Endocardial 3D Ultrasound Segmentation using Autocontext Random Forests

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Background

The high temporal resolution of 3D ultrasound images provide cardiologists with invaluable information, enabling them to observe the heart structures and their function in real time. However, automating image analysis tasks on ultrasound images is challenging due to low signal-to-noise ratio.

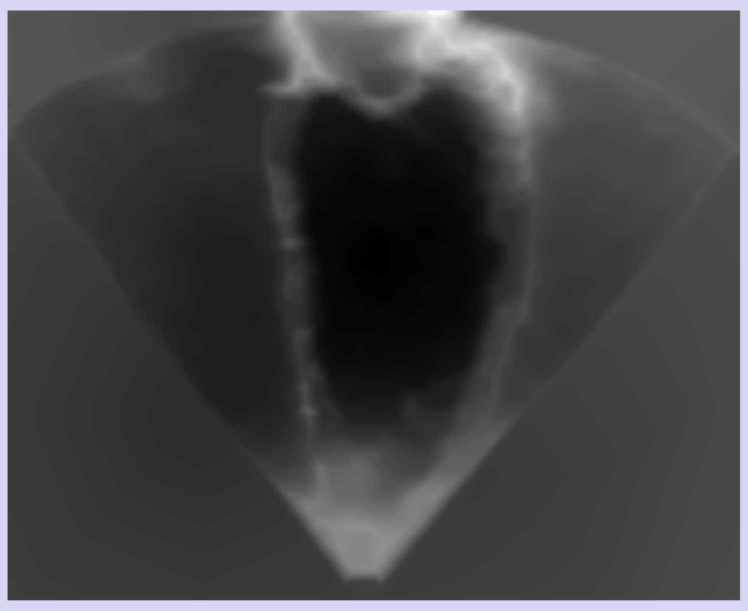
We propose a method to delineate the left ventricle (LV) endocardium border in a fully automatic manner using Random Forest classifiers[1] in an autocontext framework[2].

Geodesic features

Geodesic distance transforms[3] (GDT) increase the amount of spatial context that can be learnt by combining prediction estimates with image information. They are computed using the Euclidean distance of every pixel to the center of each class, weighted by the image gradient:

$$d(x,y) = \inf_{\Gamma \in \mathbf{P}_{x,y}} \int_0^{l(\Gamma)} \sqrt{1+\gamma^2(\nabla I(s)\cdot\Gamma'(s))^2}\,ds$$

where Γ is a path in the set of all paths $\mathbf{P}_{x,y}$ between x and y, parametrised by its arc length $s \in [0, l(\Gamma)]$, and γ is a weight between the Euclidean distance and the image gradient.

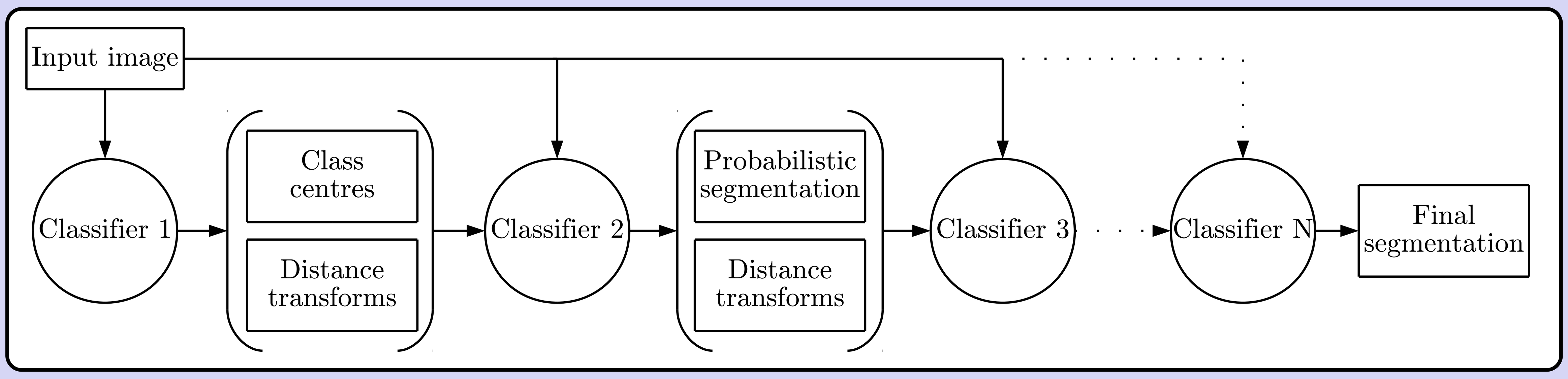


Geodesic distance map with respect to the centre of the left ventricle.

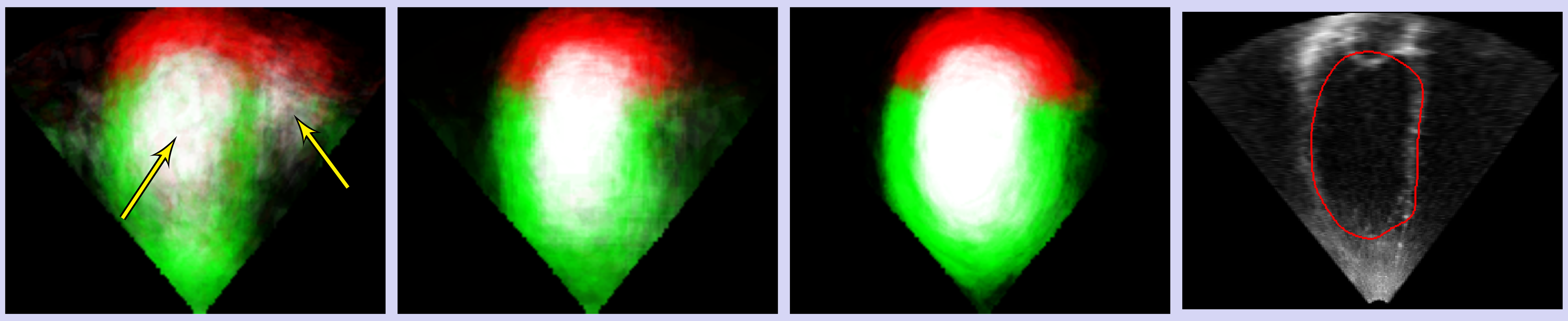
Method overview

Classes for the *mitral valve* and *myocardium* are introduced in addition to the *LV endocardium* and *background* in order to increase the amount of contextual information that can be learnt by the classifiers.

Random Forests are trained successively, each one gaining contextual information from the classification results of their predecessors (*autocontext*[2]), as described in the diagramme below:



When training the Random Forests, tests are randomly generated at every node of the trees by selecting two 3D patches of random sizes at random offsets from the current pixel and comparing their mean intensity[4]. Those patches are either both selected on the original image, or on two possibly different images among the detection probability maps of each class and the GDTs to the class centroids. The tests maximizing information gain are memorized in order to build the decision trees.



(a) (b) (c) (d)

Iterative results of the classifier:
(a,b,c) Probabilistic output of the classifier for the first three iterations of autocontext for the three classes: *mitral valve* (red), *myocardium* (green) and *LV endocardium* (white).
(d) Final segmentation at the 3rd iteration of autocontext (red contour).

The yellow arrows in (a) point to two detected heart chambers at the first iteration of autocontext. As the class centroids are selected at the end of the first iteration, only the main detection is carried out through the subsequent autocontext iterations.

Conclusion

We presented a generic image segmentation method, autocontext Random Forests, applied to the segmentation of the left ventricle endocardium in 3D echocardiography images. The only part of the method which is task specific is the choice of the different classes to segment, as these classes must enable the classifier to learn spatial context. This method can be applied to any time frame of an echocardiography sequence in a reasonable time.

Results

Speckle reduction was performed using non-local means denoising and the classifiers were trained using all frames of the temporal sequences, after propagating the ground truth segmentation of ED and ES frames using non-rigid image registration.

Segmentation results on the testing set of the CETUS challenge (Patients 16 to 30) for end-diastolic and end-systolic frames:

(a) mean absolute distance (MAD), Hausdorff distance (HD) and modified Dice score (DS)

	MAD (mm)	HD (mm)	DS (%)
End-diastolic	2.28±0.92	8.29±2.37	12.1±4.3
End-systolic	2.33±0.50	9.03±3.12	15.0±3.6

(b) correlation coefficient (CC), bias and limit of agreement (LOA) for the ejection fraction and stroke volume indices

	CC	Bias	LOA ($\mu \pm 1.96\sigma$)
End-diastolic volume (mL)	0.917	6.61	-30.85 to 44.07
End-systolic volume (mL)	0.979	-7.85	-32.21 to 16.51
Stroke volume (mL)	0.045	14.43	-26.80 to 55.65
Ejection fraction (%)	0.780	8.49	-12.58 to 29.57

In order to demonstrate the feasibility of segmenting the whole temporal sequence in addition to the ED and ES frames using the proposed method, a video is available at:

`http://youtu.be/NrxkWXBj5q0`

References

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