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Validation of Retinal Image Registration Algorithms by a Projective Imaging Distortion Model

Sangyeol Lee,

S. Lee is with the Department of Biomedical Engineering, The University of Iowa, Iowa City 52242, USA; sangyeol-lee@uiowa.edu

Michael D. Abràmoff, and

M. D. Abràmoff is with the Department of Ophthalmology & Visual Sciences, University of Iowa Hospitals & clinics, Department of Electrical and Computer Engineering, The University of Iowa, and VA Medical Center, Iowa City 52242, USA; michael-abramoff@uiowa.edu

Joseph M. Reinhardt

J. M. Reinhardt is with the Department of Biomedical Engineering, The University of Iowa, Iowa City 52242, USA; joe-reinhardt@uiowa.edu

Abstract

Fundus camera imaging of the retina is widely used to document ophthalmologic disorders including diabetic retinopathy, glaucoma, and age-related macular degeneration. The retinal images typically have a limited field of view due mainly to the curvedness of human retina, so multiple images are to be joined together using image registration technique to form a montage with a larger field of view. A variety of methods for retinal image registration have been proposed, but evaluating such methods objectively is difficult due to the lack of a reference standard for the true alignment of the individual images that make up the montage. A method of generating simulated retinal image set by modeling geometric distortions due to the eye geometry and the image acquisition process is described in this paper. We also present the validation tool for *any* retinal image registration method by tracing back the distortion path and accessing the geometric misalignment from the coordinate system of reference standard. The quantitative comparison for different registration methods is given in the experiment, so the registration performance is evaluated in an objective manner.

I. INTRODUCTION

Fundus camera imaging can be used to examine the retina to detect disorders such as diabetic retinopathy, age-related macular degeneration (AMD), glaucoma, etc. [1]. Similar to looking through a small keyhole into a large room, imaging the fundus with an ophthalmologic camera allows only a limited view at a time [2]. Thus, retinal image registration that spatially combines multiple images has the potential to increase diagnostic accuracy.

Depending on the use to which the images are put, a small overlap may mean that intensity-based statistical properties are less advantageous than feature-based registration approaches, while a large overlap, for example in sequential SLO (Scanning Laser Ophthalmoscope) imaging [3], can require intensity-based approaches. A global-to-local matching [4], a hierarchical model refinement [5], a dual-bootstrap [6], etc. are the cases that use retinal vessel network as the feature. Local intensity features [7] can be useful when an insufficient number of features are available from anatomic structure. However, an open question about retinal image registration is how to validate the performance of different algorithms in an objective way.

In this paper, we describe a methodology for (1) generating a set of simulated retinal images with a known reference standard for registration; and (2) a validation process for assessing the quality of a retinal image registration algorithm. We describe a geometric distortion model to simulate the curvedness of human retina, the nonlinearities of the optical system, and the non-stationary interactions between camera and subject. We control the amount of inter-image overlap when constructing the simulated retinal images, so simulated images with varying amounts of overlap can be generated. We assess registration performance by tracing from the image registration results back to our original ground truth image. To illustrate the usefulness of this approach, we present results comparing three different retinal image registration models.

II. METHODS

The proposed method uses a large field of view montage image (our “ground truth”) obtained by registering multiple high resolution images. Since this ground truth image is essentially used as a texture, the underlying accuracy of the registration algorithm used to create the montage is not important. We use a retinal montage so that the features and intensities in the montage resemble those in a real retina. As illustrated in Fig. 1, the input montage is cut in “cookie cutter” fashion to create a set of circular images. Then each cut is mapped through a series of transformations to incorporate the distortions due to the eye geometry and the image acquisition system. The registration algorithm under evaluation may modify the image and its coordinate system in a complicated way, but performance can be validated by tracing back along the registration and distortion path to restore the original ground truth coordinate system.

A. Generation of simulated image set

1) Montage cutting—Our method generates a set of simulated fundus images with a specified amount of overlap between adjacent images. Since the overlapping region is the only information that can be used to guide registration, the performance of various image montage algorithms can be tested by generating test sets with varying amount of overlap. Fig. 2(a) shows the outline of two partially overlapping circular regions with radius r . To simplify the analysis, we center one image at the origin, and the other at some location d along the vertical axis. Then the overlap percentage m is given by

$$m = \frac{2r^2 \sin^{-1}(x/r) - xd}{\pi r^2} \times 100[\%], \quad (1)$$

where $x = \sqrt{r^2 - y^2}$, $y = d/2$.

For a specific overlap m , a lookup table for d is used. Once d has been selected, subsequent cut centers are placed at the edge of equilateral triangle whose side length is d , so the percent overlap is consistently maintained for any pair of overlapping cuts as shown in Fig. 2(b).

2) Distortion model—During the retinal imaging process, light rays reflected from the retina travel through the cornea and a series of optical lenses. The latter effect, however, can be minimized if the camera is well calibrated to compensate for path deformation at the cornea. Therefore, the geometric projection due to the spherical-to-planar projection becomes the most dominant component in retinal image distortion.

We first simulate patient movement and eye saccadic motion between consecutive fundus camera acquisition by adding small random amounts of rotation, scale change, and shearing, represented by an affine transform model:

$$\begin{bmatrix} X \\ Y \end{bmatrix} = s \begin{bmatrix} 1 & h \\ h & 1 \end{bmatrix} \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x - x_0 \\ y - y_0 \end{bmatrix} + \begin{bmatrix} x_0 \\ y_0 \end{bmatrix}, \quad (2)$$

where θ , s , h are random rotation, scale, and shear terms selected from Gaussian distributions, and (x, y) and (X, Y) are the corresponding points before and after the transform centered at (x_0, y_0) .

The interaction between the fundus camera and the eye can be simplified if we model the camera rotating around a stationary eye for limited angular range. Based on this model, a two-step distortion model is proposed. Setting the optical magnification to unity, as shown in Fig. 3(a), a planar montage image is first mapped onto the sphere using an equidistance-conformal mapping that preserves angle and radial distances seen from the optical axis. Then, the fundus camera generates images by projecting the retina space onto the camera space. As a practical consideration, the planar-to-spherical transformation cannot be implemented without forming a discontinuity in the montage, so we present a mathematical model that directly converts the montage space into camera space. Given the anatomic radius R of the eyeball ($R \approx 12.5$ mm on average [8]), as illustrated in Fig. 3(b), a point in montage space P_m at distance h_m from the optical axis can be mapped to a point P_c at a distance h_c from the optical axis in camera space with a transformation governed by

$$h_c = R \sin\theta = R \sin(h_m/R). \quad (3)$$

Finally our distortion model applies a gradual intensity variation to simulate optical vignetting effect in which the image illumination declines as getting away from the camera axis [9]. We use the vignetting distortion model [10] that follows the cosine-fourth law as denoted by

$$I_v(x, y) = \frac{I(x, y) + 1}{V \cos^4(\arctan(1/2R)) + 1 - V}, \quad (4)$$

where I and I_v are the pixel intensities before and after distortion, and V represents the vignetting parameter.

B. Validation of retinal image registration

1) Coordinate restoration—Given a simulated retinal image set obtained from the ground truth montage using a known transformation parameters, any retinal image registration method can be applied to align the images. The proposed validation process restores the montage coordinate and compares the registration results to the known ground truth to access accuracy. Fig. 4 describes the coordinate restoration path when the number of cuts N from the montage image is three (C_0 , C_1 , and C_2). The coordinate of each cut is transformed independently along the downward distortion path and is then input to the registration algorithm under evaluation. Many image registration algorithms choose one of the images as a “reference” image, and transform the remaining images so that they are best aligned with the reference. In our case, if a registration algorithm uses the image C'_1 as the reference, the registration results (C''_0 , C''_1 , and C''_2) will be aligned into a common coordinate system. Then, the registered images will also be aligned in the original montage space if they are transformed back through the registration and distortion functions along the path for C_1 . The reasoning can be expressed mathematically by

$$\begin{aligned}\widehat{C}_k &= A_1^{-1} P_1^{-1} R_1^{-1} (C_k'') \\ &A_1^{-1} P_1^{-1} R_1^{-1} R_k P_k A_k(C_k),\end{aligned}\quad (5)$$

where $k = 0, 1, \dots, N-1$ and the transformations are defined as in Fig. 4. The coordinate restoration can be achieved along any of the reverse paths. Without loss of generality, we follow the upward path for the reference image since the registration transformation matrix for the reference is usually the identity matrix.

2) Registration accuracy evaluation—In this paper, we place a set of landmarks which is the crossing point set of virtual grid lines on the original montage space. As like the image, the coordinate elements of the evaluation point set are modified by the transform matrix for each specific step and compared to its original coordinate elements in the restored coordinate system. As the registration error metric, mean square error or median absolute deviation can be a proper choice, and we calculate the mean absolute difference (MAD) from point displacement vector;

$$\text{MAD} = \text{avg}(\text{dist}(v, \widehat{v})) \text{ [pixels]}, \quad (6)$$

where v and $\widehat{v}$ are the validation points in montage and restored coordinate respectively. By evaluating the MAD for different registration algorithms, a direct and truly objective comparison can be obtained.

III. EXPERIMENTS

We demonstrate the proposed method for obtaining a typical fundus image sequence as follows. Multiple, overlapping retinal images were obtained from normal subjects without ocular abnormalities using a 60° color fundus camera (Canon, NY). Individual images were 2393×2048 pixels encoded in 8-bit for each color channel. The OIS (Ophthalmic Imaging System, Sacramento, CA) stitching function was used to combine retinal images together to obtain reference images. Our method is implemented using Java programming language as a plug-in for ImageJ [11]. Fig. 5 illustrates the results of the montage cutting simulation for the case of a 15% overlap to get seven planar cuts.

For this simulation, we set $R = 12.5\text{mm}$, $\theta \sim N(0, 3^\circ)$, $s \sim N(1, 0.02)$, $h \sim N(0, 0.02)$, and $V = 1.0$. The simulated retinal image set is displayed in Fig. 6 where the distortion in geometry and illumination is clearly observable.

To demonstrate the utility of the proposed method, we use three geometric transform models for registration: similarity model, affine model, and radial distortion correction model [12], however, any registration method could be tested using this approach. The similarity model considers three parameters; rotation, scale, and translation. Shearing effect is added in the affine model, and the distortion correction model includes an additional factor to the affine model; the radial distortion parameter.

We prepared seven retinal images from Fig. 5, and performed pair-wise registration using each model by setting C_0 to a registration reference. The registration results are shown in Fig. 7 where the *ghost* vessel lines [4] due to geometric misalignment serve as visual indicators of registration error. Note that no information is available about the registration performance outside of overlap region. Fig. 8 represents two visualizations of error evaluation using the

proposed method. Now it becomes possible to evaluate the registration accuracy over the entire region of interest and compare the performance of registration methods in an objective manner.

IV. CONCLUSION

A novel method of validating retinal image registration is presented in this paper. The retinal imaging process is modeled and used to obtain simulated retinal images with arbitrary overlap that display random motion, spherical-to-planar projection, and vignetting. The registration accuracy is evaluated by means of coordinate restoration process. Since the developed method provides a framework for retinal image registration, it can be applied to *any* registration algorithm that agrees with our distortion model. Once a particular distortion model is available, our coordinate restoration process can be directly applied to other registration problems such as satellite image mosaicing, panoramic scene generation, etc.

Future study of the proposed method may include the design of a more realistic distortion model that can describe non-linear distortion by camera system and higher order distortion than affine deformation.

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References

1. Kanski, J. Diseases of the ocular fundus. Elsevier/Mosby; 2005.
2. Hackel RE, Saine PJ. Creating retinal fundus maps. J Ophthalmic Photography 2005;27(1):10–18.
3. Abramoff MD, Kardon R, Vermeer K, Mensink M. A portable, patient friendly scanning laser ophthalmoscope for diabetic retinopathy imaging: exudates and hemorrhages. ARVO Annual Meeting. Abstract, 2007
4. You X, Fang B, He Z, Tang Y. A global-to-local matching strategy for registering retinal fundus images. Lecture Notes in Computer Science 2005;3522:259–267.
5. Can A, Stewart C, Roysam B, Tanenbaum H. A feature-based robust, hierarchical algorithm for registering pairs of images of the curved human retina. IEEE Trans on Pattern Analysis and Machine Intelligence Mar;2002 24(3):347–364.
6. Stewart C, Tasi C, Roysam B. The dual-bootstrap iterative closest point algorithm with application to retinal image registration. IEEE Trans on Medical Imaging Nov;2003 22(11):1379–1394.
7. Cattin PC, Bay H, Gool LV, Szekely G. Retina mosaicing using local features. Medical Image Computing and Computer-Assisted Intervention (MICCAI) Oct;2006 4191:185–192.
8. Remington, LA. Clinical anatomy of the visual system. Elsevier; 2005.
9. Hoover A, Goldbaum M. Locating the optic nerve in a retinal image using the fuzzy convergence of the blood vessels. IEEE Trans on Medical Imaging Aug;2003 22(8):951–958.
10. Kim, Y.; Sim, D. Vignetting and illumination compensation for omni-directional image generation on spherical coordinate. Proc. Int. Conf. Artificial Reality and Telexistence; Nov. 2006; p. 413–418.
11. Abramoff, MD.; Magelhaes, P.; Ram, S. Image processing with ImageJ; Biophotonics International. 2004. p. 36–42. <http://rsb.info.nih.gov/ij>
12. Lee, S.; Abramoff, MD.; Reinhardt, JM. Feature-based pairwise retinal image registration by radial distortion correction. Proc. SPIE Conf. Medical Imaging; San Diego, CA: 2007. in press

Fig. 1.
Proposed method for evaluating retinal image registration methods.

Fig. 2. Montage cutting: (a) a pair of overlapping images with the overlapped area shaded; (b) Constellation of individual cuts with a desired amount of overlap.

Fig. 3.

(a) Model of the fundus camera projective distortion geometry and (b) projective retinal distortion model.

Fig. 4.

Coordinate restoration path is denoted by gray arrow line for each image and C'_1 is considered as the registration reference; no transform matrix is given to the vignetting process since it is only for intensity distortion

Fig. 5.
Constellation of cuts with 15 % overlap for $N = 7$

Fig. 6. Simulated retinal image set for C_0 , C_1 , and C_2 from left to right column. Images in the top row are from montage cutting and are applied distortions to give bottom row images; grid lines are added to illustrate geometric deformation.

Fig. 7. Pair-wise registration of C_0 and C_2 using (a) similarity model, (b) affine model, (c) radial distortion correction model; average intensity is given to the overlap region to show vessel line mismatch clearly.

Fig. 8. Registration error map of C_2 for different models: similarity (MAD = 11.295), affine (MAD = 9.256), and radial distortion correction model (MAD = 4.171) from left to right column. Images in the top row are the intensity difference between reference standard and coordinate restored image, and the displacement vector for evaluation points is displayed in the bottom row.