Journal of Medical Imaging

MedicalImaging.SPIEDigitalLibrary.org

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Abstract. Three-dimensional ultrasound segmentation of mitral valve (MV) at diastole is helpful for duplicating geometry and pathology in a patient-specific dynamic phantom. The major challenge is the signal dropout at leaflet regions in transesophageal echocardiography image data. Conventional segmentation approaches suffer from missing sonographic data leading to inaccurate MV modeling at leaflet regions. This paper proposes a signal dropout correction-based ultrasound segmentation method for diastolic MV modeling. The proposed method combines signal dropout correction, image fusion, continuous max-flow segmentation, and active contour segmentation techniques. The signal dropout correction approach is developed to recover the missing segmentation information. Once the signal dropout regions of TEE image data are recovered, the MV model can be accurately duplicated. Compared with other methods in current literature, the proposed algorithm exhibits lower computational cost. The experimental results show that the proposed algorithm gives competitive results for diastolic MV modeling compared with conventional segmentation algorithms, evaluated in terms of accuracy and efficiency. © 2018 Society of Photo-Optical Instrumentation Engineers (SPIE) [DOI: 10.1117/1.JMI.5.2.021214]

Keywords: mitral valve model; ultrasound image segmentation; image guidance.

Paper 17251SSRR received Aug. 28, 2017; accepted for publication Jan. 4, 2018; published online Feb. 9, 2018.

1 Introduction

Mitral valve (MV) disease affects about 2.5% of the general population and MV regurgitation is the most prevalent form of the disease.¹ MV repair under ultrasound guidance is generally the preferred option, but almost one third of patients with MV repair develop recurrent moderate or severe mitral regurgitation. To increase the successful rate of patient MV repair, delineating patient-specific MV model is beneficial for both planning and training clinicians to visualize and quantify MV morphology and motion.^{2,3} Reconstructing patient-specific MV models is a complicated task. To adequately validate a surgical MV repair, a physical simulator/trainer replicating the dynamic and irregular motion of the MV leaflet and its subvalvular apparatus (chordae tendinae and papillary muscles) was developed.⁴ The reconstructed model used in this simulation is capable of replicating the various forms of the patient-specific pathology and surgical MV repair.⁵

Accurate image segmentation techniques are useful for modeling the patient-specific MV from the limited quality of clinical transesophageal echocardiography (TEE) image data. There are two conventional image segmentation approaches: the active contour (AC) segmentation proposed by Chan and Vese,^{6,7} and the continuous max-flow (CMF) segmentation proposed by Yuan et al.⁸ In recent years, these segmentation approaches have been successfully applied to ultrasound images. For example, Kuo et al.⁹ proposed a segmentation method for three-dimensional (3-D) breast ultrasound images. Rajchl et al.¹⁰ proposed a hierarchical max-flow segmentation framework for multiatlas

segmentation and further studied real-time four-dimensional (4-D) ultrasound segmentation with a CMF approach.¹¹ Baxter et al.¹² analyzed an optimization-based interactive segmentation interface for multiregion problems. Bersvendsen et al.¹³ proposed a semiautomated segmentation for 3-D echocardiography. These image segmentation methods provide the practicality of MV quantification by 3-D TEE, but MV leaflet segmentation is challenging due to irregular leaflet motion throughout cardiac cycle. In the systolic phase, the MV is closed, both the anterior leaflet and posterior leaflet are coapted, appearing as a single contiguous tissue in sonography. In the diastolic phase the MV is open; however, the posterior leaflet often opens toward the direction of the ultrasound waves, which causes signal dropout at leaflet regions in TEE image data. As a result, conventional segmentation approaches often suffer from missing sonographic data leading to the inaccurate construction of the MV model.

Several significant works in recent literature are focused on these challenging issues on MV leaflet segmentations. Curiale et al.¹⁴ presented a robust detection scheme to initialize a multicavity segmentation approach without any user interaction. Sotaquira et al.¹⁵ presented a semiautomatic method for mitral annulus and mitral leaflets segmentation using a nine-point user interaction to characterize the MV morphology. Schneider et al.^{16,17} proposed a mitral annulus segmentation algorithm for closed MVs and further proposed a multistage method for segmenting the open mitral leaflets in 3-D TEE datasets. Their method combines the CMF approach, AC approach, and the constrained optical flow approach to track the mitral annulus together. Based on a large database of manually labeled images,

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Ionasec et al.¹⁸ presented an automatic segmentation method for segmenting and tracking the aortic and mitral leaflets. Pouch et al.¹⁹ proposed an automatic segmentation of the mitral leaflets using multias joint label fusion and deformable medial modeling. Although these segmentation methods were reported to be effective, they suffer from issues including computational costs^{16,17,19} and relatively low segmentation accuracy.^{14,15}

The objective of this paper is to develop an effective segmentation method for delineating diastolic MV at leaflet regions from 3-D ultrasound. To achieve this, we first present a signal dropout correction approach to recover incomplete segmentation information. We then propose a signal dropout correction-based segmentation algorithm for diastolic MV modeling. Because the signal dropout regions of TEE image volumes can be accurately estimated by the proposed signal dropout correction, the MV model is better reconstructed due to avoiding missing segmentation information. Moreover, the proposed algorithm has relatively low computational cost comparing with previous MV segmentation algorithms in recent literature.^{16,17,19} Finally, experimental results demonstrate that the proposed algorithm provides more accurate MV models at leaflet regions than the conventional algorithms.

2 Methods

2.1 Conventional Segmentation Methods

The CMF and the AC are two popular image segmentation algorithms and often used in ultrasound image segmentations. For CMF, the associated optimization formulation for image $I(x)$ is given by

$$\min_{u(x) \in [0,1]} E_1(u) = \int_{\Omega} [1 - u(x)] C_s(x) dx + \int_{\Omega} u(x) C_t(x) dx + \int_{\Omega} w(x) |\nabla u(x)| dx, \quad (1)$$

where $u(x)$ is the labeling function of the corresponding image domain Ω , $\nabla u(x)$ is the gradient of $u(x)$, $|\cdot|$ is the modulus operation, $C_t(x)$ denotes the labeling cost function w.r.t the corresponding region, $C_s(x)$ denotes the labeling cost function w.r.t the respective background region, and $w(x) \geq 0$ is a weighting function. Compared with the AC segmentation approach, the CMF segmentation method is a faster segmentation method without initial point requirement, whereas the AC segmentation method can provide a relatively smooth segmentation result. Although these two segmentation methods are somewhat effective, they may result in missing segmentation when directly applied to diastolic MV images. The major reason is that MV TEE images at diastole suffer from signal dropout so that information necessary for the segmentation used by conventional algorithms is usually incomplete. Consequently, the incomplete diastolic MV models are delineated, with regions of signal dropout interpreted as regions with no valve tissue.

2.2 Signal Dropout Correction

To reconstruct an MV model from diastole data, we first propose a signal dropout correction method for estimating the missing segmentation information. Assume there is at least an image slice with signal dropout in each 3-D TEE image to be segmented. Without loss of generality, let $I_1(x)$ denote image with no signal dropout and $I_2(x)$ denote image with signal dropout. Their labeling functions $u_1^*(x)$ and $u_2^*(x)$ are obtained by

the CMF algorithm, where $u_1^*(x)$ has complete segmentation information and $u_2^*(x)$ has not. Our task is to estimate incomplete segmentation information of $u_2^*(x)$ due to signal dropout, based on the spatial similarity of the two neighboring images within 3-D TEE image volume.

First, the absolute subtraction between $u_1^*(x)$ and $u_2^*(x)$ contains the labeling function of disjoint regions. We define $\Phi_d = \{\phi | \phi_i(x) (i = 1, \dots, r)\}$ as the labeling function set of all disjoint regions from $|u_1^*(x) - u_2^*(x)|$, where $\phi_i(x) \in \{0,1\}$ is the labeling function of the corresponding disjoint region. Let $\phi^*(x)$ be the labeling function of signal dropout regions. Then $\phi^*(x) \in \Phi_d$. Second, when the MV leaflets are open, there are usually two disjoint leaflets in the sagittal or coronal view. This implies that the number of disjoint segmentation regions is less than or equal to 2. Let $D[u_2^*(x) + \phi^*(x)]$ denote the number of disjoint segmentation regions described by labeling function $u_2^*(x) + \phi^*(x)$. Then $D[u_2^*(x) + \phi^*(x)] \leq 2$. Third, to find $\phi^*(x)$, we introduce the following binary constrained optimization problem²⁰

$$\min_{u(x) \in \{0,1\}} E_2(u) = \int_{\Omega} |f(x) - u(x)| dx + \int_{\Omega} |\nabla u(x)| dx, \quad (2)$$

where $f(x) \in \{0,1\}$ is a given binary image. It was shown that for any input binary image $f(x)$, there exists at least one global optimum function $u(x) \in \{0,1\}$. Moreover, Eq. (2) can be solved by means of relaxing $u(x) \in \{0,1\}$ to $u(x) \in [0,1]$.⁷ Let $f(x) = u_1^*(x)$ and let $u(x) = u_2^*(x) + \phi(x)$. Then, Eq. (2) can be rewritten as

$$\min_{\phi(x) \in [0,1]} E_3[\phi(x)] = \int_{\Omega} |[u_2^*(x) + \phi] - u_1^*(x)| dx + \int_{\Omega} |\nabla [u_2^*(x) + \phi]| dx. \quad (3)$$

Combining Eq. (3) and constraints $D[u_2^*(x) + \phi(x)] \leq 2$ as well as $\phi(x) \in \Phi_d$, we propose a signal dropout correction method for estimating the incomplete segmentation information by solving

$$\min E_4(\phi) = \int_{\Omega} |[u_2^*(x) + \phi] - u_1^*(x)| dx + \int_{\Omega} |\nabla [u_2^*(x) + \phi]| dx \\ s.t. D[u_2^*(x) + \phi] \leq 2, \quad \phi \in \Phi_d. \quad (4)$$

The optimization Eq. (4) can be converted into

$$\min_{\phi \in \Phi_d} E(\phi) = \int_{\Omega} |[u_2^*(x) + \phi] - u_1^*(x)| dx + \int_{\Omega} |\nabla [u_2^*(x) + \phi]| dx + \beta \{D[u_2^*(x) + \phi] - 2\}, \quad (5)$$

where $\beta > 0$ is a weight parameter. Furthermore, because Φ_d is a finite set, we have

$$\phi^*(x) = \arg \left\{ \min_{1 \leq i \leq r} E[\phi_i(x)] \right\}. \quad (6)$$

As an illustrative example shown in Fig. 1, we see that $\phi^*(x) = \phi_1^*(x)$.

Fig. 1 (a) label map $u_1^*(x)$ with no signal dropout, (b) label map $u_2^*(x)$ with signal dropout, and (c) labeling function set $\Phi_d = \{\phi_1^*(x), \phi_2(x), \phi_3(x), \phi_4(x)\}$.

By discretizing the integration defined in Eq. (5), we present a signal dropout correction algorithm described in Algorithm 1, where the initial objective value is given by

$$c_0 = \sum_x |u_2^*(x) - u_1^*(x)| + \sum_x |\nabla[u_2^*(x)]| + \beta\{D[u_2^*(x)] - 2\}. \quad (7)$$

Since the labeling function set Φ_d has fewer elements, the proposed signal dropout correction algorithm has a low computational cost. When performing Algorithm 1, we use the difference quotient formula of numerical differentiation for the computation of $\nabla u(x)$.

2.3 Proposed Algorithm

Using Algorithm 1, we first find the signal dropout region and its labeling function $\phi^*(x)$. We then fuse neighboring images for MV image correction. A fast image fusion approach is developed based on the weighted average of the images to be fused. For example, Dwork et al.²¹ presented a constrained least squares image fusion algorithm for color image fusion. We here introduce an adaptive image fusion method for MV image correction using $\phi^*(x)$ as an adaptive weight function, where the corrected MV image is given by

$$\hat{I}_2(x) = [1 - \phi^*(x)]I_2(x) + \phi^*(x)I_1(x). \quad (8)$$

Compared with other fusion methods,^{21–24} our fusion method uses an adaptive weight function.

Algorithm 1 for signal dropout correction

- 1: Input: u_1^* , u_2^* , and parameter $\beta > 0$
- 2: Compute $s_d = |u_2^* - u_1^*|$ and c_0
- 3: Find all label functions, $\{\phi_j\}_1^r$, of corresponding disjoint regions ϕ_j in s_d
- 4: **for** $j = 1$ to r **do**
- 5: $c_j = \sum_x |(u_2^* + \phi_j) - u_1^*| + \sum_x |\nabla(u_2^* + \phi_j)| + \beta[D(u_2^* + \phi_j) - 2]$,
- 6: **end for**
- 7: $k = \arg \min_{1 \leq j \leq r} c_j$
- 8: If $c_k \leq c_0$, output $u_2^* + \phi_k$. Otherwise, output u_2^*

By combining the CMF method, the AC method, and signal dropout correction method and the image fusion formula defined in Eq. (8), we propose a signal dropout correction-based segmentation algorithm presented in Algorithm 2.

2.4 Computational Cost

Algorithm 1 only requires the computation of a few objective function values $\{c_j\}$ and thus the proposed Algorithm 2 for MV image segmentation has the same computational cost as the CMF + AC segmentation algorithm. Therefore, the proposed segmentation algorithm for diastolic MV models has lower computational cost than existing segmentation algorithms.^{16,17,19}

2.5 3-D Modeling

Using the proposed algorithm, the segmentation of diastolic TEE image data can be obtained. We then use this segmentation to replicate a physical model capable of mimicking the dynamic behavior of the actual valve. To do this, the segmented polydata are loaded into CAD software (SpaceClaim2016.1, ANSYS Inc.), where we create a profile of the atrial side of the valve (the surface proximal to the TEE probe, and hence the most accurate representation of the valve shape). This profile is integrated into the CAD model of a mold for creating physical replicas. Then, the valve profile is 3-D printed using an inexpensive hobby 3-D printer (Ultimaker2, the Netherlands) and integrated into the mold. We are then able to paint a layer of silicone onto the mold, integrating nylon chordae tendinae into the silicone, based on the most probable attachment locations as indicated by our original segmentation. Finally, the patient-specific valve replicas are placed in a dynamic heart phantom for comparison with actual patient data.⁵

Algorithm 2 for MV image segmentation

- 1: Input: MV 3D TEE image data $\{I_i(x)\}_1^r$
- 2: Compute $\{u_i^*(x)\}$ by the CMF algorithm
- 3: Compute $\{\hat{u}_i^*(x)\}$ by the proposed Algorithm 1
- 4: Compute corrected MV images $\{\hat{I}_i(x)\}$ by fusion Eq. (8)
- 5: Segment $\{\hat{I}_i(x)\}$ by the AC algorithm with $\{u_i^*(x)\}$ as initial point
- 6: Output segmented results.

Table 1 Segmentation results of 10 patient TEE images in terms of DSC, MAD, and MAXD, represented as mean $\pm$ standard deviation, using two different algorithms.

Algorithm	DSC (%)	MAD (mm)	MAXD (mm)
Proposed algorithm	92.5 ± 3.6	0.29 ± 0.17	3.98 ± 1.67
CMF+AC algorithm	88.4 ± 5.56	0.44 ± 0.21	4.97 ± 1.51

3 Experimental Results

To demonstrate the performance of the proposed method, we applied the proposed combinational segmentation algorithm

and the conventional segmentation algorithm based on CMF and active contour (CMF + AC) approach to patient TEE volumes. The experiments were conducted in MATLAB R2016a on a Windows 10 64-bit desktop with an Intel i7-4770 CPU. The MV models were constructed using 3-D Slicer version 4.6.2.

3.1 Image Acquisition

The patient images were gathered with Research Ethics Board approval. All patients involved in this study were diagnosed with varying degrees of MV regurgitation. In this study, we collected MV 3-D TEE image data of 10 patients using Philips iE33. The size of each 3-D TEE image was acquired

Fig. 2 MV image segmentation results: (a), (d), (g), and (j) four MV images with signal dropout; (b), (e), (h), and (k) results obtained by CMF + AC segmentation approach; (c), (f), (i), and (l) results obtained by proposed segmentation approach.

at $\sim 200 \times 200 \times 200$ voxels with an isotropic resolution of 0.3 to 0.5 mm.

3.2 Evaluation Metrics

To quantify algorithm performance, our algorithm was evaluated using three metrics: dice similarity coefficient (DSC), mean absolute surface distance (MAD), and maximum absolute surface distance (MAXD). The manual segmentation result of each image was used as the ground truth. The manual segmentation was performed by the director of cardiac anesthesia program at our local hospital who has over 10 years of experiences in preoperative TEE.

3.3 Results

To illustrate algorithm performance, the 3-D TEE images at diastole were selected by our collaborating clinician for analysis and comparison. First, we initialized the TEE image data as the volume of interest and then performed the proposed segmentation algorithm and the CMF + AC segmentation algorithm. Table 1 shows the quantitative results for 10 patient images, described as mean $\pm$ standard deviation. From Table 1, we see that the proposed segmentation algorithm improved the accuracy in terms of evaluation values: DSC, MAD, and MAXD,

comparing with the CMF + AC algorithm. In contrast to existing segmentation results of MV images with signal dropout,^{10,13} our segmentation results gave further improvement. As an example shown in Fig. 2, we selected four MV images with signal dropout from three patients, where Figs. 2(a) and 2(d) were from the same patient. Figures 2(b), 2(e), 2(h), and 2(k) displayed the segmentation results obtained by the CMF + AC approach. Figures 2(c), 2(f), 2(i), and 2(l) displayed the segmentation results obtained by the proposed segmentation algorithm. We see that the proposed method successfully segmented the mitral leaflets, specially for signal dropout regions. In comparison, the CMF + AC algorithm gave incomplete segmentation, since the signal dropout was not corrected. Finally, the segmentation results obtained from both methods were 3-D reconstructed and displayed in Fig. 3. Figures 3(a), 3(c), and 3(e) displayed three MV models obtained by the CMF + AC approach. Figures 3(b), 3(d), and 3(f) displayed three MV models obtained by the proposed segmentation method. We observed that the three models yielded by the CMF + AC approach had holes on leaflet regions, whereas the models yielded by the proposed algorithm had no holes on the leaflets and appeared to be more smooth and intact.

4 Conclusion and Future Work

In this study, a segmentation method for delineating diastolic MV model was proposed. The proposed method utilized signal dropout correction, image fusion, CMF segmentation, and AC segmentation techniques in conjunction. Because the proposed method successfully estimated signal dropout regions of TEE image data, incomplete segmentation information was avoided and thus the MV model was correctly duplicated. Compared with conventional image segmentation algorithms for diastolic MV model at leaflet regions, the proposed segmentation algorithm has relatively low computational cost. In Ref. 16, the closed valve was segmented by first finding the thin leaflet tissue and then finding the thin-thick tissue junction, where the CMF + AC approach was used twice. In Ref. 17, the open valve segmentation was obtained by tracking the closed valve obtained from Ref. 16 frame by frame. In Ref. 19, the valve segmentation required extensive training and deformable registration, which is time consuming.

The experimental results on 10 patient images confirmed that the proposed method achieved a mean DSC of $92.5\% \pm 3.6\%$, an MAD of 0.29 ± 0.17 mm, and an MAXD of 3.98 ± 1.67 mm, respectively. The proposed segmentation algorithm successfully segmented the mitral leaflets, including the signal dropout region. Moreover, a 3-D rendered patient modeling test also demonstrates that the proposed segmentation algorithm gave more accurate MV models, in contrast to CMF + AC segmentation algorithm. All computed results showed that the proposed method can significantly improve the CMF + AC segmentation algorithm for diastolic MV models.

The proposed algorithm was implemented in MATLAB and the mean segmentation time for all the patient images is about 3 min. The computational time will be greatly reduced through parallel implementation in C++ using GPU.

Disclosures

None of the authors has any financial interests to declare.

Acknowledgments

The authors would like to thank Dr. Jing Yuan and Dr. John S.H. Baxter for their valued suggestions and help in this research.

Fig. 3 3-D-rendered MV models from three patient images: (a), (c), and (e) three MV models yielded by CMF + AC segmentation method; (b), (d), and (f) three MV models yielded by proposed segmentation method.

The authors would also like to thank the associate editor and reviewers for their encouragement and valuable comments, which helped in improving the quality of the paper.

References

1. V. T. Nkomo et al., "Burden of valvular heart diseases: a population-based study," *The Lancet* **368**(9540), 1005–1011 (2006).
2. L. W. Clements et al., "Evaluation of model-based deformation correction in image-guided liver surgery via tracked intraoperative ultrasound," *J. Med. Imaging* **3**(1), 015003 (2016).
3. T. S. Pfeiffer et al., "Model-based correction of tissue compression for tracked ultrasound in soft tissue image-guided surgery," *Ultrasound Med. Biol.* **40**(4), 788–803 (2014).
4. C. Vannelli et al., "Dynamic heart phantom with functional mitral and aortic valves," *Proc. SPIE* **9415**, 941503 (2015).
5. O. Ginty et al., "Patient-specific indirectly 3D printed mitral valves for pre-operative surgical modelling," *Proc. SPIE* **10135**, 1013517 (2017).
6. T. F. Chan and L. A. Vese, "Active contours without edges," *IEEE Trans. Image Process.* **10**(2), 266–277 (2001).
7. T. F. Chan, S. Esedoglu, and M. Nikolova, "Algorithms for finding global minimizers of image segmentation and denoising models," *SIAM J. Appl. Math.* **66**(5), 1632–1648 (2006).
8. J. Yuan et al., "A continuous max-flow approach to Potts model," *Lect. Notes Comput. Sci.* **6316**, 379–392 (2010).
9. H. C. Kuo et al., "Segmentation of breast masses on dedicated breast computed tomography and three-dimensional breast ultrasound images," *J. Med. Imaging* **1**(1), 014501 (2014).
10. M. Rajchl, J. Yuan, and T. M. Peters, "Real-time segmentation in 4D ultrasound with continuous max-flow," *Proc. SPIE* **8314**, 83141F (2012).
11. M. Rajchl et al., "Hierarchical max-flow segmentation framework for multi-atlas segmentation with Kohonen self-organizing map based Gaussian mixture modeling," *Med. Image Anal.* **27**, 45–56 (2016).
12. J. S. H. Baxter et al., "Optimization-based interactive segmentation interface for multiregion problems," *J. Med. Imaging* **3**(2), 024003 (2016).
13. J. Bersvendsen et al., "Semi-automated biventricular segmentation in three-dimensional echocardiography by coupled deformable surfaces," *J. Med. Imaging* **4**(2), 024005 (2017).
14. A. H. Curiale et al., "Fully automatic detection of salient features in 3-D transesophageal images," *Ultrasound Med. Biol.* **40**(12), 2868–2884 (2014).
15. M. Sotaquira et al., "Semi-automated segmentation and quantification of mitral annulus and leaflets from transesophageal 3-D echocardiographic images," *Ultrasound Med. Biol.* **41**(1), 251–267 (2015).
16. R. J. Schneider et al., "Mitral annulus segmentation from 3D ultrasound using graph cuts," *IEEE Trans. Med. Imaging* **29**(9), 1676–1687 (2010).
17. R. J. Schneider et al., "Patient-specific mitral leaflet segmentation from 4D ultrasound," *Lect. Notes Comput. Sci.* **6893**, 520–527 (2011).
18. R. I. Ionasec et al., "Patient-specific modeling and quantification of the aortic and mitral valves from 4-D cardiac CT and TEE," *IEEE Trans. Med. Imaging* **29**(9), 1636–1651 (2010).
19. A. M. Pouch et al., "Fully automatic segmentation of the mitral leaflets in 3D transesophageal echocardiographic images using multi-atlas joint label fusion and deformable medial modeling," *Med. Image Anal.* **18**(1), 118–129 (2014).
20. J. Yuan, J. Shi, and X. Tai, "A convex and exact approach to discrete constrained TV-L1 image approximation," *East Asian J. Appl. Math.* **1**(2), 172–186 (2011).
21. N. Dwork, E. M. Lasry, and J. M. Pauly, "Formulation of image fusion as a constrained least squares optimization problem," *J. Med. Imaging* **4**(1), 014003 (2017).
22. Y. S. Xia and H. Leung, "Performance analysis of statistical optimal data fusion algorithms," *Inf. Sci.* **277**, 808–824 (2014).
23. A. Babic, H. H. Odland, and O. Gerard, "Parametric ultrasound and fluoroscopy image fusion for guidance of left ventricle lead placement in cardiac resynchronization therapy," *J. Med. Imaging* **2**(2), 025001 (2015).
24. D. Narayanan, J. Liu, and L. Kim, "Automated segmentation of the thyroid gland on thoracic CT scans by multiatlas label fusion and random forest classification," *J. Med. Imaging* **2**(4), 044006 (2015).

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