Automated motion-artifact correction in an OCTA image using tensor voting approach

Ang Li,¹ Guang Zeng,^{1,2} Congwu Du,¹ Huiping Zhang,³ and Yingtian Pan^{1,a)}

¹Department of Biomedical Engineering, Stony Brook University, Stony Brook, New York 1194-5281, USA

²Department of Urology, Zhongnan Hospital of Wuhan University, Wuhan 430071, China

³Institutes of Urology Research of Hubei Province and Family Planning Research, Tongji Medical College, Huazhong University of Science and Technology, Wuhan 430030, China

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Optical coherence tomography angiography (OCTA) is a promising tool for imaging subsurface microvascular networks owing to its micron-level resolution and high sensitivity. However, it is not uncommon that OCTA imaging suffers from strip artifacts induced by tissue motion. Although various algorithms for motion correction have been reported, a method that enables motion correction on a single *en face* OCTA image remains a challenge. In this study, we propose a motion correction approach based on microvasculature detection and broken gap filling. Unlike previous methods using registration to restore disturbed vasculature during motion artifact removal, tensor voting is performed in an individual projected image to connect the broken vasculature. Both simulation and *in vivo* 3D OCTA imaging of the mouse bladder are performed to validate the effectiveness of this method. A comparison of *in vivo* images before and after motion correction shows that our method effectively corrects tissue motion artifacts while preserving the continuity of vasculature network. Furthermore, *in vivo* results of this technique are presented to demonstrate its utility for imaging tumor angiogenesis in the mouse bladder. *Published by AIP Publishing.*

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Optical coherence tomography angiography (OCTA) is a noninvasive technique that enables high-resolution volumetric imaging of subsurface vasculature of biological tissues.^{1,2} An OCTA image of a vascular network is constructed by computing decorrelation between sequential OCT B-scans acquired at the same cross-section. Pixels occupying the vasculature (due to Doppler blood flow) show higher decorrelation than those of static tissues.^{3,4} However, due to the limited imaging speed, tissue motion might change the OCT intensity distribution and dramatically deteriorate the correlation of static tissues within B-scans.⁵ If tissue motion is severe (e.g., for endoscopic or awake animal imaging), motion artifacts may seriously degrade the image quality and jeopardize quantitative analysis.

Approaches to correct motion artifacts have been reported, among which methods that circumvent the need for complex hardware modification are often adopted. Hendargo *et al.* presented a global-local registration method by merging noise-free parallel image strips from 2 *x*-axis and 2 *y*-axis fast-scan *en face* retinal angiograms.⁶ Zang *et al.* reported a simpler strategy for image registration on non-orthogonal scanning datasets after removing strip artifacts.⁷ Alternatively, Chen *et al.* utilized Lissajous-scan OCTA to avoid multiple volumetric scans.⁸ Although these methods can effectively reduce motion artifacts, they require repeated volumetric scans or modified scanning patterns; their performance heavily depends on the registration procedure that may not work properly on images with severe vignetting, tilting or defocus. To address these issues, we propose a

method for the removal of motion artifacts on an individual *en face* OCTA projection image based on vessel detection and gap filling.

The proposed method is designed to reserve the vascular network while eliminating motion artifacts. To achieve this goal, the vascular network is first extracted by a vessel segmentation algorithm and the false responses of artifacts are removed. As the removal of artifact strips leads to discontinuity of vasculature, we then implement a multiscale tensor voting method to restore the broken vasculature in a binary vascular mask. The corrected vascular mask is applied back to the original image to obtain the final motion-free image.

Tensor voting is a procedure to connect image tokens through tensor casting that encodes both magnitude and orientation.⁸ In a 2-D image, a tensor field is represented by a 2nd-order matrix whose magnitude and orientation are determined by eigenvalues (λ_1, λ_2) and eigenvectors (e_1, e_2). As illustrated in Fig. 1(a), the stick tensor field from pixel *x* expresses both orientation and magnitude at a receiver pixel *y*. This process is subject to smoothness and proximity that are modeled by arch length *s* and curvature κ .⁹

$$V(y) = \exp\left(-\frac{2s^2 + 2c\kappa^2}{\sigma^2}\right) * \vec{w}\vec{w}^T / \|\vec{w}\|^2, \quad (1)$$

where $s = \theta l / \sin(\theta)$ and $\kappa = 2\sin(\theta)/l$, in which *l* is the Euclidean distance between *x* and *y*. σ is the range of the voting field and *c* is the control of influence ratio between smoothness and proximity, which is optimized for $c = 16\ln(0.1) \times (\sigma - 1)/\pi^2$.¹⁰ The vector *w* in Eq. (1) is the tangent at *y* to the circle that contains *x* and *y*

$$\vec{w} = 2\vec{x}\vec{y}(\vec{x}\vec{y} \cdot \vec{v}) - \vec{v}, \quad (2)$$

^{a)}Author to whom correspondence should be addressed: yingtian.pan@stonybrook.edu

FIG. 1. Illustration of a multiscale stick tensor field applied to a simulated broken vasculature. (a) A sketch to illustrate the stick tensor field at position y from x . (b) The aperture of the stick tensor field reduces from the center to the boundary. (c) Stick tensor field in different scales. (d) Simulated vasculature with a broken gap. (e) Saliency map of (d) after constructing the stick tensor field at two segment ends.

where $\vec{x}\vec{y}$ and $\vec{v}$ are chosen to be normalized vectors. To deal with vasculature with varying diameters, a multiscale stick tensor field is implemented in our study. At the end of a vasculature segment, as shown in Fig. 1(b), a stick tensor field with full aperture β_0 is constructed in the central pixel, while the aperture of the tensor field in adjacent pixels is reduced as a function of distance to the central one. Then, the modified stick tensor field V_m can be expressed as

$$V_m(y) = V(y) \times \begin{cases} 1, & y \in A(\beta) \\ 0, & \text{other}, \end{cases} \quad (3)$$

where $A(\beta)$ is a limiting cone that constrains the aperture of the stick field, $\beta = \beta_0 - cd$, d is the distance to the central pixel, c is a constant, and β_0 and c are empirically chosen in our study to be $\pi/4$ and $\pi/30$, respectively. The magnitude of a small and a large-scale stick tensor field, as $\exp\left(-\frac{2s^2 + 2ck^2}{\sigma^2}\right)$ in Eq. (1), is illustrated in Fig. 1(c). With more focused magnitude on the boundary, this multiscale stick tensor field is able to better strengthen the locally curvilinear structure, while excluding possible motion artifact lines. As outlined elsewhere,⁹ the voting procedure is the accumulation of the tensor field at each pixel and the elongated tensor field corresponds likely to the curvilinear structure. Therefore, the saliency map $S(y)$ corresponding to the elongated tensor field is computed to characterize vasculature

$$S(y) = \lambda_1 - \lambda_2 \quad (\lambda_1 > \lambda_2). \quad (4)$$

For proof of concept, we applied this method to a simulated vasculature that has a broken gap as shown in Fig. 1(d). The stick tensor field with the corresponding scale was constructed at the ends of two adjacent segments. The tensor field within the gap tends to deform more unevenly due to the voting from two stick tensor fields, resulting in a strong

saliency map as shown in Fig. 1(e), where the missing part of the vasculature is clearly evidenced.

The multiple stick tensor field is applied together with our recently developed vessel detection algorithm based on an optimally oriented flux (OOF)¹¹ to correct motion artifacts. Figure 2(a) is an exemplary raw OCTA image suffering from motion artifacts (highlighted by green arrows). To extract the microvascular network, the OOF-based vessel detection algorithm is first applied to the raw image, in which the scale range of OOF is set to $1 \leq r \leq 5$ to cover the diameter range of microvasculature. As OOF is of high sensitivity for segmenting the microvasculature, vessel branches of low contrast in the raw image are well preserved in the vesselness map, Fig. 2(b). However, motion artifacts are also mistakenly identified by OOF to show strong responses in the vesselness map. Following a similar strategy,⁷ artifacts can be identified and then removed by selecting lines with a mean vesselness value larger than μ -times the mean vesselness value of the entire image [red strips in Fig. 2(c)], where the threshold μ ($\mu > 1.3$) is adjusted based on the image dataset. After artifact removal, the artifact-free binary vessel mask is generated from the vesselness map using a global threshold as shown in Fig. 2(c). To restore transverse gaps within the regions with artifacts, multiscale stick tensor fields

FIG. 2. Motion artifact removal from an OCTA image of a mouse bladder: (a) Raw OCTA image with motion artifacts marked by green arrows. (b) Vesselness map generated by the OOF-based vessel segmentation algorithm. (c) Binary mask of (b) showing broken vasculature after removing motion artifacts. (d) Saliency map of the stick tensor field constructed at the broken nodes of vessel segments. (e) Restored binary vasculature mask with the vasculature gap being filled as marked by yellow arrows. (f) Corrected OCTA image showing accurately restored vasculature topology.

described above are constructed at the broken spots of these vessel segments. Since the OOF can automatically estimate the orientation and the diameter of the local vasculature, we directly utilize those two measures to initialize stick tensor field. For better visualization, the saliency map $S(y)$ of the tensor field is overlapped with a binary vasculature mask, as shown in Fig. 2(d). To restore missing vessel segments while avoiding false connection, the response of missing segments $p(y)$ is determined by the combination of vesselness map $M(y)$ and saliency map $S(y)$

$$p(y) = S(y) * M(y). \quad (5)$$

The missing vessel segments are retrieved by binarizing the response $p(y)$ with a global threshold and are then summed to the artifact-free binary image [Fig. 2(c)] to form the final vasculature mask [Fig. 2(e)]. The corrected OCTA image is derived by multiplying the raw image with the final binary vasculature mask. It can be seen from both the vasculature mask [Fig. 2(e)] and the final OCTA image [Fig. 2(f)] after correction that the broken vessels induced by artifact removal are connected (yellow arrows), thus demonstrating the ability of our method to accurately restore the continuity of the microvasculature network. It should be noted that the vasculature gap filling method is performed mainly on microvasculature, because large vessel branches can be extracted without inducing artifacts using a high global threshold. Thus, for OCTA images containing large vessel branches, the final vasculature mask is generated by merging large vessels and the corrected microvasculature masks.

We further validated this method for motion-free microvascular network mapping and quantitative analysis in a mouse bladder. OCTA images were acquired at 50 kHz A-scan rate using our recently developed μ OCT system.¹² In the study, both normal mice (C57/B6, male, 12–14 weeks of age) and transgenic mice with carcinoma *in situ* of the bladder (SV40T, male, 8–10 weeks of age) were imaged, respectively. Figure 3 compares the OCTA images ($2.5 \times 3 \text{ mm}^2$) of the bladder before and after applying the tensor voting method for motion artifact removal. Without artifact removal, the vasculature network in the raw image in Fig. 3(a) is severely disturbed by horizontal strips, especially in the lower and upper left corners of the image, resulting in the washout of microvasculature (low contrast, barely identifiable). After correction of these artifacts, Fig. 3(b) shows that the OCTA image fidelity is dramatically improved. The microvascular networks which are buried under overwhelmed motion artifacts (e.g., strips) in the raw image can be easily uncovered and appear continuous and natural. The differential image in Fig. 3(c) further shows that most artifacts in the image are suppressed and the vascular architecture is preserved. We manually segmented vascular networks into a pair of zoom-in images [Figs. 3(a') and 3(b')] as ground truth. A comparison between them clearly demonstrates that topology of the microvasculature is fully restored (blue dashed line) with only slight noise (green dashed line) and missed vessel segments (purple arrows) presented. For quantitative evaluation of how the tensor voting based method improves the accuracy for vessel tracking, we compared the binary vasculature masks before and after artifact

FIG. 3. Artifact removal in an *en face* OCTA image ($2.5 \times 3 \text{ mm}^2$) of a normal mouse bladder *in vivo*. (a) Original OCTA image. (b) OCTA image after artifact removal using the tensor voting method. (a') and (b') Zoom-in images from regions of interest (dashed blue boxes) in (a) and (b). (c) Differential image between (a) and (b). (d) Statistic result of DSC analysis that reveals significant improvement in the accuracy of vasculature detection after performing artifact removal. (e) The influence of artifact severity on vascular connection; the true-positive junction rate is higher than 88% when the occupation rate is lower than 30%.

removal with the corresponding results of manual segmentation using the Dice Similarity Coefficient (DSC).¹³ DSC has a restricted range of [0,1], where a larger value indicates higher similarity between the segmentation result and the ground truth. As presented in Fig. 3(d), the statistic result reveals that $\text{DSC} = 0.814 \pm 0.03$ of the corrected vasculature mask is significantly higher than that of not corrected mask (0.709 ± 0.036 , $n = 6$, $p < 0.05$), suggesting a closer agreement with the ground truth ($\text{DSC} = 1$). Meanwhile, the influence of artifact severity, represented by the occupation rate ($\text{OR} = \frac{\text{of artifact lines}}{\text{of total lines}}$), on the performance of the proposed algorithm was evaluated. In an artifact-free image patch ($1 \times 1 \text{ mm}^2$), artificial gaps were created by randomly removing lines with different occupation rates (10%–60%). Then, the disturbed vascular network was restored by our gap filling method and the number of true-positive junctions over the number of ground-truth junctions was computed. As shown in Fig. 3(e), the true-positive junction rate is high and stable for a moderately disturbed vascular network. For instance, the true-positive junction rate is higher than 88% when 30% or less of image lines is removed, but it starts to drop rapidly when 40% or more artifacts are presented in an image.

The ability to accurately track angiogenesis will facilitate a better understanding of angiogenesis dependent

diseases and can be the key to developing therapeutic strategies. We applied this method to minimize motion artifacts to quantify tumor angiogenesis in the mouse bladder of carcinoma *in situ*. *In vivo* OCTA images of the normal mouse bladder and the mouse bladder with carcinoma *in situ* after artifact correction are presented in Fig. 4. With vessel tracking and motion-artifact removal using our algorithm, the sub-surface vasculature including the microvascular network of the bladder in corrected images [Figs. 4(c) and 4(d)] can be better visualized than the original images [Figs. 4(a) and 4(b)]. Compared with the normal bladder in Fig. 4(c), the complex tumor vasculature in carcinoma *in situ* of the bladder in Fig. 4(d) can be characterized by features such as higher density, enlarged vascular cords, uneven diameter and increased tortuosity. To quantitatively assess tumor angiogenesis, a vessel density map was generated by applying an adaptive rolling window (27×27 pixels) on the vascular skeleton.¹⁴ Figures 4(c') and 4(d') show that the vascular density is drastically increased as a result of angiogenesis that occurred in cancerous bladder. Statistical analysis in Fig. 4(e) shows that the vascular density (fill factor) of tumor vasculature (0.076 ± 0.007) is significantly higher than that of the normal bladder (0.049 ± 0.005 ; $n = 4$, $p < 0.05$).

In summary, we have presented a tensor voting approach to effectively remove motion artifacts from 3D OCTA images. Different from previously reported methods that are based on image registration, this method utilizes OOF to segment vasculature and tensor voting to correct broken vessel segments that are induced during motion-artifact removal. As the method can be efficiently performed on a single OCTA projection image, it circumvents the need for repeated image acquisition or sophisticated hardware modification for special laser scanning schemes. For proof of concept, we presented the simulation result that clearly shows that broken segments of vasculature can be retrieved by the saliency map S of tensor field (Fig. 1). Then, we validated the algorithm for

FIG. 4. OCTA images of normal bladder vs carcinoma *in situ* after artifact removal. (a) and (b) Original OCTA images of the normal bladder and of carcinoma *in situ*, respectively. (c) and (d) Motion artifact corrected image corresponding to (a) and (b) respectively. (c') and (d') Density maps corresponding to (c) and (d), respectively. (e) Statistic comparison to show significantly increased vascular density in cancerous bladder.

restoring *in vivo* OCTA images of the mouse bladder that were severely deteriorated by motion artifacts. Both visual inspection and quantitative analysis show that motion artifacts can be effectively removed and the microvascular network is restored well (Fig. 3). A comparison between uncorrected and corrected vasculature masks against manual segmentation (Gold standard) using DSC analysis [Fig. 3(d)] indicates that by performing artifact removal there is a significant improvement in the accuracy of vasculature detection (from 0.709 ± 0.036 to 0.814 ± 0.03 , $n = 6$, $p < 0.05$). Finally, we applied this method to quantitatively characterize angiogenesis in the mouse bladder with carcinoma *in situ*. After artifact removal, tumor vasculature in carcinoma *in situ* of the bladder can be identified by enlarged vascular cords, increased tortuosity and higher microvascular density (0.076 ± 0.007 of carcinoma *in situ* vs. 0.049 ± 0.005 of the normal bladder; $n = 4$, $p < 0.05$), thus demonstrating the potential of OCTA for *in vivo* longitudinal tracking of tumor microenvironment.

It is noteworthy that in the step of the constructing tensor field, the range of vote in Eq. (1) was set to $\sigma = 7$ based on pilot data, which worked well in almost all data in our study except when the gap of broken vessel segments was over the scope of tensor field. This situation merely occurred when a large segment of vasculature overlapped with artifact stripes or when artifact stripes dominated the image [e.g., Fig. 3(e)]. This issue can be partially solved by using a larger range of vote, but it will increase the possibility of false positive detection of vascular segments and the computation time of constructing tensor field. The orientation and the diameter estimated by OOF were used to initialize the tensor field, both of which tend to be inaccurate when the vasculature suffers poor contrast or artifacts (e.g., stripes crossing it) having extremely high intensity. This bias can be reduced by estimating vessel orientation and diameter using the vasculature skeleton extracted from a binary mask; however, additional algorithm is needed for vasculature skeletonization and diameter estimation, which may potentially increase the complexity of the method. One limitation of the method is that some motion artifacts cannot be effectively identified. The method used to identify motion artifacts implicitly assumes that artifact lines have remarkably higher average amplitude than others and can be identified by setting a threshold. The validity of this assumption is reduced by the fact that some motion artifacts, although uncommon, do not cross the whole image but rather are unevenly spaced on a B-scan. For the future study, more modeling work is needed to take this into account for better separation of vasculature signals and motion artifacts. Another potential limitation of the algorithm is that the geometric distortion of the vascular network caused by severe motion along the slow axis cannot be effectively corrected. To overcome this, a cross-correlation based compensation method may be introduced as an extra step after artifact removal for distortion compensation.¹⁵

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