptor which adopts Euclidean distance to calculate. Assume there are $i$ and $j$ respectively in reference images and floating images, $S_i$ and $S_j$ express their SURF feature descriptors. So, the Euclidean distance can be shown as formula (3).

$$d_{ij} = \sqrt{\sum_{t=1}^{N} \left(S_i(t) - S_j(t)\right)^2} \tag{3}$$

*N* is the dimensions of descriptor SURF.

### 2.2. The Randomized of Random Sample Consensus (R-RANSAC)

After feature points matching, there might be a certain degree of mismatch and false match. Mismatch will affect the final result of the registration, so it is necessary to filter out these Mismatching points from initial matching. At present, many kinds of purification methods such as the nearest-neighbor/ the next nearest-neighbor ratio method, bilateral matching method and Random sample consensus are widely used. RANSAC is adopted in this study [7]. Take projection transformation as example, the steps of RANSAC as follows:

a) Regard matching results as Matching candidate feature set, select 4 groups of matching points from matching candidate feature points randomly to establish system of equations, estimate eight unknown parameters of transformation matrix M.

b) To compute the transformation of remaining feature points after transformation matrix M and the distance between the candidates matching points with it. If the distance is less than a certain threshold, the candidate feature points are interior point, or it is outer point.

c) Find out the estimation with the largest number of interior point (when these interior points are equal in number, choose standard minimum variance point set), eliminate outer points, make parameter estimation with all interior points.

RANSAC can remove influence come from more serious error, but it need large amounts of computing and long time computation.

Given all this, this study adopts improved RANSAC--R-RANSAC with SPRT(Sequential Probability Ratio Test [8]). R-RANSA (The Randomized RANSAC) algorithm [9] is a algorithm that evaluates the hypothesis model. SPRT (Sequential Probability Ratios Test) is used to determine whether each tested sample data can match up with the data model. And calculate out likelihood ratio. If the likelihood ratio is larger than a threshold, it will be considered as imprecise model. Abandon this model until test all samples. Combine the two; it can refuse to error model with test small amount of sample data. SPRT with R-RANSAC not only can eliminate error matching points very well, but also shorten the matching time. It can be applied to complex image matching and registration.

## 3. Algorithm Steps

This paper combines SURF algorithm and improved RANSAC algorithm to realize the registration of medical image. The specific registration procedures are as follows:

Step1 Read the reference image and the floating image and respectively. Then pre-process the two images, that is the two images are decomposed by wavelet. Get the image of Pyramid after wavelet transform.

Step2 Extract SURF feature points in the top level with the SURF algorithm.

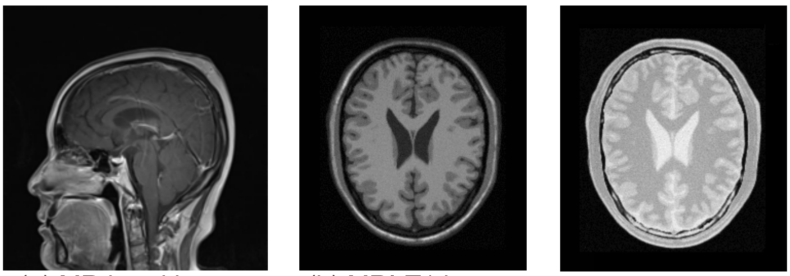
Step3 Set the extracted feature point number of the two images as “N1” and “N2”, and get the coordinates feature points of the images. The feature point as the center, and generate 64-dimensional feature descriptors. Form the descriptor as the feature vector. The feature vector “D1”of the reference image will be N1 × 64-dimensions, the feature vector “D2” of the floating image will be N2 × 64-dimensions.

Step4 Using Euclidean distance to match feature vector, and taking the similarity is less than the threshold T eigenvectors as the two images registration point.
Step5 Purified matching points. Then the improved RANSAC algorithm is used to eliminate wrong matches.
Step6 According to the purification of matching points, use the least squares method (LSM) to estimate the optimal space geometric transformation parameter.
Step7 Transform the floating image into the coordinate system of the reference image and bring it into correspondence with the reference image in space position. Complete the image registration by using the re-sampling and interpolation techniques.

## 4. Results and Analysis

Compared with the Normalized mutual information (NMI) algorithm in the Reference [10] and the SIFT-RANSAC algorithm in the Reference [11], the experiment has proved the algorithm validity from some aspects as registration robustness, accuracy and registration time and so on. In the experiment, the hardware environment is CPU Intel(R) Core i5 with 2.5 GHz in 4G internal storage. The software developing tools are Windows 7 operating system and MATLAB R2012a.

The images for experiment are chosen two groups. Figure 2(a) is normal MR head image. The image size is 512×512. The Pixel size is 1mm×lmm. Figure 2(b) and (c) are chosen from the McConnell imitating brain database of the Neurosciences Institute at McGill University in Montreal, Canada. The researcher has chosen the normal MR brain images, to be accurate, the MRI-T1images and MRI-PD images. They are strictly aligned. The image size is 221×257. The Pixel size is 1 mm×1 mm. The MR-T1 image provides clear Anatomical structure information, while the MR-PD image offers rich information about the brain function. Those images belong to different models.



(a) MR head image (b) MRI-T1 image (c) MRI-PD image

Figure 2. Brain Medical Images

The image data set of the experiment can be showed as followed Table 1:

Table 1. Experiment Data Set

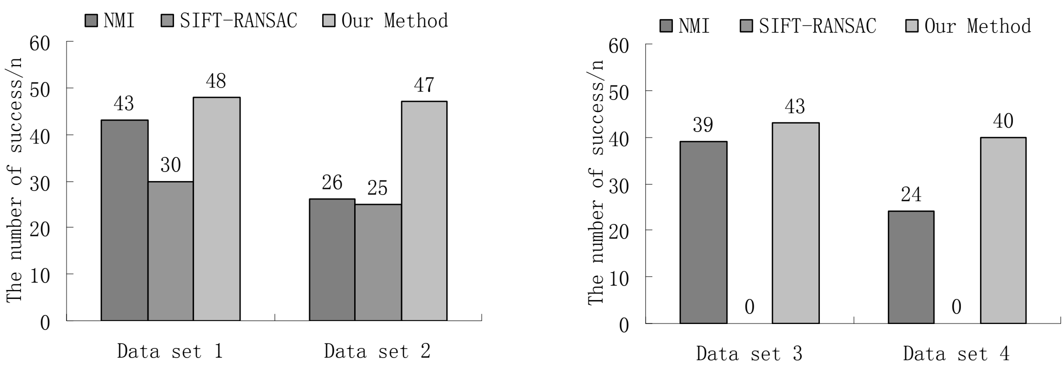
| Data Type | Modality | No. | Size/pixel | Pixel/mm | Noise/% | Intensity Non-uni formity/% |
|---|---|---|---|---|---|---|
| Mono-modality | MR,MR | 1 | 512×512 | 1×1 | None | None |
| | MR,MR | 2 | 512×512 | 1×1 | 5 | 20 |
| Multi-modality | T1 weight, PD weight | 3 | 221×257 | 1×1 | None | None |
| | T1 weight, PD weight | 4 | 221×257 | 1×1 | 5 | 20 |

### 4.1. The Robustness Analysis

The previous 4 groups of data set has been compared to test the registration robustness. The Figure 2(a) and Figure 2(b) are served as reference images, while the Figure 2(a) and Figure 2(c) are used as the floating images. The floating images were shifted randomly and transformed rotationally. The initial translation parameters are tx and ty, which are randomly chosen from two ranges: from -20mm to 20mm. The initial rotation parameterθ is randomly chosen from two ranges: from -20°to 20°. The initial mismatch parameters are made up of tx, ty and θ. The experiment has chosen 50 groups of initial mismatch parameters. The deviation between each successful registration result and the initial mismatch of translation and rotation is obtained by the Absolute Deviation. In the experiment, it is successful when the different between the getting space varied parameters and the real space varied parameters is less than the threshold. On the contrary, it is failure. According to the Reference 12, if the deviation of the rotating degree is less than one degree, the deviation of translation horizontally and vertically is less than one pixel size, such registration would reach the sub-pixel level and be evaluated a success.

The Figure 3 has counted the successful registering times of previous three registering algorithms in four data sets within different initial vary ranges. The Figure 3(a) is the registering successful times of mono-modality data set with addiction noise and without addiction noise. Seen from the figure, it is found that the successful times of the NMI algorithm are similar to the algorithm in the thesis when images without addiction noise. However, the successful registering times of the NMI algorithm has declined apparently, and our algorithm was slightly affected when images with addiction noise. For the SIFT-RANSAC, all the registering successful times are less than other two algorithms within the mono-modality data sets. The Figure 3(b) is the registering successful times of multi-modality data set with addiction noise and without addiction noise. The registering successful times of the NMI algorithm and our algorithm are less than the successful times of the Figure 3(a). The successful times of the NMI algorithm have declined apparently, and the SIFT-RANSAC algorithm was completely ineffective. In the experiment, it is found that when the images content and gray level difference are large, the registering result of the NMI algorithm is comparatively unsatisfactory. When the images are rotated in large scales or translated horizontally, all the three registering algorithms are greatly affected.

Seen from the experimental result, the thesis has put forward the registering algorithm combined DWT, SURF and improved RANSAC obtained the most successful registering times. It proved that such algorithm is more robust than the NMI algorithms and the SIFT-RANCAC algorithm.



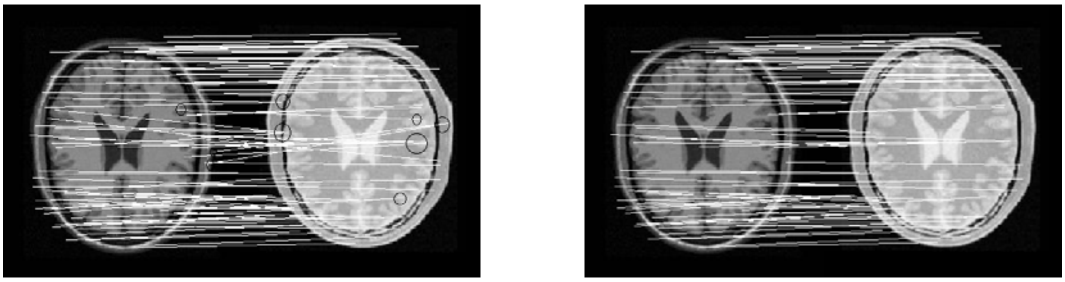

(a) Mono-modality images data sets (b) Multi-modality images data sets

Figure 3. Robustness Comparison between Three Algorithms

**4.2. Purified Matching Points**

Let the Figure 2(c) as the floating image and register it with the Figure 2(b) reference in following registration experiment. Match the similar feature point after extract feature points in the two images of the Figure 2. The results show as the Figure 4(a). It is found that the matching points exist mismatching and one to many etc. from the Figure 4(a) in the circles. These mismatch will affect the final result of the registration, so it is necessary to filter out these mismatching points from initial matching. The original matching points were purified with the R-

RANSAC algorithm. The eliminated wrong matching results show as the Figure 4(b). From the figure, the mismatching points are basically eliminated.

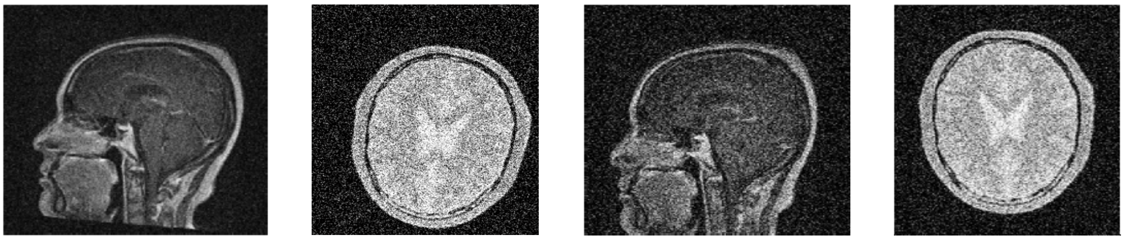


(a) Initial match (b) Match after purification

Figure 4. Purified Feature Points

### 4.3. Registering Accuracy

In order to prove the registering accuracy, the experiment chose the Figure 2(a) as mono-modality reference image and chose the Figure 2(b) as multi-modality image. The transformation of the image in Figure 5(a) and (b) form the data2 and data4 shown as follows as float image. After the registering experiment with three kinds of methods between the reference images and floating images, the registration results show as the Figure 5(a) and (b)-Only list the registration result images of our algorithm here due to the length of be confined. It is found that the registration image and the reference image is consistent basically in spatial position and anatomical structure.



(a) (b) (c) (d)

Figure 5. The Registration Results, Left to Right: (a) MR image with additive noise, (b) MRI-PD image with additive noise, (c) MR image registration results ,(d) MRI-PD weight image registration results

After the registering experiment, the registration transformation parameters are named as tx′,ty′,θ′. The absolute value (noted as $\Delta x, \Delta y, \Delta\theta$)of deviation between the registering parameters and the true parameters (noted as tx, ty,θ) are functioned as the registering accuracy. The result is showed in Table 2 and Table 3. As showed in Table 2 and Table 3, for the mono-modality image registration accuracy, the accuracy of the three methods are close, all reach the sub-pixel level, but for multi-modality image registration, our algorithm accurate is better than the NMI algorithm, basically reached a sub-pixel level, while the SIFT-RANSAC method fails.

Table 2. The MR Mono-modality Registration Results

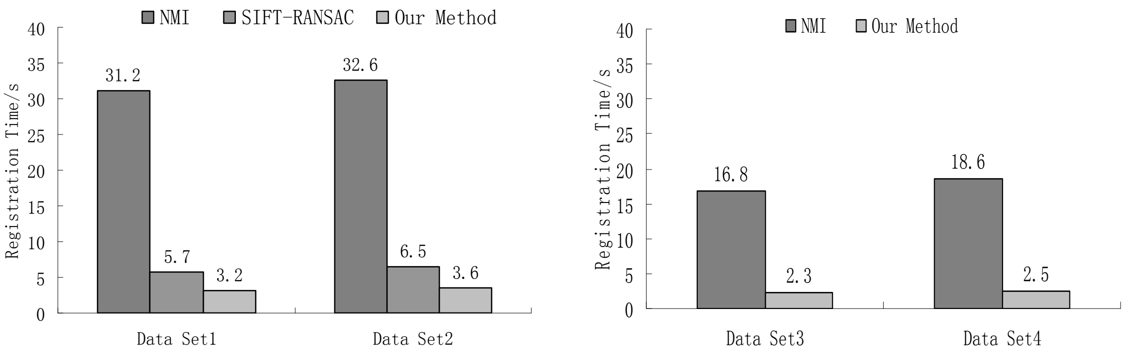
| Algorithm referred | Δx/mm | Δy/mm | Δθ/(°) |
|---|---|---|---|
| NMI | 0.472 | 0.468 | 0.113 |
| SIFT-RANSAC | 0.236 | 0.242 | 0.121 |
| Our Method | 0.186 | 0.120 | 0.035 |

Table 3. The Multi-modality of MRI T1 Weight and MRI PD Weight Registration Results

| Algorithm referred | Δx/mm | Δy/mm | Δθ/(°) |
|---|---|---|---|
| NMI | 0.783 | 0.877 | 0.771 |
| SIFT-RANSAC | / | / | / |
| Our Method | 0.636 | 0.672 | 0.586 |

### 4.4. Time Consumption Analysis

The Figure 6 has recorded the average consuming time of the three algorithms in four data sets within different initial transforming ranges. It is clearly showed in the Figure 6 that our algorithm is the fastest algorithm, and the SIFT-RANSAC algorithm is the faster algorithm, while the NMI algorithm is the slowest for the mono-modality image data sets registration. The registration of medical images requires strong robustness, high accuracy and less time consumption. Based on the comprehensive evaluation of the above experiment, the thesis proved that algorithm combined DWT, SURF and improved RANSAC algorithm has better comprehensive capability than the NMI algorithm and the SIFT-RANSAC algorithm.




(a) the data sets of mono-modality images (b) the data sets of multi-modality images

Figure 6. The Registering Time Comparison of the Three Algorithms

## 5. Conclusion

This paper proposes a Medical Image Registration algorithm Combined with SURF algorithm and R-RANSAC algorithm. The algorithm to extract feature points of medical image quickly and robustly with the SURF algorithm, generate the corresponding feature points described vector, and match initial similar featured points based on Euclidean distance. Then the improved R-RANSAC algorithm is used to eliminate wrong matches. Finally the image registration process is accomplished by estimating space geometric varied parameters according to remaining matches. The three aspects of the alignment robustness, the accuracy of registration and registration time to test this algorithm, experimental results show that, with the traditional algorithm based on NMI, as well as SIFT algorithm compared, the three aspects of the algorithm in the alignment robustness, the accuracy of registration and registration time is better than the other two traditional image registration method. The proposed algorithm to speed up the rate of registration, improved alignment accuracy and performance, has better overall performance.

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