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4/26/2016

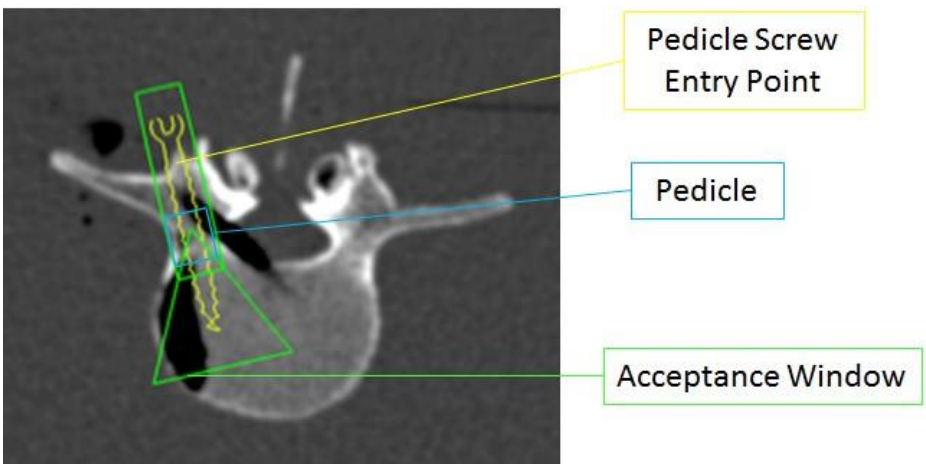
Computer Integrated Surgery II

Group 1

Critical Review: Known-Component Registration

Project Overview

The overall goal of our project is to improve pedicle screw placement procedures. Pedicles are corridor-like structures of spinal vertebrae that physicians often thread screws into for a variety of medical purposes such as deformity correction or structural support. Currently, the clinical standard of care revolves around a "free-hand" insertion of the pedicle screw into a patient's spine by a physician relying upon prior knowledge and experience. The figure below (base image courtesy of the I-STAR Lab) is an axial CT slice of a vertebra that has a model pedicle screw secured within a clinical "acceptance window" that roughly dictates acceptable placement of the screw. Given that a deviation of screw placement by a single millimeter could result in spinal cord breach, we aim to place a drill guide along a patient's body surface along a pre-planned axis using the UR5 such that a physician could readily and accurately thread a screw directly into a pedicle.



Paper Selection & Significance

Uneri, Ali, et al. "Known-component 3D-2D registration for quality assurance of spine surgery pedicle screw placement." Physics in Medicine and Biology 60.20 (2015): 8007-8024.

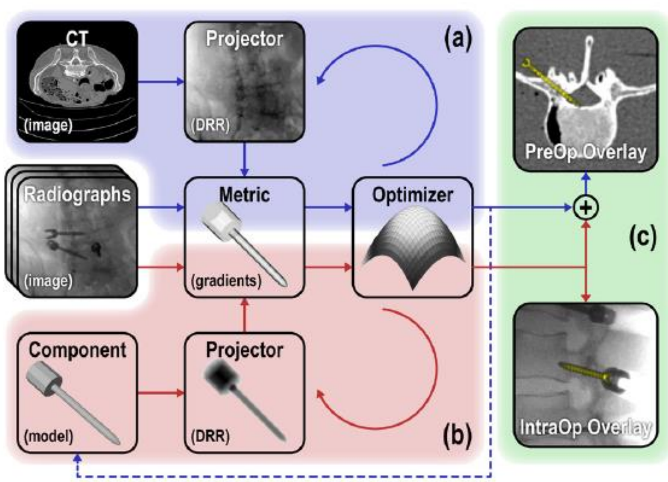
In this paper, Uneri discusses a technique known as known-component registration (KC-Reg) that utilizes robust 3D-2D registration combined with 3D component models of surgical devices such as pedicle screws (ie. "known components") that are present in 2D intraoperative radiographs. Thus, the technique allows for the registration of tools directly to a CT space which would allow us to develop a surgical assistance system without the use of an optical tracker and corresponding optically tracked tools. Our current system combines the use of an optical tracking system with fiducial registration techniques to link the operational coordinate spaces together.

Paper Background

Uneri et al. begins by presenting a similar clinical background discussed in the "Project Overview" section above, additionally citing the lack of reliability surrounding tracker guidance due to deterioration of accuracy over the course of surgeries (potentially due to anatomical deformations and motion of markers). Moreover, Uneri et al. recalls an alternative approach named 3D-2D registration that can provide 3D localization in, for example, a preoperative 3D CT volume using intraoperative 2D radiographs. An established general procedure surrounding this involves iteratively matching the intraoperative radiographs to digitally reconstructed radiographs (DRRs) from the CT until the maximum image similarity is found. The authors define a "known-component" as some surgical tool (ie. pedicle screws, fixation hardware, etc.) for which there is prior structural knowledge further discussed in following sections. Uneri et al. then elaborates upon the paper's namesake technique: KC-Reg. To evaluate the ability of this algorithm to additionally localize a known-component in a 3D space, the authors test the technique using three methods of differing knowledge of the "known-component": a simple parametric model, a more advanced parametric model with multiple sub-components, and finally an exact model (ie. CAD model).

Methods

The overall idea behind the methodology is to accomplish KC-Reg along with normal 3D-2D registration methods. Shown in the following figure is a representation of the flow.



Uneri et al. employs a similarity metric based on pixel-wise correspondence of gradient intensity. Shown below are the equations that define said metric. Given that f is the fixed radiograph, m is the moving DRR, and (i, j) denote 2D image pixel coordinates, the method seeks to maximize the gradient correlation between a fixed radiograph and some DRR.

$$\mathrm{GC}(f,m) = \frac{1}{2}(\mathrm{CC}(\nabla_x f, \nabla_x m) + \mathrm{CC}(\nabla_y f, \nabla_y m))$$

$$\mathrm{CC}(f,m) = \frac{\sum_{i,j}(f_{i,j} - \overline{f})(m_{i,j} - \overline{m})}{\sqrt{\sum_{i,j}(f_{i,j} - \overline{f})^2}\sqrt{\sum_{i,j}(m_{i,j} - \overline{m})^2}}$$

To be clear then, the optimization problem that maximizes the total gradient correlation across all projection views can be represented as

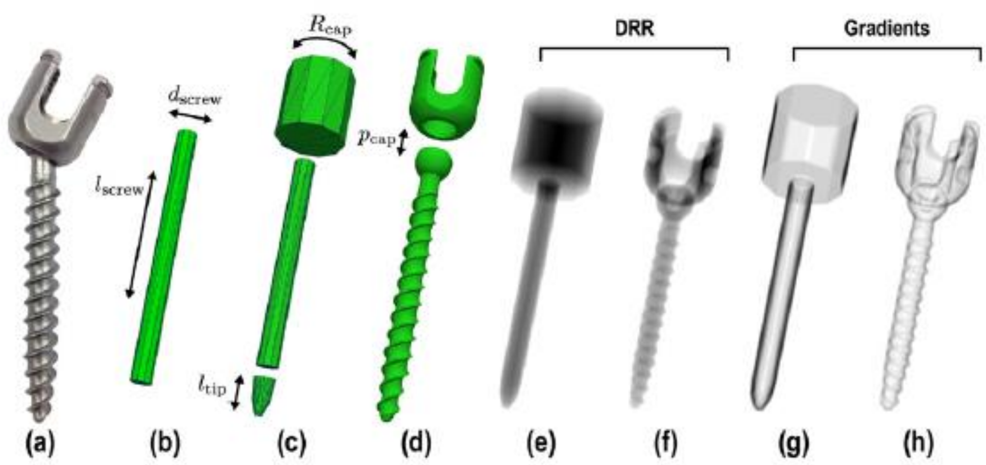
$$\widehat{\Phi} = \arg\max_{\Phi} \sum_{\theta} \text{GC}(f_\theta, m_\theta(\Phi))$$

Individual moving DRRs m for some angle θ are computed as

$$m_\theta(\Phi) = \mathcal{P}_\theta \mathcal{T}(\Phi) \circ M$$

In this manner, a known-component may be localized in the appropriate 3D space (in this case CT) along with the standard registration of patient anatomy to the accompanying 3D data.

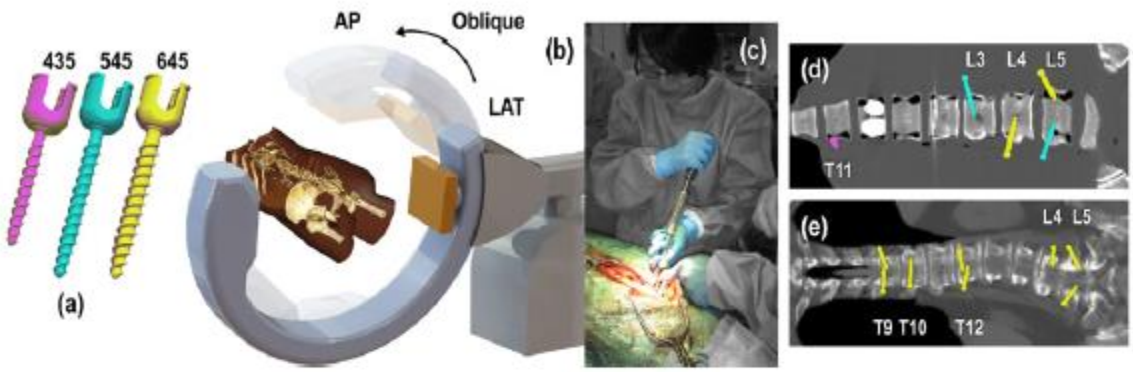
As previously mentioned, Uneri et al. makes use of several degrees of knowledge surrounding the known-component. To clarify this point, the figure below depicts the types of known-components. Given that subfigure (a) represents the original known-component (in this case a pedicle screw), the authors demonstrate three representations of the known-component. Subfigures (b) and (c) are dubbed parametrically known components (pKC) by the authors where subfigure (b) represents a cylindrical parametrization of the screw using only length and diameter of the screw shaft. Subfigure (c) represents a higher-order representation of the original screw making use of several subcomponents, in this case a polyaxial cap defined by a larger cylinder, a cylindrical shaft as before, and a custom-tapered tip. As evident in the depictions, the pKC models were represented as triangular meshes of closed surfaces allowing for low usage of memory and low-cost manipulation. Finally, subfigure (d) represents an exactly known component (eKC) in the form of a CAD model. The corresponding DRRs and gradients for the higher-order pKC and eKC are presented for reference.



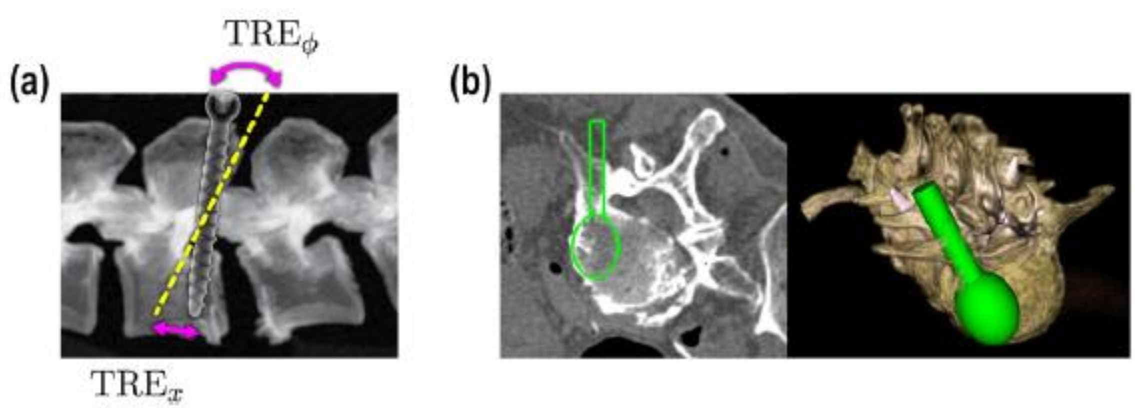
Uneri et al. clarifies that there are several key considerations necessary to accommodate the components within the registration framework: image acquisition, parameter initialization, 3D-2D projection approach, and parameter optimization. To elaborate, the image acquisition makes use of radiographic view separated by at least 15 degrees, the parameter initialization constrains the search space of the algorithm based upon pre-planned trajectories, the DRR projection approach makes use of a fast ray-triangle technique established by Moller and Trumbore (1997), and the parameter optimization function was slightly adjusted simply to account for multi-component pKC representations.

Experiments & Results

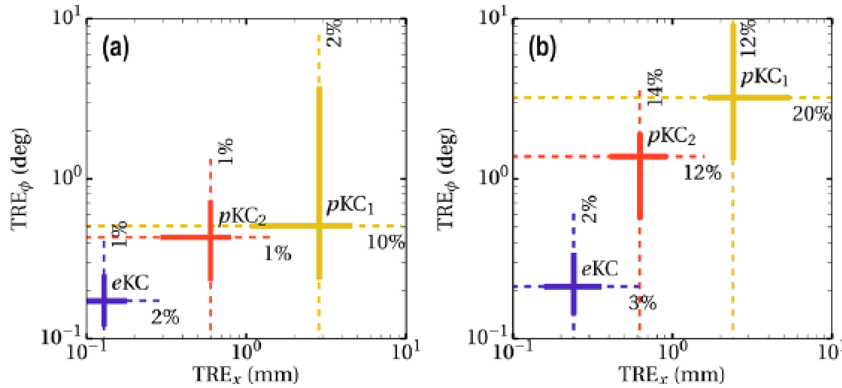
Performance evaluation experiments were performed in two setups: an anthropomorphic body phantom and a human torso cadaver. The intraoperative radiographs were obtained using a mobile C-arm [see subfigure (b) below], and the phantom and cadaver had pedicle screws implanted in the lumbar and thoracic regions of the spine as shown in subfigures (d) and (e) respectively below. Preoperative CT data was available.



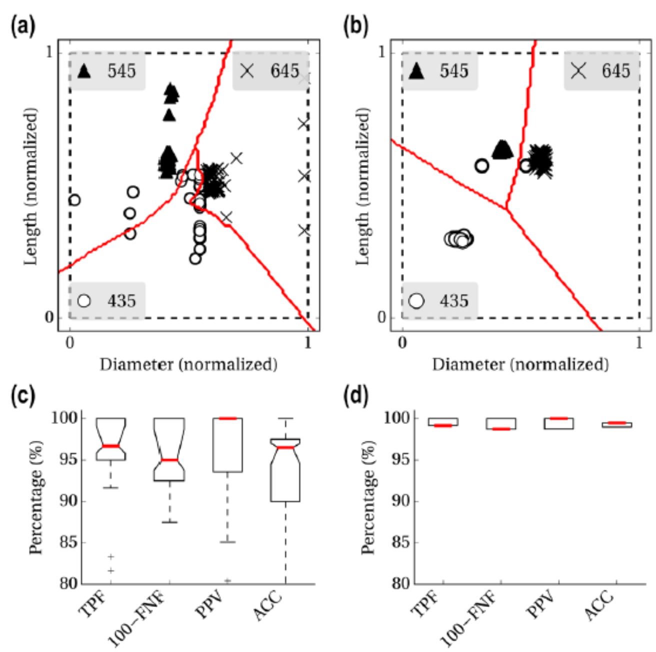
Uneri et al. assesses three measures for quality assurance: geometric accuracy of registration, verification of device consistency, and visualization of registered component within acceptance windows. First, to assess geometric accuracy, Uneri et al. computes the target registration error (TRE) in terms of the translational (x) and rotational (ϕ) components. The ground truth was computed from 200 projections acquired over a semicircular arc using the mobile C-arm (excluding AP/lateral/oblique views used in 3D-2D registration to avoid bias). Thereafter, the TRE was computed using the screw tip locations and screw principle axes as shown in subfigure (a) below. Subfigure (b) happens to show an improved acceptance window compared to the first one presented in this review—in this case, there is an ellipsoid end that defines a region that is more reflective of what is clinically accepted.



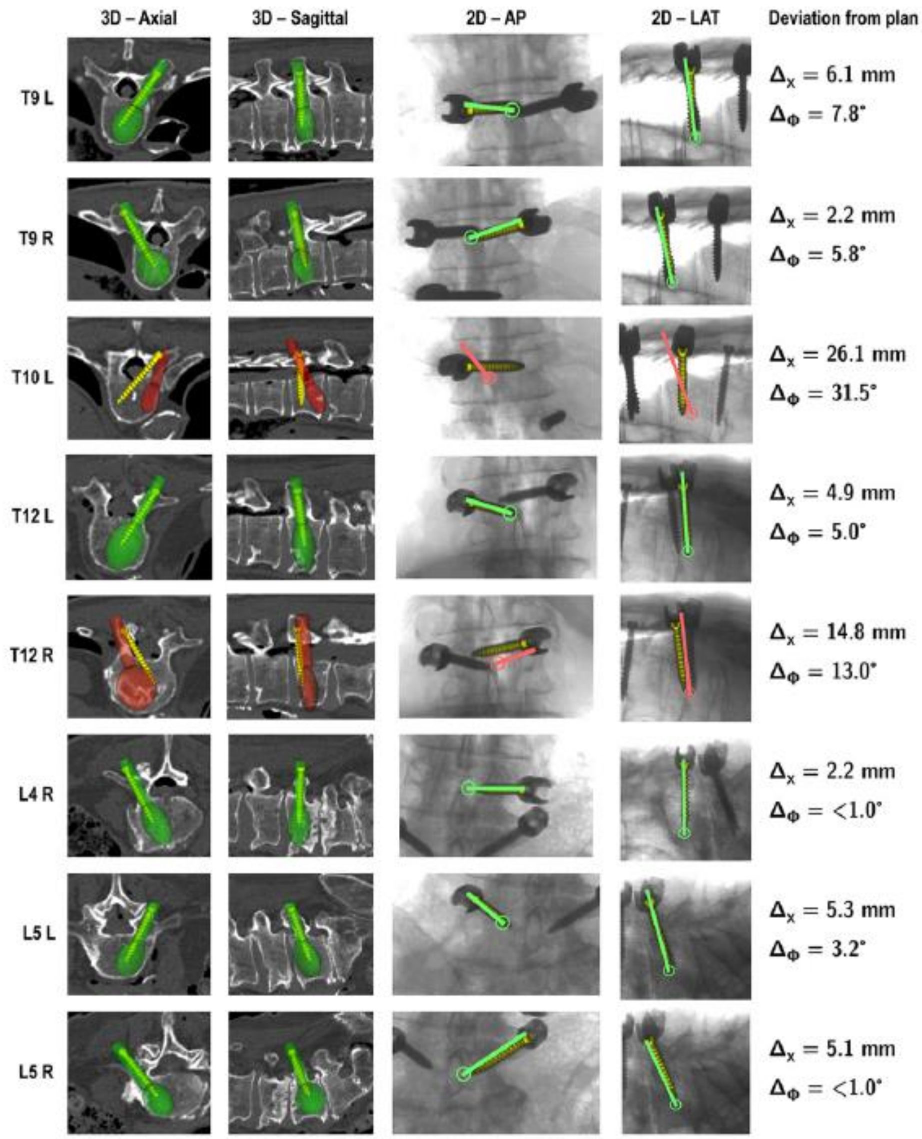
In the following figure, subfigure (a) reflects the phantom TRE results and subfigure (b) reflects the cadaver TRE results. After analysis of the results, it is clear in the figure below that the TREs for the different types of known-components differed in an intuitive manner. That is, the trend that is shown suggests that greater component knowledge offers better (lower) TRE values such that eKCs has the lowest associated TRE and the most generic pKC had the highest TRE. Most strikingly, the median translation TRE for the eKC method (phantom) was 0.2 mm and the median rotational TRE for the eKC method was 0.2 degrees such that 92% of registrations were within the gold standard TRE accuracy levels of <1 mm in translation and <5 degrees in rotation. Errors were higher in general for the cadaver which Uneri et al. theorizes to be due to the more variable anatomy of the cadaver.



To briefly summarize the device verification portion of quality assurance, 200 data samples of registration component shapes (length and diameter of screws) were used to train a multi-class learning-based classifier which is further elaborated upon in results below. The general trend is that classification is easier using the components with greater associated knowledge. Subfigure (a) was the classification using the most generic pKC and subfigure (b) was the classification using the multi-component pKC. Subfigures (c) and (d) show the associated classification performances for (a) and (b) respectively where TPF is the true positive fraction (TP / P), FNF is the false negative fraction (FN / P), PPV is the positive predictive value (TP / (TP + FP)), and ACC is accuracy defined as (TP + TN) / (P + N).



Finally, the quality assurance component of visualization relative to the acceptance window is depicted below. Green indicates proper placement while red indicates unacceptable placement. The 2 red regions had screws that were intentionally misplaced indicating that KC-Reg was able to identify the "acceptability" in all cases correctly.



Assessment

Overall, the paper presented lucid explanations of the technique's evaluations and paved the way for promising future works. The background presented comprehensively covered the major concepts that were integral to understanding the methods involved. As for the reasons surrounding the differences in results, the paper offered feasible explanations as to why some errors may have been lesser or greater in magnitude compared to others. Finally, although the paper presents a fairly straightforward figure outlining the flow of the KC-Reg technique, the underlying mathematics were not as graphically well-represented. In other words, the paper opts for a more numerical approach to explaining the mathematical methods which potentially could have benefited from one or two additional graphics.

Conclusion

In summary, Uneri et al. present a high-utility method for localizing a surgical tool within a 3D volume. Further testing is warranted as to how well our setup responds to this method, but assuming we achieve similar levels of error, KC-Reg would provide a powerful means of operating our setup. Specifically, the optical tracking component of our system could be entirely removed thereby removing physical clutter in an operating environment in addition to the variable reliability that is inherent to tracking systems. If we were to model our drill guide via CAD software, we would effectively have an eKC model to work with that would likely provide us with the best possible results.