Automatic MRI Prostate Segmentation based CNN-ASM

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1 Method description

This abstract proposed a method for segmenting the prostate on magnetic resonance (MR) images. An overview is given here, and a detailed manuscript is in preparation.

As shown in Fig.1, at first 3D Haar features are used [1] to detect an ROI of the prostate. This will remove a large number of negative samples for the next voxel classification. Then context and location features are extracted to train a probability boosting tree (PBT). To improve the distinguish ability of samples near the boundary which are hard to be classified by simple hand-crafted features, a convolution neural network (CNN) is used to train a two-class classifier. The CNN classifier shows good performance in identifying negative samples near the prostate boundary. The final result of our proposed feature variant probability boosting tree (PBT) is shown in Fig. 1(d), which indicates better than traditional PBT [2] in Fig. 1 (b). The result of PBT was used to pre-segmentation the prostate and for further shape model initialization. Then a convolution neutral network was used to train a boundary model. These types of voxels near, inside, and outside the boundary are extracted for training a boundary priori model based on CNN deep learning. Then a two-level active shape model similar to our previous published method [3] based on the CNN boundary model was used for final segmentation refinement.

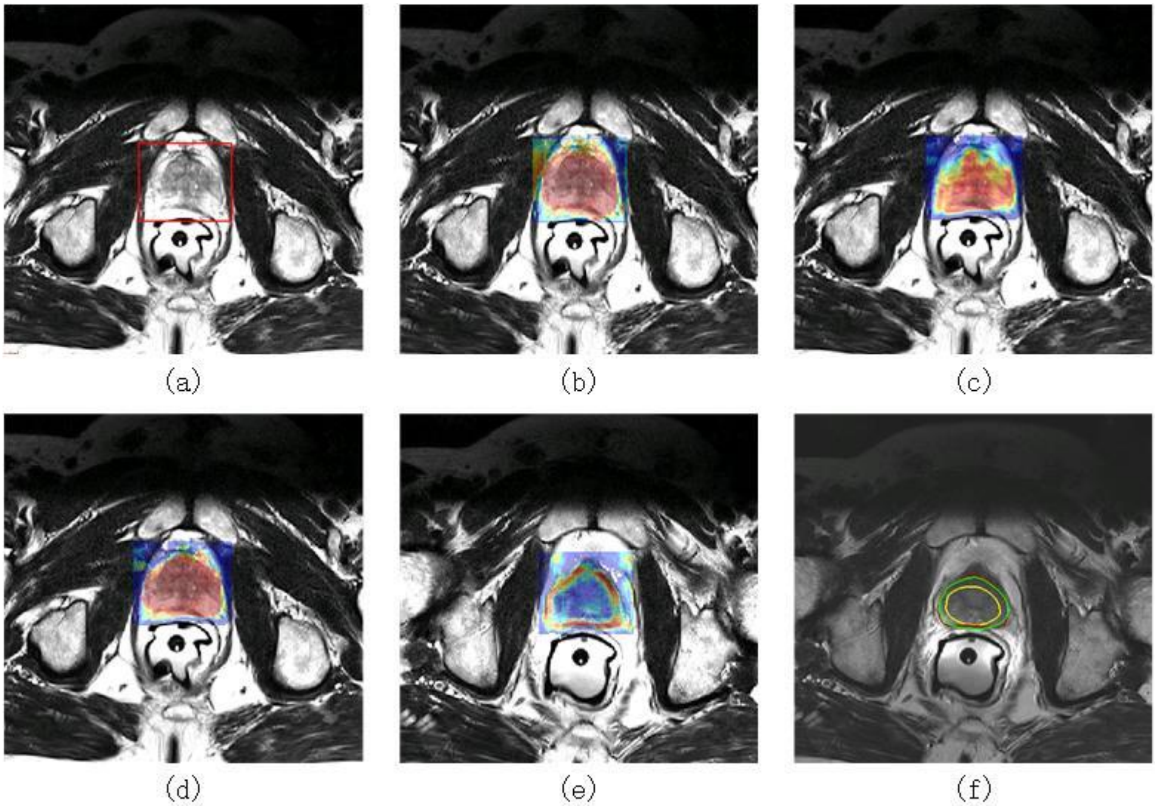

Fig.1 Illustration of our method. (a) is the result of 3D Haar ROI detection, (b) is the probability map of the first-level PBT classifier, (c) is a CNN classifier focused on identifying the negative samples around the prostate boundary, (d) is the result of our PBT classifier, (e) is a boundary probability map of the CNN boundary classifier, (f) is the two-level ASM fitting result guided by (e), the yellow contour is an SSM model initialized based on (d), the blue one is an active shape fitting result, and the red one is the final free deformation result.

References

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