Interactive CNN Robot User Investigation for Medical Image Segmentation

Mario Amrehn1, Maddalena Strumia2, Markus Kowarschik2, and Andreas Maier1,3

1 Pattern Recognition Lab, Friedrich-Alexander University Erlangen-Nürnberg (FAU), Erlangen, Germany
2 Siemens Healthineers AG, Forchheim, Germany
3 Erlangen Graduate School in Advanced Optical Technologies (SAOT), Erlangen, Germany

Introduction

Interactive image segmentation (ISS) bears the advantage of correctional updates to the current segmentation mask when compared to fully automated systems. ISS is especially useful for guided inter-operative medical image processing of a single patient.

Our Approach

Incorporate human-computer interaction (HCI) data as additional input for segmentation into neural networks. We simulate this HCI data during training with SOTA user models, also called robot users, which aim to act similar to real users given interactive image segmentation tasks.

Experiments & Results

We analyze the influence of chosen robot users, which mimic different types of users and scribble patterns, on the segmentation quality. Networks trained with robot users with the most spread out seeding patterns generalize well during inference with other robot users.

Methods

Dense Image Segmentation CNN

Random Sampling (rand) Seeds are placed at random. \( r_{\text{rand}} = 10\% \) of seeds are drawn with the label inverted i.e. are misplaced.

Random sampling from GT (rand_gT) \( r_{\text{rand}} = 0\% \). Number of seeds per interaction is \( r_{\text{gt,rand}} \in \{1.5, 10\} \).

Kohli et al. (kohli12)1, 2 Uses the segmentation image and GT to place one seed point in the center of largest, wrongly labeled image area.

Xu et al. (xu16)3 Samples \( I_{\text{xu16}} \in \{1.5, 10\} \) FG and \( B_{\text{xu16}} \in \{1.5, 10\} \) to place seed points at random constrained by a minimum distance to established seeds. BG seeds are either sampled inside a margin around the object’s contour or in the entire BG.

Wang et al. (wang17)5, 4 Places seeds at random on falsely labeled image areas (similar to kohli12, but not limited to the center). Small areas are ignored with threshold \( I_{\text{wang17}} \in \{10, 20, 30, 40\} \) in pixels.

Results

Multiple Robot User Seed Placement Patterns

\begin{itemize}
  \item Mean Dice scores per robot user over all input images per interaction/seeding step.
  \item Segmentation by GrowCut6.
\end{itemize}

Prediction Outcome of Personalized CNNs for other Robot Users

\begin{itemize}
  \item Segmentation’s Dice scores in each of the 27 \( \times 27 \) cells.
  \item Given a trained segmentation model \( m(\cdot) \) (row) and a robot user’s (column) test seeds as input.
  \item Higher Dice scores are depicted as lighter shades of gray.
  \item Each model \( m(\cdot) \) was trained beforehand only on robot user’s seeding training data.
\end{itemize}

Conclusions & Outlook

\begin{itemize}
  \item CNNs trained with rule-based robot users to place seeds almost at random (rand, rand_gT, xu16) yield similar segmentation results when other user input patterns are utilized during inference.
  \item Robot user input with more distinct seeding patterns like wang17 generates trained networks which are better adjusted to their seeding, but do not generalizing well to other input patterns.
  \item Therefore, it is a necessity to train on personalized seeding patterns formalized as individual robot users, where a high similarity to the input patterns of the real user operating the system is imperative.
\end{itemize}

References


Contact

Mario Amrehn

Pattern Recognition Lab
Friedrich-Alexander University Erlangen-Nürnberg (FAU)
Erlangen, Germany

+49 9131 85 27826
maro.amrehn@lau.de

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