



Left Ventricle Segmentation in Cardiac Ultrasound Using Hough-Forests With Implicit Shape and Appearance Priors

Fausto Milletari¹, Mehmet Yigitsoy¹, Nassir Navab^{1,3}, and Seyed-Ahmad Ahmadi²

- 1. Computer Aided Medical Procedures, Technische Universität München, Germany
- 2. Department of Neurology, Klinikum Grosshadern, Ludwig-Maximilians-Universität München, Germany
- 3. Computer Aided Medical Procedures, Johns Hopkins University, USA

Motivation

US has advantageous properties for cardiac imaging
 Radiation free

Related Work

Pedestrian segmentation using Hough forests [1]
Automatic LV segmentation based on deep learning [2]

- Real-Time
- Cardiac functionality assessed via Left Ventricle volume estimation
- Manual segmentation of Left Ventricle ^{*} is time-consuming

Our contribution

- Fully automatic segmentation method based on Hough forest
 - Incorporates shape and appearance knowledge
 - Predicts position of the LV center
 - Predicts probabilistic segmentation

Training Stage



Each data-point from training images

- Corresponds to a patch
- Is described by N-dimensional intensity based feature vector

150 .

- Carries spatial displacement between itself and LV center
- Is associated with segmentation patch from ground truth
- Is associated with appearances occurring

Testing Stage

- Object center localization
 - Classification of each data-point
 - Data-points that are classified as foreground vote for LV center
 - Votes are weighted by confidence and accumulated into volume
 - Position of maximum accumulation is LV center
- **Contour Estimation**

- 2 Possible **segmentations** @ these positions
- 3- Typical **intensity patterns** @ these segmentations

tensity Patch

Information extracted during training

- in correspondence of segmentation
- Foreground = boundaries in US image

Votes accumulation volume

- Each vote falling near LV center re-projected to position x of the data-point that cast it
- Obtain segmentation patch \boldsymbol{S}_{p} corresponding to the vote from the code base
- Recover intensity patch I_p corresponding to S_p
- Apply segmentation \bm{S}_p at location of data-point after weighting with truncated NCC between \bm{I}_p and the intensities around \bm{x}
- Accumulate segmentation patches and normalize to obtain final segmentation



Results

- 15 end-diastolic test images:
 - Mean Absolute Distance: 2.37 mm
 - Mean Hausdorff distance: 9.52 mm
 - Mean mod. Dice coefficient: 0.123
- 15 end-systolic test images:
 - Mean Absolute Distance: 2.93 mm
 - Mean Hausdorff distance: 8.64 mm
 - Mean mod. Dice coefficient: 0.166



Modified Dice



5 4 4.31 4.414 3.47 3.38 3.45 3.64 3.913 3.22 3.02 2.82 3.03 3.41 3.243 2.48 2.4953 2.24 2.15,1 2.121.7474 1.56 1.87 1.57 MAD (mm) 1

#16 ED #16 ES #17 ES #17 ES #17 ES #18 ED #18 ES #19 ES #19 ES #20 ED #22 ES #22 ES #22 ES #22 ES #22 ES #25 ED #25 ED #25 ES #26 ES #25 ES #26 ES #26 ES #26 ES #27 ES #26 ES #27 ES #27 ES #28 ED #28 ES #28 ED #28 ES #28 ES #28 ED #28 ES #28 ES #28 ES #28 ES #28 ES

Conclusions

- Bigger segmentation patches generate smoother contours
 More shape than appearance regularization
- Outliers during classification do not degrade performance
 - Unless their votes accumulate in strong peaks
 - Prefer features that are directionally discriminative instead of class discriminative

References

[1] Rematas, K., Leibe, B.: Efficient object detection and segmentation with a cas- caded hough forest ism. In: Computer Vision Workshops (ICCV Workshops), 2011 on. pp. 966–973 (Nov 2011)
[2] Carneiro, Gustavo, Jacinto C. Nascimento, and António Freitas. "The segmentation of the left ventricle of the heart from ultrasound data using deep learning architectures and derivative-based search methods." *Image Processing, IEEE Transactions on* 21.3 (2012): 968-982.

