2018 IEEE 14th International Conference on e-Science

Analytics Pipeline for Left Ventricle Segmentation and Volume Estimation on Cardiac MRI using Deep Learning

Mai H. Nguyen*, Ehab Abdelmaguid*, Jolene Huang*, Sanjay Kenchareddy*, Disha Singla*, Laura Wilke*, Marcus Bobar*, Eric D. Carruth*, Dylan Uys*, Ilkay Altintas*, Evan D. Muse†, Giorgio Quer†, Steven Steinhubl†
*University of California, San Diego
†Scripps Translational Science Institute
La Jolla, CA U.S.A.

***Index Terms*—medical image analysis, cardiac MRI, deep learning, semantic segmentation, volume estimation**

The left ventricle (LV) is the largest chamber in the heart and plays a critical role in cardiac function. Non-invasive cardiac imaging modalities (e.g., cardiac magnetic resonance (CMR), transesophageal echocardiography (TEE), and computed tomography (CT)) are commonly used to study LV size and function in addition to other cardiac structural aspects such as valvular disease, and are invaluable tools for the diagnosis and management of heart disease. However, the process of analyzing cardiac images is time-consuming and labor-intensive. Automatic LV segmentation and volume estimation from cardiac images are thus essential in providing efficient and consistent analysis.

Deep learning methods have been used for many image processing tasks with great success, and have also been applied to medical image analysis in recent years. Most research in cardiac image analysis uses CMR since this imaging modality is considered the gold standard for studying heart health. LV segmentation refers to the task of detecting the LV contour, especially of the endocardial surface. Volume estimation refers to estimating the LV cavity volume. LV volumes at end-systole (ES) and end-diastole (ED) are used to calculate ejection fraction (EF), an important measure used for diagnostics and treatment. LV segmentation and volume estimation from CMR are challenging tasks. Difficulties arise from many sources: variability in image quality and contrast, anatomical differences, artifacts from imaging instruments, as well as errors and variations introduced by the imaging process. The wide-ranging and challenging nature of these issues is apparent in the myriad of approaches that have been proposed to address them. We have experimented with many of these proposed approaches and compared their effectiveness on publicly available datasets. Our work offers an analytics pipeline consisting of the best methods we found for preprocessing, modeling, and postprocessing cardiac MR images for LV segmentation and volume estimation using deep learning.

Our approach segments the LV cavity in each short-axis (SAX) slice, computes the LV area and volume for each slice, then sums all per-slice LV volumes to estimate the overall LV volume. We use a U-Net, a deep learning model originally created for image segmentation in biomedical applications but have been applied to other domains as well. In our approach, a U-Net is trained on the segmentation task by predicting the LV contour in each input CMR image. The contours are then used as input to a separate process to calculate the LV volume. In this volume calculation process, ES and ED frames are determined in each slice, then summed across all slices to determine the LV volume for each patient.

We make use of three publicly available data sources: Sunnybrook Cardiac Data (SCD), Automated Cardiac Diagnosis Challenge (ACDC), and Kaggle Second Annual Data Science Bowl. All three datasets provide 3D MRI cines from patients, encompassing multiple pathologies. The SCD and ACDC datasets also provide LV contour labels drawn by experts, while the Kaggle dataset comes with LV volume labels at ES and ED. We use the SCD and ACDC datasets to train the U-Net on the LV segmentation task, and the Kaggle dataset to test our volume estimation process.

In building our pipeline for LV segmentation and volume estimation, we experimented with many methods for preprocessing, segmentation, and volume estimation. For preprocessing, we tested methods to address variation in image orientation, contrast normalization, pixel spacing, and pixel variance. We also used alternative ways to perform ROI (region-of-interest) detection. For segmentation, we evaluated the effects of image size; various ways to add data augmentation; different loss functions; model ensembles; along with the usual model tuning related to batch normalization, dropout, batch size, and convolution parameters on the U-Net predictions. For volume estimation, we incorporated techniques to remove extraneous predicted contours; determine ED and ES frames in each slice; and address anomalies such as zero-predictions, patients with too few slices, and slices out of order.

We discuss findings from our investigation into different techniques for processing and analyzing CMR images and present the methods giving best performance in an end-to-end analytics pipeline for LV segmentation and volume estimation. This pipeline can serve as an initial step towards analyzing CMR at scale to aid in non-invasive cardiac disease detection.

Corresponding author: Mai H. Nguyen, email: mhnguyen@ucsd.edu

978-1-5386-9156-4/18/$31.00 ©2018 IEEE
DOI 10.1109/eScience.2018.00065

ACKNOWLEDGMENTS

This work was supported in part by NIH grants 1UL1 TR001114 and 1UL1 TR002550-01, and NSF-1730158 for Cognitive Hardware and Software Ecosystem Community Infrastructure (CHASE-CI)

REFERENCES

[1] Ehab Abdelmaguid, Jolene Huang, Sanjay Kenchareddy, Disha Singla, Laura Wilke, Mai H. Nguyen, and Ilkay Altintas, "Left ventricle segmentation and volume estimation on cardiac mri using deep learning," in *eprint arXiv:1809.06247 [cs.CV]*, 2018.

[2] "Automated cardiac diagnosis challenge," https://www.creatis.insa-lyon.fr/Challenge/acdc/databases.html, 2017.

[3] Booz Allen Analytics and Data Science, "Tutorial: Cardiac cine mri process with dr. arai," www.youtube.com/watch?v=yZXfvXiJwLc, 2016.

[4] Cardiac Atlas Project, "Sunnybrook cardiac data," http://www.cardiacatlas.org/studies/sunnybrook-cardiac-data/, 2009.

[5] Julian de Wit, "3rd place solution for the second national datascience bowl," http://juliandewit.github.io/kaggle-ndsb/, 2016.

[6] Huaifei Hu, Zhiyong Gao, Liman Liu, Haihua Liu, Junfeng Gao, Shengzhou Xu, Wei Li, and Lu Huang, "Automatic segmentation of the left ventricle in cardiac mri using local binary fitting model and dynamic programming techniques," *PloS one*, vol. 9, no. 12, pp. e114760, 2014.

[7] Paul Jurczak, "0.036023 score without looking at the images," https://www.kaggle.com/c/second-annual-data-science-bowl/discussion/18375, 2015.

[8] Kaggle, "Second data science bowl cardiac challenge data," https://www.kaggle.com/c/second-annual-data-science-bowl/data, 2015.

[9] "Keras: The python deep learning library," https://keras.io/.

[10] Ira Korshunova, Jeroen Burms, Jonas Degrave, and Joni Dambre, "Diagnosing heart diseases in the data science bowl: 2nd place, team kunsthart," http://blog.kaggle.com/2016/04/13/diagnosing-heart-diseases-with-deep-neural-networks-2nd-place-ira-korshunova/, 2016.

[11] Tencia Lee and Qi Liu, "Automatic left ventricle voume calculation in cardiac mri using convolutional neural network," https://github.com/woshialex/diagnose-heart/blob/master/TenciaWoshialex_model_documentation.pdf, 2016.

[12] Fangzhou Liao, Xi Chen, Xiaolin Hu, and Sen Song, "Estimation of the volume of the left ventricle from mri images using deep neural networks," *arXiv preprint arXiv:1702.03833*, 2017.

[13] Gongning Luo, Suyu Dong, Kuanquan Wang, Wangmeng Zuo, Shaodong Cao, and Henggui Zhang, "Multi-views fusion cnn for left ventricular volumes estimation on cardiac mr images," *IEEE Transactions on Biomedical Engineering*, 2017.

[14] Rudra PK Poudel, Pablo Lamata, and Giovanni Montana, "Recurrent fully convolutional neural networks for multi-slice mri cardiac segmentation," in *Reconstruction, Segmentation, and Analysis of Medical Images*, pp. 83–94. Springer, 2016.

[15] Olaf Ronneberger, Philipp Fischer, and Thomas Brox, "U-net: Convolutional networks for biomedical image segmentation," in *International Conference on Medical image computing and computer-assisted intervention*. Springer, 2015, pp. 234–241.

[16] "Get acquainted with u-net architecture + some keras shortcuts," https://spark-in.me/post/unet-adventures-part-one-getting-acquainted-with-unet, 2017.

[17] Nima Tajbakhsh, Jae Y Shin, Suryakanth R Gurudu, R Todd Hurst, Christopher B Kendall, Michael B Gotway, and Jianming Liang, "Convolutional neural networks for medical image analysis: Full training or fine tuning?," *IEEE transactions on medical imaging*, vol. 35, no. 5, pp. 1299–1312, 2016.

[18] Mattson Thieme and Tony Reina, "Biomedical image segmentation with u-net," https://ai.intel.com/biomedical-image-segmentation-u-net/, 2018.

[19] Phi Vu Tran, "A fully convolutional neural network for cardiac segmentation in short-axis mri," https://arxiv.org/abs/1604.00494, 2016.

[20] Kaicheng Wang and Yanyang Kong, "Diagnosis of heart disease via cnns," http://cs231n.stanford.edu/reports/2016/pdfs/331_Report.pdf, 2017.

[21] Xulei Yang, Zeng Zeng, and Su Yi, "Deep convolutional neural networks for automatic segmentation of left ventricle cavity from cardiac magnetic resonance images," *IET Computer Vision*, vol. 11, no. 8, pp. 643–649, 2017.