Spotlights: A Robust Method for Surface-Based Registration in Orthopedic Surgery

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ABSTRACT

Fast, simple and effective registration methods are needed in a wide variety of computer-assisted surgical procedures in which readily locatable anatomical landmarks are not available. Orthopedic procedures about the knee, in particular, are adversely affected if the registration accuracy exceeds about 1 mm in translation or about 2° in rotation, and the proximal tibia and distal femur are typically devoid of small distinct features. Surface-based least-squares registration methods can be used, but are susceptible to poor initial pose estimates and to error contamination during intraoperative data collection.

We have developed a fast, statistically robust method for surface-based registration. The method is based on the iterative closest point (ICP) algorithm, and fits a set of sparsely measured data points to a planar facet model. An initial registration estimate is obtained by having the user contact the anatomy in a set of general anatomical regions (rather than contacting distinctive features). A small number of additional data points are acquired to refine the registration. Starting from the initial estimate, a robust scored perturbation method is used to find an initial registration. This is followed by an M-estimate ICP registration which is taken as the final registration. Simulation results show that this method is robust for data sets containing up to 25% gross outliers.

The method has been tested *in vitro* on plastic bone models, where it robustly outperformed the least-squares estimate and maintained the required 1mm/2° accuracy. The *in vivo* use of spotlights in computer-enhanced osteotomies of the knee and wrist have confirmed that the method is easy to use and sufficiently accurate.

1. Introduction

Registration of a patient to a medical image is often performed by finding a rigid transformation that minimizes the squared residual error between the surgical points and points on a model derived from a 3D medical image. One widely cited surface-based registration method is the iterative-closest-point (ICP) method of Besl and McKay [2]; for this local-search method, computation speed and registration accuracy are dependent on how an initial registration estimate is chosen. Two widely acknowledged problems with ICP-like surface registration methods are (1) the need for a good initial estimate, and (2) that minimizing the sum-of-squared residual error is optimal only when the measurement errors have Gaussian distributions. If measurements are accidentally taken far from the target anatomy (e.g., if a foot pedal is accidentally hit or if the contact point is outside the CT scan region), then a least-squares error measure can produce poor results.

Here we present a fast, robust method for surface-based registration. The use of robust statistical methods provides reliability and accuracy in the presence of outliers. We use a method for finding an initial registration that is easy to use in practice, requiring only that the the surgeon contact the anatomy in a set of general anatomical regions (rather than at specific anatomical landmarks). The user interface presents the surgeon with a visualization of the target anatomy in which these restricted regions are individually illuminated, so the process is termed *Spotlight* registration. Figure 1 shows an example surface mesh of the proximal tibia and four spotlight regions. The contact points, along with the spotlight regions are used to compute the initial registration. The registration is further refined by the use of a robust optimization procedure. The surgeon may then collect additional points within the exposed anatomical region for further refinement. A perturbation technique is used to refine the initial estimate, and a robust M-estimator is then used to obtain the final estimate of the registration. The method is fast and provides reliable results.

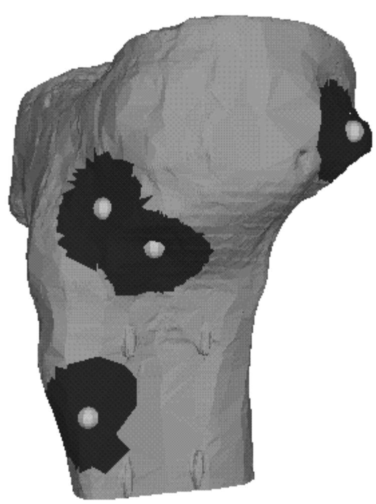


Figure 1: A surface mesh of a phantom proximal tibia, derived from computed tomography, and four spotlight regions for registration. The spheres mark the centers of the spotlights.

2. Robust Surface-Based Registration

Rigid-body surface-based registration is the process of finding a transformation from a set of measured points on the target anatomy to the model surface derived from the medical image. Let $P = \{\mathbf{p}_i\}$ be a set of n surface-data points measured from the target anatomy by the surgeon, let $X = \{\mathbf{x}_i\}$ be the set of all points on the surface model, and let $T(\tau)\mathbf{z} = R(\hat{q})\mathbf{z} + \mathbf{t}$ be a rigid transformation of a point $\mathbf{z}$. The registration goal is to find both the rigid-body transformation T and some n-element subset Y of model surface locations X to which the target anatomy locations P project under T. In the presence of errors the anatomical points P will not in general project exactly onto Y. A least-squares solution to the surface-based registration can be stated as the minimum, over τ and $Y \subseteq X$, of

$$F_2(\tau, Y) = \sum_{i=1}^{n} \|\mathbf{y}_i - T(\tau)\mathbf{p}_i\|^2 \tag{1}$$

where $\mathbf{y}_i \,\epsilon\, Y$. In the general case this is a non-convex minimization problem with multiple local minima.

Statisticians have long been aware of the need for robust methods of parameter estimation [10, 15]. Robust methods have been applied widely in the computer vision community for many estimation problems, including pose estimation [6, 11, 12] which is mathematically similar to the registration problem. Grimson *et al.* [5] performed point-to-surface matching by progressively refining the registration using a series of objective functions. Although it was not stated explicitly, their final objective function is the Huber [10].

Many robust estimation techniques use *M-estimation*, in which the L_2 norm in (1) is replaced with a robust norm to yield an objective function of the form

$$F_M(\tau, Y) = \sum_{i=1}^{n} \rho(\mathbf{y}_i - T(\tau)\mathbf{p}_i;\, \sigma) \tag{2}$$

where $\rho(r;\, \sigma)$ is the robust norm applied to the residual r, and σ is a scale parameter that depends on the form of the expected error distribution. One robust estimator that has reportedly provides good performance on 3D range data [14] is the Tukey biweight:

$$\rho(z;\, \sigma) = \begin{cases} \frac{\sigma^2}{2}(1 - (1 - \frac{z^2}{\sigma^2}))^3 & \text{if } z \leq |\sigma| \\ \sigma^2/2 & \text{otherwise} \end{cases} \tag{3}$$

We used ranked scores of perturbations of the least-squares estimator to improve the initial registration. We then used a robust M-estimator version of ICP to refine the registration further. These estimators form the basis of a fast and accurate method for surface-based registration.

The main stages of our surface-based registration method are:

1. Spotlight data are gathered intraoperatively. The surgeon contacts points on the exposed anatomical regions that correspond to the spotlights shown on a monitor, as in Figure 1.
2. The initial contact points are first matched to the spotlight *centroids* on the model using a simple least-squares minimization method [9].
3. The initial contact points are then matched to the spotlight *surface regions* on the model, using a least-squares ICP method.

4. The surgeon then contacts another set of points on the relevant exposed anatomical region. These locations should be chosen to cover the anatomy that will be involved in the image-guided surgery, and should provide sufficient translational and rotational constraints on the registration.
5. The initial registration, along with the full set of contact points, is then scored. The initial registration is repeatedly perturbed, and the least-squares residual for each point is calculated. The perturbation with the largest number of residuals that are all less than a user-supplied threshold is taken as the best initial registration estimate.
6. Finally, the perturbation registration estimate is then refined further using a version of the ICP algorithm that incorporates the robust Tukey-biweight M-estimator.

Each iteration of the ICP algorithm actually involves two estimation steps: given a registration estimate, one needs to find the set of closest points on the surface to the transformed data points. It is important that this search for the closest points be fast because it is one of the most computationally demanding steps of the algorithm. From these closest points on the surface, one then needs to update the registration estimate.

2.1 Finding Nearest Neighbors on a Surface Model

Given a registration, the ICP method requires that one solve the nearest-neighbor problem: For each point $\mathbf{p}_i$ and a model X, the point $\mathbf{x}_i$ in X that is nearest to $\mathbf{p}_i$ under the transformation must be found. If X is a triangulated surface mesh then the facet containing $\mathbf{x}_i$ must be found so that $\mathbf{x}_i$ can be calculated. Exhaustive search over all facets is too time-consuming for models containing tens of thousands of facets.

Although heuristics have been proposed for finding the facet containing the nearest point [1, 13], one can in fact guarantee that a nearest neighbor is always found. For each model facet, find the centroid and the largest centroid-to-vertex distance. Record the largest centroid-to-vertex distance found over all facets, R, and build the k-D tree using the facet centroids. To find a nearest neighbor, first find the nearest centroid and compute its distance r. Use the region search algorithm of [1] to find all facet centroids within the sphere of radius $R + r$ centered on the data point. Finally, exhaustively search all returned facets to find the true nearest neighbor.

In practice this algorithm can return a large number of facets, especially when the datum $\mathbf{p}_i$ is very far away from the model or if the model contains some unusually large facets. The requirement can be relaxed by limiting the number of returned facets to a fixed number (to reduce computation time). Compared to exhaustive search, speed increases of more than two orders of magnitude were observed for models containing tens of thousands of facets.

2.2 Refinement of Registration Using Perturbation

Even when started from a reasonable spotlight estimate, traditional ICP and simplistic robust variants suffer from “trapping” by converging to a local non-global minimum of the registration parameters. The usual robustness remedy is to perturb the solutions at the first, and possibly subsequent registration estimates [5, 7]. One alternative is to use a perturbation technique to conduct a local search through the possible registrations, seeking the registration that gives the best least-squares fit for the largest number of points. This alternative can be accomplished heuristically by means of a simple search procedure.

Our implementation sampled sixty-four points uniformly from a unit hemisphere to define sixty-four axes of rotation. The surgical data were rotated, about their mutual centroid, around each of these axes by ± 3 degrees and the Euclidean residual errors were calculated. For each of the 128 rotations, if half of the transformed surgical data had residuals that were less than a provided threshold value (1 mm) then the rotation was noted. The perturbation that produced, for at least half the surgical data, the minimum maximum residual was deemed to be the perturbation that gave the best initial fit to the refinement surgical data.

2.3 Robust Registration Estimation

A robust version of ICP was produced by modifying the process of updating the registration. This requires a solution to the absolute orientation problem, for which Horn's method provides a common least-squares solution.

To obtain an M-estimate of absolute orientation, we use an iteratively reweighted least-squares modification [8, 6] of Horn's method [9]. The scale parameter σ in Equation (3), is estimated, following Rousseeuw [15], as a function of the parameters τ by using the median of absolute deviations of the residuals: $\mathbf{r}_i(\tau) = \mathbf{y}_i - T(\tau)\mathbf{p}_i$:

$$\sigma = 1.4826 \operatorname*{median}_{i=1..n} \left(\|\mathbf{r}_i(\tau)\| - \operatorname*{median}_{i=1..n} \|\mathbf{r}_j(\tau)\| \right) \tag{4}$$

3. *In Vitro* Experiments

One application of computer-enhanced orthopedic surgery is to the high tibial osteotomy, for which the surgical exposure is limited to the anterolateral aspect of the proximal tibia. The only distinctive landmarks are the tibial tubercle (which is concealed by the patellar tendon) and the fibular head (which is mobilized from the tibia by osteoclasis). Spotlight registration was examined as an alternative to fiducial registration, which is very accurate but invasive.

As a standard comparison, we also considered the procedure of pedicle-screw insertion into a lumber vertebra, for which the posterior aspect of the ends of the transverse and superior articular processes provide prominent landmarks.

3.1 Materials and Preparation

A plastic tibia and L4-vertebra (Sawbones, Vashon, WA) were instrumented with three titanium-alloy anchor screws of 1.9 mm diameter (Wright Medical Devices) that acted as fiducial markers. The phantoms were imaged by computed tomography, and decimated isosurface models were produced. The tibial mesh contained 34,537 vertices and 68,564 triangular faces, and the vertebral mesh contained 27,096 vertices and 54,904 faces. The fiducial locations in CT coordinates were found using a previously validated center-of-mass calculation [3] and the locations were verified with Roentgen stereogrammetric analysis.

The phantoms were fixed in frames and the fiducial markers were contacted using a six-degree-of-freedom mechanical pointer (FARO Technologies, Lake Mary, FL) to obtain a registration that bore a known error to ground truth [4]. For the tibial phantom, twelve 10 mm$\times$10 mm squares were drawn on the surface in the area of typical surgical exposure and 100 data points were collected for each square, attempting to keep the datum spacing as uniform as possible. For the vertebral phantom, eight 8 mm$\times$8 mm squares were drawn on the surface and data were collected as for the tibial phantom. Four spotlights of radius 10 mm were sampled with 100 data points each from the tibial phantom, and similarly for the vertebral phantom (with spotlights of radius 7.5 mm). Figure 1 shows the 3D tibial model and the spotlight locations.

3.2 Methods

A data set consisted of one point from each spotlight and one refinement point from each square on the surface, yielding a total of sixteen points for the tibial phantom and twelve points for the vertebral phantom. One thousand sets were randomly selected and assessed by six different procedures. For all but Step 1, all data in the set were matched to the entire isosurface:

1. Paired-point least-squares registration of initial data to spotlight centers.
2. Scored perturbation registration, starting from the registration of Step 1.
3. Robust Tukey-estimator registration, starting from the registration of Step 2.
4. ICP least-squares registration, starting from the registration of Step 1.
5. Robust Tukey-estimator registration, starting from the registration of Step 1.
6. Robust Tukey-estimator registration, starting from the registration of Step 4.

The purpose of Steps 1, 2, and 3 are to provide an overall estimate of robust registration. Step 4 is the traditional ICP registration, to which robust estimates can be compared (it also acts as an initial estimate for a robust estimates). Step 5 is a robust M-estimator started from a naive initial estimate, and Step 6 is a robust M-estimator started from an ICP estimate.

Traditionally the results of a registration with parameters τ are reported in terms of the root-mean-square of the residual errors between the data P and the nearest points $Y \subseteq X$ derived from the model points X. As we have shown in earlier work [4] this fails to describe the errors arising from incorrect estimates of the rotational parameters, so we use an axis-angle decomposition to analyse the results.

Suppose that the ideal transformation is $T_I(\tau)$. One can form the *residual* transformation between a given $T(\tau)$ and the ideal $T_I(\tau)$ as

$$D(\tau) = T(\tau)T_I(\tau)^{-1}$$

The matrix R_D of the transformation $D(\tau)$ is a rotation about an axis k by an angle θ. This angle is the angular error of the given $T(\tau)$ and is important because the angular error produces an increasingly large positional error of a transformed point as the point is increasingly far from the region from which the registration was derived. By comparison the translational error, which is the translational component of $D(\tau)$, is constant for all points.

To compare the results of surface registrations to the fiducial registration, the surface registration was applied to the measured location of fiducial marker nearest to the spotlight centroid. The distance between the transformed marker and the CT coordinate of the fiducial location was then calculated. The ideal registration transformation is unknown, so $T_I(\tau)$ was taken to be a registration derived from the fiducial markers (which were adjacent to the spotlight regions).

3.3 Results

The experiments produced an ensemble of 1,000 registrations for analysis, which represent a sampling of how the spotlight registration to an anatomical region might perform in practice. For each registration in this ensemble we calculated the angular error as the rotational difference between the sample registration and the fiducial registration. Histograms of the registration results of each step were produced, and are shown in Figure 2 and Figure 3.

4. An *In Vivo* Pilot Clinical Study

Spotlight registration has been conducted on six patients in Kingston General Hospital. Each patient presented with osteoarthritis confined to the medial tibiofemoral compartment and were deemed appropriate for high tibial osteotomy. Five of the six patients were instrumented with the type of fiducial markers used in the *in vitro* study. In each case the process of drilling 4mm Kirschner guide wires for a modified Coventry procedure was performed with the spotlight registration. Registration was validated visually by contacting bony surfaces both within and outside the spotlight regions, and by contacting the fiducial markers when they were present and unmoved by dissection.

The ultimate use of registration is in providing an appropriate treatment, so a standard outcome measure was used. Postoperative A/P radiographs were measured to determine the radiographic angle between the tibial plateau and the tibial shaft. From this angle was subtracted the intended correction angle. The resulting correction errors are tabulated in Table 1.

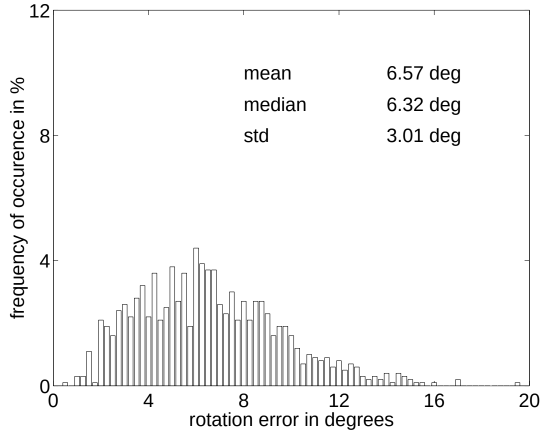
Table 1: Osteotomy correction errors arising from computer-enhanced surgery with spotlight registration.

	Patient Number					
Valgus correction	1	2	3	4	5	6
error (degrees)	$+1.5°$	$-1.5°$	$-1.5°$	$-1.5°$	$+0.5°$	$-1.0°$

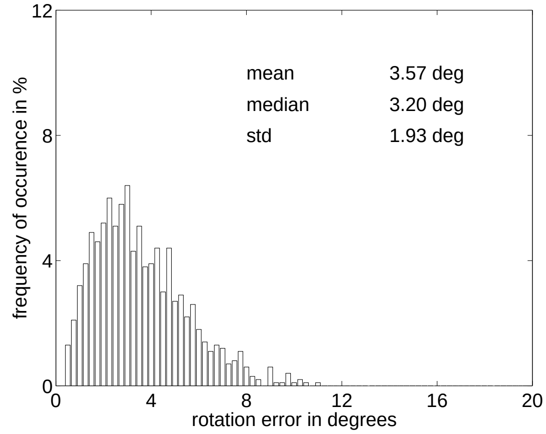
5. Discussion

The *in vitro* results for the tibial phantom demonstrate the utility of robust registration, as well as the sensitivity of robust estimators to the initial estimate. The final M-estimates of the registration had a median rotational error that was about 60% of the conventional ICP estimate, which is significant. However, if the M-estimator was started from the ICP registrations then the error was a little less than 80%, which is significantly different from our method and from the ICP method. Naive use of the M-estimator, starting it from a closed-form registration to the spotlight centroids, produced registrations for which the median rotational error was almost 10% larger than the simple ICP method.

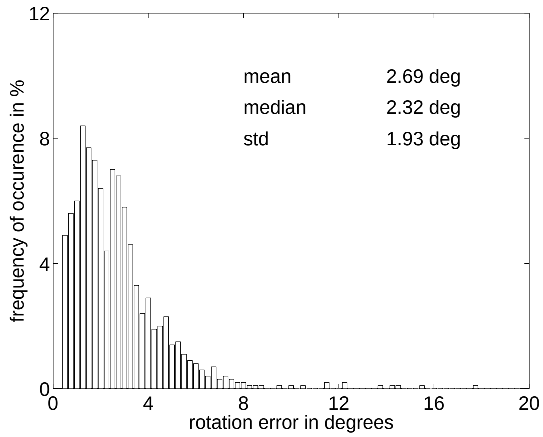
The *in vitro* results for the vertebral phantom confirm the utility of least-squares registration. Our initial sampling produced poorer results than would be expected from a surgeon's careful use of paired-point matching. The ICP method produced very accurate registrations, with a median rotational error of slightly more than $2°$. Our robust method was slightly worse: the median error was reduced, but the histograms show that the perturbation step carried the registrations near local minima into which the M-estimator was



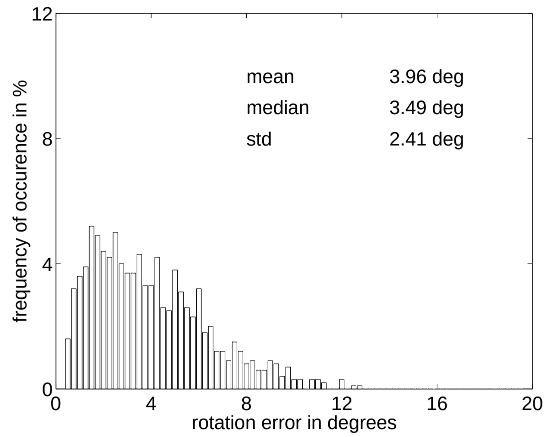
Step 1: LS to centroids



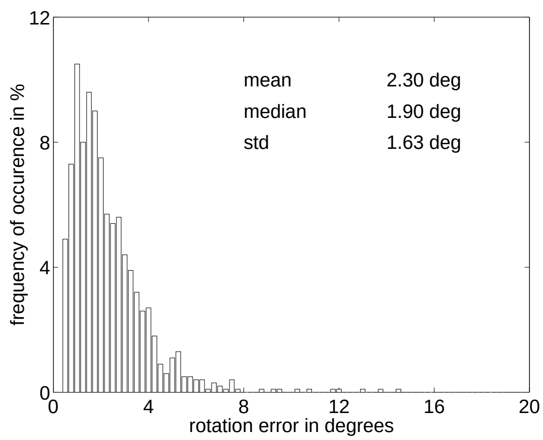
Step 4: ICP to surface



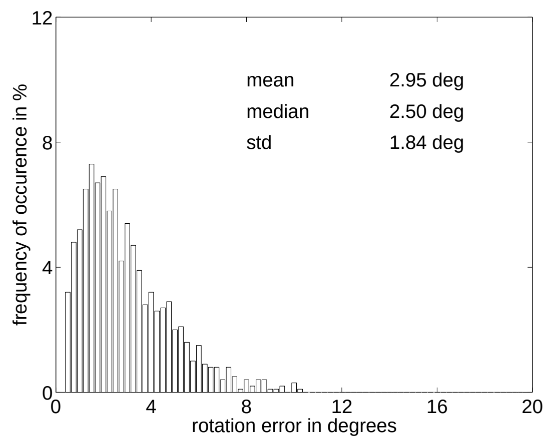
Step 2: Scored perturbation



Step 5: M-estimator from centroids

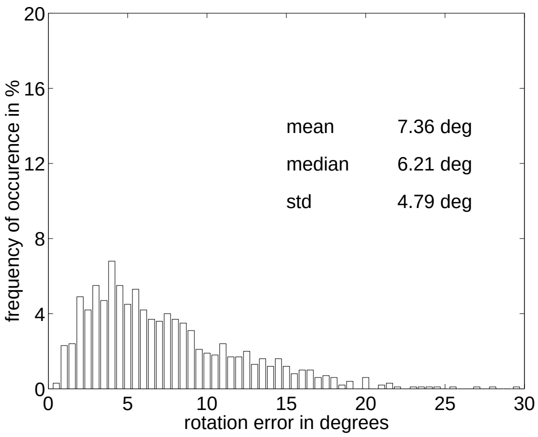


Step 3: M-estimator from perturbation

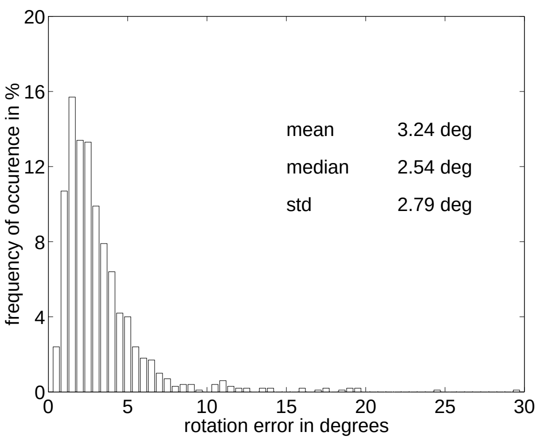


Step 6: M-estimator from ICP

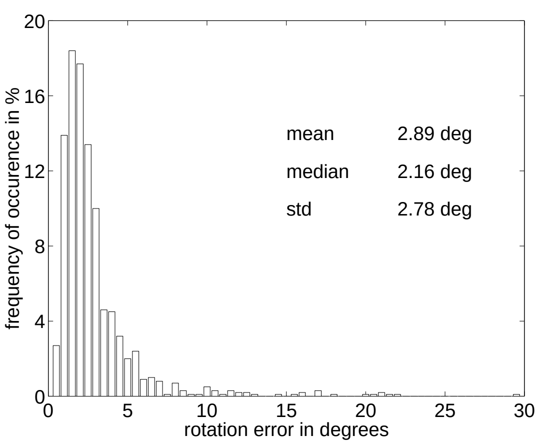
Figure 2: Tibial rotational errors from 1000 sets of physical surface data, 16 points per set. Rotational error was calculated as the maximum expected feasible deviation of nearby fiducial points.



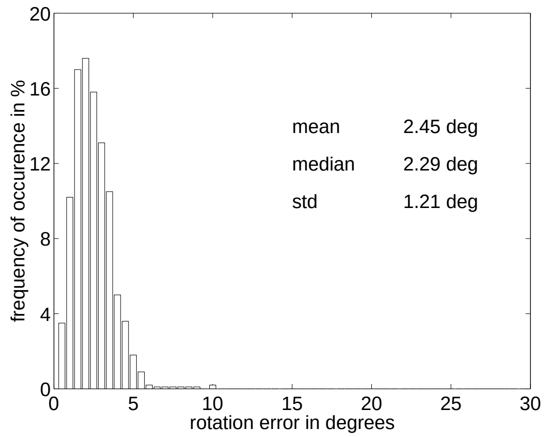
Step 1: LS to centroids



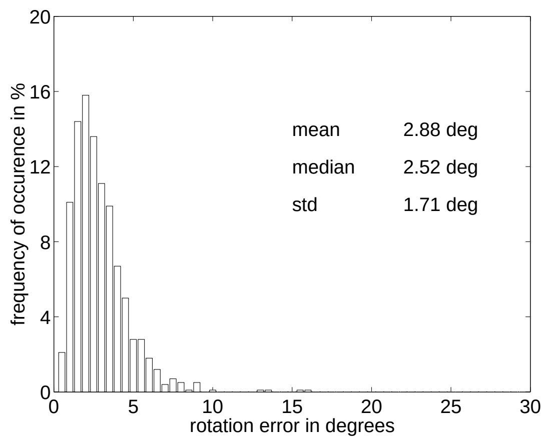
Step 2: Scored perturbation



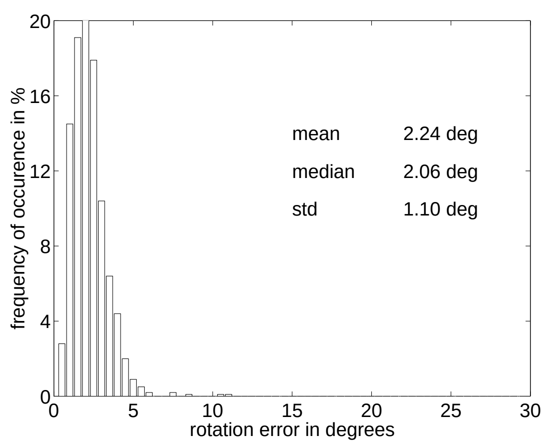
Step 3: M-estimator from perturbation



Step 4: ICP to surface



Step 5: M-estimator from centroids



Step 6: M-estimator from ICP

Figure 3: Vertebral rotational errors from 1000 sets of physical surface data, 12 points per set. Rotational error was calculated as the maximum expected feasible deviation of nearby fiducial points.

"trapped". Starting the M-estimator from ICP produced a stable result for which the median error was about 10% less than that of ICP.

The *in vivo* results measure the accuracy of the entire process of computer-enhanced surgery: CT (including patient motion), isosurface extraction, decimation, computer-based planning, registration, the physical processes of resection and reduction, and angular measurement from plain radiographs. The maximum error of $2°$ in the pilot study compares very favorably with the results by traditional methods.

The main contributions of this work are the development of an intraoperative data-collection scheme that is easy to use, and the implementation of a pair of robust statistical methods for estimating 3D surface registration. The methods have been tested extensively in the laboratory and have been used in early clinical trials. The codes run in a few seconds on common UNIX workstations.

Robust statistical methods are important for registration because they provide a sound mathematical basis for the attenuating the influence of outliers in the data. For intraoperative use we suggest that they are superior to manual editing of the data and to *ad hoc* methods of outlier attenuation. However, the implementation of robust methods requires care, especially in choosing a starting point. Robust methods, like nonlinear least-squares methods, will converge to local minima. This was particularly evident in the study of the vertebral phantom.

In summary, robust surface registration of surgical data to CT-derived isosurfaces is a potentially useful in computer-enhanced surgery. The local nature of the search still leaves the method subject to "trapping", and we recommend that such methods continue to undergo visual verification by the surgeon until validated global registration methods are devised.

Acknowledgments

This research was supported in part by Communications and Information Technology Ontario, the Institute for Robotics and Intelligent Systems, the Natural Sciences and Engineering Research Council, and by an Alfred P. Sloan Research Fellowship to DJF. Marker implantation and osteotomy procedures were performed in Kingston General Hospital by Dr. Paul Fenton, Dr. Mark Harrison, and Dr. John Rudan.

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