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Planning, Guidance, and Quality Assurance of Pelvic Screw Placement Using Deformable Image Registration

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Abstract

Percutaneous pelvic screw placement is challenging due to narrow bone corridors surrounded by vulnerable structures and difficult visual interpretation of complex anatomical shapes in 2D x-ray projection images. To address these challenges, a system for planning, guidance, and quality assurance (QA) is presented, providing functionality analogous to surgical navigation, but based on robust 3D-2D image registration techniques using fluoroscopy images already acquired in routine workflow. Two novel aspects of the system are investigated: automatic planning of pelvic screw trajectories and the ability to account for deformation of surgical devices (K-wire deflection).

Atlas-based registration is used to calculate a patient-specific plan of screw trajectories in preoperative CT. 3D-2D registration aligns the patient to CT within the projective geometry of intraoperative fluoroscopy. Deformable known-component registration (dKC-Reg) localizes the surgical device, and the combination of plan and device location is used to provide guidance and QA. A leave-one-out analysis evaluated the accuracy of automatic planning, and a cadaver experiment compared the accuracy of dKC-Reg to rigid approaches (e.g., optical tracking).

Surgical plans conformed within the bone cortex by 3–4 mm for the narrowest corridor (superior pubic ramus) and >5 mm for the widest corridor (tear drop). The dKC-Reg algorithm localized the K-wire tip within 1.1 mm and 1.4° and was consistently more accurate than rigid-body tracking (errors up to 9 mm).

The system was shown to automatically compute reliable screw trajectories and accurately localize deformed surgical devices (K-wires). Such capability could improve guidance and QA in orthopaedic surgery, where workflow is impeded by manual planning, conventional tool trackers add complexity and cost, rigid tool assumptions are often inaccurate, and qualitative interpretation of complex anatomy from 2D projections is prone to trial-and-error with extended fluoroscopy time.

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1. Introduction

Percutaneous pelvis fixation is a challenging surgical procedure involving implants and tools inserted along narrow trajectories within bone corridors of the pubis, ischium, and ilium. Prior to screw insertion, a Kirschner wire (K-Wire) is often inserted within such cortical boundaries to facilitate subsequent insertion of a cannulated screw (i.e., a cylindrical screw inserted over the K-wire). Such K-wires are commonly ~20–30 cm in length and easily deform along their trajectory – e.g., deflecting at the inner bone cortex. The K-wire is then used to guide cannulated screws to their target. The shape of the pelvis allows the definition of common anatomical trajectories for screw placement (Giannoudis et al., 2007), including: anterior column through the superior pubic ramus (Roult et al., 1995), the anterior inferior iliac spine (AIIS) to posterior superior iliac spine (PSIS) (Schildhauer et al., 2002), and posterior column (Starr et al., 1998). Other common trajectories include iliosacral fusion at S1 or S2 (Roult et al., 1993).

Since the trajectories are up to 15 cm long (Puchwein et al., 2012) and usually accessible via fairly constrained minimally-invasive entry points, mobile C-arm fluoroscopy is a common means to support such procedures. A series of x-ray images is typically acquired to visualize surgical devices within the anatomy in real time and assist accurate placement of K-wires and screws step by step along the trajectory. The C-arm acquires fluoroscopic images from various perspectives (e.g., inlet and outlet views of the pelvis) to provide the surgeon with a (qualitative) 3D reckoning of the implant or tool location with respect to the bone shape. Trial and error is common, requiring multiple exposures and insertions to reach the narrow bone corridor. With less control over deeply inserted wires, the surgeon must sometimes remove the wire altogether and start again along a modified path. Such procedures often involve extended fluoroscopy times – upwards of 123 sec per screw (Gras et al., 2010). Long learning curves are required for surgeons to develop the expertise required for safe, accurate device placement with a minimum of fluoroscopy and insertion attempts.

One means to address such challenges is surgical navigation, in which device placement is guided using sensors and visual feedback (usually overlay on CT). Navigation based on optical tracking (Peters, 2006) has been widely applied in neurosurgery (Helm et al., 2015) and orthopaedic surgery – e.g., pelvic screw insertion (Barrick et al., 1998; Xu et al., 2013; Wong et al., 2015). In such procedures, the bone and tool are marked with fiducials to allow the tracker to identify their positions. The position of the (rigid) patient anatomy and tools are then registered to the patient's preoperative CT or intraoperative cone-beam CT (CBCT), usually via a rigid-body marker on the patient as a reference coordinate system. Since CBCT is not always available, guidance concepts using fluoroscopic overlay of the surgical device have also been researched (Gao et al., 2011; Wong et al., 2015). Recent work on pelvic

guidance proposes augmented reality (Wang et al., 2016) and 3D-printed guide templates (Chen et al., 2016).

The assumption of rigidity between CT and the patient requires that the pelvis is not strongly displaced by a fracture – a reasonable assumption for simple undisplaced fractures, which constitute a majority of fragility fractures (Rommens et al., 2017). Deformation of the implant, however, such as bending of the K-wire or even the fixation screw, introduces geometric error for rigid tracking. Although electromagnetic tracking (Lehmann et al., 2015) can overcome this problem by tracking the tip instead of an external rigid body, such systems experience a loss of accuracy in proximity to metal (such as the C-arm or implant) (Yoo et al., 2013; Lugez et al., 2015) and may require custom instrumentation to track devices within the body. Moreover, all of these concepts require additional devices in the OR, taking space and time for setup.

3D-2D registration can address many of these limitations (Markelj et al., 2012). Recent work demonstrates accurate localization of surgical devices using the concept of rigid “known components” (Uneri et al., 2015). Prior knowledge is used to determine the 3D device location from 2–3 fluoroscopic images acquired in routine workflow. With the patient registered via 3D-2D registration of preoperative CT and intraoperative fluoroscopy, visualization (CT overlay) analogous to surgical navigation can be created without additional devices in the OR. Recent work on deformable known components (dKC) (Uneri et al., 2016) relaxes the constraints of device rigidity, allowing deformable devices such as K-wires to be localized for surgical guidance.

As with any surgical navigation system, definition of a surgical plan is helpful in providing guidance relative to the *intended* device placement. Moreover, definition of a surgical plan provides the basis for quality assurance (QA) at the end of the case in terms of differences between the intended and delivered surgical product (Uneri et al., 2017). Although manual planning of trajectories is certainly possible, manual interaction in 3D volumetric images adds labor-intensiveness and variability to standard workflow. In the work reported below, we therefore incorporate an atlas-based registration method to *automatically* calculate a surgical plan in the patient’s preoperative CT (or intraoperative CBCT).

In this work, a system for automatic planning, guidance, and QA is presented, which provides trackerless localization of deformable surgical devices in the patient. Atlas-based registration is used to automatically define patient-specific device trajectories (“plan”), and 3D-2D registration of the CT and fluoroscopic views already acquired in routine workflow is performed with deformable registration of devices (K-wires) for guidance analogous to surgical navigation.

2. Background

2.1. Atlas of Surfaces and Surgical Trajectories

A surgical plan provides a basis against which to compare the locations of devices or tools in surgical guidance and QA (Uneri et al., 2017). Although manual annotation of desired trajectories is certainly possible, it requires additional workflow and interaction with 3D

images in a way that can be time-consuming and disruptive to workflow. Automated trajectory planning can be achieved from 3D preoperative images using shape description of certain bones, e.g., spinal pedicle planning (Knez et al., 2016; Solitro and Amirouche, 2016; Goerres et al., 2017) or acetabular screws (Banerjee et al., 2016). In these works, a surface of bone (or parts of it) is manually or semi-automatically obtained to optimize a trajectory with respect to constraints based on shape, geometry, bone density, and/or statistical commonality. Recent work (Goerres et al., 2017) proposed an atlas-based approach for automatic trajectory planning from a set of surfaces with reference trajectory annotations therein. Patient-specific trajectories were determined from an atlas registration of the bone shape and from an optimization with respect to statistical commonality of the registered reference trajectories. Expert annotations are used to define prior knowledge in the reference trajectories of the atlas and allow different definitions regarding techniques and surgeon's preference. This concept relates prior knowledge about screw trajectories to the pelvis shape, but since patient-specific pelvis shape is not directly given by the voxel grid data structure, an algorithmic interpretation of the image data is required. A common approach involves deformable registration of an anatomical representation (e.g., an atlas) to the patient's CT. Such registration can be accomplished by methods based on active shape models (ASM), previously researched for the pelvis (Lamecker et al., 2004; Seim et al., 2008). We apply ASM registration for trajectory estimation.

For ASM registration, a statistical shape model (SSM) was created to represent plausible shape deformations. Variations in point distributions (representing the shape) were modeled using a principal component analysis (PCA) of corresponding surface vertices (x_j, y_j, z_j) derived from the atlas surfaces $S_i, i \in [1, \dots, n]$. Vertex correspondence was achieved by non-rigid deformable registration of Coherent Point Drift (CPD) (Myronenko and Song, 2010) using a template surface (a randomly selected atlas member) registered to all remaining surfaces in the atlas. Corresponding points were then concatenated to obtain the vector

$$\mathbf{x}_i = [x_1, y_1, z_1, \dots, x_k, y_k, z_k] \quad (1)$$

which is then used for the PCA. The resulting eigenvectors (principal components) are stored in a matrix $P \in \mathbb{R}^{3k \times n}$. A specific shape instance is defined by the model parameters $\mathbf{b} \in \mathbb{R}$, which scale the principal components P of the corresponding landmarks. Any input surface can therefore be recreated from the SSM using $\mathbf{x}_i = \bar{\mathbf{x}} + P\mathbf{b}_i$. To limit the number of parameters in the following optimization, only the largest $d \ll n$ eigenvalues were used, following a coarse-to-fine hierarchy of $d = 1$ to 2 to 4 to 8.

2.2. Registration of Atlas Surfaces to Patient CT

A surface representation of the patient's pelvis is obtained by fitting an ASM (Cootes et al., 1995) to the patient's CT. The model instance $\mathbf{y}$ is described by shape parameters $\mathbf{b}_{\text{ASM}}$ and a similarity transform T_{ASM} :

$$\mathbf{y} = T_{\text{ASM}}(\bar{\mathbf{x}} + P\mathbf{b}_{\text{ASM}}) \quad (2)$$

Point adjustments are locally estimated by iteratively evaluating the image appearance at each vertex, and the most globally representative shape described by the SSM is selected. To estimate the point adjustments $\mathbf{y}_p$, 1D profiles perpendicular to the shape boundary are evaluated from CT. At each vertex, the point adjustment is defined by the position of highest image gradient magnitude along the profile. This procedure is done on several scales – a coarse-to-fine strategy with decreasing probe spacing and increasing image resolution. Once the adjustments are determined, a new pose T_{ASM} is estimated by applying a General Procrustes Analysis (GPA) (Gower, 1975), giving new landmark displacements $\mathbf{y}_s$. The shape parameters are then updated by

$$\Delta \mathbf{b} = P^T \tilde{T}_{\text{ASM}}^{-1} (\Delta \mathbf{y}_s) \quad (3)$$

where $\tilde{T}$ refers to rotational and scaling components of T .

2.3. Surface-Based Trajectory Planning

The ASM yields a sparse displacement field for each atlas surface to the input image. This transforms a set of pelvis surfaces from a previously defined atlas to the patient's pelvis shape in image data. Following the previous concept for spinal pedicle planning (Goerres et al., 2017), surface deformation can be used to transfer expert knowledge of ideal trajectories to new and unknown shapes.

To apply the deformation to the trajectory within each pelvis, Mean Value Coordinates (MVC) (Ju et al., 2005) interpolate a volumetric deformation field based on closed surfaces. Trajectory annotations are modeled as cylinder surfaces C_i . Each vertex of these cylinders is transferred using MVC, leading to the deformed cylinder surfaces $\tilde{C}_i$. The pose of a new trajectory (“plan”) is optimized by maximizing the overlap volume of the deformed cylinders $\tilde{C}_i$. Binary images of the surfaces (0.5 mm voxels) are then aggregated into an accumulation map $A = \sum_{i=1}^n \tilde{C}_i$ as illustrated in Fig. 2.

Rigid intensity-based registration of a straight binary cylindrical trajectory I (taken as the moving image) is performed to maximize its overlap with the accumulation map (taken as

the fixed image), with initialization provided by the mean annotations $\bar{\mathbf{a}}^{(j)} = \frac{1}{n} \sum_i \tilde{\mathbf{a}}_i^{(j)}$. Transformation parameters $\mathbf{z}$ with 6 degrees of freedom (DoF) are optimized to obtain the transformation T_{plan} , applied using linear interpolation. The sum of squared difference of intensity at each voxel defines the cost function:

$$E(\mathbf{z}) = \frac{1}{2} \sum_x [I(T_{\text{plan}}(\mathbf{z})) - A]^2. \quad (4)$$

To maximize accumulated overlap despite subtraction in the cost function E , the intensity values of I are multiplied by the number of atlas members n to match the maximum possible intensity in the accumulation map A . The cost function $E(z)$ is minimized using gradient descent optimization.

2.4. 3D-2D Patient Registration

Registration of the patient to the CT image can be performed using 3D-2D registration of fluoroscopy images. This approach has been applied to spine labeling (Otake et al., 2012, 2013), and extended in subsequent work (De Silva et al., 2016) to provide robustness in the presence of surgical implants. The basic workflow is in Fig. 3, where dotted lines highlight the patient registration. The rigid transform of the CT image T_{CT} is iteratively updated to optimize similarity between digitally reconstructed radiographs (DRRs) and the fluoroscopy images. The result aligns the CT volume V_{CT} with the patient location in C-arm coordinates. The registration maximizes similarity between the fixed radiograph (f) and moving DRR (m) by pixel-wise gradient correlation (GC) (Penney et al., 1998):

$$GC(f, m) = \frac{1}{2} \left\{ \frac{\nabla_x f \nabla_x m}{\|\nabla_x f\| \|\nabla_x m\|} + \frac{\nabla_y f \nabla_y m}{\|\nabla_y f\| \|\nabla_y m\|} \right\} \quad (5)$$

with ∇ denoting the gradient operator. The moving DRR is computed for a given gantry pose θ by integrating along rays $\vec{r}_\theta$ through the transformed volume $V_{CT}(T_{CT})$ resulting in $DRR(V_{CT}, T_{CT}) = \int_{\vec{r}_\theta} V_{CT}(T_{CT}) d\vec{r}_\theta$. Integrals were discretized using trilinear voxel interpolation of the volume V_{CT} . The GC similarity between radiographs R_θ and DRRs was optimized according to the covariance matrix adaptive evolutionary strategy (CMA-ES) algorithm (Hansen et al., 2003) with a population size of 400 and an initial standard deviation of $\sigma = 10$.

$$T_{CT} = \arg \max_T GC \sum_{\theta} \left(R_\theta, \int_{\vec{r}_\theta} V_{CT}(T_{CT}) d\vec{r}_\theta \right) \quad (6)$$

The transform T_{CT} was represented by a vector that concatenates position and Euler angles. Consistent with previous work (Uneri et al., 2014), three views with separating angles of at least 20° were used. Further details of the C-arm setup and view configuration are in section 3.2.2.

2.5. Known-Component Registration

To localize the position and orientation of a K-wire during insertion, a registration is computed in which, instead of the CT volume V_{CT} , a parametrizable mesh object $K(p)$ (viz., a cylinder of variable length and size) is resized and transformed to provide an optimal match of its DRRs with the x-ray projections:

$$\hat{p} = \arg \max_p \sum_{\theta} GC \left(R_{\theta}, \int_{\vec{r}_{\theta}} K(p) d\vec{r}_{\theta} \right) \quad (7)$$

This known-component (KC) method is based on rigid registration concepts demonstrated previously in spinal pedicle screw placement (Uneri et al., 2015, 2017). KC registration (KC-Reg) is illustrated in Fig. 3 by dashed lines. Recent work incorporated deformation to the component (Uneri et al., 2016).

3. Methods

We present a system for planning, guidance, and QA of percutaneous pelvic screws. An overview of the framework is shown in Fig. 1 with pre- and intra-operative stages in top and bottom rows. Preoperatively, an atlas containing pelvis surfaces and expert annotations of standard percutaneous trajectories are deformably registered to the patient's CT. Manual annotation or segmentation of the patient CT is not required. A new trajectory is optimized based on these transferred trajectories to provide an individual trajectory plan for the patient. The planning is therefore automatic and requires only validation/confirmation of the resulting trajectories (with opportunity to revise if desired). Intraoperatively, 3D-2D registration is used to align the CT to fluoroscopic images. Once the patient is aligned, 3D-2D deformable known-component registration (dKC-Reg) is used for 3D localization of a K-wire or screw. The location can then be overlaid on CT for guidance analogous to surgical navigation. Two or more fluoroscopic images are required for accurate 3D-2D localization - e.g., the same views commonly acquired in fluoroscopic guidance. By providing computer-assisted guidance, the system described here aims to reduce radiation dose by providing quantitative 3D localization rather than qualitative visualization/interpretation, which is subject to trial and error. Moreover, quantitative comparison of the wire location (or screw location at the end of the case) with the planned trajectory allows QA of the surgical product.

3.1. Automatic Trajectory Planning

3.1.1. Pelvis Atlas—An atlas was created from data in The Cancer Imaging Archive (Clark et al., 2013) using CT datasets of the lymph nodes (Roth et al., 2014; Seff et al., 2014). A relatively small ensemble of ($n = 12$) female pelvises was manually segmented by a technician trained regarding pelvic anatomy in CT. Each segmentation was converted to a closed surface representation S_i (triangulated mesh) and remeshed (Valette and Chassery, 2004) to obtain approximately $k \approx 5000$ equidistant vertices on each. The atlas in the current work is based on a fairly small number of shapes and uses a phenotype (female pelvis) that exhibits fairly broad shape variation. This challenges the ASM registration in that the principal components are derived from few samples (contrary to the high dimensionality) and that the patient shape is not precisely reflected in the sample data. Thus, while the atlas itself may not be generalizable to other work and applications, the method presented below for atlas-to-image registration is hypothesized to be sufficiently robust for purposes of automatic trajectory planning.

For each shape in the atlas, three screw trajectories (Superior pubic ramus, AIIS to PSIS, and Iliac crest to posterior column) were manually defined by the entry point $a_i^{(e)}$ and tip location $a_i^{(t)}$. The trajectory annotations were performed twice for each case as a check on intra-observer variation and were verified by a fellowship-trained orthopaedic surgeon, focusing on compromise between maximum trajectory length and maximum distance to cortical boundaries along the trajectories. The distal tip was also positioned at the cortex, which is beneficial to stability and allows using the trajectory definitions for placement from both directions (e.g., anterior or posterior approach to the superior ramus)

3.1.2. Robust Registration of Atlas Surfaces to Patient CT—Since point adjustment estimates are error-prone (e.g., when the gradient magnitude of another bone is determined) mismatch between ASM and image data can occur. Limitations of the original ASM algorithm applied to clinical data have been addressed in part by optimizing point displacement estimates using pattern recognition (Heimann and Meinzer, 2009). We focused instead on maintaining the stability of the surface model transform T_{ASM} . High noise in the estimates was overcome by randomly selecting subsets of estimates and searching for the subset that produces the best surface model transform T_{ASM} . This approach works without training data and relies on local peak intensities (e.g., HU gradient), which works well in CT data with respect to gradients from bone cortex. For this purpose, we use the Random Sample Consensus (RANSAC) (Fischler and Bolles, 1981). In each iteration, a fixed number of points $n_{pts} = 20$ was randomly selected and used as input for the GPA. The resulting transform is then applied on the current model instance y and the sum of gradient magnitudes for all vertices is computed. After a fixed number of iterations $n_{it} = 50$, the transform with the highest sum is taken as the new transform T_{ASM} . This transform stabilization is an ASM extension independent of the underlying SSM and is therefore hypothesized to provide a robust registration, even if there is a certain amount of shape mismatch at distal locations (e.g., atlas is limited in representing the actual patient shape).

3.1.3. CT-Based Trajectory Planning—Surgical planning is accomplished directly in the image data using a single model-to-*image* registration. In previous work, many surface-to-*surface* registrations were performed, requiring that the patient image be segmented to provide the input surface (whereas the current method operates on the patient image directly without segmentation). In the current work, Mean Value Coordinates (MVC) (Ju et al., 2005) were based directly on the parameters of the ASM and can be applied to all trajectory definitions in the atlas. By contrast in previous work (Goerres et al., 2017), the MVC were computed for each atlas surface individually to transfer the trajectory definitions therein. To incorporate the effect of the deformation on the trajectory within each pelvis in the atlas, MVC were applied to interpolate a volumetric deformation field based on the surface representation of the SSM. MVC allow one to deform an annotation $a_i^{(j)}$ associated with an atlas surface $\bar{x} + Pb_i$ to the annotation $\tilde{a}_i^{(j)}$ relative to the deformed shape $\bar{x} + Pb_{ASM}$ in Cartesian coordinates using the mean value transformations. This MVC approach was then applied according to the concept described in the Background section 2.3. to transfer the expert annotations and optimize the trajectory.

3.1.4. Evaluation of Atlas Registration and Surgical Trajectories—A leave-one-out cross-validation of the atlas members was performed. For each leave-one-out atlas (of size $n - 1$), the remaining member $i := \text{ref}$ was used as reference for analysis of registration accuracy and surgical trajectory. To evaluate atlas-to-CT registration accuracy between the ASM output surface Q (defined by y) and the manually annotated atlas surface S_{ref} , we computed the minimum distance between a vertex q on Q to the closest vertex on surface S_{ref} :

$$d_{\min}(q, S_{\text{ref}}) = \min_{s \in S_{\text{ref}}} |q - s|. \quad (8)$$

To measure the difference between surface Q and S_{ref} , the distance $d_{\min}$ was applied to all vertices in $q \in Q$ and summarized in the root mean square (RMS) surface error:

$$d_{\text{rms}}(Q, S_{\text{ref}}) = \sqrt{\frac{1}{|Q|} \int_{q \in Q} d_{\min}^2(q, S_{\text{ref}}) dQ}. \quad (9)$$

To determine a sufficient number $n_{\min}$ of atlas members for the atlas-to-CT registration, subsets of different atlas size were extracted. For each atlas size $n_{\min} > 3$, the subsets $\bigcup_{v=\mu}^{n_{\min}+\mu} \{S_v\}$, $\mu = [0, \dots, n - n_{\min}]$ were created, and a leave-one-out analysis was applied to each. The leave-one-out analysis provided evaluation in unseen data, noting that the ASM was recomputed in each case excluding the target shape to reduce or eliminate bias. Evaluation via a fairly small atlas may provide a slightly overestimated mean (and higher variance) in accuracy compared to completely external data or k -fold cross-validation. Evaluation with larger sample size to predict the best possible registration accuracy in a clinical setting remains of future interest. All shapes in the atlas were used in the registration process (apart from leave-one-out cross-validation). A more optimal selection of shapes could further improve registration, as suggested by (Aljabar et al., 2009).

To evaluate the planning method described above, the accuracy of the trajectory estimate, $(t^{(e)}, t^{(t)})$, was evaluated in comparison to the “reference” trajectory $(a_{\text{ref}}^{(e)}, a_{\text{ref}}^{(t)})$. Various sample points $t^{(e)}, \dots, t^{(j)}, \dots, t^{(t)}$ were equidistantly spread along the trajectory ranging from -7.5 to 7.5 cm with respect to the center of the calculated trajectory. The sampled points $t^{(j)}$ were projected onto the reference trajectory $(a_{\text{ref}}^{(e)}, a_{\text{ref}}^{(t)})$ to measure the distances $|\text{proj}(t^{(j)}) - t^{(j)}|$. Additionally, the distance to surface $d_{\min}(t^{(j)}, S_{\text{ref}})$ was evaluated at each sample point $t^{(j)}$ (see Eq. (8)) to analyze proximity to bone cortex.

3.2. K-Wire Guidance and QA

3.2.1. Deformable Known-Component Registration—Since K-Wires are prone to deformation, we apply a deformable cylinder component based on recent work (Uneri et al., 2016). Instead of alternating a rigid transform $T_K(\tilde{p})$, $\tilde{p} \subset p$ of the known-component, B-spline knots are varied to deform the wire model. Therefore, the parameter vector p of this component describes the wire shape by a radius r and a B-spline deformation:

$$B(u) = \sum_{i=0}^n \alpha_i N_{i,h}(u) \quad (10)$$

where control points α_i are a subset of the parameter vector p , and $N_{i,h}$ are the B-Spline basis functions. Endpoints of the wire model were defined to be tangent to the B-Spline derivative at the first and last control point. We modeled the K-wire as a cubic spline with $h = 3, 4, 5$ knots of order $n = 3$ and initialized with 1.6 mm radius.

In addition to the basic dKC-Reg concept, a rigid tip was incorporated (Fig. 3) and a coarse-to-fine strategy was applied, which successively increases image resolution and deformability of the KC. Initially, a rigid multi-start is performed such that the KC is reinitialized 10 times, each with a different segment (position and length) of the plan applied. This procedure allows compensation for the (possibly unknown) field-of-view of the C-arm and to compensate for the unknown (and changing) position along the plan during insertion. The result with highest GC is taken as the input for the three consecutive stages of increased image resolution and dKC deformability. The pixel binning was reduced in three steps from $2 \times 2 \text{ mm}^2$ to $1.5 \times 1.5 \text{ mm}^2$ and then to $1 \times 1 \text{ mm}^2$, and the number of B-spline knots was increased from 3 to 4 to 5.

3.2.2. Cadaver Experiment—The performance of dKC-Reg was evaluated in a study involving a human cadaver in which a selection of K-wires was delivered following standard pelvic trajectories. With the cadaver placed in supine position (Fig. 4, an elderly female, moderately obese, dissected at the upper humerus and mid-femur), K-wires were inserted into the left hip through the superior pubic ramus, from the AIIS to the PSIS, and from the iliac crest to the posterior column. These trajectories are visualized in Fig. 4(b–d). At three or four positions along each trajectory, images were acquired as described below. The wires were inserted by a fellowship-trained orthopaedic surgeon using Stryker K-wires of 3.2 mm diameter with threaded tip. Before the experiment, the cadaver was scanned using a multidetector CT (MDCT) scanner appropriate to preoperative planning (120 kVp, 500 mAs, $0.35 \times 0.35 \times 0.80 \text{ mm}^3$ voxels; Philips Brilliance 64-slice MDCT).

A motorized mobile C-arm (Cios Alpha, Siemens, Erlangen, Germany) as shown in Fig. 4 was used for both fluoroscopy and CBCT reconstruction (for truth definition) of K-wire placement. At each K-wire position delivered to the cadaver, three “inlet” and “outlet” views $\theta = \{-37.6^\circ, -10.2^\circ, 15.9^\circ\}$ that are commonly acquired in pelvic trauma fluoroscopy were acquired (125 kVp, ~ 0.9 mAs at 15 fps) and used for 3D-2D K-wire localization. A complete orbit of the C-arm covering 300° was acquired for CBCT in which the tip segment of the K-wire was manually annotated. Geometric calibration was performed using a BB phantom (Cho et al., 2005). The angular and orbital arcs were calibrated separately with the phantom in two different positions, and the two calibrations were aligned to a common 3D coordinate system by 3D-2D registration of the CBCT volume to 75 orbital projections ranging from -37.6° to 15.9° about the LR axis (omitting the three views used for 3D-2D to avoid bias in the solution). For patient registration, the transform T_{CT} was manually initialized, dislocated from the solution by $40.5 \pm 31.8 \text{ mm} / 25.3 \pm 22.6^\circ$ (median $\pm$ interquartile range, IQR). The component was initialized based on the plan registered to the

preoperative CT image as described above, differing from CBCT tip annotation by $78.1 \pm 44.3 \text{ mm}/6.4 \pm 3.3^\circ$ (median $\pm$ IQR).

3.2.3. Evaluation Methods—KC-Reg was evaluated in cadaver studies in terms of the wire tip location and orientation for rigid and deformable approaches. Based on manual point annotations in CBCT, the true wire tip was approximately represented by two points $c_l^{(t)}$ (at the tip) and $c_l^{(e)}$ (1.5 cm away from the tip) for each trajectory step $l \in \{1a-1d, 2a-2c, 3a-3c\}$ as shown in Fig. 4(b–d). Reference rotation was derived from the vector $c_l^{(e)} - c_l^{(t)}$ using Euler angles and stored in the rotation matrix $R_l^{(t,e)}$.

Tip error evaluation of the rigid KC-Reg compared the reference $R_l^{(t,e)}, c_l^{(t)}$ to the optimized transform T_K . The optimized transform was separated to rotation and translation, where r_l is derived from the principal axis of the known-component (third column of the rotational component), $r_l^{(t,e)}$ is accordingly derived from the reference $R_l^{(t,e)}$, and t_l is the translation. The deviation in positional (mm) and angular ($^\circ$) measurements was computed by:

$$\text{TRE}_x(l) = \|t_l - c_l^{(t)}\|_2 \quad (11)$$

$$\text{TRE}_\phi(l) = \cos^{-1} \frac{r_l \cdot r_l^{(t,e)}}{\|r_l \cdot r_l^{(t,e)}\|} \quad (12)$$

Similarly, the tip evaluation of the deformable known-component compared the reference to the first B-spline knot α_0 with an additional offset transform T_{tip} for the rigid tip extension (with respect to tip direction $B_i'(\alpha_0)$).

$$\text{TRE}_x(l) = \|T_{\text{tip}} \cdot B_l(\alpha_0) - c_l^{(t)}\|_2 \quad (13)$$

$$\text{TRE}_\phi(l) = \cos^{-1} \frac{B_l'(\alpha_0) \cdot r_l^{(t,e)}}{\|B_l'(\alpha_0) \cdot r_l^{(t,e)}\|} \quad (14)$$

The analogous performance of optical trackers (using externally fixed markers and a rigid body model of the tracked tool) was estimated by investigating the effect of wire deformation to a geometric straight line. We assumed the rigid-body marker of the tracking system to be located near the bone entry point. To evaluate the geometric error introduced by wire deformation between the tip and the positioning of the rigid body marker at the outer bone cortex, a straight line was created from the B-spline direction $B_u^i(u)$ and a manually annotated point at the entry-point cortex intersection (mapped to obtain u). The Euclidean

distance of the wire tip $T_{\text{tip}} \cdot B(\alpha_0)$ was then compared to this straight line to determine the mislocation introduced by deformation. The resulting estimate is conservative in that it respects only the perpendicular deviation of the wire tip to the straight line, whereas an optical tracker would also have an additional error along the straight line (as bending a tracked tool affects the length).

4. Results

4.1. Registration Accuracy: Pelvis Atlas

The leave-one-out analysis showed RMS surface error of 2.3 ± 0.6 mm. As shown in Fig. 5, the RMS error reduced to less than 4 mm after 40 iterations and to ~ 2 mm in another 130 iterations. A linear regression suggests slow improvement in accuracy with additional members (-0.03 mm/atlas member). The error in atlas registration for the cadaver image was 1.8 mm. As shown in Fig. 6, the error evaluated at each surface vertex location showed low error in smooth areas and higher error near strong curvature, protrusions, and depressions. Fig. 6 also shows example registrations for the leave-one-out atlas evaluation (Fig. 6(b)) and the cadaver preoperative CT (Fig. 6(c)) with the registered atlas contour overlaid in green. As in the vertex evaluation, slightly larger errors are observed near higher curvature – e.g., the iliac crest and pubic symphysis – while smoother areas overall – e.g., across the iliac wing and superior pubic ramus – the registration is typically within 1 mm.

4.2. Registration Accuracy: Planned Surgical Trajectories

The distance between the planned trajectory and the bone cortex characterizes the suitability of the plan with respect to safety (i.e., conformance within the bone corridor). The cortex distance along each planned trajectory was evaluated in the leave-one-out analysis as summarized in Fig. 7, showing the closest vertex distance between sample points along the trajectory and the pelvis surface. Results are shown for the automatically calculated trajectory (top row) and for the reference trajectory (bottom row), showing a similar overall pattern with respect to surrounding anatomical structures, with mean distance deviating by ~ 1 – 2 mm. A positive distance indicates conformance within the bone, with mean trajectory-to-inner-cortex distance was: (i) $+3$ – 4 mm for the superior ramus, (ii) $+5$ mm for AIIS to PSIS, and (iii) $+4$ – 5 mm for the iliac crest to posterior column. A small number (1–2) of outliers was observed in registration near trajectory endpoints.

The accuracy of the trajectory calculations was further characterized by comparison to the expert reference. Two distributions were compared – calculated-vs-expert; and expert-vs-expert (to assess intra-observer variability in repeat definition) – as shown in the top and center rows of Fig. 8, with p-values (bottom row) along the trajectory suggesting a lack of statistically significant difference between the two distributions. Overall, the results show mean difference ~ 2 – 3 mm in narrow bone corridors, with higher deviations at the trajectory endpoints – similar to the intra-observer deviations. Statistically significant differences at the endpoints of the iliac crest reflect variations in possible entry points, whereas differences at the narrowest section of the superior ramus (~ 1 – 2 mm) suggests a high degree of consistency for the expert in traversing the center of the corridor, whereas the automatic algorithm permits a wider variation (but still within the corridor) – i.e., while statistically

significant, the differences do not appear clinically significant with respect to achieving a safe trajectory.

Similar performance was found for the automatically calculated trajectories in the cadaver study. Fig. 9(a), shows the distance between the automatic and reference trajectories, showing similar overall deviations as the leave-one-out evaluation in Fig. 8. Fig. 9(b–d) show slices of the CT overlaid with both the atlas registration (yellow) and calculated trajectory (green).

4.3. dKC-Reg Accuracy for Guidance and QA

Fig. 10 summarizes results of dKC-Reg localization of the K-wire in cadaver studies. The result illustrate the limitations of rigid tracking, with errors up to 9.1 mm at the tip evident between the deformable KC model and a straight rigid extrapolation from the entry point. As shown in Fig. 10(c), the coarse-to-fine registration was essential to reducing geometric error (and especially outliers) – with a rigid model showing up to 28.9% rate of outliers in TRE_x , because the tip of the wire was not reached. An example of such behavior is shown in Fig. 10(b), in which the (yellow) outline of a rigidly registered KC model is overlaid on a fluoroscopic image from the cadaver experiment. Although the model aligns with the K-wire, rigidity constrains the component to a line segment and fails to encompass the full (curved) length of the wire. Deformable dKC-Reg resolved such constraint, yielding TRE_x and $TRE_\phi \sim 1$ mm and $\sim 1^\circ$, respectively, and reducing outliers.

5. Discussion and Conclusions

We have presented a system for planning, guidance, and QA of percutaneous screw placement in orthopaedic pelvis surgery. Based on a preoperative CT and an atlas of pelvis surfaces and trajectory definitions, three standard fluoroscopy images were used to determine K-wire pose and deformation. The K-wire location (including deformation) can be overlaid on CT images in a manner analogous to surgical navigation. By determining the patient's pelvis shape in CT data, a surgical plan is calculated using statistical knowledge of reference trajectories in the pelvis atlas. The planned trajectory is then compared to the K-wire registration to measure deviation for purposes of QA. For example, Fig. 11 illustrates guidance of K-wire placement at an intermediate step along insertion in the superior ramus. The automatically planned trajectory is shown in green. The deformably registered K-wire is shown in yellow, presented either in Fig. 11(a) fluoroscopic views or (b–d) CT image slices (or volumetric renderings). Figure 11b shows an example in which the wire is not on target and significantly deviates from the plan. The wire tip is propagated forward along the current trajectory to give navigation-like feedback via straight line projection (visualized by a thin yellow line with measurement grid). Given that the continuation exits the bone, the path shows that the trajectory is deviating from the optimal course, and the surgeon should re-direct the approach to stay within the bone corridor. Early detection of such deviation in path may also save time (and dose) compared to conventional fluoroscopy, because deviations are detected early, allowing prompt course correction. Fig. 12 similarly illustrates application to QA of device delivery. The surgical plan and registered K-wire are again shown in yellow and green, respectively, and example QA tools are illustrated as highlights

of cortical breach (red) and distance between planned and delivered trajectories (yellow-green colorscale along the K-wire). The system has the potential to reduce fluoroscopy time due to reliable, quantitative trajectory localization that to guide the approach and reduce trial and error.

Atlas-based registration provided accurate, segmentation-free alignment to pelvis CT images, achieving comparable results to related work focusing on pelvis modelling and registration (Lamecker et al., 2004; Seim et al., 2008). This was achieved even though the statistical shape model was limited by the relatively small atlas used in the present work. An important factor for this was using the RANSAC extension for robust registration, whereby stable results were achieved with just two atlas members. Without this extension, the original ASM algorithm (Cootes et al., 1995) did not converge to a stable result. However, the non-deterministic nature of RANSAC introduced minor fluctuations (smaller than 0.3 mm), which contributed to the non-monotonic behavior of the boxplot in Fig. 5b.

The goal of this study was to present an atlas-to-image registration method for purposes of trajectory planning, recognizing that the fairly small atlas used in the current work may not, in itself, be sufficiently generalizable to other applications. Specifically, the evaluation demonstrated successful registration even using a relatively small number of atlas members ($N = 12$) with a fairly broad phenotype (i.e., female, for which pelvic shape variations are believed to be greater than for male). Evaluation of the ASM registration was not exhaustive and instead focused specifically on the accuracy of trajectory planning, rather than the accuracy of bone surface registration. Planned trajectories for K-wire placement in the pelvis demonstrated an acceptable level of accuracy, in part because the accumulation map (from which the trajectories are determined) was robust against small deviations in surface registration. If a case were to exhibit a strong, high-frequency variation in surface shape in proximity (within a few mm) to the trajectory, then the accuracy of planning would be adversely affected. However, the accumulation based on even a small atlas did not exhibit such effects in this work, and the reliability of automatically calculated trajectories did not appear to be substantially affected by the relatively small atlas size nor the common challenges of active shape models at depressions and protrusions, which may be addressed by additional methods (Heimann and Meinzer, 2009; Kainmueller et al., 2013). The current framework is applicable to undisplaced fractures (which constitute the majority of insufficiency/fragility fractures) and does not directly account for displaced fragments. One may envision, however, application of registration methods developed for fracture reduction (Jiménez-Delgado et al., 2016) to better permit calculation of trajectories for fragmented bones as well. Generalizability of the concept also allows extension to 3D-2D approaches that relate x-ray image content directly to a 3D deformable statistical atlas (Yao and Taylor, 2003; Chintalapani et al., 2007; Ehlke et al., 2013).

Evaluation of the distance between K-wire trajectories and the bone cortex demonstrated that calculated trajectories safely traverse bone corridors with margin sufficient for common screw sizes (Attias et al., 2005). Calculated trajectories showed close agreement (mean ~ 1 – 2 mm) with expert reference trajectories in narrow corridors (e.g., superior ramus). Larger discrepancy (mean ~ 3 – 6 mm) was observed at trajectory endpoints but are in accordance with intra-observer variability, with no statistically significant difference detected between

reference and calculated entry point locations. We observed 1–2 outliers in trajectory (at the superior pubic ramus) that did not provide sufficient space for common screw sizes, resulting from limitations in the atlas-to-image registration and in the statistical modelling of the pelvis shape, which in its current form may underrepresent some modes of shape variation in pelvic subtypes (Caldwell and Moloy, 1933).

The dKC-Reg method provided accurate (1–2 mm) localization of the deformed K-wire tip from three fluoroscopic views acquired in routine workflow. By contrast, a rigid-body model (as with surgical tracking) exhibited errors up to 9.1 mm due to K-wire deformation. The deformable (dKC-Reg) registration method further improved performance compared to rigid (KC-Reg), providing robustness to outliers and accurate registration along the entire (curved) K-wire. The presence of additional wires or implants that are not present in the CT could potentially affect the dKC registration. Previous work (De Silva et al., 2016) examined the question of such mismatch specifically, demonstrating robust registration, depending on the choice of similarity metric. Such methodology can be integrated in the dKC-Reg method reported here. In the current work, the GC similarity metric provided sufficient robustness against content mismatch in the patient registration step, and other work (De Silva et al., 2016) showed potentially improved performance using gradient orientation (GO) similarity. In the dKC device registration step, GC similarity specifically focuses on gradients associated with the interventional device and is therefore an appropriate choice. Although the patient- and dKC-registration could generally be performed in parallel, both registrations are required for purposes of guidance and QA of device placement. Sequential application was used to initialize the dKC component closely to the planned trajectory (transferred through patient registration), thereby significantly reducing the time compared to searching in the whole projection image.

One can envision workflow for dKC-Reg guidance according to a “step and shoot” process similar to current fluoroscopy guidance – e.g., two or three steps along the length of a long (>10 cm) wire trajectory – to assess the accuracy of approach. Such step and shoot workflow is common in fluoroscopically guided procedures (c.f., real-time navigation with a surgical tracker, which is likely unnecessary for K-wire placement in bone). We anticipate that the dKC-Reg system will provide valuable information at the beginning of wire insertion (to validate the entry point and initial trajectory), when traversing narrow bone corridors or vulnerable anatomical structures (e.g. articular surfaces, nerves, vessels, and other soft tissue), and at the end of the trajectory (to confirm final placement). The intra-operative registration methods were implemented in a basic form on GPU, requiring 30 s for patient registration and ~1–3 min for dKC-Reg in its current, rudimentary implementation (depending primarily on the depth of the coarse-to-fine cascade). The dKC-Reg algorithm could be further accelerated using a space-partitioning data structure for faster access of triangles in the mesh projection. Pre-operative (atlas-based) registration is not time critical, with sufficient time between acquisition of the CT and the time of surgery. The ASM registration was computed in ~3 min, and each trajectory required ~30 s, depending on the resolution of the accumulation map.

Future work includes extension of the atlas to the whole pelvis and sacrum (c.f., left-side pelvis in the current work) and investigation of additional trajectories, such as sacroiliac

screws (Routt et al., 1993). Application to other surgical sites and applications (e.g., femoral neck fractures and spinal pedicle screw placement) are also of interest, where automatic planning, guidance, and intraoperative QA could benefit surgical precision and outcomes.

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Figure 1. Flowchart illustration of the system for planning, registration, guidance, and QA in pelvic trauma surgery.

Figure 2.

Automatic planning of pelvic screw trajectories. Reference trajectories (cylinders C_i) from the atlas are transformed via the deformation defined by the ASM surface-to-image 3D deformable registration. The superposition of registered trajectories (deformed cylinders $\tilde{C}_i$) yields an accumulation map for trajectory pose optimization.

Figure 3. 3D–2D registration. (a) Flowchart for the 3D-2D registration process. Patient registration uses only the five top boxes connected by dotted lines. Deformable known-component registration (dKC-Reg) uses the five bottom boxes connected by dashed lines. (b) Definition of parameters used for rigid or deformable component registration.

Figure 4.

Cadaver studies. (a) C-arm setup with cadaver for 3D and 2D imaging. (b–d) Three standard screw trajectories for pelvic trauma surgery shown in projections of cadaver and K-wire. Three or four steps are annotated along each trajectory: Superior pubic ramus; AIIS to PSIS; Iliac crest to posterior column.

Figure 5.

Atlas-to-CT registration performance evaluated as surface distance errors in leave-one-out analysis. (a) RMS error as a function of number of iterations. (b) RMS error as a function of atlas size, with a dotted line overlay showing linear regression (slope -0.03 mm per additional atlas member).

Figure 6. Example Atlas-to-CT registration. (a) Rendering of template surface, colored according to the average surface distance error. Example CT slices are shown for (b) atlas and (c) cadaver. The outline of the registered atlas is highlighted by green contours.

Figure 7.

Conformance of trajectories within bone corridors. (Top row) automatically calculated trajectories. (Bottom row) manually defined reference trajectories. Positive values indicate conformance within the bone corridor, and negative values indicate a breach of the bone cortex.

Figure 8.

(Top row) Comparison of automatically calculated trajectories and expert reference trajectories in terms of the distance between trajectories at equidistant sample points. (Middle row) Intra-observer reproducibility in trajectory definition. (Bottom row) P-values (paired t-test) along the trajectory, showing an overall lack of statistically significant difference between calculated and reference trajectories.

Figure 9.

Automatic trajectory planning in the cadaver study. (a) Distance between automatically planned trajectory and the reference trajectory at equidistant sample points along the trajectory. (b–d) CT slices overlaid with outline of registered atlas (yellow) and calculated trajectory (green) for three trajectories: (b) superior ramus, (c) AIIS to PSIS, and (d) Iliac crest to posterior column.

Figure 10.

Registration error for different rigid and deformable K-wire localization. (a) Illustration of geometric error from wire deformation – up to ~9 mm with rigid-body assumption (e.g., optical tracking). (b) Example outlier (failed registration) and TRE for an example rigid KC registration. (c) TRE for multistage deformable dKC registration.

Figure 11.

Registration for planning and guidance. During K-wire insertion, the dKC model (yellow) is registered to three radiographs (two shown in (a)) and overlaid on CT (b–d). As common in surgical navigation, slices are aligned to the axis of the K-wire tip segment, yielding (b) quasi-coronal, (c) quasi-axial, and (d) quasi-sagittal views of the planned and delivered trajectory relative to surrounding patient anatomy.

Figure 12.

Registration for surgical QA. Following K-wire placement, the dKC model (yellow) is registered to three radiographs (two shown in (a)) and overlaid on preoperative CT (b–d). Example QA measures are illustrated to highlight cortical breach (red) and deviation from the planned trajectory (yellow-green colorscale).