Automated 3D Muscle Segmentation From MRI Data Using Convolutional Neural Network

Shrimanti Ghosh[1], Pierre Boulanger[1], Scott T. Acton[2,3], Silvia S. Blemker[3], Nilanjan Ray[1]

[1] Department Of Computing Science, University Of Alberta, Edmonton, Alberta, Canada
[2] Department Of Electrical & Computer Engineering, University Of Virginia, USA
[3] Department Of Biomedical Engineering, University Of Virginia, USA

Introduction

- ❑ Current methods of muscle segmentation in MRI images require a high-level of user input.
- ❑ Manual segmentation is usually accurate but is impractical and tedious for large dataset.
- ❑ We propose an automated segmentation algorithm for human leg muscles from 3D MRI data using deep convolutional neural network(CNN).
- ❑ A structured-output CNN architecture is fine-tuned in an end-to-end fashion.
- ❑ CNN outperforms the conventional model-based approach Active Appearance Model (AMM).

3D to 2D Parametric Mapping

- ❑ A generalized cylinder is used to model 3D human leg muscles [1].
- ❑ Series of closed contours which are stacked in the z-direction.
- ❑ Represent the 3D structure of a muscle by using two 2D parametric images.
- ❑ The two 2D parametric images are: $x(z, t)$ and $y(z, t)$, so that the muscle boundary has the coordinates: $(x(z, t), y(z, t), z)$, where $t \in [0, 1]$.

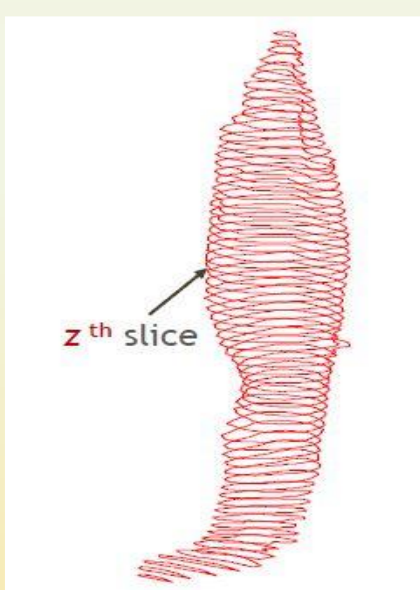

Figure 1.
Stacked closed contours

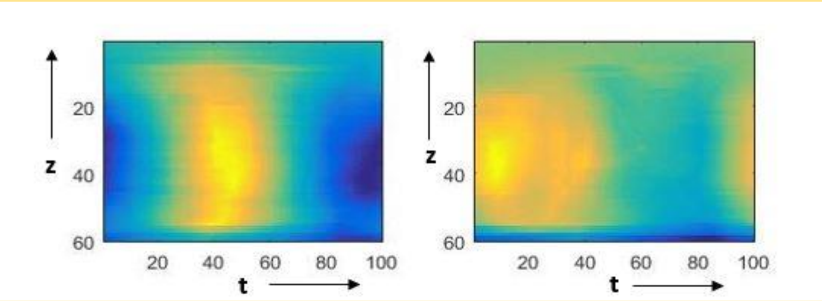

Figure 2.
Segmentation of 3D MRI stack

Proposed deep CNN

- ❑ We applied deep CNN architecture of the regression network AlexNet to our problem.
- ❑ We used a pre-trained AlexNet which has 21 layers and about 61 million parameters [2].
- ❑ First convolutional layer and the last fully connected layers are modified by changing initial weights. L2 normalization layer is added at the end.

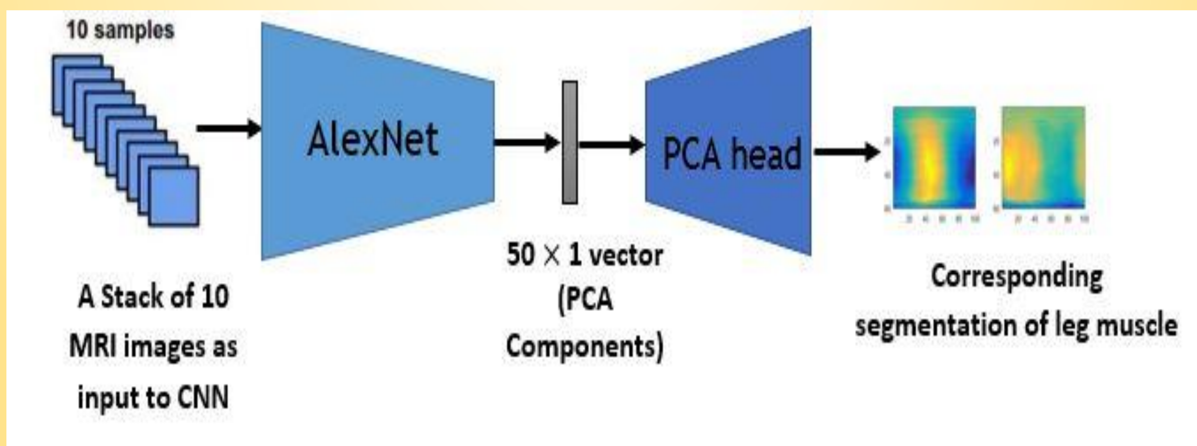

Figure 3.
Our proposed CNN architecture

Dimensionality reduction by PCA

- ❑ The input to our CNN is a 256-by-256-10 gray scale image and the structured response vector is 2000-by-1.
- ❑ We reduced the dimension of the output vector from 2000-by-1 to 50-by-1 using PCA and imposed a strong structured regression approach [3].
- ❑ The training was performed with 100 epochs, batch size of 6, learning rate 10^{-6}.
- ❑ We reconstruct 3D cylinder (two 2D images) from 50 PCA components.

Results

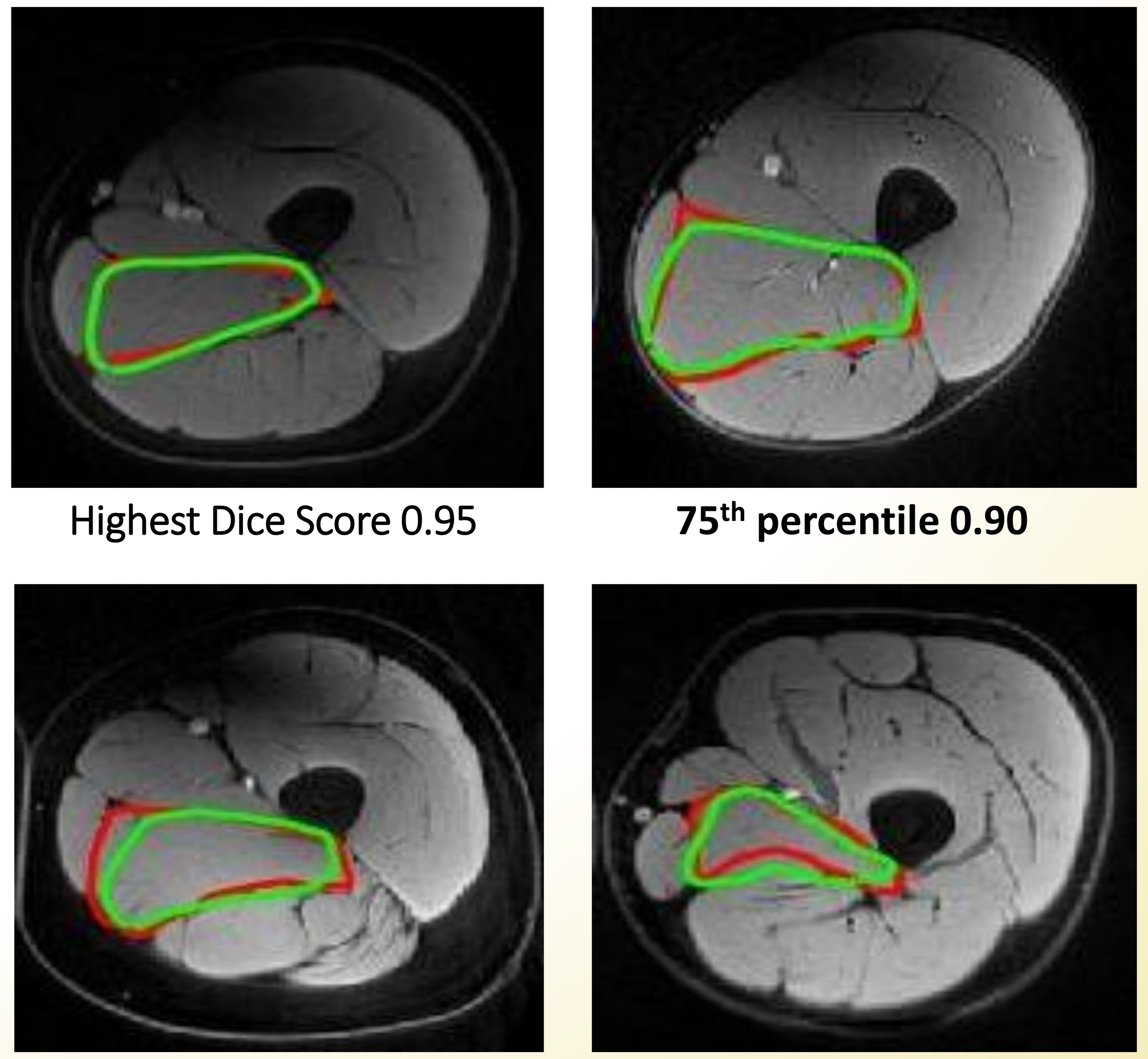

Figure 4.
Results from CNN (manual ground truth as red & obtained segmentation as green)

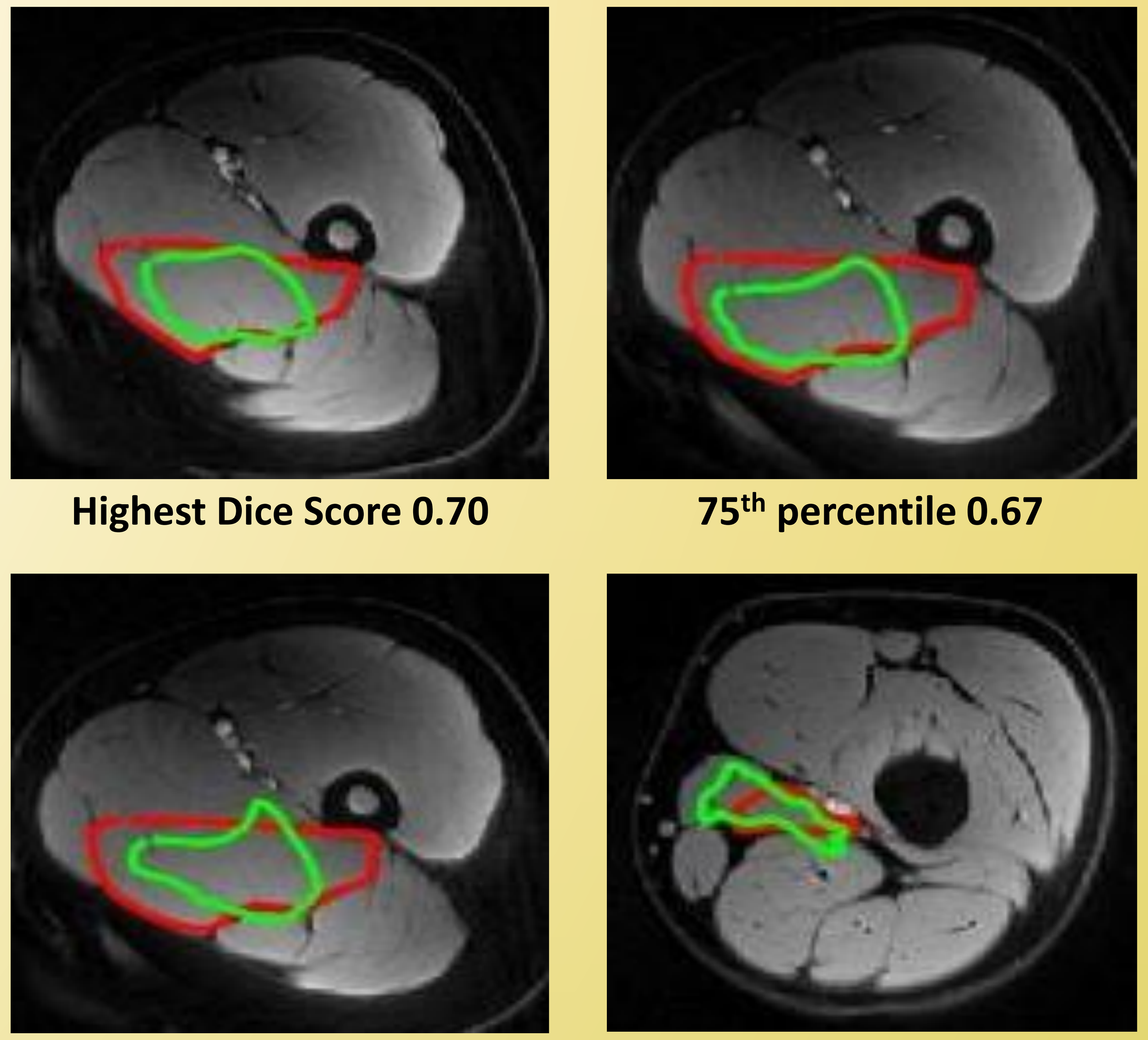

Figure 5.
Results from AAM (manual ground truth as red & obtained segmentation as green)

Conclusion

- ❑ We compared our method with Active Appearance Model [4].
- ❑ The method is useful for automated segmentation but one of the disadvantages of this is, it requires the initial position of segmentation contour for prediction which is automated by Otsu's thresholding method [5].
- ❑ The average Dice score is 0.85 using CNN, whereas the AAM yields a Dice score of 0.60.
- ❑ One of the biggest advantages of deep learning based method is that no initialization is needed.

References

1) Nilanjan Ray, Satarupa Mukherjee, Krishna Kanth Nakka, Scott T. Acton, Silvia S. Blanker, "3D-to-2D mapping for user interactive segmentation of human leg muscles from MRI data", Signal and Information Processing (GlobalSIP), IEEE Global Conference, 2014.
2) A. Krizhevsky, I. Sutskever, and G. E. Hinton. "ImageNet classification with deep convolutional neural networks". In NIPS 2012.
3) Gene H. Golab and Charles F. Van Loan, "Matrix Computations", Third Edition, The Johns Hopkins University Press, London.
4) T.F. Cootes, G.J Edwards, and C,J. Taylor "Active Appearance Models", IEEE Transactions on Pattern Analysis and Machine Intelligence 2001.
5) N. Otsu, "A threshold selection methods from grey-level histograms," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 9, pp. 62-66, 1979.