Interactive CNN Robot User Investigation for Medical Image Segmentation

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Introduction

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

Our Approach

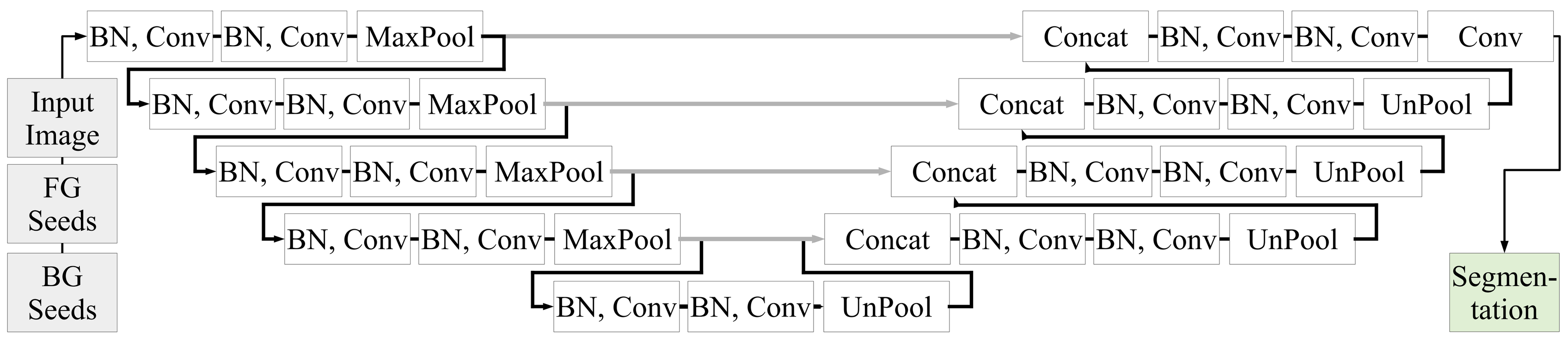
Incorporate human-computer **interaction** (HCI) data as additional input for segmentation into **neural networks**. We simulate this HCI data during training with SOTA user models, also called **robot users**, which aim to act similar to real users given interactive image segmentation tasks.

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.

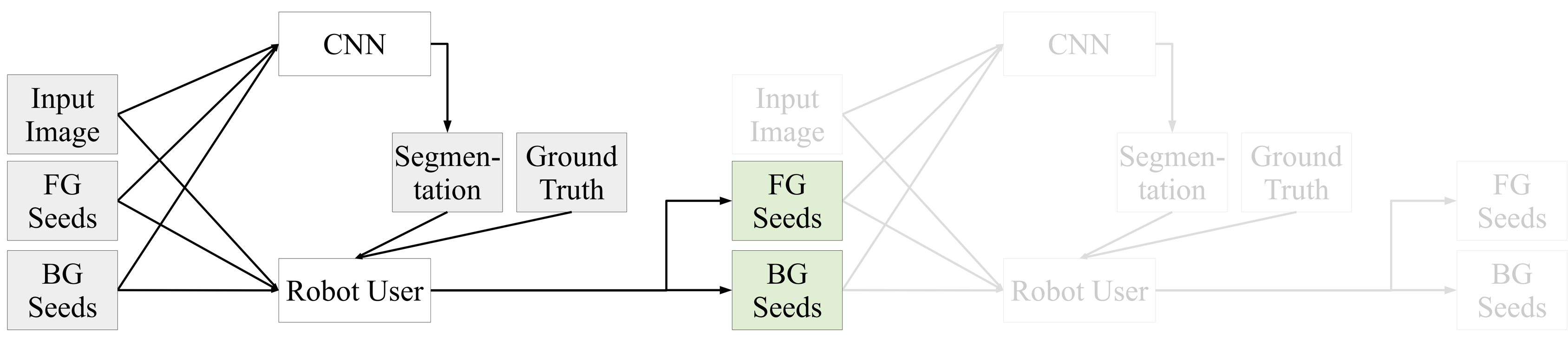
Methods

Dense Image Segmentation CNN



Schematic convolutional neural network topology with skip-connections. The input channels include foreground (FG) and background (BG) seed information. Before each convolution, batch normalization (BN) is applied. Dense outcome segmentation mask of size 256^2 pixels (green).

Seed Generation via Robot User



A robot user bases its seed placement decision process on up to five different inputs (gray): input image, previous foreground and background seeds, current segmentation mask, and ground truth segmentation mask. The outcome of a robot user system is a new set of proposed seed points (green).

Investigated Rule-based Robot Users

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

Random sampling from GT (rand_gt) $r_{rand} = 0\,\%$. Number of seeds per interaction is $n_{rand\_gt} \in \{1, 5, 10\}$.

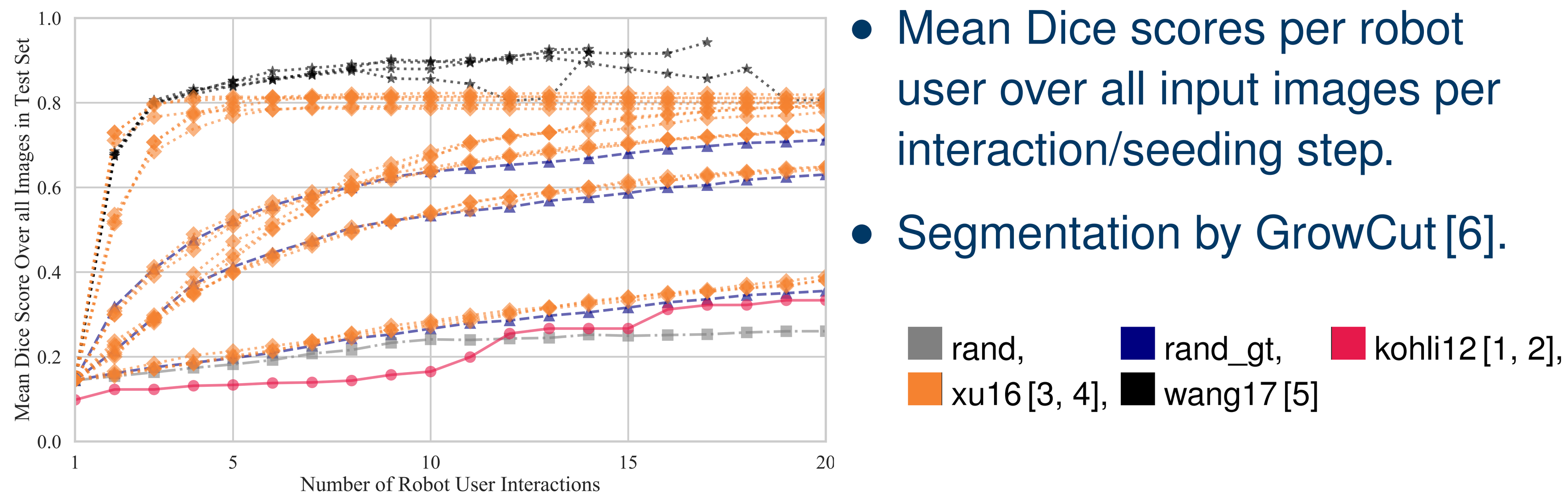
Kohli et al. (kohli12) [1, 2] Uses the segmentation image and GT to place one seed point in the center of largest, wrongly labeled image area.

Xu et al. (xu16) [3] Samples $f_{xu16} \in \{1, 5, 10\}$ FG and $b_{xu16} \in \{1, 5, 10\}$ BG 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 $t_{wang17} \in \{10, 20, 30, 40\}$ in pixels.

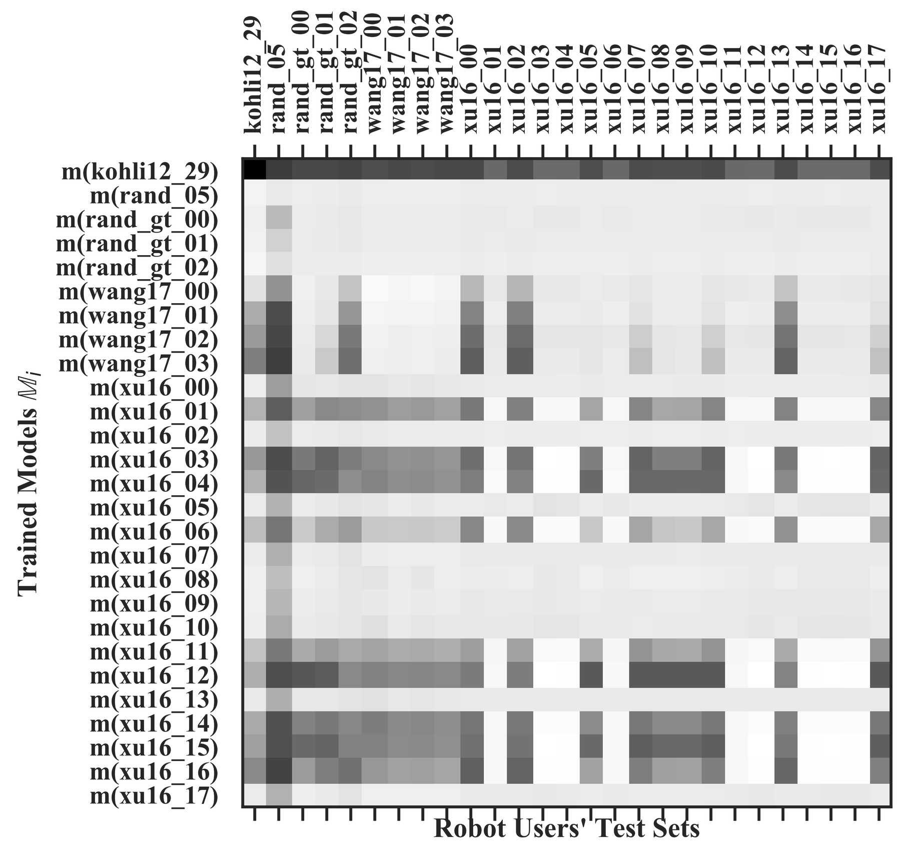
Results

Multiple Robot User Seed Placement Patterns



- Mean Dice scores per robot user over all input images per interaction/seeding step.
- Segmentation by GrowCut [6].

Prediction Outcome of Personalized CNNs for other Robot Users



- Segmentations' Dice scores in each of the 27 × 27 cells,
- given a trained **segmentation model m(.) (row)** and a **robot user's (column)** test **seeds** as input.
- Higher Dice scores are depicted as lighter shades of gray.
- Each model $m(i)$ was trained beforehand only on robot user i's seeding training data.

Conclusions & Outlook

- 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.
- 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**.

→ 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.

References

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