Published in final edited form as:

Conf Proc IEEE Eng Med Biol Soc. 2010 ; 2010: 53–56. doi:10.1109/IEMBS.2010.5626302.

3D OCT Eye Movement Correction Based on Particle Filtering

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Abstract

Three-dimensional optical coherence tomography (OCT) is a new ophthalmic imaging technique offering more detailed quantitative analysis of the retinal structure. Eye movement during 3D OCT scanning, however, creates significant spatial distortions that may adversely affect image interpretation and analysis. Current software solutions must use additional reference images or B-scans to correct eye movement in a certain direction. The proposed particle filtering algorithm is an independent 3D alignment approach, which does not rely on any reference image. 3D OCT data is considered as a dynamic system, while location of A-scan is represented by the state space. A particle set is generated to approximate the probability density of the state. The state of the system is updated frame by frame to detect A-scan movement. Seventy-four 3D OCT images with eye movement were tested and subjectively evaluated by comparing them with the original images. All the images were improved after z-alignment, while 81.1% images were improved after x-alignment. The proposed algorithm is an efficient way to align 3D OCT volume data and correct the eye movement without using references.

Keywords

Particle Filtering; 3D OCT; Eye Movement Correction; Retinal Image Processing

I. Introduction

Spectral domain optical coherence tomography (SD-OCT) is a new high resolution imaging technique in ophthalmology, capable of achieving three-dimensional (3D) volume samplings of target tissue within 2 seconds [1]. 3D OCT retinal images are composed of a series of cross-sectional scans (B-scan, frame, x-z plane in Figure 1A) from top to bottom of the scanning region on retina. Each B-scan consists of certain number of high-resolution one-dimensional scans in the z direction (A-scan). An ideal 3D OCT volume data is illustrated in Figure 1A.

3D OCT imaging of the retinal layers may offer more detailed and accurate quantitative analysis of the retinal structure than even before. This will likely improve objective assessment ability, early detection and monitoring the progression of eye diseases, such as glaucoma, diabetic retinopathy and others. Eye movement during 3D SD-OCT scanning, however, creates significant spatial distortions in the 3D data that may adversely affect image interpretation and analysis (Figure 1B). The involuntary eye movement, such as micro-saccade and drifting, may occur at up to 15Hz oscillation (mainly horizontal). Therefore it is common to have a distorted 3D OCT image, although the amplitude of the eye movement varies. Spatial integrity restored (non-distorted) 3D OCT data is the essential foundation of quantitative and reproducible OCT measurements.

3D OCT eye movement correction is a challenging problem due to the complicated factors of eye movement. For example, micro-saccade makes local discontinuities likely generating inter- B-scan movement (x-movement, Figure 1C). Drifting makes stretching/shrinking in 3D volume data in all directions likely generating intra- B-scan movement. The fore-aft eye movement may generate z-movement (Figure 1D).

Some hardware solutions were made by the OCT manufactures to solve the eye movement problem in certain direction. Cirrus HD-OCT (Carl Zeiss Meditec, Inc., Dublin, CA) provides two additional diagonal B-scans as the references, which are used mainly to correct z-offset [2]. Spectralis HRA-OCT (Heidelberg Engineering, Inc., Heidelberg) is using a real time eye motion tracking system to track eye movement, guide OCT to the proper location, and repeat the B-scan if there was eye movement detected during scanning [3]. There are a few publications regarding the use of image processing software technology to correct eye movement in 3D OCT volume data. Ricco *et al.* [4] proposed a local image registration algorithm to correct the xy- eye movement. A 2D OCT fundus image (generated by averaging each A-scan, Figure 1C) was enhanced and locally registered on a static reference image using affine transform model. Xu *et al.* [5] introduced another global image registration approach based on the shape context algorithm [6] to also correct xy-movement. The retinal blood vessels were first detected on the OCT fundus image [7] and static reference image [8] respectively. One vessel map was then globally registered on the other using two-dimensional (2D) deformable model computed by the vessel shape context.

All the previous studies used additional reference images or scans to correct 3D OCT image. However, not all the 3D OCT devices provide an additional B-scan or 2D reference image. In this paper, a particle filtering algorithm is proposed to automatically align A-scans and correct xz- eye movement artifacts in 3D SD-OCT images. The approach is independent and does not rely on any reference images.

II. Method

Particle filtering has been recognized as an effective target tracking algorithm due to its accuracy, robustness and flexibility in nonlinear and non-Gaussian systems [9]. The basic idea of particle filtering is to present the target by state space model and convert target tracking into state estimation problem. The state at a given time in the dynamic system is estimated by its simulated probability density generated from a set of weighted samples, called particles.

The spatial distortion in the 3D OCT data is the combined effect of several eye movement factors. Moreover, the spatial variation between A-scans comes from natural anatomy as well. Particle filtering is a suitable approach to solve this nonlinear alignment problem. Based on our results, the algorithm is more stable to correct x- and z-movement separately rather than one step xz-movement correction. Therefore, in this paper, x-movement correction is first performed by an implementation of particle filtering algorithm [10], following by the z-movement correction. The kernels of particle filtering include state space, system dynamics, observations, and state estimation.

A. State Space

The 3D OCT volume data generated from consecutive B-scans is considered as a dynamic system, represented by $\mathbf{X}_t$, where the first B-scan is set to be time $t = 0$. The state space is represented in the spatial domain as the 3D location of A-scan, denoted by $\mathbf{X}_t \{a_t(x, y, z)\}$. A number of A-scans are selected on the first B-scan ($t = 0$) as the initial states, denoted by $\mathbf{X}_0 \{a_0^1(x, y, z), a_0^2(x, y, z) \cdots a_0^M(x, y, z)\}$, where M is the number of states in state space. The

state of the system (the locations of the selected A-scans) is updated frame by frame using particle filtering, in order to detect the eye movement.

For each state, a set of weighted samples is generated as particles in the previous frame. Particles are predicted by a system dynamics model in the current frame. An observation model is designed to compute the likelihood between each particle and the state in previous frame, which is used to approximate the probability density of the state. The displacement of the state in the current frame is obtained by taking the expectation.

B. System Dynamics

A linear regressive model is chosen for the system dynamics between adjacent B-scans, written as

$$\mathbf{X}_t = \mathbf{A}\mathbf{X}_{t-1} + \mathbf{B} \quad (1)$$

where matrix $\mathbf{A}$ is initially set to an identity matrix and matrix $\mathbf{B}$ is set to a zero matrix respectively. Two matrices are updated from two previous sequences $\mathbf{X}_{t-1}$ and $\mathbf{X}_{t-2}$.

C. Observation Model

A window-based similarity measurement is used to estimate the observations at time t , written as

$$\mathbf{Y}_t \{y_t^{1,n}, y_t^{2,n} \dots y_t^{M,n}\}, n=1 \dots N \quad (2)$$

where $y_t^{m,n}$, donates the observation of the n^{th} particle for the m^{th} state at time t . The similarity is computed based on the mean of absolute differences (SAD) between the candidate and reference window in the feature space.

In the proposed algorithm, 3D OCT volume data is first aligned in the x direction. Therefore, z direction independent features are extracted from each of the A-scans. One-dimensional (1D) Haar-function filters with different window sizes are applied on each A-scan to generate A-scan features. We used two different 1D Haar-features as shown in Figure 2, where -1 and 1 regions have the same window size. The features taken are max, min, max-min, and 0th to 4th moments of Haar-function filter responses. Other features including mean, standard deviation, skewness, and kurtosis, are taken from each A-scan as well.

D. X- and Z-Movement Estimation (State Estimation)

For each state at time t , $\mathbf{X}_t \{a_t^m(x, y, z)\}$, $m=1 \dots M$, a weighted particle set is generated in previous frame based on a Gaussian distribution, written as:

$$\mathbf{S}_t \left\{ \left\{ w_t^{1,n}, s_t^{1,n} \right\}, \left\{ w_t^{2,n}, s_t^{2,n} \right\} \dots \left\{ w_t^{M,n}, s_t^{M,n} \right\} \right\}, n=1 \dots N \quad (3)$$

where N is the number of particles and w is the particle weight, initially set to $1/N$. A system dynamics model is applied on each particle to predict the location of the particle in the current frame. In particle filtering, the state posterior distribution can be approximated by the observations of weighted particles, denoted as

$$p(\mathbf{X}_t \{a_t^m\} | \mathbf{Y}_{1:t} \{y_{1:t}^m\}) \sim \sum_{n=1}^N w_t^{m,n} g(s_t^{m,n}) \quad (4)$$

The weights of particles $w_t^{m,n}$ are proportional to observations $y_t^{m,n}$ by computing the likelihood between the window of predicted location in the current frame and the window of the state in previous frame. Particles' weights are normalized as $\sum_{n=1}^N w_t^{m,n} = 1$. The displacement of each given state in current B-scan is obtained by estimating the functional state's expectation, $\hat{E}g(X_t\{a_t^m\}) = \sum_{n=1}^N w_t^{m,n} g(s_t^{m,n})$. In this study, the state is updated by the weighted summation of particles with top 10% largest weights.

For the x-movement estimation, state space is simply reduced to one dimension, denoted as $X_t\{a_t(x)\}$. Because only sparse A-scans are set to the states, the final x-movement between adjacent B-scans is optimized by a linear model using the states in the current and previous frame, written as

$$a_t(x) = \beta a_{t-1}(x) + \gamma \quad (5)$$

where β and γ are coefficients of linear movement model. The x-movement is corrected by aligning the entire B-scan to the previous B-scan based on the linear models.

After x-movement is corrected, the same procedures are applied on the corrected 3D data to estimate z-movement. The state space is reduced to one dimension in z direction, denoted as $X_t\{a_t(z)\}$, while feature space is set to the original A-scan intensity value. All the A-scans at $t = 0$ are set to the initial states. The z-movement is corrected A-scan by A-scan based on the state updates in each frame.

E. Evaluation

The performance of the proposed algorithm was subjectively evaluated by comparing the processed and original 3D OCT images side by side. Each processed image was evaluated with respect to overall x-movement correction and z-movement correction. The x correction looked at the global blood vessel continuity on OCT fundus image. In anatomy, the retinal pigment epithelium (RPE, Figure 3A,B) layer in the retina is close to flat within 6×6 mm OCT scan region. Therefore, overall z correction considered whether RPE layer was flat or not on the horizontal and vertical center B-scans generated from 3D OCT volume data. The results were labeled as improved, equivalent, and degraded.

III. Results and Discussion

Seventy-four 3D OCT images centred at optic disc, taken from 25 healthy and 49 glaucomatous eyes, were acquired using SD-OCT (Cirrus HD-OCT). The image resolution is 200×200×1024 samplings in a cube of 6×6×2 mm. All the images were confirmed to contain clearly observable z-movement, blood vessel discontinuities, and/or optic disc distortions. Particle filtering was applied on the 3D OCT volume data frame by frame to firstly correct x-movement and then z-movement. The overall 3D OCT correction took 7 minutes using MATLAB.

An example of the results of particle filtering based 3D OCT alignment is given in Figure 3. Original 3D OCT volume data with spatial distortion is illustrated in Figure 3A. Blood vessel discontinuity generated by micro-saccades could be observed on its OCT fundus image (Figure 3C). Particle filtering approach efficiently corrected micro-saccades and z-movement by aligning B-scans and A-scans. The corrected 3D OCT volume data and its corresponding OCT fundus image are shown in Figure 3B,D. Table 1 gives the subjective evaluation of the processed images with respect to x- and z-movement corrections

respectively. All the images were improved after z-alignment, while 81.1% images were improved after x-alignment.

Based on the current 3D scan type, y-movement is mostly generated from drifting, which is a slow and continuous eye movement difficult to be observed. Therefore y-movement correction was not studied in this paper.

IV. CONCLUSIONS

The main difficulties of 3D OCT eye movement correction are the complicate eye movement factors and the lack of reference. In this paper, a particle filtering approach has been presented to automatically align 3D OCT volume data in xz direction. The algorithm does not rely on any reference image or scan. Experimental results show the proposed algorithm is an efficient way to correct eye movement and provide spatial integrity restored 3D OCT data, which is an essential foundation of the quantitative OCT analysis.

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Figure 1.

An example of a 3D OCT image. (A) 3D OCT image composed of consecutive B-scans, each B-scan consists of a certain number of A-scan. (B) 3D OCT image with eye movement. (C) OCT fundus image, generated by averaging intensity values of each A-scan. The blood vessel discontinuity and optic disc distortion are illustrated. (D) 3D OCT volume data with z-movement (arrows).

Figure 2.
1D Haar-feature filter. (A) 2-window Haar-feature, (B) 3-window Haar-feature

Figure 3.

An example of 3D OCT eye movement correction using particle filtering. (A) 3D OCT volume data with eye movement, (B) Corrected 3D OCT volume data, (C) OCT fundus image with blood discontinuity generated from eye movement, (D) Corrected OCT fundus image.

Table 1

Subjective evaluation of 74 processed 3D OCT images

	Grade	Evaluation
X-movement correction	Improved	60 (81.1%)
	Equivalent	13 (17.6%)
	Degraded	1 (1.4%)
Z-movement correction	Improved	74 (100%)
	Equivalent	0 (0%)
	Degraded	0 (0%)