Active Learning with FilterNet for Calf Muscle Compartment Segmentation

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Background

- **Calf Muscle**: tibialis anterior (TA), tibialis posterior (TP), peroneus longus (PL), soleus (SOL), gastrocnemius (GAS)

- **Importance**: volumetric and structural changes are important for myotonic muscle diseases, e.g., Myotonic Dystrophy Type 1 (DM1), Juvenile Onset Myotonic Dystrophy Type 1 (JDM)

- **MRI imaging**: sensitivity to dystrophic changes

- **Challenging**: large variations in muscle shape and MR appearance; limited cost for annotation.
Data & Goal

Data: 93 patients of 47 healthy, 46 disease, with 175 T1-weighted MR image and corresponding expert-traced ground truth segmentation images.

Goal:

• Design a fully automated approach for **3D segmentation of five calf muscle compartments simultaneously**
• Develop **Deep LOGISMOS** [1], combining two well-established algorithmic strategies – deep learning and LOGISMOS graph search and demonstrate Deep LOGISMOS improves segmentation performance in comparison with state-of-the-art segmentation techniques
• Present a **deep active framework** that combines **deep learning** and **active learning** to reduce annotation effort. Significantly reduce annotation effort while attain the best performance.

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Method/Framework

- Annotated patients’ samples
- Unannotated patients’ samples

Deep LOGISMOS

FilterNet → Trained Model

Active Learning

Select Samples

Apply

Annotate

Add into annotated samples

Request new annotation
**Method/FilterNet** [2]

1. **Block Difference**
   
   \[ A(c_{in}, c_{out}) = c_{out} + \text{element-wise addition} \]

   \[ B(c_{in}, c_{out}) = B(c_{in}, c_{out}) \]

2. **Cost Function Difference**
   
   \[ \text{Edge Gate } F_{\text{edge}}(I|σ = 1) = k_G \ast k_L \ast I \]

   \[ L = (1 - \lambda)L_r + \lambda L_e \]

3. **LOGISMOS for Post-processing**

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Method/Active Learning

- **Key Issue:** How to determine the ‘worthiness’ of a candidate for annotation

- **Major approaches:**
  - Uncertainty-based approach: degree of information
  - Diversity-based approach: prediction consistency
  - Expected model change: change to current model parameters or outputs if we knew their labels

- **Preliminary Design (uncertainty + diversity)**
  - Uncertainty: Monte Carlo Dropout [3] $\rightarrow e$
  - Diversity: Consistency among annotated candidate patches (original + augmented patches) $\rightarrow d$

$$C_i = \lambda_1 e_i + \lambda_2 d_i$$

- $C_i$: $i$th candidate
- $e_i$: uncertainty of $C_i$
- $d_i$: diversity of $C_i$
- $\lambda_1, \lambda_2$: trade off's between $e_i$ and $d_i$
Experimental Settings

- 4-Fold cross-validation
- **GPU**: NVIDIA Tesla V100 with 32G of memory
- **Training Parameters**:
  - SGD optimization
  - Initial learning rate=0.0005, divided by 5 every 10 epochs.
  - Batch size=16.
  - Initial $\lambda = 0.001$, multiply by 10 every 10 epochs.
  - $W_n = [0, 0.2, 0.2, 0.15, 0.15, 0.3]$, $\alpha_{nt}=[0.05, 0.2, 0.2, 0.15, 0.1, 0.3]$ for background, TA, TP, Sol, Gas, PL, respectively.
  - Total epochs=30
- **Evaluation**: DICE Similarity Coefficient (DSC); Jaccard; Absolute Surface-to-Surface Distance; Relative Surface-to-Surface Distance; D2 Score $\left(\frac{5}{e_{ASSD} + 4e_{abs(RSSD)}}\right)$. 
Results/FilterNet

Original

Ground Truth

UNet 3D

FilterNet

IOWA
Results/Active Learning (to be continued…)

Still working on to get the final best results….

Predicted preliminary results:
state-of-the-art segmentation performance can be achieved by using 50% training data
Next Steps

- Innovations of the network architecture and the cost function for better segmentation performance.

- Innovations of selection criterion for active learning.

- More effective way of updating the learner/classifier when getting new annotated samples.

- Further: Selecting most influential slices of one patient’s 3D image.
Thank You