Inception Based Medical Image Registration

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Abstract. Biological tissue has strong absorbability and strong scattering, which may lead to edge blur, low signal-to-noise ratio and so on, which affects the registration of medical images. This chapter simulates and makes the biological tissue imitation image data set under the above conditions, cleverly designs a regression structure embedded in the U-net Inception module, and forms an unsupervised deep learning medical image registration method. It is applied to the biological tissue imitation data set for the first time. The experimental results show that the image registration method based on SIFT, ORB, BRISK, AKAZE and so on can not successfully complete the registration work because it can not find a sufficient number of effective key points on the data set, SURF although it can complete the registration work. But the effect is weaker than the proposed method. Based on the medical image registration method proposed by Inception, this chapter can effectively solve the problem of biological tissue image registration with strong absorption and strong scattering.

Keywords: Medical image registration · Unsupervised · Inception · Unet

1 Introduction

Image registration technology is a high-dimensional optimization process. The aim is to find an optimal spatial transformation to map the corresponding points of two or more images obtained under different image devices and different time conditions to a specified space, that is, to register two or more images obtained by different imaging devices at different time [1] space. At present, image registration technology is widely used in medical image processing, word recognition, material mechanics, remote sensing data analysis and computer vision. Medical image registration technology is an indispensable key step in medical image analysis. It is a prerequisite for medical image fusion, segmentation, contrast and reconstruction.

Medical image registration is an important research direction in medical image processing. It is often necessary to analyze the image data of the same patient with different shooting time and different scales in clinic, and medical image registration technology is needed at this time. Image registration algorithm finds the corresponding relationship between the search data, transforms the image space mapping, rearranges the pixel position in the image, so that the patient area or tissue and organ with diagnostic significance in the target image has the consistency of space and gray diagnosis standard, so as to

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provide more accurate auxiliary diagnosis results for doctors. Therefore, the selection of accurate registration algorithm needs to be associated with the object of study and image characteristics in order to obtain good diagnostic results.

At present, image registration methods emerge in endlessly. If classified, they can be divided into the following three types: (1) registration method based on gray information; (2) registration method based on transform domain; (3) registration method based on feature point.

The registration method based on gray information adopts the content of image gray information, so it is called gray registration method. The algorithm mainly uses the optimization algorithm to search the transformation parameters when the registration function reaches the extreme value. It mainly includes the error square sum algorithm (SSD) [2], the normalized correlation (NCC) [3], the maximum likelihood (ML) [4], the mutual information (MI) [5] method and so on the registration method based on transform domain is usually based on Fourier transform [6] and wavelet transform [7], and the image transformation is registered in frequency domain. The method has low computational complexity and good anti-noise ability, and can meet the real-time requirements of registration in some fields.

The registration method based on feature points can solve the image registration of different scales, different rotation angles and even different modes. The scope of application is the most extensive. Scale invariant feature transformation (SIFT) [8] is a classical algorithms in registration method based on feature points. SIFT doesn't change as the image scales and rotates. Part of the situation changes in light and camera view, successfully applied in the registration of visible images. Some other improvements have been made in the feature-based methods such as SURF [9] and BRISK [10], which are mainly to improve the computational efficiency. Compared with SIFT and SURF, they can't retain the edges due to the Gaussian filtering, which will lose the position accuracy and uniqueness. Based on KAZE algorithm [11], the fast explicit diffusion algorithm for accelerating features in nonlinear scale space (AKAZE) [12] introduces an efficient improved local differential binary descriptor (M-LDB) [13], which improves the repeatability and uniqueness compared with SIFT and SURF algorithm.

Deep learning and the development of neural network provide a new direction for image registration. Because neural network can imitate human visual mechanism and obtain feature expression at different scales in image, the feature information of image can be generalized better. This makes the algorithm based on deep learning and neural network have unparalleled prospect in image registration research [14]. P. Weinzaepfel [15] combined deep learning with optical flow for image registration. In recent years, there are [16, 17] registration methods based on deep learning. These methods belong to supervised image registration methods, and the training process of network has a strong dependence on annotated data. Medical image data sets are often small and difficult to label. So it is difficult to meet the learning of neural networks. The spatial conversion function (STN) method [18] allows the network to explicitly process transformations by exploiting the invariance of convolution. It can realize the registration of unsupervised learning in the training stage of neural network.

2 Inception-Based Image Registration Networks

2.1 Inception Structure

The Inception structure [19] first proposed by Christian Szegedy et al. The deep convolution neural network built by this structure has achieved the best detection and classification performance in the ILSVRC14. Its structure is shown below (Fig. 1).

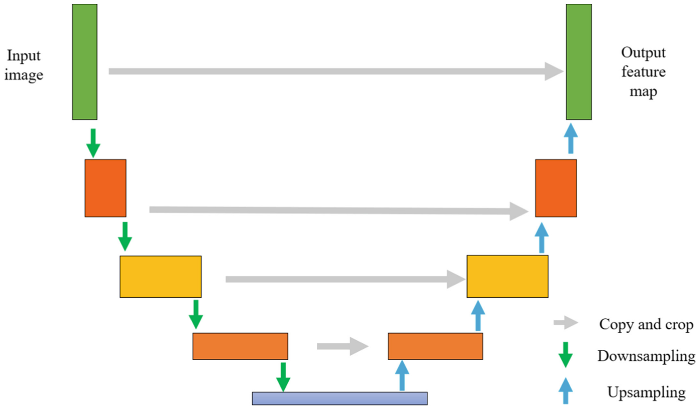

Fig. 1. Inception structured chart

This structure carries on the convolution operation with the convolution kernel size of 1,3,5 and the maximum pooling operation for the incoming input from the upper layer, and then centralizes the results of each branch and continues to pass backward as the output of the next layer. Based on the split-conversion-merger strategy, it makes full use of multiple filters of different scales. The fusion of different features learned by multi-scale receptive field is more beneficial to the network to learn objects of different sizes in the image. The 1×1 convolution added before different scale convolution kernels in Inception structure can reduce the computation and introduce more nonlinear transformations into the network to enhance the learning ability of the whole network to the features.

2.2 U-net Structure

A U-shaped network structure [20] has been proposed by the method which has won many firsts in the ISBI cell tracking competition. It performs well in the field of biomedical image segmentation such as fundus retinal segmentation and lung image segmentation. The detailed structure is shown below (Fig. 2).

U-net structure obtains different size feature layers by convolution and pooling operation, and adds feature channels through upsampling process. This design enables the network to be regarded as a combination of encoder and decoder composed of neural network. It is beneficial for the network to mine higher value features through less data sets. At the same time, the feature fusion method of the U structure splicing links each

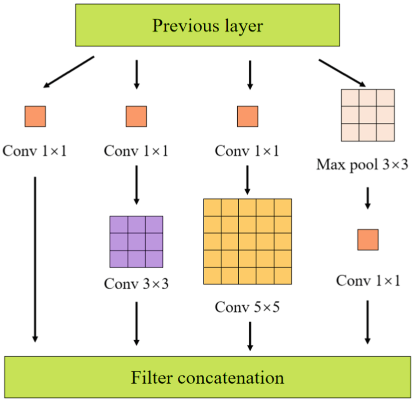

Fig. 2. U-net structure diagram

feature together on the channel dimension, so that more image texture information can be propagated smoothly in the higher resolution layer. Further improve the learning ability of the network.

2.3 Inception-Based Image Registration Network Structure

As a common processing technique in medical image field, registration is more complex than classification, segmentation and detection. It has a very important application in the field of medical image such as detection of lesions, navigation surgery, diagnosis of diseases and so on. This method designs an image registration network structure based on Inception by skillfully combining Inception and U-net structure, and further explores the unsupervised deep learning technology in the field of medical image registration (Fig. 3).

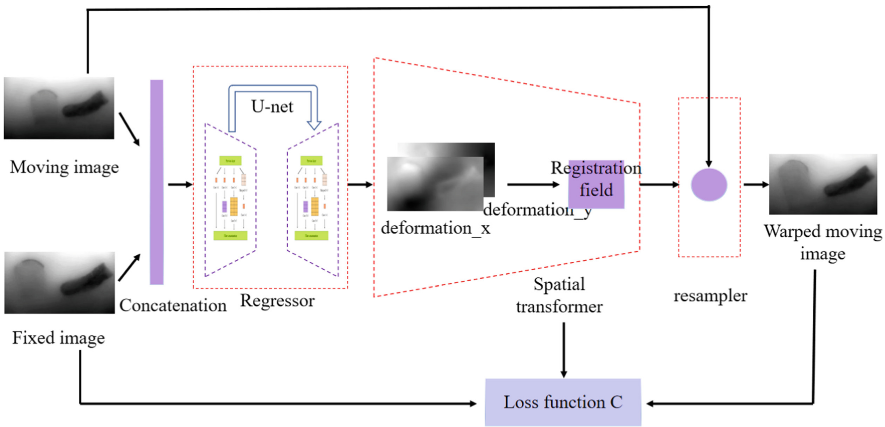

Fig. 3. Inception - based image registration network

This registration network structure is mainly composed of three modules: regression module, spatial conversion module and resampling module, in which regression module is composed of U-net embedded in Inception module. The whole network takes fixed image and floating image as input, outputs the registered mapping image after learning and transformation, and calculates the similarity measure and the value of positive smoothing constraint between the fixed image and the mapped image, which is used as loss function, and updates the parameters by gradient descent method. The loss function formula is as follows:

$$C(f, m, \phi) = C_{sim}(f, m^{\circ}\phi) + \lambda C_{smooth}(\phi) \tag{1}$$

Among them, f and m represent fixed image and floating image respectively, ϕ represents transformation field, $m^{\circ}\phi$ represents floating image after transformation, C_{sim} is used to measure the similarity between the result image and the transformed image, C_{smooth} is regularization term, and constraint space is smooth deformation.

Based on the Inception cleverly designed image registration network structure, it has a multi-scale receptive field self-coding decoder, and allows the original low-level features to participate in the high-level operation, which greatly enriches the diversity of available features. In addition, as an unsupervised deep learning network structure, this network is more suitable for medical image field data set small, calibration data less.

3 Experimental Results and Analysis

The 700 images and fixed images in the dataset are trained in pairs of input image registration network based on Inception. The learning rate is set to 4e-4, and the trained registration network is tested. The test comparison diagram is shown below (Fig. 4).

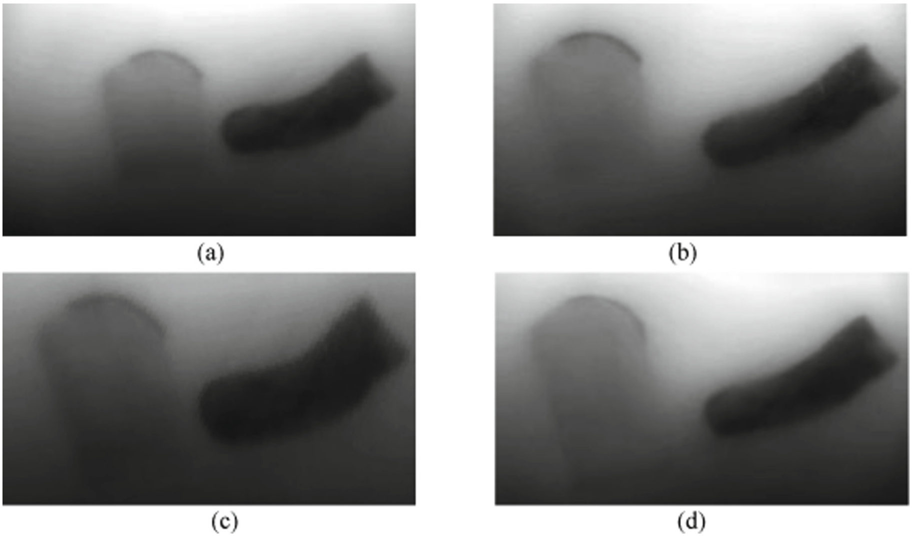

Fig. 4. Image registration

As shown above, (a) is a floating image, (b) is a fixed image, (c) represents the image obtained by registration after detecting key points by SURF method, and (d) represents the image obtained after processing by the method proposed in this chapter. The floating image and the fixed image have great fuzziness, the effective key point is difficult to find, the ORB, BRISK, AKAZE method can not get the effective result, the SURF method obtains the transformed image by the limited key point registration. The image of the SURF method retains the texture of the floating image, but the vertical stretch of the image makes the shape of the simulated heterogeneous body inconsistent with the fixed image. Compared with the fixed image, the result image obtained by this method is closer to the fixed image in shape, and the registration effect is better.

4 Conclusion

This chapter introduces the Inception structure and U-net structure. An Inception-based image registration network is designed by using the ingenious chimerism of Inception and U-net, and it is first applied to the biological tissue imitation dataset with sparse effective feature points. Then this chapter introduces the preparation of experimental data sets, and compares the key points of different methods for the detection of experimental data sets and ordinary natural images, and analyzes the reasons why some classical registration schemes can not effectively complete the registration task. Lastly, through the experimental study, the method can accomplish the task of medical image registration which can not be completed by SIFT, ORB, BRISK, AKAZE and other methods because of blurred image and sparse feature points, and achieve the image registration effect better than the classical SURF method in the whole and details.

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