33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Retinal Image Registration Based on Multiscale Products and Optic Disc Detection

Dimitris Koukounis, Lindsay Nicholson, David R.Bull, and Alin Achim

Abstract— **This paper presents a new approach to segmentation-driven retinal image registration. The proposed algorithm aims to help physicians to detect changes that occur in the blood vasculature due to various diseases. The proposed approach uses multiscale products, which augment the difference between blood vessels and the rest of the retina. The result of scale multiplication is then iteratively thresholded in order to obtain a binary map of vessels inside the retina. For the registration part, the centre of the optic disc is detected and used as control point. Having determined both the position of the blood vessels and the centre of the optic disc, translational and rotational differences between the images can be eliminated and registration can be achieved. The centroid of the optic disc is used as the center of rotation. The final registration is then achieved by searching the best match between the two images using a XOR operation.**

I. INTRODUCTION

Image segmentation and registration are two of the most important steps in medical image analysis. The purpose of segmentation is to partition the image into meaningful regions which share similar characteristics. In the case of retinal images, the structure of interest is the blood vasculature that has to be distinguished from the rest of the retina. The segmented vasculature is often used to guide registration for more accurate results.

Registration is concerned with spatially aligning two or more images of the same scene captured in different periods of time and from different views. Aligning human retinal images is a difficult task as there are translational and rotational differences that need to be considered. Scaling distortions are neglected because it is assumed that when capturing the images from humans the subject is at the same distance from the camera. By translational missalignments we refer to vertical and horizontal discrepancies that may occur due to changes in the sitting position of the subject. Rotational differences are due to head leaning and/or ocular torsion.

The main goal of this study is to develop an algorithm which automatically and efficiently segments the blood vessels from human retinal images and then uses segmentation results as basis for registration. The purpose is to help physicians to diagnose and monitor diseases like diabetes and uveitis that can evolve very rapidly and can threaten sight. These diseases are causing various damages to the blood vessels.

Several methods were proposed in the literature for retinal image segmentation and registration. In [1], the authors proposed a retinal image registration method based on distinctive local features, which they refer to as partial intensity invariant feature descriptors. These points are corners uniformly distributed across the retina and are used as control points to drive the registration process. The algorithm proposed in [2] introduces the detection the optic disc based on the fact that usually has a circular shape and that is the brighter region in the retina.

This paper proposes an accurate and robust approach for segmenting blood vessels by using multiscale products in combination with iterative thresholding. A similar approach was used in [3] for segmenting immunomicroscopy images. Then the optic disc is detected in order to remove translational mismatches between the images and drive a point matching registration. Segmentation results are used to eliminate rotational differences. This is achieved by rotating one image and then using a XOR operator. The minimum XOR across the image determines the angle that corresponds to the best match between the two images.

The structure of the paper is as follows. Section II describes the theoretical preliminaries used to develop the algorithm. The proposed algorithm is then described in Section III. Section IV presents results and finally, in Section V we conclude the paper.

II. THEORETICAL PRELIMINARIES

A. Multiscale Products (MSP)

Multiscale products can be used as an edge detection technique that apart from detecting edges, has an additional advantage in that it also removes noise, which does not propagate across scales. On the other hand, features of high saliency will have a large value coefficient in multiple adjacent scales which means that the difference between the desired features and the background will be increased [3].

Essentially, multiscale products are used in combination with the stationary wavelet transform in order to take advantage of the multiresolution representation, which the wavelet transform provides. The technique is based on the persistency property of the wavelet transform, which determines coefficients of similar relative magnitudes to propagate at the same relative positions across scales.

D. Koukounis, David R. Bull and A. Achim are with the Department of Electrical and Electronic Engineering, University of Bristol, Merchant Ventures Building, Woodland Road, Bristol BS8 1UB, UK, {dk7486; dave.bull; alin.achim}@bristol.ac.uk. Lindsay Nicholson is with the Departments of Ophthalmology, and Cellular & Molecular Medicine, University of Bristol, Medical Sciences Building, Bristol, BS8 1TD, UK, l.nicholson@bristol.ac.uk.

The stationary wavelet transform is a particular type of wavelet representation that has two main advantages in comparison with other wavelet transform implementations. Firstly, it is translational invariant, and secondly, the size of the different subbands is constant across scales [4].

The wavelet coefficients are given by:

$$\frac{1}{2}\psi\left(\frac{x}{2}\right) = \phi(x) - \phi\left(\frac{x}{2}\right) \quad (1)$$

Where $\psi(x)$ is the wavelet function and $\phi(x)$is the low-pass scaling function.

The implementation of the inverse transform is done by using the following equation:

$$C_{o,l} = C_{j,l} + \sum_{j=1}^{J} W_{j,l} \quad (2)$$

Where j is the maximum scale and $C_{j,l}$ the approximations computed by the interlaced convolution.

Mathematically multiscale products can be represented as follows:

$$P_J(x,y) = \prod_{i=1}^{J} W_i(x,y) \quad (3)$$

Where J is the highest scale of the computed correlation and $W_i(x,y)$ represents the wavelet coefficient at scale i and location (x,y).

B. *Iterative Thresholding*

Iterative thresholding is a technique used to calculate an optimum value which can be used to convert an RGB image to a binary black and white image.

In order to calculate the optimum threshold value, the RGB image is first converted to a grayscale image. Then, the histogram of the image is separated into two parts by using a starting threshold which is equal to the mean value of the histogram. Next, for each part of the histogram, a new mean threshold value is calculated. The average of these two values is derived and the above two steps are repeated until there is no more change in the threshold value.

III. PROPOSED METHOD

A. *Blood Vessels Segmentation*

As explained in Section II, in our work edge detection is achieved through the use of MSP. Based on the *persistency* property of the wavelet transform, the MSP technique leads to a clear separation between edge and non-edge regions in the image. Subsequently, thresholding can be employed for accurate segmentation of blood vessels in the retina. Fig. 1 shows a pair of retinal images with Fig. 2 illustrating the result of MSP.

Since it is desirable for the developed algorithm to be unsupervised, an automatic technique for choosing the threshold value is needed. Iterative thresholding is employed since it is a widely used technique of choosing the appropriate threshold value automatically. The value calculated by the iterative thresholding is very close to one that one would select manually and the results are very good.

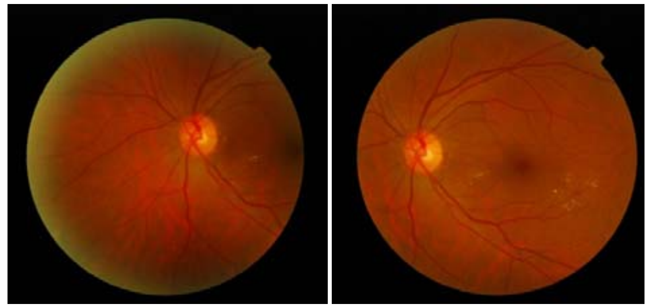


Fig. 1. Original retinal Images

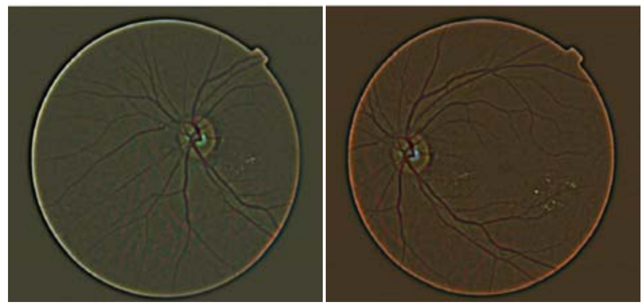


Fig. 2. Images after scale multiplication

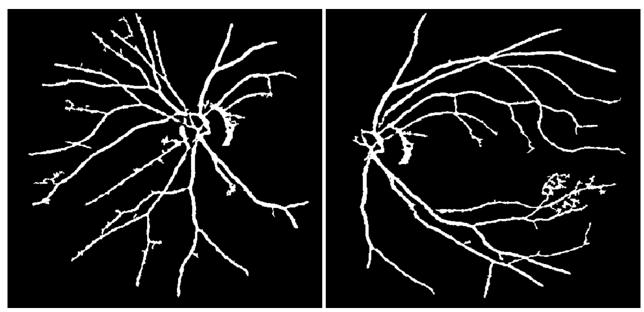


Fig. 3. Segmented Images

The pixels with values above the threshold correspond to vessels and are depicted in white, while the pixels below the threshold correspond to the background. Fig. 3 shows the result of thresholding the MSP of the images in Fig. 2.

B. *Registration based on segmentation*

Image registration techniques can generally be separated in four distinct types: 1) elastic model-based; 2) point matching methods; 3) correlation-based and 4) Fourier-domain based [6]. Due to the structure of the retinal images and the inherent distortions, the most common approach to retinal image registration is point-matching [7].

1) *Optic Disc Detection:*

The detection of the centre of the optic disc is necessary in order to drive the point matching registration. The process for detecting the optic disc is based on the fact that the optic disc is the brightest region of the fundus [2].

During the first step of the process the RGB image is converted into the HSV colour space. This is done because the HSV colour space is more sensitive to high contrast regions and to luminance which makes it more appropriate for optic disc localization.

Then, we employ again thresholding in order to distinguish the pixels with high magnitude by selecting the threshold value to be the largest value of the equalised histogram. Morphological processing (dilation and erosion) is subsequently used to connect neighboring pixels that are disconnected following the thresholding operation.

The largest area of high luminance pixels connected together corresponds to the optic disc. The area of all regions with high luminance is calculated and the region with the largest area is considered to be the optic disc. After optic disc detection, centroid calculation is used to specify the center of mass of the region that corresponds to the centre of the optic disc.

2) XOR-based registration

The result of applying the technique in the previous section is that we can readily account for translational differences between the two images by matching the two centers. We also need to correct the rotational differences between the images. In [8], Chanwimaluang *et al* used Exclusive OR (XOR) to correct translational discrepancies but the results were not perfect.

In our work, we are using the XOR operator (see Table 1) in order to remove rotational differences between the images since the translations are accounted for by matching the centers of the optic discs.

Inputs		Outputs
0	0	1
0	1	0
1	1	0
1	0	1

Table 1. XOR Truth Table

On the binary images obtained via the segmentation scheme described previously, XOR can be used to find the angle that corresponds to the best match between the two images. During the registration process, the reference image is fixed while the image needing to be registered is rotated from 0 to 360 degrees. For every possible angle, the two images are compared using XOR. As it can be seen from Table 1, when the corresponding pixels on the images are similar then the XOR result is 0. When the pixels are different the result is 1. For each rotational angle the sum of the matrix resulting from applying the XOR operator is calculated. When the minimum sum is obtained, it means that the difference between the two images is minimal. The corresponding angle is used to remove the rotational differences between the two images and hence completely register them. The diagram in Fig. 4 shows the whole algorithm starting from the segmentation until the final result is obtained.

IV. Results

We performed extensive experiments in order to assess the quality of our developed algorithms. Different qualitative assessment measures were proposed in the literature to assess image segmentation/registration results [9]. These include accuracy/precision, robustness, algorithm complexity, assumptions verification, and execution time.

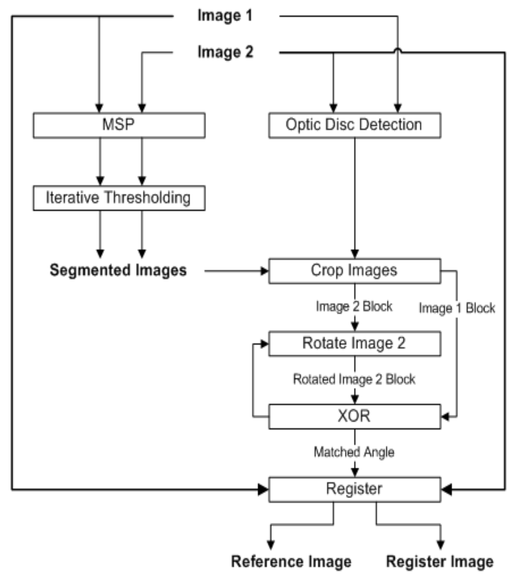


Fig. 4. Block Diagram showing the proposed registration algorithm.

For the purpose of this communication, we quantified our results by visually assessing them in light of the aforementioned measures, as well as by providing execution times.

In order to evaluate our algorithm, we made use of a database of more than 70 retinal images collected at the Bristol Eye Hospital.

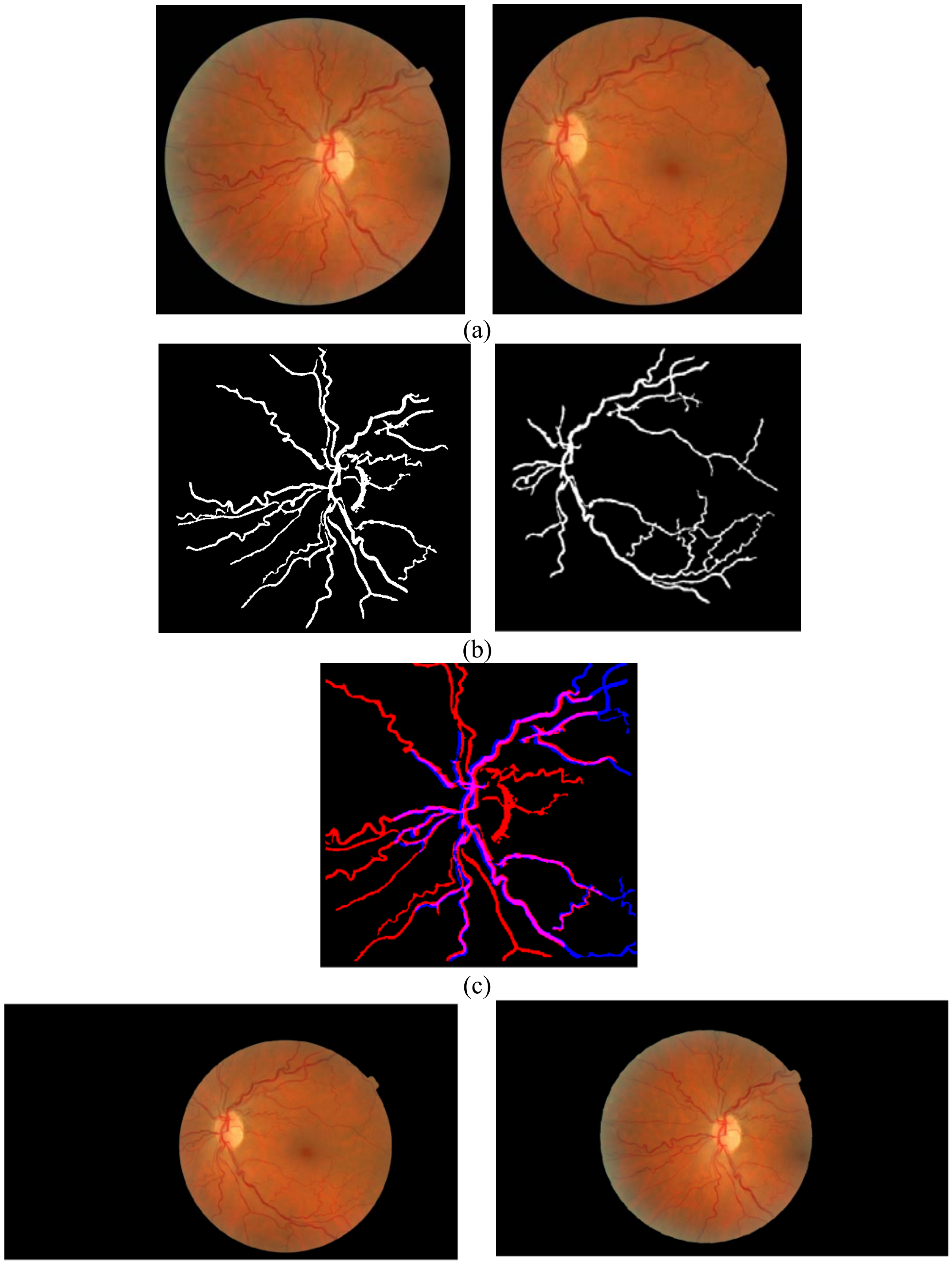
First, the segmentation part of the algorithm was tested independently, as the rest of the algorithm depends on its accuracy. The execution time needed to segment two retinal images, of size 531x800 pixels was 28.98s on an Intel Centrino Core 2 @ 2GHz. Typical segmentation results are presented in Fig. 3 and in Fig 5(b). The two figures show that the retinal vasculature is segmented almost perfectly with virtually unnoticeable over-segmentation. This lays a good basis for further image registration as a next step in our algorithmic development.

Since the segmentation results were accurate and reliable, they could be used for segmentation-driven registration. Based on an accurate optic disc detection as well, we have next assessed the merits of our proposed registration method. Clearly, on observing the results in Fig. 5(d), it can be seen that the two images were registered with high accuracy.

The execution time for the registration part of our algorithm for a full $0^o - 360^0$ search with a step of 1^0 was 124.12s.

V. Conclusion and Future Work

In this paper, a novel unsupervised segmentation-driven retinal image registration algorithm has been introduced. The proposed registration approach is able to correct both translational and rotational displacements in the input images. This is achieved through a two step approach that involves optic disc detection, which helps eliminate translational differences, followed by blood vessels segmentation, which is used to drive the angular registration of the image pair. Our current work focuses on designing change detection algorithms for the temporally preregistered retinal images, to enable automatic correlation of changes in vessels topography with specific disease progression. Results will be presented in a future communication.



(a)

(b)

(c)

(d)

Fig. 5. (a) Original images. (b) Segmented images. (c) Registration of segmented images. (d) Registered Images

REFERENCES

[1] Jian Chen, Noah Lee, Jiang Zheng, R. Theodore Smith and Andrew F. Laine: "A Partial Intensity Feature Description for Multimodal Retinal Image Registration," IEEE Transactions on Biomedical Engineering, vol. 57, no 7, July 2010.

[2] Shijian Lu and Joo Hwee Lim: "Automatic Optic Disc Detection From Retinal Images by a Line Operator," IEEE Transactions on Biomedical Engineering, Vol. 58, no. 1, January 2011.

[3] J.-C. Olivo-Marin:"Extraction of spots in biological images using multiscale products,"Pattern Recognition, Vol. 35, No. 9, pp.1989-96, 2002.

[4] J.-L. Starck, F. Murtagh: "Astronomical Image and Data Analysis," 2nd ed. Springer–Verlag Berlin Helderberg, 2006.

[5] T.W. Ridler and S. Calvard: "Picture Thresholding Using an Iterative Selectin Method,"Man And Cybernetics, Vol. SMC-8, NO. 8, August 1978

[6] L. G. Brown: "A survey of image registration techniques," ACM Computing Surveys, vol. 24, no. 4, pp. 325–376, 1992.

[7] F. Laliberté, L. Gagnon and Y. Sheng: "Registration and Fusion of Retinal Images—An Evaluation Study," IEEE Trans. Med. Imag., vol. 22, pp. 661–673, May 2003.

[8] T. Chanwimaluang, G. Fan and S.R. Fransen, "Hybrid Retinal Image Registration," IEEE Trans. On Information Technology in Biomedicine, Vol. 10, No. 1, January 2006

[9] J.B.A. Maintz and M.A. Viergever: "A Survey of medical image registration," Oxford Uni. Press, Med. Imag. Analysis, vol.2, no.1, pp. 1-36, 1998.