

Development and Evaluation of a GUI using AI-assisted Algorithm for Catheter Reconstruction in MR-only Gynecological Interstitial HDR Brachytherapy

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INTRODUCTION

During MRI-guided HDR gynecological brachytherapy, several catheters are inserted through a standard template. Current approach, manual reconstruction of the implanted catheters, is time-consuming. We developed a novel deep-learning-assisted-semi-automatic (DLASA) algorithm and a Graphical-User-Interface (GUI) for catheter reconstruction. We present the GUI and robustness of DLASA algorithm.

METHOD

A GUI was built using open-source Python libraries. The algorithm and workflow are shown in Figure 1 and 2, respectively. All catheters are localized at a reference image slice which is the slice just before the catheters enter into the standard template. Information in the input file is passed to U-Net model to identify all possible catheter positions in a given image slice. Then, the true location of each catheter is tracked by finding the extrema in T1- and T2-weighted MR images. Once reconstruction is completed, catheter positions are saved to xls file. Modified Napari 3D orthogonal viewer is used to view and edit reconstructed catheter position on three cardinal image planes. To evaluate the algorithm's catheter tracking performance, catheter reconstruction is compared with a manual reconstruction for 25 patients.

Figure 1. Co-registered T1 and T2 images are used for catheter reconstruction as the they appear bright and dark, respectively. T1 and T2 images were used separately to train models to obtain the probability masks. The post processing box was used to use the information on input files (i.e. # of needle, digitization on the starting slice, free length of each needle, use of tandem) to reach final catheter reconstruction.

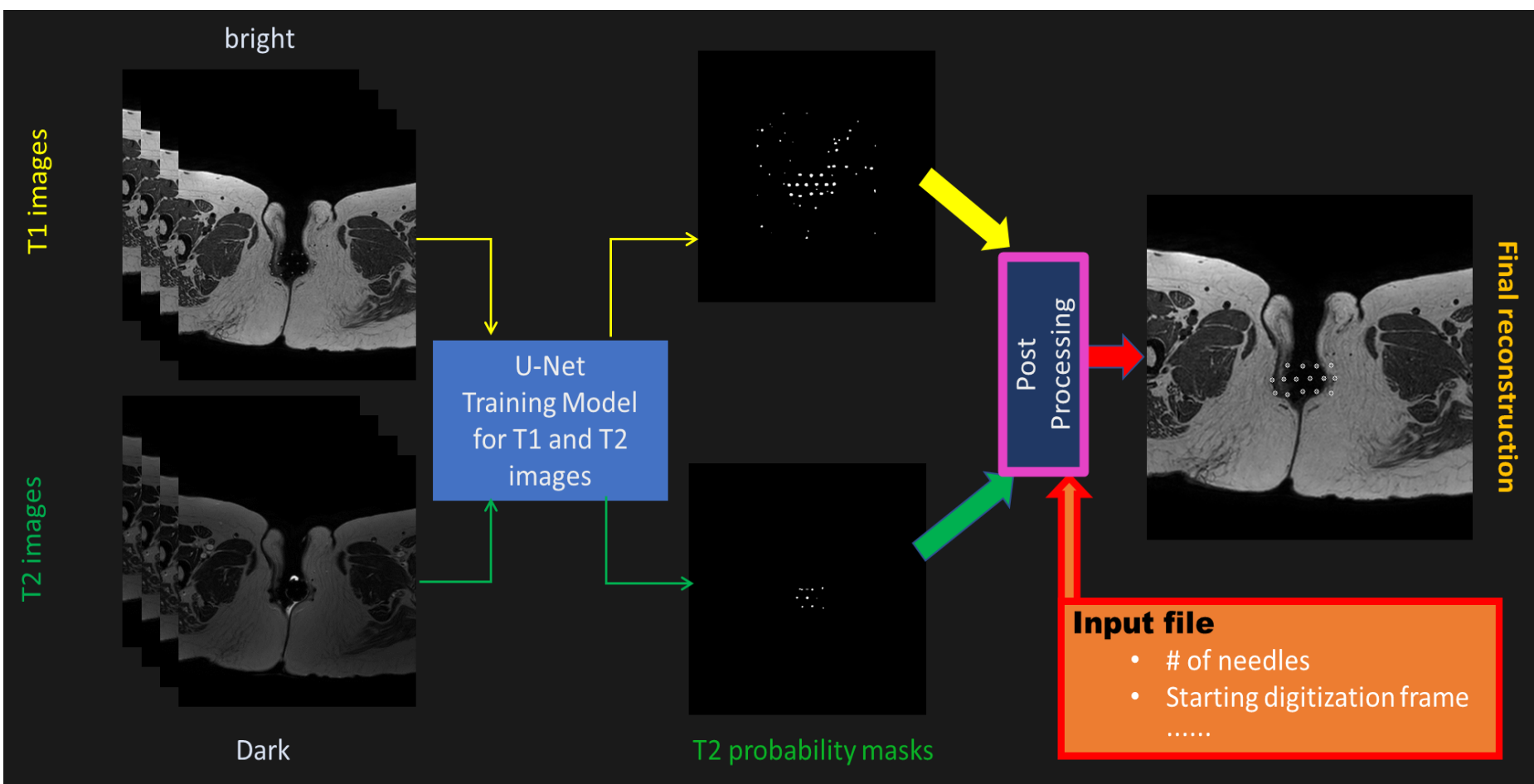
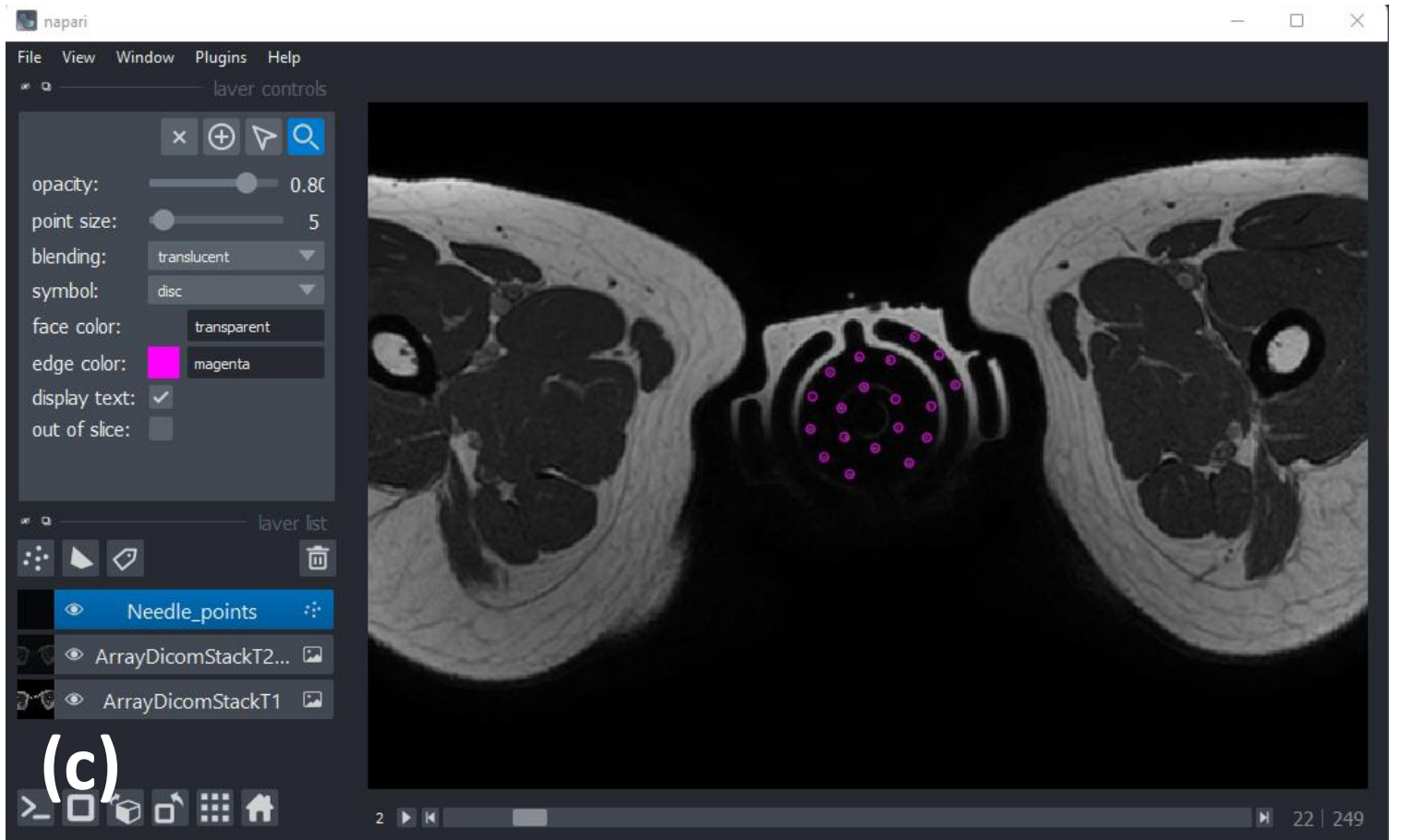
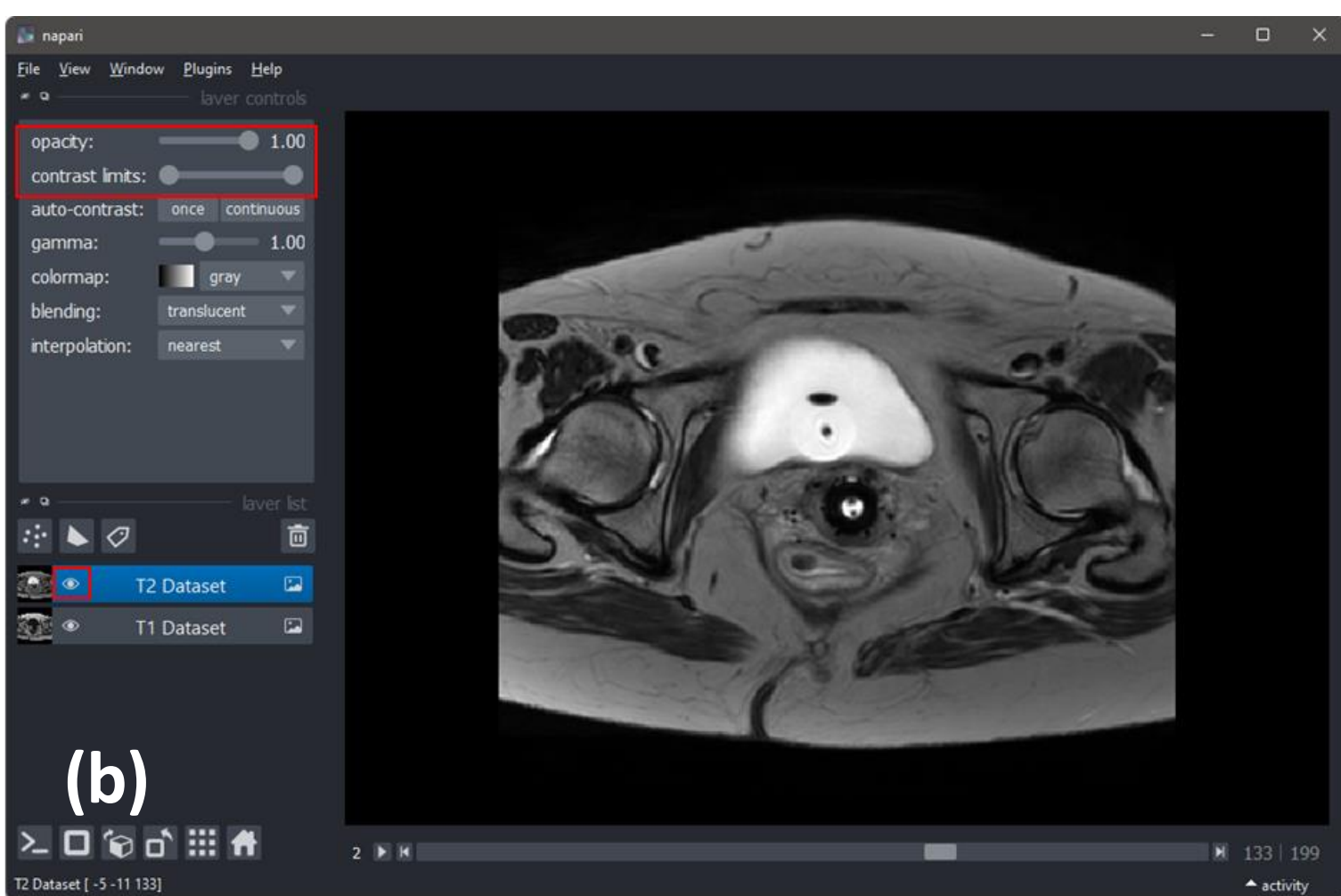
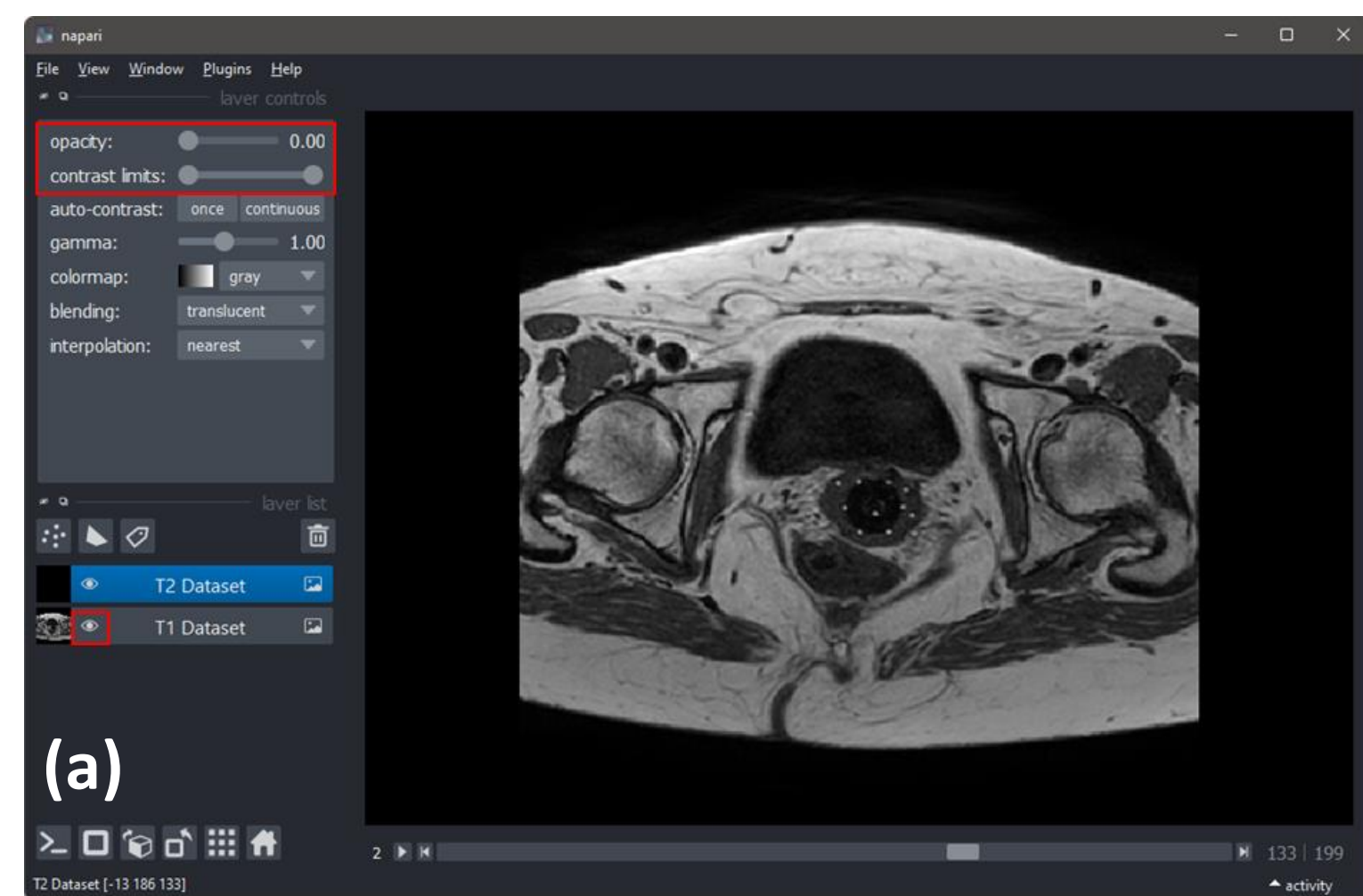
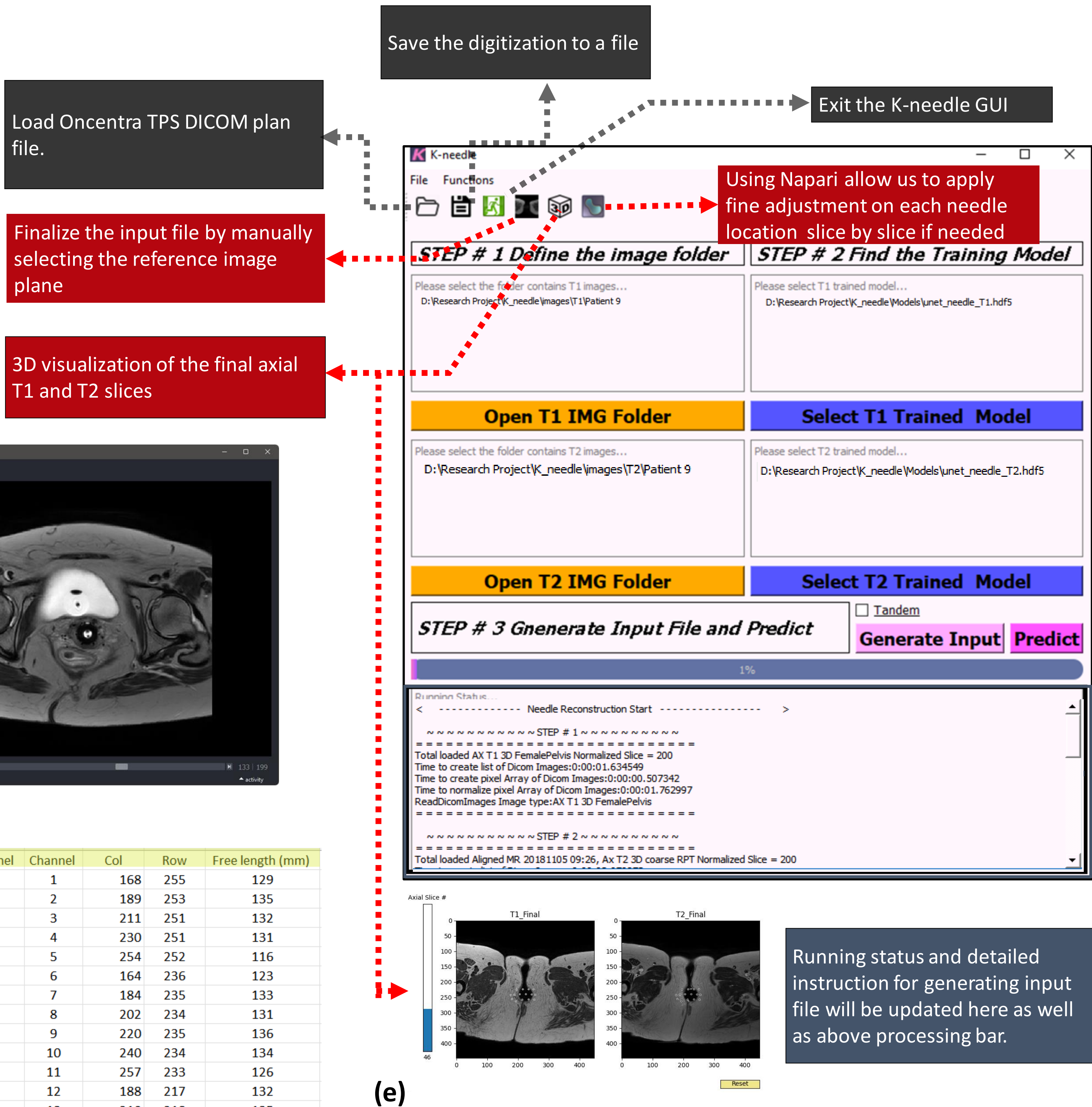


Figure 2 (a-b), overlap layer view of T1-3D and T2-3D image dataset. Window/level is adjusted for better visualization of catheter locations. Selection of the catheter locations in the reference slice is shown in (c). Followed with manually inputting the free length of all channels, the final input file (d) is completed. We can start the catheter reconstruction by clicking the GUI interface in (e); By clicking the Napari ICON, the catheter reconstruction can be visualized at different planes (f-g). Fine adjustments of digitization can be done in orthogonal views (h). When satisfied with the digitization, we can save the final catheter digitization information.

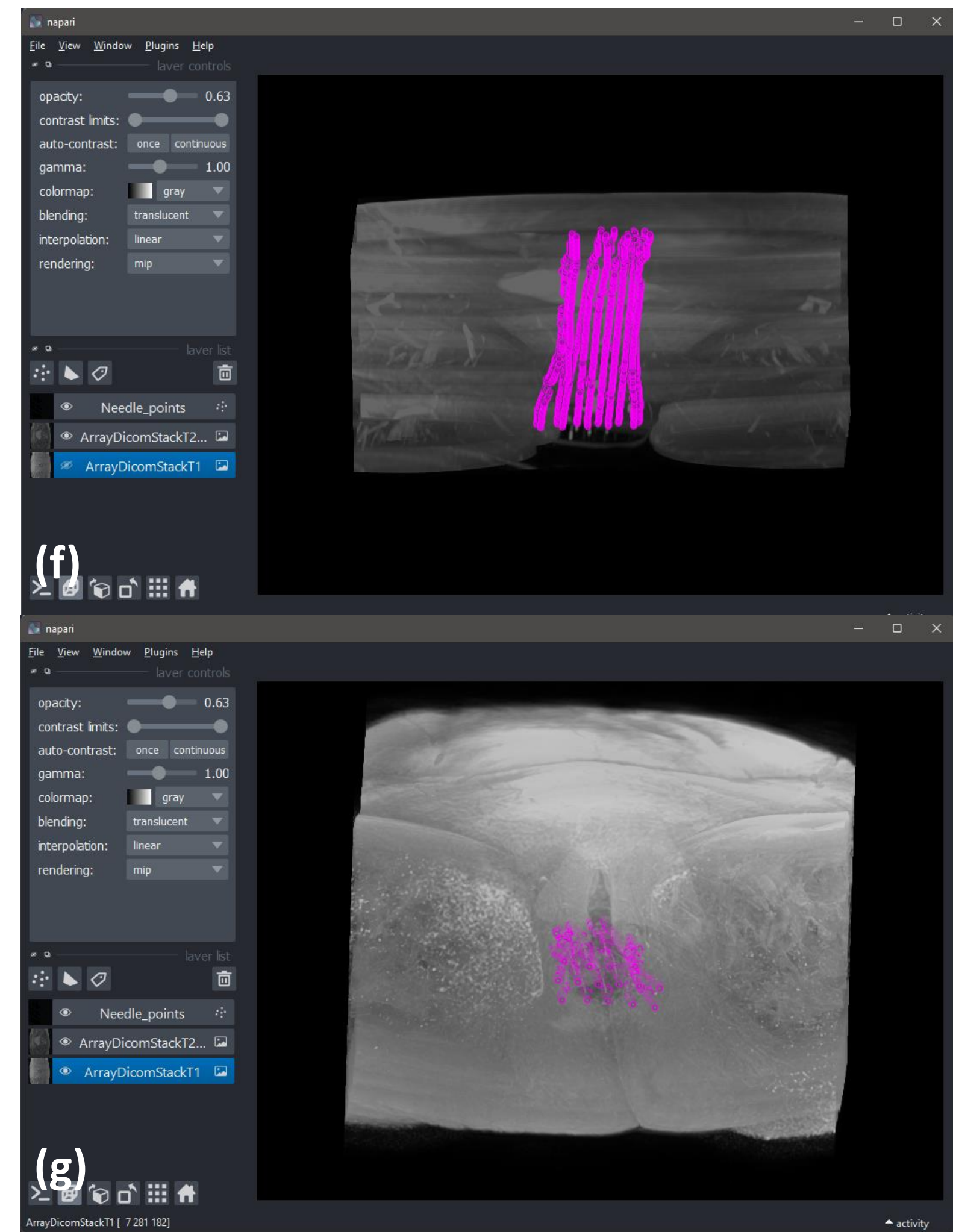


Starting Slice	End Slice	Total channel	Channel	Col	Row	Free length (mm)
20	180	15	1	168	255	129
			2	189	253	135
			3	211	251	132
			4	230	251	131
			5	254	252	116
			6	164	236	123
			7	184	235	133
			8	202	234	131
			9	220	235	136
			10	240	234	134
			11	257	233	126
			12	188	217	132
			13	210	218	135
			14	230	217	135
			15	252	215	123



(e)

Running status and detailed instruction for generating input file will be updated here as well as above processing bar.



(h)

RESULTS

For 15/25 patients, the catheters reconstruction agreed with the manual reconstruction (mean error=0.4mm, SD=0.7mm. Among them, slightly over 97% of reconstruction positions had error < 2mm. The AI-assisted reconstruction shows great deviations from manual reconstruction for rest of the patients. In term of speed, more than 50% time was saved compared to manual reconstruction. This speed can potentially be increased with newer computing hardware. The rest 10/25 patients' reconstruction doesn't agree well with the manual reconstruction due to the false positive detection by training model.

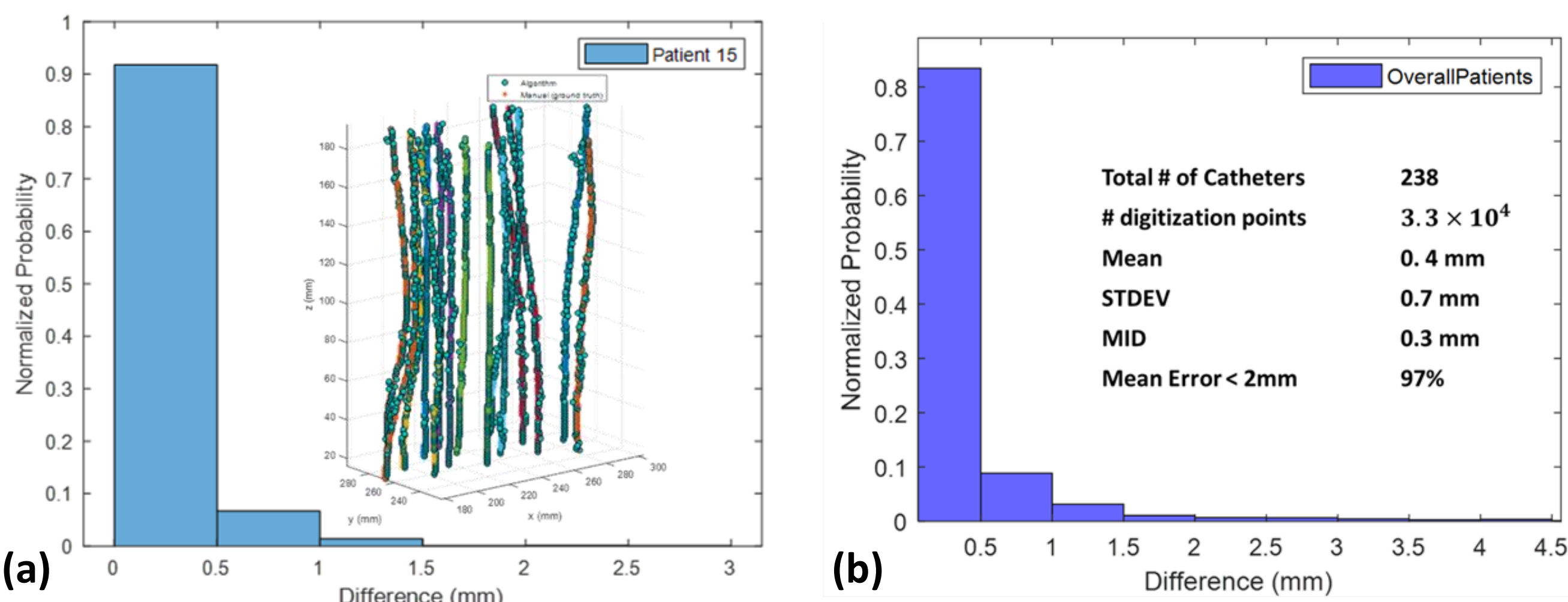


Figure 3 (a) As an example of Patient #15, the AI assisted digitization performance shows a great agreement with the manual digitization by experienced operator. (b) For 15 patients, the catheters reconstruction agreed with the manual reconstruction (accuracy is within 0.4mm and standard deviation is 0.7 mm, the % of digitization positions with the mean error < 2 mm amongst digitization positions is over 97%).

CONCLUSIONS

The adoption of this GUI in the brachytherapy workflow has potential to improve treatment efficiency by reducing planning time, clinic resources, and manual selection errors. Future work include reducing the false positive by fine tuning the DLASA, examine GUI with more patients, and test GUI's output in TPS for further evaluation.

REFERENCES

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- Shaaer, A., Paudel, M., Smith, M., Tonolet, F., & Ravi, A. (2022). Deep-learning-assisted algorithm for catheter reconstruction during MR-only gynecological interstitial brachytherapy. *J. Appl. Clin. Med. Phys.*, 23(2). <https://doi.org/10.1002/acm2.13494>