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Registration of SD-OCT en-face images with color fundus photographs based on local patch matching

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Abstract. Registration of multi-modal retinal images is very significant to integrate information gained from different modalities for a reliable diagnosis of retinal diseases by ophthalmologists. However, accurate image registration is a challenging, we propose an algorithm for registration of summed-voxel projection images (SVPIs) with color fundus photographs (CFPs) based on local patch matching. SVPIs are evenly split into 16 local image blocks for extracting matching point pairs by searching local maximization of the similarity function. These matching point pairs are used for a coarse registration and then a search region of feature matching points is redefined for a more accurate registration. The performance of our registration algorithm is tested on a series of datasets including 3 normal eyes and 20 eyes with age-related macular degeneration. The experiment demonstrates that the proposed method can achieve accurate registration results (the average of root mean square error is 128μm).

Keywords: retinal image registration· summed-voxel projection images· color fundus photographs· blood vessel· similarity function·

1 Introduction

Spectral domain optical coherence tomography (SD-OCT) is an useful ophthalmic imaging modality that can generate three-dimensional high-resolution cross-sectional images of retina, and display various aspects of retina tissues, such as structural in-

formation, lesion location, blood vessels, and so on [1]. A summed-voxel projection image (SVPI) can be generated directly from the three-dimensional SD-OCT retina data, which produces an image showing the retina surface en face, similar to the color fundus photographs (CFPs). As a result, registration of SVPIs with CFPs is very important for both clinical and research purposes because registration can fuse the structural and functional information gained from different modalities [2]. Registered SVPIs can also be recognized as a convenient universal technique for the calibration of any fundus image [3].

Gray values may vary considerably between retinal images from the different modalities. Therefore, the registration methods based on gray usually perform not well. Compared with the registration methods based on gray, based on feature registration methods are more suitable for multi-modal retinal image registration. However, to our best knowledge, there are not a lot of researches [4-7] on registration of SVPIs with CFPs.

In the process of image acquisition, the eye movement or image sensor jitter will cause the distortion of image, such as rotation and translation, which make the position of the same feature point non-correspondence. Li et al. [4] recently presented an algorithm to register SVPIs with CFPs; this method utilized the Euclidean distance and normal direction difference to overcome the above problem. However, the algorithms [6, 7] used the global similarity to register the SVPIs and CFPs. The registration accuracy is relatively low because these methods do not consider the influence of distortion. Therefore, this paper employs local blood vessel features to extract the feature points, and to select the matched point pairs, which solve the difficult problems of the distortion image registration. This method basically has following advantages: (1) the local blood vessel features can describe the detail information of retinal image; (2) the local maximization of the similarity function can nicely search the matched point pairs. The proposed method improves the salience of feature description and reduces the influence of distortion.

2 Method

A good registration process requires enough image features presented in both of images, which are uniformly distributed, and are not influenced by other conditions. The most significant features of multi-modal retinal images utilized by retinal image registration are blood vessels. The multi-scale top-hat operator is improved for segment-

ing blood vessels. Then local maximization of the similarity function between the CFP and SVPI is computed to extract the feature matching points for calculating the quadratic transformation coefficients to register the CFPs and SVPIs. The algorithm flow chart is shown in Fig. 1.

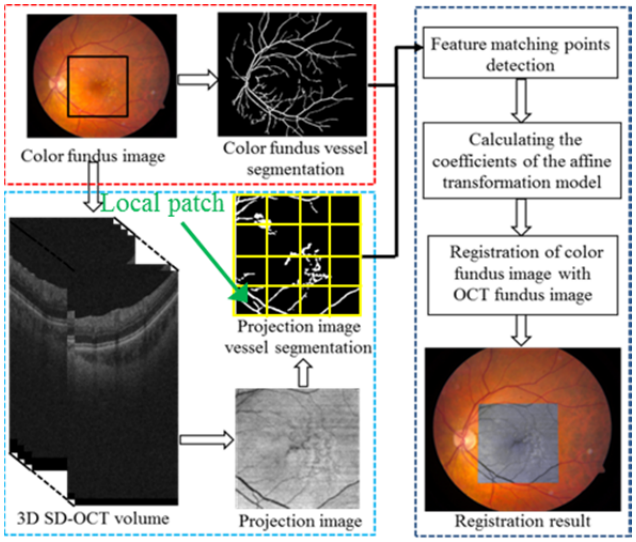

Fig. 1 Flowchart of registration of SD-OCT fundus image with color fundus photograph

2.1 Blood Vessel Detection

The detection of blood vessels in our algorithm involves two parts: the detection of blood vessel in SVPIs and in CFPs, respectively. Because the blood vessels have different size, we apply a series of top-hat operators with different scales, covering the whole range of possible width of the vessels, to segment blood vessels.

Since blood vessel has an arbitrary direction, "disk" shape is selected to construct a structure element in our method. The multi-scale top-hat operator, as used by Mendonca et al. [8], is defined as follows

$$tophat\left(Img\right) = Img - \min\left(open\left(close\left(Img, w_2\right), w_1\right), Img\right) \tag{1}$$

where Img is the retinal image, w_2 represents the structuring element of a close operator, which radius is 2. While w_1 indicates the structuring element of an open operator. The radius of w_1 varies from 1 to 8, which produces eight different results. Averaging consecutive paired images produces four results to reduce the effect of noise

$$avgimg = \frac{\left(tophat_i + tophat_{i+1}\right)}{2}, i = 1,3,5\cdots \tag{2}$$

For each pixel, the final result will be given by a maximum value on the values for each scale. Different weights for different scale are weighted to obtain each pixel value which can compensate for the weaker pixel. The method is defined as following

$$mimg = \max\left(mimg, w \times \left(l - 2 \times i + 1\right) * avgimg_i\right) \tag{3}$$

where $avgimg_i$ represents the i-th average result. i value varies from 1 to 4. w denotes the weight with 5. The initial value of $mimg$ is 0. l is the maximum scale value.

In the end, a series of post-processing operations are applied to reduce some false blood vessels: (1) A erosion operation of the disk structural element with radius 1 is utilized to prune the blood vessel. (2) Some small objects are removed based on the area of the connected region.

Blood Vessel Detection in CFPs

The inverted green channel is utilized to extract blood vessels using the improved multi-scale top-hat operator. The performance of segmentation is tested on the DRIVE database [9] including 20 samples, and its average accuracy, sensitivity, specificity are 0.9558, 0.6179, 0.9884, respectively.

Blood Vessel Detection in SVPIs

Currently, a few approaches are used to generate the SD-OCT fundus images from SD-OCT volumetric data, and they are all based on the idea of using depth-wise averaging of each individual A-scan [10, 11]. In order to make blood vessels appear more clearly in fundus projection images, we propose a novel projection method between the RPE layer and IS-OS layer segmented by the multi-scale 3D graph search method [12] to generate the fundus image, based on the depth average of A-scan values, analogous to that done in [10].

$$SVPI\left(x, y\right) = \frac{1}{Z_2\left(x, y\right) - Z_1\left(x, y\right)} \sum_{z=Z_1(x,y)}^{Z_2(x,y)} I\left(x, y, z\right) \tag{4}$$

where $Z_1(x,y)$ and $Z_2(x,y)$ represent the layer boundary location of IS-OS layer and RPE layer, respectively. Finally, the proposed blood vessel detection method is employed to segment the inverted SVPIs.

2.2 Local Feature Matching Point Detection

Blood vessel skeletons are extracted by a fast parallel thinning algorithm [13], which can be considered as the main features. A SVPI is evenly divided into 16 small (4×4) patches as shown in Fig. 1. Each patch considered as a window is used to traverse the whole CPFs for detecting local matching points based on the local maximization similarity. The local similarity function is defined as following

$$LSF(m,n) = \frac{OverlapCount}{Count} \tag{5}$$

Where $OverlapCount$ indicates the overlapping number of blood vessels. While $Count$ represents the total number of blood vessels between two image blocks. m and n are y-coordinate and x-coordinate of a 4×4 image matrix.

Each of the extracted overlap region is classified as an "effective image block" or a "non-effective image block" by comparing LSF with the threshold th. The threshold is set here as 0.33. By removing the "non-effective image block", the "effective image block" is retained for matching point's extraction. We extract three non-adjacent matched point pairs from the skeleton of blood vessel image block that is corresponded to "effective image block". We need to determine four image blocks (top left corner, bottom left corner, top right corner, bottom right corner) whether exist matched point pairs or not, for the matching point pairs of each image block may affect the registration result. Matched point pairs are extracted by the nearest distance between the image blocks and the matched pixel pairs.

2.3 Estimating the Transformation Coefficients and Matching

The quadratic model [14] is selected to estimate the transformation parameters because the retina surface is a roughly planar over small regions. Given the matched point pairs, the transformation coefficients are estimated as the following two steps. In the first step, a coarse estimation of transformation coefficients is performed on the matched point pairs to generate a coarse registration result.

Followed by the second step, a more accurate estimation of transformation coefficients will be accomplished. The coarse registration result is extracted in order to narrow the search region of feature matching points. The matched CFP is evenly split into 4 small (2×2) local patches. Four image blocks considered as four windows are used to traverse the corresponding local CFP block for extracting matching points. Finally, we extract two non-adjacent matched point pairs from the skeleton of blood vessel image block that is corresponded to the matched image block. In this manner, we obtain a set of accurate matched pairs to compute transformation coefficients. The optimal transformation coefficients are chosen as the final output of our algorithm.

3 Experimental results and analysis

We used our datasets (23 eyes) to test the performance of our algorithm. Each image pair includes one CFP (2392×2048 pixels) and one SVPI (512×512 pixels) obtained by intensity summation along A-scans of SD-OCT volumetric data. All of the datasets were obtained using a Cirrus SD-OCT device (Carl Zeiss Meditec, Inc., Dublin, CA).

In our experiment, 10 matching points that are crossover points were drawn manually, and then feature points on the SVPIs were mapped onto CFPs using the transformation coefficients computed by our registration method. We then computed the Root Mean Square Error (RMSE) with manually labeled feature points on the CFPs. The blood vessel overlap ratio was also regarded as another evaluation index.

We compared registration results with the methods in [6] (method1) and [7] (method2). Fig. 2(a) presented the registration errors of three registration algorithms in microns. The RMSE of our method was less than the other two methods, while the registration results in mehtod2 were slightly better than those in method1. The reason which leads a large RMSE was that the method1 only used image similarity to accomplish retinal image registration. Our method took advantage of the local blood vessels feature for accurate the matched point pairs extraction; therefore the registration results of our method were relatively better than the other two methods. The RMSE of some samples were large because some lesion regions, such as drusen, geographic atrophy and so on, may greatly influence the detection of blood vessels. The quality of retinal images also affected the registration results. Blood vessel overlap ratio also met the rule that the smaller the RMSE, the greater the overlap ratio, as shown in Fig. 2(b). Fig. 3 showed the registration results of three registration algorithms. The RMSE in microns were displayed along with each image.

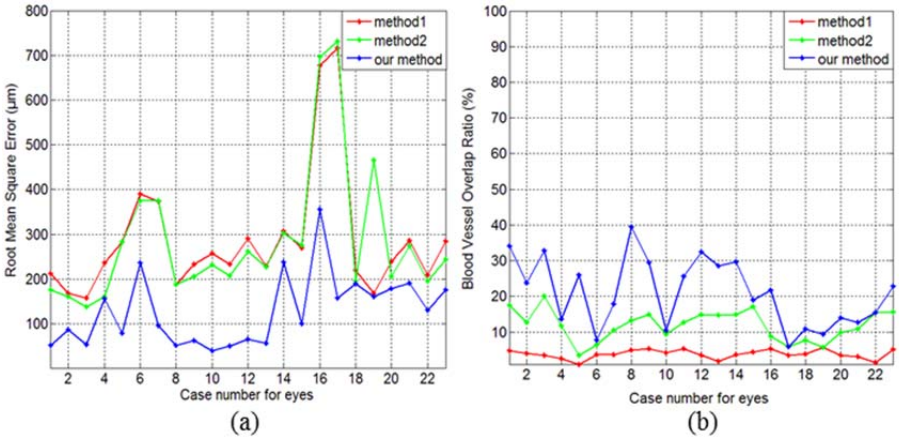

Fig. 2 (a) Root mean square error (in microns). (b) Blood vessel overlap ratio (%)

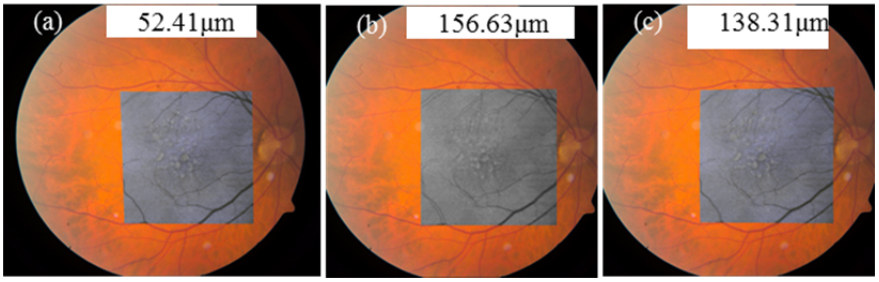

Fig. 3 (a) (b) (c) the registration results in our method, method1 and method2, respectively

4 Conclusions

In this paper, we have presented an automatic algorithm for registration of SVPIs with CFPs. The matched point pairs are extracted by searching the local maximization of the similarity function between the two blood vessel images. We utilized the matched point pairs to gain a coarse registration and redefine a search region for a more accurate registration. The experimental results show that our method can work well. The quality of SVPIs is the most mainly factor affecting the performance of registration algorithm.

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