A PASSIVE, IMAGE-BASED NAVIGATION TOOL FOR REAL-TIME MR-GUIDED PERCUTANEOUS INTERVENTIONAL PROCEDURES

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Introduction. Percutaneous interventional procedures such as biopsies, drainages and ablations are regularly performed using image guidance with ultrasound, computed tomography and x-ray fluoroscopy. Needle visualization and navigation are the primary motivations for performing these procedures under image guidance. Long thought to be an ideal modality for guiding these procedures because of its ability to more clearly visualize soft tissue lesions, MRI has seen slow clinical adoption due to limitations associated with equipment accessibility, physician access to patients within the scanner, and procedure speed. The recent introduction of high field wide bore scanners, which provide high SNR diagnostic imaging and open up access to patients, has stimulated increased use at a number of large clinical research sites. MRI needle visualization can vary significantly depending on the pulse sequence, field strength, sampling bandwidth, encoding direction, needle composition, and needle orientation, but generally appears as a signal void. Navigation techniques reported include freehand, stereotactic systems, active tracking, and augmented reality techniques [1]. Other than freehand, these techniques require additional equipment and/or modification of existing equipment. Therefore, we sought to determine the feasibility of developing a passive, image-based navigation tool exploiting the signal void properties of the needle for needle guidance and tracking during real-time MRI.

Methods. The navigation tool is implemented in C++ using Radbuilder, a prototyping platform based on OpenInventor [2]. It is fully integrated into the Interactive Front End [3], a prototype for real-time visualization of up to three imaging planes with interactive control of imaging parameters, such as slice position and orientation, through a specially designed multiplanar real-time imaging sequence (GRE, TrueFISP). The navigation tool is comprised of three main components: a planning module, a needle detection module, and a tracking module.

Planning. This module provides multi-planar reconstruction of any 2D stack or 3D image data set and is used to set the entry and target points for needle insertion. The resulting trajectory path is defined and displayed, used as input for the needle detection module, and visualized during real-time imaging.

Needle Detection. For initial needle detection, parallel imaging planes are positioned orthogonal to the trajectory path at user-defined distances from the entry point. During insertion of the needle through the entry point, the signal void associated with the needle appears. Using background subtraction with exponential moving average analysis, candidate points are identified as the needle. Connected component labeling [4] and feature (e.g. size, circularity, intensity, target path proximity) analysis are then used to isolate the most likely candidate in each image, and the user is prompted to confirm or edit the selected points.

Needle Tracking. Following initial needle detection and confirmation, real-time needle tracking is activated. The underlying strategy for tracking is based

on model fitting the needle artifact to a regular cylinder defined by an entry point, needle tip and radius (Figure 1). A cost function is defined with respect to the needle artifact by weighting image pixels according to their position relative to the needle. By optimizing the cost function to find the best fit of the model to the image data, an estimate of the current needle position is determined and used to automatically realign the imaging planes. Currently three imaging planes are used during tracking with two different layouts provided: a) two planes parallel and one orthogonal to the direction of the needle, or b) one plane parallel and two orthogonal to the direction of the needle.

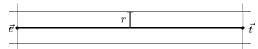
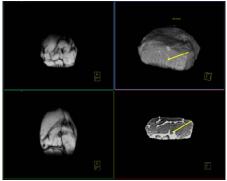
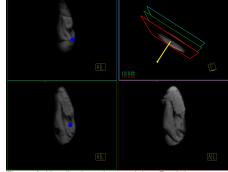


Figure 1: Cylindrical needle model with the entry point \vec{e} , needle tip \vec{t} , radius r and centerline from entry to tip.

Results. To date, the navigation tool has only been tested on a meat sample with targeting success achieved and confirmed after complete needle insertion by repeating the high resolution imaging used for planning. Figures 2-4 demonstrate the individual components of the navigation tool in use, respectively.





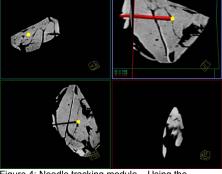


Figure 2: Planning module – Multiplanar reconstructions of diagnostic images that clearly visualize the target anatomy are used to define the entry point, target point and trajectory path (yellow line).

Figure 3: Needle detection module – Real-time, multi-slice imaging perpendicular to the target path is performed during insertion of a needle into a meat sample with successful needle detection (blue circles).

Figure 4: Needle tracking module – Using the cylindrical model and cost function optimization, the needle was navigated successfully to its target location (yellow circle) with auto-update of the planes.

Conclusions. A navigation tool for guiding and tracking targeted needle placement using image-based methods is presented. Further evaluation is needed, including in-vivo testing and optimization, but it is anticipated that the tool should improve the workflow and speed of real-time, MR-guided percutaneous interventional procedures by providing complete methods for planning, detecting and tracking the needle without the need for additional equipment.

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[3] Lorenz CH et al. Proc. ISMRM 2005; p. 2170.

[4] Shapiro LG and Stockman GC. Computer Vision, Prentice Hall 2002; pp. 69-73.