TECHNIQUES FOR TEMPORAL REGISTRATION OF RETINAL IMAGES

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ABSTRACT

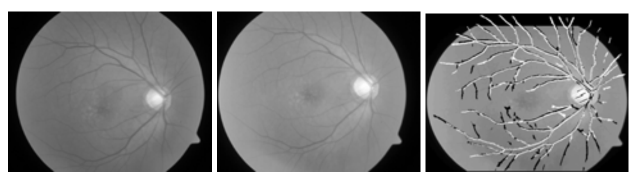
Temporal registration of retinal images is helpful to provide physicians important information in tracking the evolution of eye-related diseases. The vascular structure of the retina is the most appropriate feature representation for registration. This paper describes a fast chamfer matching applied to the vascular structure to align pairs of fundus images. While the fast chamfer matching is able to achieve successful alignment consistently, it fails to find correct model parameters in a few cases. To alleviate this problem, we propose a non-parametric elastic matching method. The two matching algorithms are tested on 98 pairs of temporal fundus images. We found that elastic matching gives better performance than the fast chamfer matching method where there are 3 failure cases were reported.

1. INTRODUCTION

Vascular structure of retina plays an important role in revealing the severity of eye-related diseases [1]. The vessels are distributed over the entire retina. Since these vessels are visible in all the fundus images, the vascular structure is the most appropriate feature representation for fundus image registration [2]. Temporal registration of vascular structures is one of the important applications in ophthalmology because a patient is often screened at regular intervals for the development of eye diseases. By comparing the photographs taken at different times, physicians can evaluate the progress of the diseases and decide what appropriate treatments should be taken.

Figure 1(c) shows an example of the extracted vascular structures superimposed onto the original eye fundus images in Figures 1(a) and 1(b) after registration. This indicates that with appropriate temporal registration, we are able to highlight the similarities/ differences in the two images.

Ritter [3] used the full image content for alignment and mutual information as the similarity measure. However, methods based on mutual information are unable to deal with the registration of total surface of eye fundus images. Zana [4] used the vascular tree for bifurcation points identification. A Bayesian Hough transform was then used to find the best parameters of a weak affine transformation. Pinz [5] developed an affine registration algorithm using randomly selected sample points from the extracted vessels as intermediate symbolic representation. Both methods have reported success to some degree on the premise that the selected salient points are sparse so that the affine transformation is able to achieve a global maximum. However, vascular structures of one or both fundus images to be registered are usually not sparse as the vessels are typically close to each other. In addition, it is not uncommon for a large number of vessels to be totally absent in one of the images due to over-exposure. In such cases, registration methods based on the parametric affine model are unable to produce a correct matching. To provide sufficient flexibility required for accurate local alignment, an elastic matching approach which used active contours (snakes) was proposed by Jasiobedzki [6]. The main disadvantage of this method is that the active contours are attracted only to features that they are initially close to. This means that the method will fail whenever the translation between images is large.



(a) (b) (c)

Fig. 1. Temporal registration of fundus images. (a) Green image with extracted vascular structure. (b) Green image a year later with extracted vascular structure. (c) Registration results.

In this paper, we propose two matching methods for fundus mages registration using vascular structure features. A fast hierarchical chamfer matching is first implemented based on an approximate Euclidean distance transformation which forms a goodness of fit objective function. This method is incorporated with the parametric model of rigid affine transformation. However, the fast chamfer matching method suffers from problem of being

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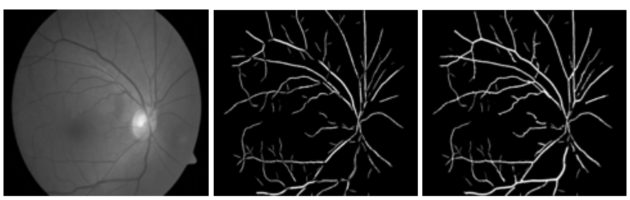
trapped in local minimal. To overcome this problem, we design a non-parametric elastic matching algorithm for temporal registration of retinal images. To the best of our knowledge, this is the first attempt that utilizes fast hierarchical chamfer matching and elastic matching algorithms for fundus image registration.

2. EXTRACTION OF VESSEL FEATURE

The success of feature-based registrations is largely dependent on the quality of the identified features. For retinal image registration based on extracted vessels, a robust method is needed to detect the vascular structure of retina as reliably as possible. Existing approaches to enhance and extract vessels in retinal images includes: two-dimensional Gaussian filters [4,6], top-hat mathematical morphological filters [5], wave propagation and trace-back mechanism [7], fuzzy connected object delineation principles [8].

Here, we employ the technique described in [9] to extract the vascular structure. The technique is to enhance vessels and segment them out of background by using Laplacian of Gaussian filter and morphological filters (Figure 2(b)). In order to recover missing intersection points and some partially detected vessels, a morphology reconstruction process is performed based on a dynamic local region growing (Figure 2(c)).



(a) (b) (c)

Fig. 2. (a) Gray level retinal image, (b) Segmented vessels (c) Reconstructed vascular structure.

3. REGISTRATION USING VASCULAR STRUCTURE

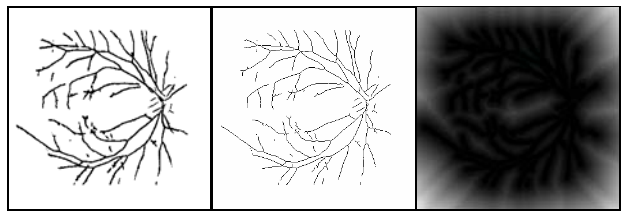
3.1. Fast Chamfer Matching

The registration of eye fundus images is a non-trivial task. This is because there is a huge amount of distortion in the images caused by eye movement as well as optical limitations of the imaging system. The first method we propose for temporal registration of retinal fundus images is the fast chamfer matching method similar to [10]. The idea behind is to search for the local optimal transformation at a coarse resolution with a large number of initial positions with acceptable computation load and allow a few candidates to next finer levels for global optimal transformation search.

The weak affine transformation model of translations and rotation is adopted as follows:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \quad (1)$$

One of the vascular trees is called the *Template* image and the other the *Input* image. Thinning is performed so that the resulting patterns consist of lines with one pixel wide only. A sequential distance transformation (DT) is applied to create distance map for the *Input* image by propagation local distances. A 3×3 pixel neighborhood is used and local distance values are 3 and 4 for horizontal/vertical and diagonal neighbors of each line pixel respectively. Figure 3(c) presents the distance image of Figure 3(b).



(a) (b) (c)

Fig. 3. (a) Vascular structure used as *Input* pattern in matching process. (b) Skeleton of vascular structure. (c) Distance image of (b) representing the original level: the larger the distance, the lighter the tone.

The *Template* is superimposed on the *Input* distance image. The measurement of goodness of match is in the form of a distance function which is defined as the squares of the pixel values of distance image that the *Template* image hits.

$$Dist = \sum_{p(i,j)\in Template} DM_{Input}(p(i,j))^2 \quad (2)$$

where p(i,j) is a non-zero point on the *Template* image and *DM* is the distance map created for the *Input* image.

It is obvious that a perfect fit between the *Template* and *Input* images will result in a minimum value of the distance function. Finding the optimal transformation is equivalent to finding the global minimum of the distance function.

Starting from each node of a grid in the parameter space, the search proceeds by varying only one parameter of the distance function at a time, keeping all the other parameters constant. The step-length for the translation parameters is one pixel shift. The step-length for the rotation angle is computed according an approximation equation [10] which is 0.5 degrees in our experiments. If a smaller distance value is found, the parameter value is updated and a new search of the neighbors of the smaller distance continues. The process stops when there is no change of the distance.

The matching is performed at different resolutions of the original images from the coarsest to the finest to achieve acceptable computational load. We employ a process called down-sampling whereby each four pixels block of the original image is represented by one pixel to obtain various resolutions. Optimal local positions with distances larger than a threshold are rejected and only those with smaller distances are used as initial positions for matching in the next finer resolution level. When the search at the zero level (original image) is completed, global optimal transformation corresponds to the smallest distance.

3.2. Elastic Matching

Although the affine transformation-based fast chamfer matching algorithm works well for retinal fundus images in most cases, the possibilities for the algorithm to be trapped by local minimization in parameter space of the objective function still exist in the case where the extracted vascular structures are very dense. One way to tackle the problem is to do an exhaustive search in the parameter space with large number of seed points. However, the computation load would be so heavy that the implementation is impractical. In order to achieve optimal matching for all situations, we propose the use of elastic matching [11] for retina registration. It has been proven that the elastic matching method is able to effectively avoid begin stuck in local minimum by using an elaborately designed function and appropriate starting parameters. We provide a brief explanation of the matching algorithm in [11] below.

Let the two binary vascular structures to be registered be the *Template* pattern and *Input* pattern respectively. Thinning is performed so that the resulting patterns consist of lines and curves with one pixel width. Single short lines and short branches are removed since they are noises for matching process, and the remaining lines and curves are approximated by fitting a set of straight lines which are derived by using a minimum square error procedure. Each resulting straight line is then divided into smaller segments of approximately equal length. Each of these short straight lines is referred to as an 'element' which is represented by its slope and the position vector of its midpoint. Both vascular structures are in turn represented by a set of elements. Hence, the matching problem becomes that of matching two sets of elements. The number of elements in the two patterns need not be equal.

The *Template* and *Input* patterns are first overlapped, as shown in Fig. 4(a). The elements in the *Template* are then gradually attracted towards the *Input* elements in successive iterations under the guide of a defined energy function defined as follows.

$$E_1 = -\alpha K_1^2 \sum_{i=1}^{N_I} \ln \sum_{j=1}^{N_T} \exp\left(-\left|\mathbf{T}_j - \mathbf{I}_i\right|^2 \big/ 2K_1^2\right) f\left(\theta_{Tj,Ii}\right) + \beta \sum_{j=1}^{N_T} \sum_{k=1}^{N_T} w_{jk}\left(d_{Tj,Tk} - d_{Tj,Tk}^0\right)^2 \quad (3)$$

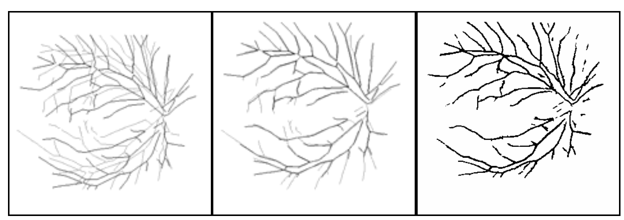
where N_T = number of *Template* elements, N_I = number of *Input* elements, $\boldsymbol{T}_j$ = position vector of the midpoint of the jth *Template* element, θ_{Tj} = direction of the jth *Template* element, $\boldsymbol{I}_i$ = position vector of the midpoint of the ith *Input* element, θ_{Ii} = direction of the ith *Input* element, $\theta_{Tj,Ii}$ = angle between *Template* element T_j and *Input* element I_i, restricted within 0-90°, $f(\theta_{Tj,Ii})$ = max(cos $\theta_{Tj,Ii}$, 0.1), $d_{Tj,Tk}$ = current value of $|\mathbf{T}_j - \mathbf{T}_k|$.

$d^0_{Tj,Tk}$ = initial value of $|\mathbf{T}_j - \mathbf{T}_k|$

$$w_{jk} = \left[\exp\left(-\left|T_j - T_k\right|^2 / 2K_2^2\right)\right] \Big/ \left[\sum_{n=1}^{N_T} \exp\left(-\left|T_j - T_n\right|^2 / 2K_2^2\right)\right]$$

Note that K_1 and K_2 are the size parameters of the Gaussian windows which establish neighborhoods of influence, and are decreased monotonically in successive iterations.

The function consists of two terms: the first term measures the overall distance between the two patterns while the second term measures the deformation of the *Template* pattern. Minimizing this function tends to move *Template* elements towards the corresponding *Input* elements with minimum deformation to achieve optimal matching. For each element, a neighbourhood of influence is defined so that the element follows the weighted mean movement of neighbours. Initially, a large neighbourhood is defined. The size of this neighbourhood is gradually decreased in successive iterations as we fine tune the alignment.



(a) (b) (c)

Fig. 4. (a) Overlapped image of the *Template* pattern (black lines) and the *Input* pattern (gray lines) before matching and (b) Overlapped image of the patterns after matching. (c) Generated vascular structure in terms of the deformed template.

At the end of the iteration, the corresponding parts of the two vascular structures should hopefully be the nearest to each other as shown in Figure 4(b). In order to generate the final matched vascular structure, for each *Template* element, the displacement vector is first computed. Next, the nearest element is identified for each pixel of the *Template* vascular structure and its displacement vector is considered to be the displacement vector of that pixel. The deformed vascular structure is generated by moving every pixel of the original vascular structure as guided by its own displacement vector. To make the deformed structure locally smooth, a neighbourhood of correlation is defined to compute the pixel displacement vector rather than just using the displacement vector of the nearest element: The amount of movement for each pixel is given by a weighted sum of the displacement vectors of the elements in a correlation window. In our experiments, the window includes three elements. An example of the generated vascular structure is shown in Figure 4(c).

4. EXPERIMENTAL RESULTS

The image database that we use in this study consists of 35 fundus images of both the left and right eyes from three patients. The time interval at which we acquire the images vary from two days to one and half a year. The fundus images are captured using a digital fundus camera. The image size is 512×512×8. Figure 2(c) shows an example of the extracted vascular structure of gray level retinal fundus image in Figure 2(a) by the reconstruction method [9]. We pair the 35 fundus images in different order to obtain a total of 98 pairs.

The depth of multi-resolution in the fast chamfer matching method is set to 4, resulting in the size of the 4^{th} level images being 32×32. There are 54 initial positions at the lowest resolution, namely: 3×3 translation points, separated by 3 pixels, and 6 equidistant rotation angles.

In the elastic matching method, each line or curve is approximated by fitting a sequence of short straight lines ('elements') of about 20 pixels long. The neighbourhood size parameters were set to 60 pixels.

Visual inspection seems to be natural to judge the 'success' or 'fail' in registration. However, it is unreliable. Here, we develop a quantitative criterion to evaluate matching/registration accuracy. The centreline mapping error (CME) is defined as follows.

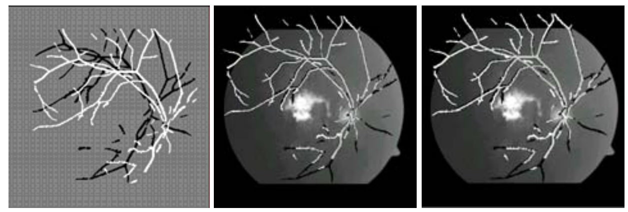
$$CME = \frac{1}{N} \sum_{\substack{p(i,j)\in Input \\ p(i,j)\in Template}} DM_{Input}(p(i,j))^2 \qquad (4)$$

where N is the total number of feature point p(i,j) of the *Template* vascular features and DM is the distance map created for the *Input* vascular features.

Transformations with the centreline mapping error smaller than a threshold such as 2.0 pixels are considered successful registrations. A registration example is given in Figure 5.

5. CONCLUSION

In this paper, we have described two matching algorithms for registering pairs of fundus images based on the recovered vascular features. The fast chamfer matching employs a rigid affine transformation and is consistent to the physical model of human eyes. Alignment is successful in most cases when the vascular structures to be registered are sufficiently sparse. A non-parametric elastic matching method is also proposed to alleviate the problem of local minimization trap for the fast chamfer matching. Experiments on 98 pairs of temporal fundus images show that the elastic matching algorithm is able to achieve a 100% rate of successful registration while 3 cases have failed for the fast chamfer matching method.



(a) (b) (c)

Fig. 5. Temporal registration of fundus images with highly difference between two extracted vascular structures. (a) Overlapped image, registration results (b) by fast chamfer matching method and (c) by elastic matching method.

6. REFERENCES

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