Passive Needle Tracking with Deep Convolutional Neural Nets for MR-Guided Percutaneous Interventions

Jonathan Weine[1,2], Eva Rothgang[1,3], Frank Wacker[4], Clifford R. Weiss[5], Florian Maier[1]

[1]Siemens Healthineers, Erlangen, Germany; [2]TU Dortmund University, Dortmund, Germany; [3]Ostbayerische Technische Hochschule Amberg-Weiden, Weiden, Germany; [4]Hannover Medical School, Hannover, Germany; [5]Johns Hopkins University School of Medicine, Baltimore, MD, USA

Purpose. During percutaneous interventions knowledge of needle position and orientation is crucial to get effective diagnostic (e.g. biopsies) or therapeutic results (e.g. thermal ablation). Automated needle tracking approaches are anticipated to reduce the duration of percutaneous interventions, due to the reduction of manual slice positioning steps. Passive tracking methods have the advantage that no additional hardware is needed. In the past, conventional image processing methods have been employed for this task[1,2]. Recently, deep convolutional neural nets (CNN) were used in image processing with excellent results[3]. This work investigates the capability of a deep learning algorithm to detect needles in porcine in-vivo images.

Methods. The CNN was trained on image data acquired during MR-guided swine studies (10 animals). All images were acquired in an IRB approved study (cf. [2]). The bSSFP image data (BEAT IRTTT, Siemens Healthineers, Erlangen) contains different needle paths, slice orientations, and matrix sizes. A total of 1979 images containing a needle artifact have been manually annotated (non-clinician) and split into training and validation sets by study to minimize similarity of training and validation images (1634/345). During training, augmentation (rotation, zoom, translation) was randomly applied on every image to create well distributed artifact positions and sizes. The algorithm was implemented with Tensorflow[5] and trained on an NVIDIA Tesla (V100-SXM2-16GB) for 250 epochs (8 h). An Encoder-Decoder model similar to UNet[4] was designed. The collapsing arm was five blocks deep with each block containing two convolutional layers (3x3-kernel, ReLU) followed by a batch norm and a 2x2-max pooling. The number of filters is successively doubled after each pooling. The input is symmetrically padded such that the valid padding during convolution is compensated and the output image has the same size as the input. In the decoding part, the transposed convolution is followed by concatenation of activation maps from the encoding part and two convolutional layers. As loss function a sigmoid-cross-entropy with pixel wise Gaussian weighting by distance to the needle was used (optimizer: adaptive gradient descent).

Results. Model complexity and the hyper parameters dropout rate, learning rate, number of epochs, loss weight scale and L_2 kernel regularizing scale have been chosen by comparing the inference on the validation dataset. In Figure 1 the inference of representative images from the validation set thresholded at 0.5, 0.6 and 0.7 is shown. On a test subset thresholded at 0.6 and filtered by TP score >0.1 (319 images with acceptable performance) the segmented area corresponding to the needle was extracted. The Euclidian distance [mm] to the annotated tip position (Median= 4.4, Q_{60}=5.24, Q_{90}=16.9) and angular difference [°] to the label (Median=0.2, Q_{60}=1.1, Q_{90}=6.8) was derived.

Conclusions. The initial results show that CNNs can be employed to successfully detect a needle in interventional *in-vivo* MR images. Images in which needles are clearly separated from tissue are segmented precisely (Fig. 1a), but the algorithm needs to be improved on images that contain banding artifacts of the same size as the needle (Fig. 1b). The results show that the algorithm could benefit from additional information like pulse sequence parameters to learn the orientation dependent artifact appearance and an AI based position extraction. In a next step, the algorithm will be trained on larger number of datasets and human in-vivo image data. The method is a promising approach to create a robust and general method for tracking needles in MR-guided interventions.

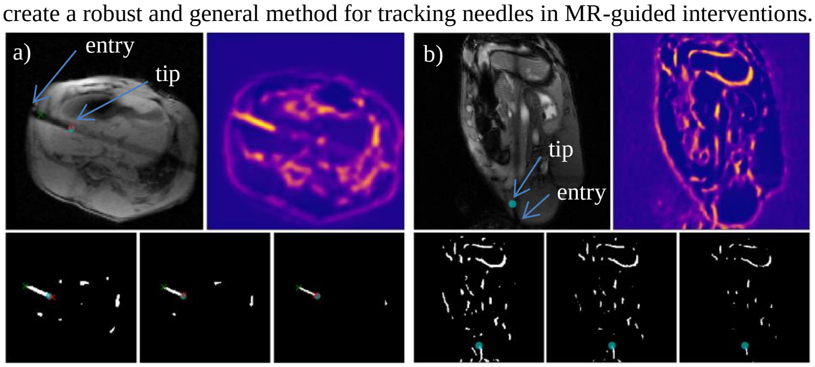

Fig1: Image and inference (top row), thresholded inference (0.5, 0.6, 0.7) (bottom row). Annotated needle tip (cyan dot). a) Extracted tip (red cross) and entry point (green cross). Average of positions is plotted into input image. b) Image and inference with banding artifacts.

References [1]DiMaio et al; Stud Health Technol Inform. 2006; 119:120-5. [2]Rothgang et al; JMRI. 2013; 37: 1202-1212. [3]Shen et al; Annual review of biomedical engineering. 2017; 19: 221–248. [4]Ronneberger et al; MICCAI. 2015; 9351:234-7 [5]Abadi et al; TensorFlow: A System for Large-Scale Machine Learning