SYMMETRIC DIFFEOMORPHIC REGISTRATION AS SEGMENTATION POST-PROCESSING METHOD

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ABSTRACT

UNets and many other segmentation schemes make structural errors regarding topology and adjacency. We formulize a post-processing problem that resolves these issues and propose a naive approach to the problem. In particular, the problem involves receiving the neural network output, which consists of pixel-wise probability for each label. The values returned are a diffeomorphic image that preserves structural information while minimizing difference to the probabilistic network output. We implement a simpler approach to the problem through Symmetric Diffeomorphic Image Registration with the standard sum-squared difference. We observe low improvements even with the naive method. This shows the promise of further study into the problem.

***Index Terms*—** Diffeomorphism, Segmentation, Echocardiography

1. INTRODUCTION

UNets generally make topological and adjacency errors.

Hu et. al's [1] proposed a loss function that enforces a segmentation to have the same topology as the ground truth, i.e., having the same Betti number, to create topologically-correct output. However, this does not guarantee adjacency correctness. The appearance-based network [2] also concerns with removing artifacts and conform the neural output to a heuristically determined shape of the label, but this harms the performance of the network as mentioned in [3].

A similar post-processing idea can also be seen in Agostina et al. [4], which improves the anatomical correctness of biomedical image segmentation algorithms.

In this paper, we define a class of problem that solves the mentioned issues, and potentially create anatomically correct segmentations.

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2. METHODS

We formulate our problem as follows:
Input: The network's softmax output tensor of size $C \times H \times W$.
Output: Minimize the difference from a structurally-correct template to the softmax'ed network output.

2.1. Symmetric Diffeomorphic Registration

Define a diffeomorphism ϕ of domain Ω, such that

$$\phi I = I \circ \phi(\mathbf{x}, t = 1),$$

where t is time, **x** is a spacial coordinate. Then the map ϕ can be obtained through integration of velocity fields in time:

$$\phi(x, 1) = \phi(x, 0) + \int_0^1 \mathbf{v}(\phi(\mathbf{x}, t), t)dt,$$

where $\mathbf{v}(\mathbf{x}, t)$ on Ω is a square-integrable, continuous vector field. The distance between two images is then $D(\phi(\mathbf{x}, 0), \phi(\mathbf{x}, 1)) = \int_0^1 \|\mathbf{v}(\mathbf{x}, t)\|_L \, dt$, where the functional norm is then $\|\cdot\|_L$ regularizes the velocity field. Avants et al. [5] then divides image registration diffeomorphisms into two halves, where the template (the moving image) and the target (the static image) contribute equally to the deformation:

$$E_{sym}(I, J) = \inf_{\phi_1} \inf_{\phi_2} \int_{t=0}^{0.5} (\|\mathbf{v_1}(\mathbf{x}, \mathbf{t})\|_L^2 + \|\mathbf{v_2}(\mathbf{x}, t)\|_L^2) dt + \int_\Omega |I(\phi_1(0.5) - L(\phi_2(0.5))|^2 d\Omega$$

where distance is defined as the sum-squared difference as described in [6].

2.2. Naive method

As a base case, we will simply apply the mentioned SyN with SSD on the network's output label instead of the probabilistic map as a suboptimal solution to the problem.

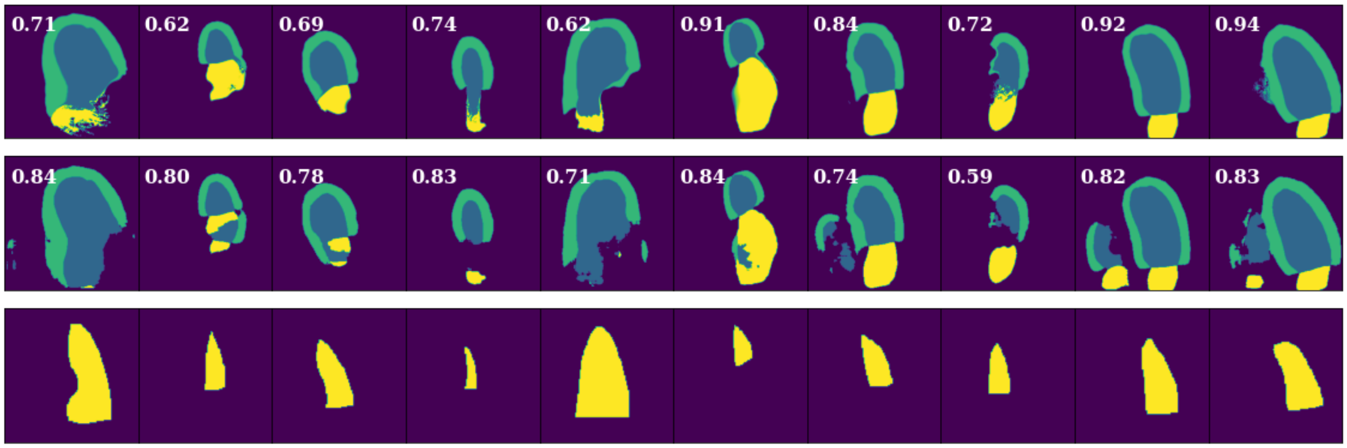

Fig. 1: On the first row, five columns on the left display worst cases, while five columns on the right display best cases. The second and third row correspond to network output and ground truth.

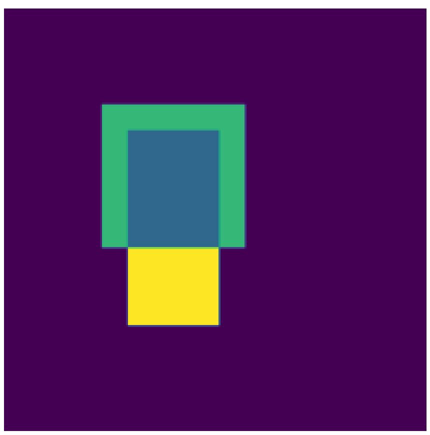

Fig. 2: A simple topologicaly correct representation of 2D heart segmentation. Their adjacency is heuristically determined from labels.

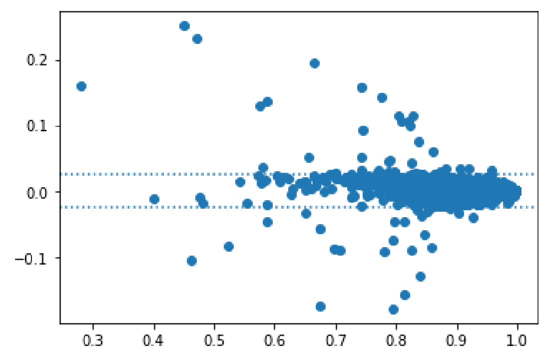

Fig. 3: Bland-Altman plot showing difference in performance between Warped vs. No Warp. The x-axis shows the No Warp Dice scores, while the y-axis describes the change in scores when we apply SyN. While improvements were found in worst-performing instances, mixed results are observed in better cases.

3. EXPERIMENTAL RESULTS

We'll evaluate its effectiveness through an experiment on the output of the Convolutional Neural Network for 2D Echocardiography described in Tran et. al.'s[7]. The model was trained on the dataset CAMUS [3] and evaluated on the test set of the large EchoNet-Dynamic clinical dataset from Stanford [8].

In this experiment, we deform a simplistic structurally-correct template (**Fig. 2**) to network output to the EchoNet, as shown in **Fig. 1**.

We achieved improvements even with this simple naive method. We report a mean Dice of 0.897 to 0.895 ($p \ll 0.01$), with statistical significance derived from a paired Wilcoxon test.

Fig. 3 shows that the naive method performs well on worst-performing cases, but performs worse on some better cases.

4. CONCLUSION

We have identified a class of problems that solves the issue of structural errors in segmentation output, namely topological and adjacency errors. We further show that such a direction holds promise by experimenting with a naive approach to the problem. The result shows a statistically significant improvement in the generalization problem of the particular problem of the convolutional neural network for 2D echocardiography.

A future direction to solve the stated problem could be to modify the distance D function to accommodate the probabilistic level of confidence of the network. This way, the optimization path should be much smoother than that of the argmax'ed output in the naive method demonstrated in this paper.

5. REFERENCES

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6. COMPLIANCE WITH ETHICAL STANDARDS

This research study was conducted retrospectively using human subject data made available through registered access from the following sources:

- CAMUS: "Cardiac Acquisitions for Multi-structure Ultrasound Segmentation,"
  https://www.creatis.insa-lyon.fr/Challenge/camus
  see also
  https://doi.org/10.1109/TMI.2019.2900516
  Ethical approval beyond citation was not required.
- EchoNet-Dynamic: "A Large New Cardiac Motion Video Data Resource for Medical Machine Learning,"
  https://echonet.github.io/dynamic/
  Non-commercial research use agreement was required.
  Ethical approval beyond citation was not required.