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Research on the ROI registration algorithm of the cardiac CT image time series

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ABSTRACT

Objective: Based on the Scale-invariant feature transform (SIFT) features, a novel registration algorithm is proposed to solve the problems including the large amount of data emerged from the cardiac image registration process, time-consuming issue and the lower registration accuracy.
Method: First of all, the region of interest (ROI) of the image to be registered is extracted; then, the feature points of the image are extracted by using the SIFT algorithm; finally, a novel registration algorithm which combines the adopted K-d tree Nearest Neighbor (KNN) Best-Bin-First (BBF) algorithm with the random sampling consensus (RANSAC) algorithm is employed to achieve the registration algorithm and to enhance the registration accuracy, so as to solve the high dimensionality of feature vector and easier mismatching issues.
Result: The experimental results are as follows: first of all, the amount of data processed during the registration is reduced by 60%–80% after extracting the ROI without destroying the original image data. Secondly, the registration time is reduced by 50%–70%, compared with the traditional registration algorithm. Thirdly, the whole registration precision increases by 10%–20% by using the BBF algorithm to match the feature points and using the RANSAC algorithm to filter the mismatching.
Conclusion: The proposed algorithm equipped with the robustness and stability can greatly reduce the time required for registration, improve the registration accuracy.

0. Introduction

Medical image registration technology, as the key technology of image fusion and surgical navigation, has received great attention and developed rapidly in recent years. For example, the registration of plantar pressure images proposed by Oliveira and Tavares has already been applied to the clinical diagnosis [1,2]. However, many problems have emerged, such as the large amount of data processed during the registration process, time-consuming issue, low accuracy, non-rigid deformation of the images and so on, which greatly restricts the applications of the medical image registration technology in clinics [3–6].

In order to reduce the amount of data emerged from the registration process, Guryanov [7] et al. proposed to use the fast adaptive bidirectional empirical mode decomposition (FABEMD) to extract the most essential model of the images and calculate the downsampling rate accordingly. That algorithm has high computational complexity. Although it has extracted the most essential model, it does not necessarily have diagnostic significance and its downsampling can change the original image data. Zhao [8] et al. applied Rényi mutual information of feature points to the image registration so as to avoid the computational overhead of calculating the mutual information of the whole image, which reduces the amount of data to be registered from a certain perspective. However, the Rényi mutual information is calculated based on the feature points, and the computational complexity of extracting the feature points is still very large. Esteban [9] et al. suggested to use image segmentation technology to extract homogeneous regions, and then do registration, which shows a higher registration accuracy. However, based on the fact that the segmentation registration is restricted by the accuracy of its algorithm, which may lead to quadratic deformation of the image such as the damage to the organ edge, and reduce the registration accuracy. In order to solve the problems existing in the amount of registration data in the above algorithm,

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this paper suggests to extract the image area which the specialists are interested in without sacrificing the original image data, so as to reduce the amount of data and reduce the interference of the outside world. Furthermore, using the registration algorithm for its processing improves the registration accuracy.

Aiming to solve the problems of the long registration time and low registration accuracy, Ullah [10] et al. use the hierarchical registration strategy to complete the global pre-registration based on SIFT features so as to achieve basic registration of the two images. Furthermore, completing the registration by using the differential homeomorphism log-Demons algorithm to fit the local regions of the two images accurately can improve the registration accuracy and reduces the residual error and the computational complexity. Compared with the algorithm fully based on image gray intensity, this algorithm reduces the registration time to a certain extent, but it still does not meet the requirements of clinical application. In addition, the hierarchical registration strategy must sacrifice a certain degree of precision so as to improve the registration speed, because the balance between the speed and accuracy has not been resolved [2,11]. For the larger deformation of the non-rigid image, Pawar [12] et al. proposed to use the adaptive refinement grid and hierarchical B-spline function, which is based on the minimized energy function, to update the registration control points dynamically, so as to achieve the minimized image differences and complete the registration. The experimental results show that the registration accuracy is high, but the algorithm takes a long time.

In view of the above shortcomings such as long registration time, low registration accuracy and the non-rigid deformation of the image to be registered., this paper proposes a registration algorithm which combines the improved K-d tree Nearest Neighbor (KNN) Best-Bin-First (BBF) with the random sampling consensus (RANSAC). Aiming to solve the problems of high dimension and mismatching issue of SIFT feature vector, BBF algorithm proposes to build the data index and improve the shortcomings of requiring repeated comparisons of the traditional K-d nearest neighbor, so as to reduce the searching, matching time of the feature points and achieve the exact matching of SIFT feature vector; aiming to solve the mismatching issue of feature point pairs, the RANSAC algorithm is put forward to calculate the spatial transformation parameters to eliminate the effects of mismatching, fit the image to be registered accurately and achieve registration. Compared with the traditional K-d nearest neighbor algorithm, the experimental results show that the algorithm in this paper can better match the feature point pairs and enhance the registration accuracy.

1. The criteria of selecting the region of interest (ROI)

ROI is a part of image received the specialists' prior attention [13]. In general, in the medical image, ROI is a region of decisive significance for the doctor's diagnosis, accounting for 20% to 40% of the image area, while the region of non-interest is mainly as a reference. For example, as for the brain tumor CT images, the tumor area is the ROI, while the region of non-interest refers to the area surrounded by the tumor with the coordinate reference significance.

The selection of the ROI is not the same for different registration images and registration algorithms. Ye [14] and other scholars proposed to use middle-value filtering idea combined region growing and mathematical morphology operator algorithms to select the ROI. Zhang [15] and other scholars use frequency domain analysis and significant regional detection algorithm to select the ROI. The computational complexity of above algorithms are high, and because of the complexity of the medical image, the selected area cannot guarantee that the selected area is the interested area of the doctors.

In a cardiac CT images, in order not to affect the diagnosis, doctors usually designated the cardiac area of the CT image center as the ROI. For example, for (A) and (a) cardiac CT images in Fig. 1, the central cardiac area is the doctor's interested area, while the spine, ribs and lungs surrounded by the central part are regions of non-interest. However, in a few special cases, specialists may also select a particular area as the ROI based on specific particular diagnostic requirements, according to special cases or special patients, which requires the doctors to select according to their own understanding of the images. As a result, from the perspective of engineering applications, it is necessary to propose the extraction way of the ROI which is more appropriate to the diagnostic needs. The ROI extraction method employed in this paper has been described in experiment two of chapter four.

Fig. 1 shows the images of four patients (The A, B, C, D are on behalf of the patients, respectively). The cardiac CT, Fig. 1(A)–(D) are taken at different times and the images of extracting the ROI, Fig. 1(a)–(d), are the corresponding images. Fig. 2 shows the distribution images of the SIFT feature points of the cardiac CT images and their ROI images. After extracting the ROI, the data of every part has changed in the registration process. Fig. 3 shows the data comparison before and after extracting the ROI. Respectively, (a) is the comparison image of the data quantity emerged from the registration process before and after extracting the ROI, (b) is the comparison image of feature points quantity and (c) is the comparison image of the feature points extraction time (Fig. 4).

Through the analysis of a motor cycle of the cardiac CT images and the data statistics of the Cardiac CT images of four different patients taken at different times, the conclusions are as follows: firstly, ROI extraction can reduce 53% to 70% data during the process of registration; secondly, the distribution of the feature points extracted from the ROI is not consistent with the distribution of those extracted from the original image. The feature points extracted from the ROI are more representative of the details of that body area and its distributions are more well-distributed, which is conducive to improve the registration accuracy; thirdly, ROI is the dense area of feature points; fourthly, the ROI extraction can effectively reduce 46% to 65% extraction time of the feature points.

2. BBF(Best-Bin first)algorithm

K-d tree is a binary search tree structure, which accomplishes the data classification through the partition of the K-dimensional data space. In essence, the K-d tree is a balanced binary tree [16,17]

2.1. The establishment of the K-d tree

Given a two-dimensional dataset $S = \{(x_1, y_1), (x_2, y_2), \cdots, (x_n, y_n)\}$, including n sets of data. The K-d tree can be established according to the following strategies:

The knots of defining the K-d tree are as follows:

dom_elt	split	left	right

Among which, dom_elt represents a sample point of the space like (x_1, y_1); *split* represents the serial number of the fractal dimension, 0 for the axis X, 1 for the axis Y; left represents the set of samples in the left subspace; right represents the set of samples in the right subspace; Bin refers to the separating hyperplane, which is cross the representative sample point represented by dom_elt and perpendicular to the direction axis indicated by the split.