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Registration of retinal images from public health by minimising an error between vessels using an affine model with radial distortions

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ABSTRACT

In order to estimate a registration model of colour eye fundus images made of an affinity and two radial distortions, we introduce an estimation criterion based on an error between the vessels. In [1], we estimated this model by minimising the error between characteristics points. In this paper, the detected vessels are selected using the circle and ellipse equations of the overlap area boundaries deduced from our model. Our method successfully registers 96 % of the 271 pairs in a Public Health dataset acquired mostly with different cameras. This is better than our previous method [1] and better than three other state-of-the-art methods. On a publicly available dataset, ours still better register the images than the reference method.

INTRODUCTION

- Diabetic Retinopathy (DR) screening programmes have led to the creation of large public databases of colour eye fundus images.
- Longitudinal analyses are facilitated by registering the images
- A registration model is necessary to correct:
 - (1) the different positions of the patient (rotation, translation, scaling)
 - (2) the change of the camera (scaling and radial distortion)
 - (3) the radial distortion caused by the projection of the retina (a spherical cap) onto the sensor plane
 - (4) the radial distortion due to the camera optics
 - (5) the contrast changes between the images.
- The registration of some eye fundus images with a small overlap using SIFT points presents noticeable differences [1]. Let us address this issue.

METHOD

Let $p_1, p_2 \in \mathbb{R}^2$ be two corresponding points in images 1 and 2.

Model

$$u_{k_2}(p_2) = H[u_{k_1}(p_1)]$$

↙
↑
↘
 Radial distortion Homography Radial distortion

where $H = \begin{bmatrix} A & t \\ 0^T & 1 \end{bmatrix}$. A is a non singular matrix of \mathbb{R}^2 representing the linear applications (rotation, translation, scaling).

The radial distortion u_k of real parameter k is equal to $u_k(p) = \begin{bmatrix} \frac{p-c}{1+k|p-c|^2} + c \\ 1 \end{bmatrix}$, c is the image centre.

Estimation

The homography parameters are first initialised with SIFT points.

The homography and the radial distortions are then estimated with an approximation of a squared distance between vessels:

$$d^2(s, \mathcal{R}) \approx \frac{d}{d-\rho} \left[(s-r) \cdot \overline{T}_r \right]^2 + \left[(s-r) \cdot \overline{N}_r \right]^2$$

↙
↖
↑
↘
↗
 Source point Reference vessel Closest point of s in \mathcal{R} Tangent vector in r Normal vector in r

d : signed distance between s and r . ρ : signed curvature radius at point r .

Equations of the overlap area

Only the vessels in the overlap area are used in the error $d^2(s, \mathcal{R})$.

Initially, each image FOV (field of view) is delimited by a circle of centre $[x_i, y_i]$ and equation $x^T C_i x = 0$, where $x = [x, y, 1]^T$

and

$$C_i = \begin{bmatrix} 1 & 0 & -x_i \\ 0 & 1 & -y_i \\ -x_i & -y_i & -r_i^2 + x_i^2 + y_i^2 \end{bmatrix}$$

After registration:

- Both circles are distorted by a radial correction. Their radius becomes $r_i^u = \frac{r_i}{1+k_i r_i^2}$ and their equation $x^T C_i^u x = 0$
- The circle 1 is also distorted by the homography H and becomes an ellipse $x^T C_1^r x = 0$, where $C_1^r = (H^{-1})^T C_1^u (H^{-1})$

The overlap area equation is: $\begin{cases} x^T C_1^r x \leq 0 & \leftarrow \text{ellipsoid} \\ x^T C_2^u x \leq 0 & \leftarrow \text{circle} \end{cases}$

References:

- [1] Noyel G, Thomas R, Bhakta G, et al. Superimposition of eye fundus images for longitudinal analysis from large public health databases. Biomed Phys Eng Express. 2017;3(4):045015.
- [2] Lee S, Abramoff M, Reinhardt J. Feature-based pairwise retinal image registration by radial distortion correction. SPIE. 2007;6512:6512201–6512210.
- [3] Hernandez-Matas C, Zabulis X, Argyros AA. An experimental evaluation of the accuracy of keypoints-based retinal image registration. IEEE Eng Medicine Biol Soc. 2017:377–381.
- [4] Yang G, Stewart CV, Sofka M, et al. Registration of challenging image pairs: Initialization, estimation, and decision. IEEE Trans Pattern Anal Mach Intell. 2007; 29(11):1973–1989.

RESULTS

Public Health (PH) dataset – DESW

69 randomly selected patients with diabetes from Diabetic Eye Screening Wales (DESW), UK. Patients had different stages of retinopathy and their pupil was dilated. Each patient had 4 images per screening. We selected a series of 271 images pairs with an approximate screening interval of one year.

63 % of the pairs were captured with different cameras. 10 pairs had a small overlap area (about 30 % of the an image surface).

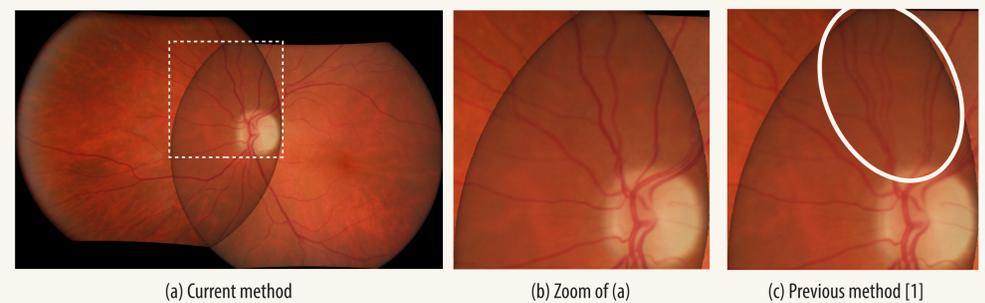
The registration results were classified by an expert in two categories:

- No noticeable difference (**correct**)
- Noticeable difference (**incorrect**): (b.1) Differences of a small diameter vessel, (b.2) differences of the size of a large diameter vessel or (b.3) even larger

Table 1. Decreasing percentage of successful superimpositions for five

Method	% correct
Current model (vessels)	96%
Current model (SIFT points) [1]	92%
Lee et al. [2]	88%
“REMPE” [3]	75%
“gdbicp” quadratic [4]	74%

Figure 1. Superimposition of a pair with a small overlap



A publicly available dataset: FIRE

129 images forming 134 image pairs divided in 3 categories:

- \mathcal{S} : 71 pairs with high overlap and no anatomical changes
- \mathcal{P} : 49 pairs with small overlap and no anatomical changes
- \mathcal{A} : 14 pairs with high overlap and large anatomical changes

For each pair, a ground truth of 10 corresponding points is available.

Figure 2. Registration curves. The error threshold is the value under which a registration is considered as successful. The y-axis is the percentage of successful registrations.

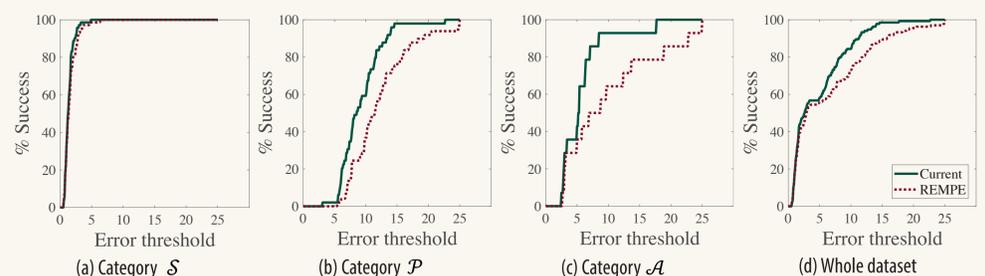


Table 2. Area under curve (AUC) for each category and the whole dataset.

Method	\mathcal{S}	\mathcal{P}	\mathcal{A}	FIRE
Current method	0.942	0.632	0.768	0.810
“REMPE” [3]	0.935	0.511	0.599	0.745

CONCLUSION

- Using the vessels improves the results obtained with our model especially for images with a small overlap
- In a public health dataset, our method is better than 4 state-of-the-art-methods
- In the FIRE dataset, our method is better than the reference one