Automatic Initialization for 3D Bone Registration

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ABSTRACT

In image-guided bone surgery, sample points collected from the surface of the bone are registered to the preoperative CT model using well-known registration methods such as Iterative Closest Point (ICP). These techniques are generally very sensitive to the initial alignment of the datasets. Poor initialization significantly increases the chances of getting trapped local minima. In order to reduce the risk of local minima, the registration is manually initialized by locating the sample points close to the corresponding points on the CT model.

In this paper, we present an automatic initialization method that aligns the sample points collected from the surface of pelvis with CT model of the pelvis. The main idea is to exploit a mean shape of pelvis created from a large number of CT scans as the prior knowledge to guide the initial alignment. The mean shape is constant for all registrations and facilitates the inclusion of application-specific information into the registration process. The CT model is first aligned with the mean shape using the bilateral symmetry of the pelvis and the similarity of multiple projections. The surface points collected using ultrasound are then aligned with the pelvis mean shape. This will, in turn, lead to initial alignment of the sample points with the CT model. The experiments using a dry pelvis and two cadavers show that the method can align the randomly dislocated datasets close enough for successful registration. The standard ICP has been used for final registration of datasets.

Keywords: Registration, ICP, Automatic initialization, Bone atlas

1. INTRODUCTION

Registration is an essential part of almost any Computer Aided Orthopedic Surgery (CAOS) application. ICP[1] and its numerous variations remain the most widely used registration method. A large body of scholarly work has been dedicated to improve the robustness and speed of the standard ICP.[2–7] One of the well-known problems of ICP is its notorious tendency to fall into local minima. A variety of solutions have been proposed to reduce the risk of local minima. Among them, random sampling has been one of the popular approaches. Masuda and Yokoya[8] employed random sampling and least median of squares regression to increase robustness by rejecting outliers. They successfully applied their methodology to range images taken by two separate rangefinders. Trucco *et al.*[3] reported a larger field of attraction using a similar approach that alters the rotation estimation of ICP. This method is robust to substantial amount of missing data and outliers. In another work, sample points are randomly perturbed in order to make the algorithm move out of local minima.[4] This approach increases the capture range, however, it also increases the number of iterations needed for convergence. None of these approaches directly address the problem of initial alignment.

Euclidean invariant features are also utilized to form a new distance function which decreases the probability of being trapped in local minima.[6] Shape features such as curvature, moment invariants, and spherical harmonics invariants are used for this purpose. Using shape features is only possible if these features can be robustly estimated in the datasets that are being registered. Therefore, applying feature based techniques to registrations involving sparse datasets seems to be difficult.

In a recent study, a registration method based on unscented Kalman filter is introduced to map two point sets in presence of additive Gaussian noise.[7] This method incorporates the estimate variances of the transformation

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Medical Imaging 2008: Visualization, Image-guided Procedures, and Modeling, edited by
Michael I. Miga, Kevin Robert Cleary, Proc. of SPIE Vol. 6918, 69182P, (2008)
1605-7422/08/$18 · doi: 10.1117/12.772632

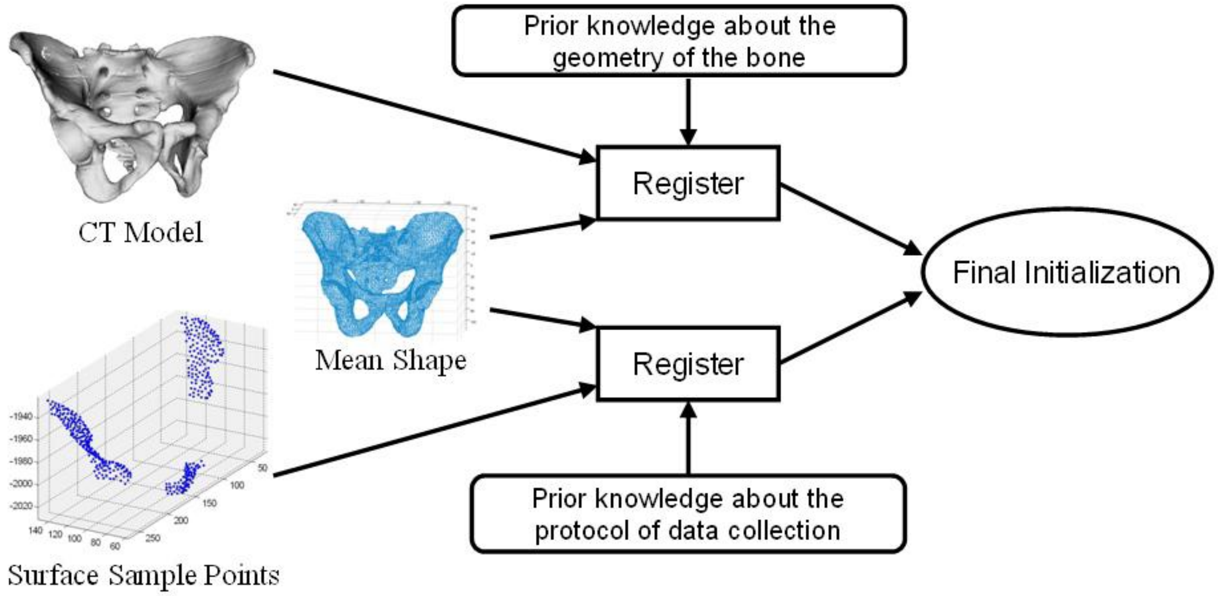


Figure 1. The block diagram of the initialization.

parameters and the convergence model in order to improve sensitivity of ICP to initial alignment. The unscented Kalman filter takes into account the nonlinearity of the system as it converges.

Despite all improvements, a fully automatic registration without manual initialization is not yet reliable for most clinical applications. Manual initialization is most likely unavoidable for a general registration method without utilizing any prior information. One reason is that usually the sample points do not cover the whole surface of the bone due to limited accessibility of the bone. For instance, the points collected from the surface of pelvis in total hip replacement surgery are sparse and only cover a small portion of the pelvis. In such cases, the collected sample points might be matched to several parts of the bone. In addition, geometric features cannot be reliably defined on such sparse data. Manual initialization resolves the problem since the user locates the points close to final solution avoiding false matches. In this process, the user employs his or her knowledge about the shape of the object and the rough correspondence of data to carry out the manual initialization. Therefore, addition of the prior knowledge about the geometry and shape of the object and other application-specific data can be extremely helpful for a reliable and fully automatic registration.

In this paper, we present a method that employs prior information to initially align the sample points collected using tracked ultrasound images with the CT surface model of the bone for ICP registration. The main idea is to exploit a mean shape of the pelvis surface created from a large number of CT scans as the prior knowledge to guide the initial alignment. The mean shape encodes the average anatomical structure of the bone. The CT model and sample points are both registered to the mean shape. The plane of symmetry of pelvis bone is found using Principal Component Analysis (PCA). Having the bilateral symmetry, the alignment is constrained to only one rotation about the normal vector of the plane of symmetry. The ambiguity is resolved by comparing multiple projections of the CT model and the mean shape. In order to register the sample points to the mean shape, the areas from which the data is most likely obtained are manually marked on the mean shape. The selection of these areas does not need to be repeated since the same mean shape is used for all registrations.

The algorithm is specifically developed for registration of sample points collected from surface of a "male pelvis" using our "pre-defined" data collection protocol. However, it can be easily adapted for other applications with the main requirement being the availability of a mean shape of the anatomy that is being registered.

2. METHODOLOGY

The block diagram shown in Figure 1 depicts the overall process of the initialization. The sample points and the CT model are roughly registered to the mean shape. The combinations of the two transformations from these registrations gives the final initialization. The following sections describe each part of this process in details.

2.1 Mean Shape

The mean shape is taken from a statistical atlas of pelvis constructed from several healthy patient CT scans.[9] The atlas contains a three dimensional mesh of average male pelvis, bone densities, and modes of variation. Here, only the surface mesh of the mean shape is used.

2.2 CT to Mean Shape Registration

The first step is to register the surface model of the bone to the mean shape. Both the CT model and the mean shape are "complete" models of the bone which means the model describes the total surface of the bone. This makes the registration rather easy, and there are a number of approaches that can be used for this task. We have employed a simple method that relies on the completeness and symmetry of the bone. The registration involves four stages:

1. The centroids of the CT model and the mean shape are matched (leaving three degrees of freedom i.e three rotations).
2. The planes of symmetry of the CT model and the mean shape are found and aligned (leaving one degree of freedom).
3. The CT model is rotated about the line that passes through the centroid and is orthogonal to the symmetry plane. For each angle, the two models are projected on the symmetry plane and two orthogonal planes that are also orthogonal to the symmetry plane.
4. The projections are compared. The angle for which the three projections are best matched is found.

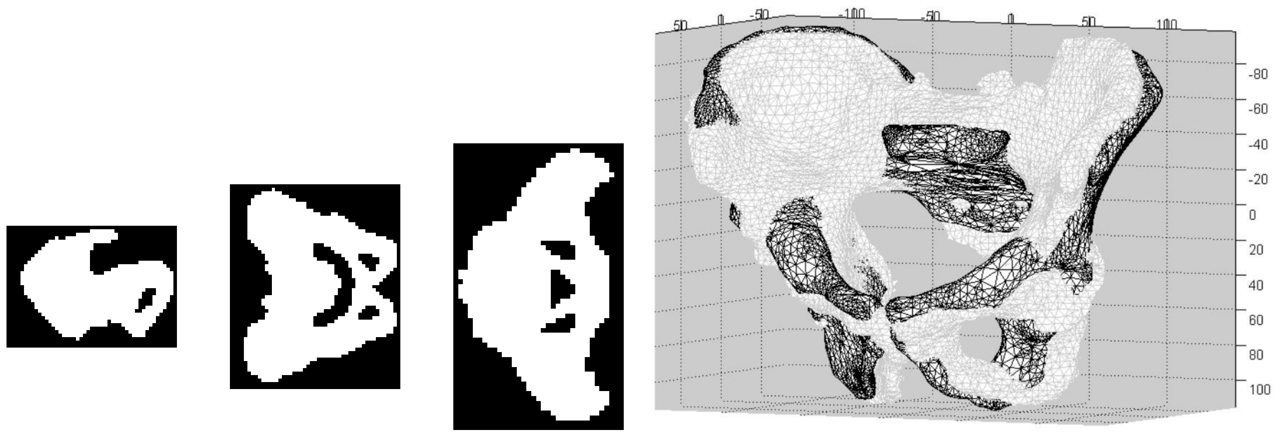
The centroid is a reliable feature since the whole model of the pelvis is available. The translation parameters are uncovered by matching the centroid, which limits the degrees of freedom to only three rotations.

To find the plane of symmetry, PCA is carried out for both models. It can be shown that one of the principle axes lies in the plane of symmetry.[10] The centroid and the principle axes define three planes from which only one is the plane of symmetry. The plane of symmetry is discovered by reflecting the points against each of the three planes. In the ideal case, the reflected points will be placed exactly on the top of their corresponding points. In the real scenario, the distance of the reflected points to the closest point is measured. The plane with the smallest average distance is selected as the plane of symmetry.

Matching the plane of symmetry leaves us with only one degree of freedom, which is rotation about the orthogonal line that passes through the centroid. The model could also be rotated 180 degrees about the symmetry axis. We have implemented a brute force technique to resolve these ambiguities by applying small rotations to the model. Hierarchical search or other minimization techniques can also be used to increase the speed and accuracy of this process.

The final transformation is found by applying small-angle rotations to the model and the 180-degree rotated version of the model. For each angle, the CT model is projected to three orthogonal planes (see Figure 2(a)). The result is then compared with the projections of the mean shape. The similarity is defined as the sum of the overlapping area of projections. The angle for which the similarity is maximized determines the final parameter of initialization.

Figure 2(b) shows one example of the registered CT and the mean shape models. The two meshes differ in shape and fine structures, but the overall features of the male pelvis are constant. In the current implementation, we do not compensate for large scale variations that might be important when the pelvic model belongs to a child.



(a) (b)

Figure 2. a) three projections on three orthogonal planes. b) the CT model (dark) registered to the mean shape (bright).

2.3 Point Set to Mean Shape Registration

The next step is to align the sample points collected from the surface of pelvis with the mean shape. The prior knowledge about the method of data collection is utilized for this purpose. It should be noted that the proposed method with our current implementation can only register the points collected using our pre-defined method of data collection. Nonetheless, it can be easily modified to handle data collection protocols of other applications as described later on.

In our experiments, sample points were obtained from three regions of the pelvis bone: The left and right iliac crest containing the anterior superior iliac spines, and the body of the pubis containing pubic tubercles. These areas are manually marked on the mean shape as shown in Figure 3. To do this, constant minimum and maximum values are applied to x, y, and z coordinates of the points. The selected area does not need to be accurately marked and does not change for the experiments. Equivalently, the data is not always collected from the exact same locations as described by the protocol.

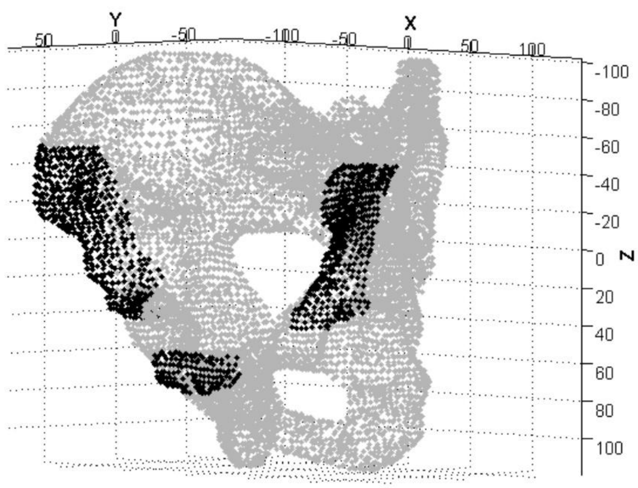


Figure 3. Manually selected points on the mean shape. The selected points and the mean shape points are shown in black and gray colors respectively.

The sample surface points are only aligned with the marked areas of mean shape. The marked areas on the mean shape gives us partial correspondence of the points. Each group of points is matched with the corresponding group on the mean shape. For this purpose, the centroid of each group is separately computed. Having the correspondences of the centroids, the closed-form solution is found using the method introduced by Horn.[11]

Since there are three separate regions apart from each other, the rotation is easily recovered with an acceptable accuracy. Two iterations of ICP gives finner point set to mean shape registration. For the ICP iterations, only the points that their closest points fall within the selected region on mean shape are used.

For other applications in which the data is collected from distinct regions and stored separately, a similar approach can be taken. If the samples are collected all at once from one region, the sequence of the data collection can be used for registration by labeling the mean shape with a similar sequence. Basically, any information about the method of data acquisition that provides approximate correspondences can be employed for this registration. Obviously, the method is not applicable to the cases for which the acquisition does not have any specific order.

2.4 Final Alignment

The previous registrations transform the coordinate frames of the pelvic model and the sample points to the coordinate frame of the mean shape. The advantage of using the coordinate frame of the mean shape is that it remains constant for all registrations. This enables us to perform final adjustments in order to further reduce the probability of registration failure. We applied a small translation in positive "Y" direction to the sample points. Since the positive "Y" direction points away from the anterior pelvis plane, this translation places the sample points above the surface of pelvis which ensures that the points are not attracted to adjacent surfaces during ICP registration.

3. RESULTS

The presented method was evaluated using three sets of experiments: a dry bone experiment and two cadaver experiments. The following describes the details of these experiments.

3.1 Data Acquisition

CT scan of the whole pelvis was acquired for each experiment with the slice thickness of 1 mm. The CT scan was composed of about 260 slices of each 512 by 512 pixel (with the pixel size of 0.7 mm). The pelvis was segmented in CT images using ANALYZE (Mayo Clinic, Rochester, Minn.). The marching cubes implementation of VTK combined with other VTK filters were employed to create the mesh model of the pelvis.

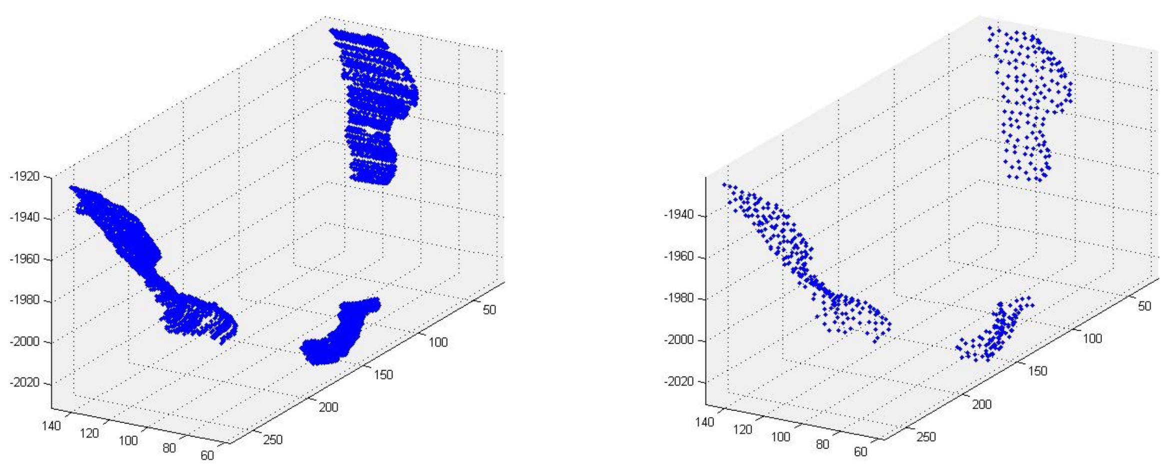


Figure 4. An even distribution of the sample points is achieved by randomly sampling the results of segmentation of ultrasound images. The figure on the left shows the segmented points from the surface of the dry bone, while the figure on the right depicts the randomly sampled points.

The Sample points were collected using tracked ultrasound images. The images were acquired from a SonoSite portable ultrasound system with a high frequency transducer. Passive markers were attached to the transducer and were tracked with a "Polaris" camera (NDI). The images were captured through the s-video output of the ultrasound machine. Custom software were used to synchronize and save the tracking information and the ultrasound images. The bone surface was segmented in the images using the segmentation algorithm introduced in.[12] The images were acquired from the left and right iliac crest containing the anterior superior iliac spines, and the pubic bone. The data from each region was saved separately in distinct folders. Figure 4 left shows an example of the surface points collected from the dry pelvis bone.

The images were rapidly collected by sliding the ultrasound transducer against the cadaver's skin over the areas of interest. The dry bone was sank in water in order to collect the ultrasound images.

It can be seen in Figure 4(left) that the collected points are very dense at some regions but there are also a few gaps in data. Basically, multiple images are collected from almost the same location while no images are obtained from another part leaving some gaps behind. The main reason is the irregularity of the free hand motion. In an extreme situation, this can shift the centroid of the points which lessens the accuracy of initialization. The density of the points are evened out by randomly sampling the points (see Figure 4 right). The samples are not allowed to be closer than 3 mm to each other. Random sampling increases the speed of the process, gives a more realistic average error measure, and eliminates the possible initialization drifts caused by over concentration of the points in one region.

3.2 Experimental results

For each experiment, the ultrasound points were aligned with the CT model of the bone using the proposed algorithm. The standard ICP technique was then used to accurately register the sampled surface points to the CT model. The same mean shape, selected region of interest in the mean shape, and ICP parameters were used for all experiments. Figure 5 shows the initialization and ICP registration results of one of the cadaver experiments.

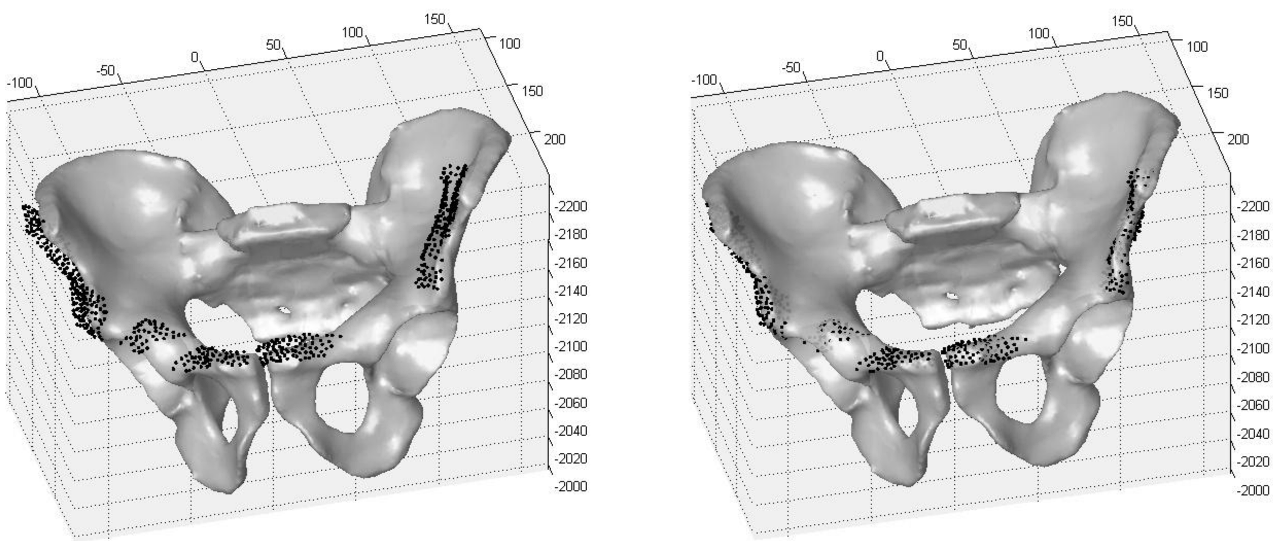


Figure 5. The results of automatic initialization and ICP registration of the first cadaver experiment. The figure on left presents the automatically initialized points, while the figure on right displays the ICP registration results.

To evaluate the robustness to initial position and orientation, the CT model and sample points were randomly relocated in space prior to registration. The three rotation parameters were randomly selected over the full range of rotation. The three translation parameters had uniform distribution with the values between ± 10 cm. The proposed method was then applied to find the rough alignment. This was followed by the standard ICP to obtain accurate registration. This experiment was repeated 100 times for each of the three experiments. Table 1 presents the average error and standard deviation of the experiments. The same experiment was also carried out without any initialization (Table 1. The reported error is the average distance of the sample points from the closest point on the surface of the mesh model. The registration was successful for all of the ICP registrations with the automatic initialization. The low standard deviation in errors values confirms that the initialized registration has been independent from the starting location.

In contrary, when initialization was not used, the chance of successful registration remained very low. The number of the registrations for which the error has been less than 3 mm is computed and shown in Table 1. If we define an error of larger than 3 mm as failure of registration, only in 12 cases out of 300 experiments without initialization the registration did not completely fail. In addition, the number of iterations required for convergence was almost doubled compared to the initialized registrations.

Table 1. Results of 100 registrations with and without automatic initialization.

Experiment	Error/STD of ICP without init. (mm)	# of cases with less than 3 mm Error	Error/STD of ICP with init. (mm)	# of cases with less than 3 mm Error
Dry Bone	8.092/4.728	4	1.128/0.001	100
Cadaver one	7.267/3.778	1	1.617/0.046	100
Cadaver two	8.152/3.821	7	1.426/0.003	100

The time required to initialize the registration was about two minutes on average. A 3.2 GHz P4 computer with 1 GB of RAM was used for all of the experiments. The method was implemented in MATLAB and no code optimization was employed.

4. CONCLUSION AND FUTURE WORK

We presented an automatic initialization method that aligns sample points collected from the surface of pelvis with the mesh model constructed from the CT scan. This initial alignment was followed by ICP registration to obtain high registration accuracy. In our approach, a mean shape of pelvis and the information on data collection protocol were used as prior knowledge to guide the initialization. In order to evaluate the algorithm, one dry bone experiment and two cadaver experiments were carried out. The automatic initialization was applied before standard ICP registration. The results displayed the effectiveness of the algorithm in making the registration independent of the starting location of the datasets eliminating the need for manual initialization.

The proposed method is intuitive and flexible, and can be easily extended to other applications. It also demonstrates how various types of information can be incorporated into the registration process. This is specifically important since for most applications, the information such as the bony anatomy from which the samples are collected and the data collection protocol is known. The main requirement would be the availability of a mean shape of the anatomy.

As discussed earlier, bilateral symmetry of the pelvis largely helped restrict the search parameters for the registration of CT model to the mean shape. This increased the speed of convergence and made the registration robust to dissimilarities of the pelvises. Shape symmetry appears to be a very robust feature for registration tasks since there exists a large degree of symmetry in the human bony anatomy. Symmetry can be applied for registration only when the collected data has preserved the symmetric properties of the bone. Therefore, it is not directly applicable to sparsely acquired sample points. In addition, the symmetry of some of the bony anatomies such as femur is not global. However, local symmetry of these anatomies could also be used in the process of registration.

The presented results imply the potential of the mean shape as a simple feature detector. The mean shape helped us customize and guide the initialization. The real advantage was that the mean shape remains constant for all of the registrations. This made the addition of customized information to the mean shape possible without loss of the generality of the registration for each application.

One direction for future work would be to mix the initialization and registration steps to achieve a more accurate registration and faster convergence. The adaptation of the current work for other numerous CAOS applications, and a complete validation with larger number of datasets are also necessary. Finally, the current implementation should be optimized to increase the speed and to meet the demands of clinical applications.

5. ACKNOWLEDGMENT

The authors would like to thank Dr. Danny Song, Dr. Emad Boctor, and Hassan Rivaz for their help with cadaver experiments, as well as William R. Kenan, JR Fund Award for providing the cadaver. This work is supported by the National Science Foundation under grant EEC-9731478.

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