Fully-Automated Femoral Coordinate System Definition for Constructing Statistical Shape Model of Distal Femur

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Abstract: This paper primarily proposes a method of implementing statistical shape model (SSM) of distal femur by automatically determining subject-specific femoral coordinate system (FCS). These have a wide range of applications in both biomechanical, 3D image analysis, knee model design and surgical planning. The main challenge in implementing SSM of distal femur as being complex in shape and a part of the whole femur, is to find correspondence across subjects automatically for the purpose of aligning training subjects to a reference coordinate space. While conventional correspondence is observer-dependent and time consuming, this study is intended to tackle these drawbacks by proposing a fully user-independent method to accurately extracting the FCS using 3D magnetic resonance (MR) images of isolated knee because of its popularity in knee surgery due to high spatial resolution. The proposed methods are based on morphological analysis of distal femoral bone in 3D MR image to locate the anatomical features automatically. Afterward an SSM has been constructed by utilizing the implemented FCSs in a set of volumetric MR images. Images were reconstructed and synthesized in each dimension from the model, and finally were evaluated by benchmarks index-generalization ability. In addition, possible application of the implemented FCS could be volumetric image (CT/MR) matching of distal femur, etc.

Keywords: Distal femur, Anatomical landmark, Magnetic resonance image, Knee surgery, Coordinate system, Knee model

1. Introduction

Statistical shape models (SSMs) consist of the mean shape and a number of modes of variation from a set of training data [1,2], which have a wide area of applications including reconstruction of both healthy as well as actual patient-specific anatomy analysis. Recently, SSMs have drawn substantial attention to the field of image analysis, such as model based medical image segmentation, surgical planning and biomechanical analysis.

Specifically, due to the inherent characteristic of having prior-information about the shape and appearance, the SSMs are also considered as powerful tools for segmenting 3D knee MR images [3]. In addition, it is well-known that the outcome of pre-operative surgical planning and post-operative investigation in osteoarthritis (OA) or knee surgery strongly depends on proper quantification of knee components, i.e., femoral and tibial bones. Hence, reliable shape model of distal femur to be utilized in clinical application is required. The SSM of femoral bone can be used for quantification in knee surgeries, such as, automated segmentation of femoral bony region to be applied for further computation in computer-aided surgical planning of anterior cruciate ligament (ACL) reconstruction as suggested by Morita et al. [4].

One of the primary challenges in constructing SSM of femur, in particular for distal femur (isolated knee), is to establish correspondence across subjects automatically for the purpose of alignment of the training subjects. It is essential to align all training subjects in a common coordinate system [5,6]. Standard methods include anatomical landmark based alignment because of high throughput. Thus, the first objective of this work is to propose a fully automated method for determining the femoral
coordinate system (FCS) of the distal femur in individual subjects.

Most of the conventional methods define the FCS as three orthogonal axes: the medial-lateral (ML), superior-inferior (SI), and anterior-posterior (AP) directions. According to the standard methods [7], pelvic, femur and tibia are required in constructing these axes of femur, where knee ML axis is usually derived by fitting cylinder or sphere to femoral condyles. Center of the femoral head is used to define another axis (also known as mechanical axis) which ends at the SI axis of distal femur. Third axis is defined orthogonal to both (ML and SI) axes.

In contrast, in case of isolated knee or distal femur with exclusion of proximal femur and distal tibial section, it is necessary to define FCS alternatively without the center of the femoral head. However, the challenges in implementing automated anatomical coordinate system of distal femur are irregularity of anatomical shape, and lack of proper anatomical information of the femur, being a part of the whole bone. Some methods have been proposed for automated determination of anatomical axes in different anatomical joints including knee, pelvic, hip [7]. Some studies reported automated methods to determine a particular anatomical axis of clinical interest; for example, Ref. [8] measured epicondyle axis automatically by using 2D X-ray radiograph images, and Ref. [9] proposed an automated technique to extract femoral shaft (anatomical) axis based on geometric entity fitting using computed tomography (CT) images for the purpose of pre-operative planning of intramedullary rod insertion in femur.

Ref. [10] proposed an anatomical coordinate system for 3D lower extremity alignment assessment of component position after total knee arthroplasty, later which was also used to automated image registration for lower extremity and implant position alignment assessment [11], as well as 3D dynamic motion analysis of ACL deficient knees [12]. Ref. [10] proposed a bone coordinate system (but not automated) by utilizing the whole femur and proximal tibia; however, it is necessary to automate the whole procedure, particularly for distal femur.

The first contribution of this work is to propose an automated method for subject-specific anatomical coordinate system determination of the distal femur. It is based on bony-region area profile which was acquired from 3D magnetic resonance (MR) images. The possible application of the implemented FCS is to contribute, for registering femoral bone images to construct SSM as well as multimodal image (CT/MR) registration, in both biomechanical and knee surgical planning. Finally, robustness of the proposed method has been evaluated by rotating the images thoroughly a set of angles around a group of arbitrary axes.

Secondly, this paper has focused on a method of constructing automated femoral SSM by utilizing the determined FCS. This study employed MR images of knee collected from a robust database which includes the femoral bone from all ethnicity with wide shape varieties. The principal difficulties of determining anatomical coordinate system of femoral bone were irregularity of anatomical shape, even in ethnicity [13], and being a part of the femur, it lacks proper anatomical description, such as anatomical axis. This paper has solved the problems by automatically determining the individual FCS. The FCS was used for aligning images to a base space, followed by affine transformation, and hence voxels of registered images were re-scaled to voxels of equal size. After that, the SSM of femoral bone was constructed by applying principal component analysis (PCA) [14] to a large matrix obtained from the registered MR images. Then images were reconstructed and new images were also synthesized by utilizing standard deviation (SD) ratio in each dimension from SSM. Finally, the performance of implemented SSM was evaluated by generalization ability. While our previous study [15] investigated the possibility of using anatomical coordinate system to construct SSM of distal femur, however, here we have described the methodology thoroughly, proposed fully automated method, and evaluated both methods (FCS and SSM) with quantitative indices and also included more training subjects which were not done previously.

This paper is structured as follows. Section 2 explains images used in this study. In Section 3, an automated FCS determination and an SSM construction method are proposed. The outcomes of this work are discussed in Section 4. Finally, Section 5 concludes the study.

2. Preliminaries

2.1. Anatomical description of distal femur

Distal femur being a part of compound physiological joint (known as, knee joint) of human body has anatomical variation, even in ethnicity [13]. However, it is trapezoidal in shape, and narrower anteriorly than posteriorly (Figure 1). It is anatomically characterized by two

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regions – distal epiphysis and distal metaphysis. The distal metaphysis is almost cylindrical in shape, and there is a sharp discontinuity with fewer bony area in proportion to distal epiphysis in their joining region called physiis. At the lower end, distal metaphysis is broadened into two curved (rounded areas) condyles – medial and lateral condyles, which are mainly articulate with the tibia and patella, forming the knee joint. Anteriorly the two condyles form a joint for articulation with the patella which is known as patellar surface. Posteriorly both condyles are separated by a deep intercondylar fossa of comparatively less bony area, and forms the knee joint with tibia (B) (from, musculoskeletalkey).

2.2. Data description

To implement and test the proposed method, a set of MR images of knee acquired using T1 and T2-weighted imaging sequences, were processed. A database contains images, scanned with different field strengths (1.0, 1.5 and 3.0T) using a variety of MR scanners in the sagittal plane with a pixel spacing of 0.39 mm by 0.39 mm and a slice thickness of 1.0 mm. Each image of a subject comprises around 300 sagittal slices to acquire the whole knee joint. The datasets include bony region masks of the subjects which were segmented interactively by experts, and the bony region consists of the cancellous bone and the cortical bones but does not contain the cartilage. The study employed bony region masks to segment the femoral bone. In this study, the MR images are considered for analysis with respect to MR coordinates, where x, y and z axes are represented approximately along AP, SI, and ML of the femoral bone, respectively. A coronal plane is perpendicular to the ground, and it divides the femur into anterior and posterior portions (green plane). A sagittal plane (xz) is also perpendicular to the ground, and it divides the femur into medial and lateral portions (red plane). Finally, an axial or transverse plane (xy) is parallel to the ground, and it divides the femur into inferior and superior portions (blue plane). These volumetric planes are perpendicular to each other. Figure 2 depicts three types of MR volumetric planes along with a distal femur. In the first pre-processing step, binary images of the distal femur were extracted from the label data by thresholding. Then, 3D model of the distal femur was implemented.

Figure 1. Anatomy of the distal femur. Distal femur is anatomically divided into two regions – distal epiphysis and distal metaphysis (A). Distal metaphysis, the distal part of femoral shaft, is almost cylindrical in shape, and has fewer bony area proportion to later one. Distal epiphysis comprises medial and lateral condyles which are separated by intercondylar fossa of comparatively less bony area, and forms the knee joint with tibia (B) (from, musculoskeletalkey).

Figure 2. Magnetic resonance images: (left) raw MR image, (middle) femoral bony mask, (right) volume rendering of the femoral bone with orientation of the volumetric planes, coronal (green color), sagittal (dark red color), axial (blue color), and Medial (M), Lateral (L), Superior (S) and Inferior (I) direction.
3. Proposed Methods

3.1. Automated determination of FCS

Figure 3 conceptualizes the overall methodology for identifying the anatomical landmarks for determination of FCS without any manual intervention. The proposed method is based on bony area profile scheme, and comprises the following three main steps, and the methodology is elucidated thoroughly below.

(Step 1) Calculate center of mass of all cross-sectional areas – transverse planes – of the binary MR volume data along SI direction. After that body axis ($BA$) is demarcated by the first principal axis, obtained by applying PCA to the centers of mass of the planes.

(Step 2) Extract epiphysis-metaphysis interface plane ($Yc$), and the plane ($Zc$) at center of intercondylar region to separate both condyles. Then, calculate the center of condyles by fitting sphere using least-squared method (LSM), and the joining line of the centers of both condyles defines the condylar axis ($CA$).

(Step 3) Define FCS where the origin is the mid-point of the condyles, and $BA$, $CA$ and their outer product are y, z and x axes, respectively.

To determine $BA$, the proposed method (refer to step 1 in Figure 3), firstly, calculates center of mass of the transverse planes along SI direction by utilizing binary MR volumetric data as shown in Equation (1). Afterward, the variability of the centroids from planes to planes is approximated by applying PCA. Finally, the $BA$ of the femur is defined by the first Eigenvector (also known as first principal component, PC1), corresponding to the largest eigenvalues obtained by matrix decomposition as shown in Equation (2), where $S$ is covariance of data matrix, $D_{BA}$; $v$ and $\lambda$ are Eigenvectors and Eigenvalue vectors, respectively. $BA$ is calculated by Equation (3).

$$D_{BA} = \begin{pmatrix} x_1^2 & y_1^2 & z_1^2 \\ x_2^2 & y_2^2 & z_2^2 \\ \vdots & \vdots & \vdots \\ x_i^2 & y_i^2 & z_i^2 \end{pmatrix}$$ (1)

$$Su = \lambda v$$ (2)

$$BA = v(x, y, z)|_{\arg(\max(\lambda))}$$ (3)

$CA$ is determined by using cross-sectional area bony profile of sagittal planes of distal femur, which is the number of bony voxels in each sagittal plane (Figure 4A). It is used to identify the location along the ML direction that corresponds to the center of intercondylar region (Figure 1B) which has fewer sectional areas than that of...
the medial and lateral condylar region because of the presence of intercondylar fossa as shown in Figure 4A. Here, each peak corresponds to the femoral condyles; however, the characteristic of the peak, corresponding to the medial condyle, is flattened toward the medial direction. Thus, discriminant analysis method [16] is applied for automated calculation of Z-cutting plane (Zc), corresponding to the lowest sectional area, and is located at the center of the intercondylar region (Figure 4A).

Figure 4. Cross-sectional bony area profile of distal femur versus bone length. Cross-sectional area profile of axial planes was used to identify the locations along the length of the disal femur corresponding to interface of the distal metaphysis (bone shaft/length) and epiphysis (femoral condylar region).

There is a sharp discontinuity of sectional-area at the interface (metaphysis-epiphysis). Cross-sectional area profile of axial planes of the segmented condylar region is calculated to identify the plane (Yc) that corresponds to interface of the metaphysis and epiphysis. It is basically a cross-sectional bony area profile of the segmented condylar (medial/lateral) region versus bone length (Figure 4B). The Yc is determined by maximizing the 1st derivative sectional area profile of transverse planes (between consecutive planes) along length as per Equation (4), where s is the cross-sectional area of the planes.

\[ Yc = \arg \max_{\Delta s} \{ f'(\Delta s) \} \] (4)

Subsequently, the distal femur is divided, in sagittal side, into two regions – medial & lateral section – at sagittal plane Zc. Next, the distal metaphysis from each condylar region (medial and lateral sections) is isolated, in the axial side at plane Yc, which has variability along medial and lateral regions in each subject, is derived individually for each segmented section (medial & lateral). After that each condylar region is approximated at the posterior side to extract the estimated femoral condyle (Figure 4). Finally, a set of 3D points (surface voxels) of each condyle is fitted independently to a sphere by LSM [17,18] to estimate centers of the condyle. Lastly, a condylar axis (CA) is determined by a line connecting the centers of both condyles.

The vectors, both BA and CA, are not perpendicular to each other, because of the variation in bone morphology, and there is no intersect among them as well; thus both of these together cannot form axes of the coordinate system. As illustrated in step 3 (Figure 3), this study defines the FCS as an x-y-z orthonormal coordinate system, in which origin (O) of the FCS is set to the midpoint between the centers of medial and lateral condyle (C1 & C2 in Figure 3). z-axis goes through medial and lateral epicondyle region, y-axis is defined at the origin but in parallel to femoral BA, and finally x-axis (marked as circle, refer to step 3 in Figure 3) which is directed toward medial-lateral side of the knee, is a cross vector of z- and y-axes. And the CA makes a small angle with the x-axis. The whole algorithm is proceeded automatically.

3.2. Statistical shape model construction

Shape property in an SSM is independent of similarity transformations (translation, rotation, and scaling). In statistical shape modeling, shape change due to similarity transformations should not be involved because of making it as specific as possible. Thus it is essential in the first step to align all training instances to a common coordinate system to reduce correspondence error due to differences of patient’s pose/position. The individual FCSs determined by Section 3.1 are used to align all training subjects to a common base space. The pose and position of the subjects are normalized to a reference coordinate frame of isotropic voxel dimension by applying affine transformation so that the origin of FCS moves to the origin of the base space, and the three femoral
coordinate axes are identical to those of base space. Hence, all training subject’s femoral labeled images are registered in the same base space, and re-scaled to isotropic-size voxel.

Positive and negative distances are assigned by applying signed distance transformation to each aligned image from the bony surface to outside and inside region of femoral bone, respectively. This study uses 6 neighbor Euclidian distance and a value of zero to the bony surface voxels. After that, shape vector which is a high dimensional array is constructed from the signed distances of all subjects, in which the number of rows and columns equals the number of voxels of the image (\(N_i\)), and the number of subjects (\(N_s\)), respectively. Shape vector \(F\) represents each shape as shown by Equation (5), where \(f_i(t)\) is the signed distance of subject \(i\) at voxel \(t\). In this \(N_s \times N_i\) matrix, each row corresponds to each subject.

\[
F = \begin{pmatrix}
f_1(1) & f_1(2) & \cdots & f_1(N_p) \\
f_2(1) & f_2(2) & \cdots & f_2(N_p) \\
\vdots & \vdots & \ddots & \vdots \\
f_{N_s}(1) & f_{N_s}(2) & \cdots & f_{N_s}(N_p)
\end{pmatrix}
\]  

(5)

After the alignment, dimensionality of the training set can be reduced by PCA, a sort of linear dimensionality reduction method based on orthogonal transformation where the shape variation can be best described by a small set of modes. Every aligned shape is described by a set of signed distance in vector \(F\) (Equation (6)). Firstly, averaging over all \(N_s\) samples yields mean shape (Equation (6)), where \(F_i\) is the \(i\)th training image, and corresponding covariance matrix, \(C\) of \(F\) is given by Equation (7). Finally, PCA of the \(C\) describes the principal modes of variation, \(V\) (Equation (8)) which is derived from the training sets.

\[
\bar{F} = \frac{1}{N_s} \sum_{i=1}^{N_s} F_i
\]  

(6)

\[
C = \frac{1}{N_s-1} \sum_{i=1}^{N_s} (F_i - \bar{F}) (F_i - \bar{F})^T
\]  

(7)

\[
CV = \lambda V
\]  

(8)

\(V\) and \(\lambda\) are Eigenvector and Eigenvalue matrices which are represented by Equation (9) and Equation (10), respectively, where \(N_E = N_s - 1\).

\[
V = \begin{pmatrix}
e_1(1) & e_1(2) & \cdots & e_1(N_E) \\
e_2(1) & e_2(2) & \cdots & e_2(N_E) \\
\vdots & \vdots & \ddots & \vdots \\
e_{N_s}(1) & e_{N_s}(2) & \cdots & e_{N_s}(N_E)
\end{pmatrix}
\]  

(9)

\[
\lambda = \begin{pmatrix}
\lambda_1(1) & 0 & \cdots & 0 \\
0 & \lambda_2(2) & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & \lambda_E(N_E)
\end{pmatrix}
\]  

(10)

where each column, \(e(j) = [e_1(j), e_2(j), \ldots, e_{N_s}(j)]^T\), is the \(j\)-th Eigenvector.

\[
\theta_i = (f_i - \bar{F})V
\]  

(11)

In SSM, it is possible to approximate all shapes in the training datasets by using the mean shape and a linear combination of modes of majority variation weighted by appropriate shape parameters (Equation (5)). Consider a PC score \(\theta_{test}\) calculated using Equation (11) from a feature vector, \(F_{new}\), of a test subject. The femoral bone shape of the subject is reconstructed by

\[
\bar{F} \approx \bar{F} + \theta_{test}V^T
\]  

(12)

4. Results and Discussion

The proposed methods have been applied successfully in a set of volumetric MR images of distal femur for automated determination of FCSs and construction of SSM of the isolated knee. The algorithms have been implemented in MATLAB, R2016, software package (The Math Work Inc., Natick, MA, U.S.A.), and validated by a generalization ability.

4.1. Automated femoral coordinate system determination

Anatomical landmarks were identified automatically as shown in Figure 3. In all cases, the center of the intercondylar region was corresponding to the minimum value in the bony area profile of distal femur (Figure 4A). The interfaces of the distal metaphysis and epiphysis were automatically identified in the sectional area profile of each condylar sections (medial and lateral) as there is anatomical variation in each section (Figure 4B). Finally, the condyle regions were approximated to articular surface in the posterior side by using the sectional area profile of each condyle section. The location variations of the landmark along the ML, SI and AP sides were ob-
served in every subject, which are thought to be influenced primarily by the distinction of bone morphology.

FCSs of subject were determined using the proposed method without any manual intervention as shown in Figure 5. \textbf{BA} is running along the middle of the distal femur toward the inferior side, as shown in Figure 5 (left). The contours of approximated condyles were fitted to a sphere by LSM method to calculate their centers (Figure 5 (middle)). Figure 5 (right) shows the determined FCS of the distal femur where condyle axis, \textit{CA}, is depicted by a line. The origin of the FCS is located at the mid-point of both condyles, in the intercondylar region, and on the line connecting the centers of two spheres which were approximated to the articular facet of the femoral condyles. The x-, y-, and z-axes of the FCS are defined along ML (left-right), SI (bone shaft), and AP directions, respectively. The orthogonality of the three axes was verified by dot product. In addition, obviously, the z-axis was directed toward the condylar axis (ML). Moreover, the x-axis maintains orthogonality to both y and z axes, except \textit{CA} axis, because it was calculated by cross product of the body and condylar axes.

It is not feasible to compare the performance of the proposed method to the other methods because different studies evaluated their methods on different datasets [6]; furthermore, there are some individual varieties among the subjects. Hence the following procedure has been used for accuracy evaluation of the proposed method. To evaluate robustness of the synthesized FCS for each subject, the original shape was rotated through an angle around an arbitrary axis, and then translation as well as orientation difference before and after rotation were also recorded [19,20]. Basically, a set of 10 rotation axes (A.1, A.2, \ldots, A.10), defined arbitrarily, was tested for multiple evaluations of each subject with the range of rotation angles (0° to ±10° with a step of 2°). The deviation angles ($\delta$) of FCSs before and after the rotation were compared for evaluation, where the smaller deviation angle ($\delta$) means more robust method.

![Figure 5. Automated FCS determination: (left) bone axis (BA) running along the center of the distal metaphysis in sagittal view; (middle) contour fitting of a condyle to a sphere by LSM; (right) automated FCS in coronal view](image)

### Table 1. Average rotational deviations over all subjects for each type of arbitrary axis (A.1 to A.10). Mean and standard deviation (S.D) are also mentioned

<table>
<thead>
<tr>
<th>Axis / Rot. angle</th>
<th>-10</th>
<th>-8</th>
<th>-6</th>
<th>-4</th>
<th>-2</th>
<th>0</th>
<th>2</th>
<th>4</th>
<th>6</th>
<th>8</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>A.1</td>
<td>0.62</td>
<td>0.5</td>
<td>0.4</td>
<td>0.2</td>
<td>0.09</td>
<td>0</td>
<td>0.08</td>
<td>0.22</td>
<td>0.45</td>
<td>0.5</td>
<td>0.65</td>
</tr>
<tr>
<td>A.2</td>
<td>0.75</td>
<td>0.6</td>
<td>0.6</td>
<td>0.05</td>
<td>0.08</td>
<td>0</td>
<td>0.07</td>
<td>0.08</td>
<td>0.54</td>
<td>0.4</td>
<td>0.7</td>
</tr>
<tr>
<td>A.3</td>
<td>0.88</td>
<td>0.98</td>
<td>0.5</td>
<td>0.4</td>
<td>0.08</td>
<td>0</td>
<td>0.06</td>
<td>0.3</td>
<td>0.48</td>
<td>1.1</td>
<td>1.2</td>
</tr>
<tr>
<td>A.4</td>
<td>0.62</td>
<td>0.5</td>
<td>0.4</td>
<td>0.2</td>
<td>0.07</td>
<td>0</td>
<td>0.07</td>
<td>0.25</td>
<td>0.41</td>
<td>0.53</td>
<td>0.6</td>
</tr>
<tr>
<td>A.5</td>
<td>1.1</td>
<td>0.62</td>
<td>0.3</td>
<td>0.09</td>
<td>0.08</td>
<td>0</td>
<td>0.07</td>
<td>0.1</td>
<td>0.25</td>
<td>0.56</td>
<td>0.98</td>
</tr>
<tr>
<td>A.6</td>
<td>1.22</td>
<td>0.69</td>
<td>0.5</td>
<td>0.4</td>
<td>0.07</td>
<td>0</td>
<td>0.06</td>
<td>0.45</td>
<td>0.52</td>
<td>0.7</td>
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</tr>
<tr>
<td>A.7</td>
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<td>0.85</td>
<td>0.6</td>
<td>0.4</td>
<td>0.05</td>
<td>0</td>
<td>0.06</td>
<td>0.5</td>
<td>0.6</td>
<td>0.92</td>
<td>0.75</td>
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<tr>
<td>A.8</td>
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<td>0.7</td>
<td>0.3</td>
<td>0.09</td>
<td>0.08</td>
<td>0</td>
<td>0.07</td>
<td>0.09</td>
<td>0.23</td>
<td>0.4</td>
<td>1.4</td>
</tr>
<tr>
<td>A.9</td>
<td>1.3</td>
<td>0.95</td>
<td>0.6</td>
<td>0.05</td>
<td>0.09</td>
<td>0</td>
<td>0.07</td>
<td>0.08</td>
<td>0.56</td>
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</tr>
<tr>
<td>A.10</td>
<td>1.2</td>
<td>0.75</td>
<td>0.65</td>
<td>0.4</td>
<td>0.08</td>
<td>0</td>
<td>0.06</td>
<td>0.5</td>
<td>0.6</td>
<td>0.7</td>
<td>1.42</td>
</tr>
</tbody>
</table>

| Mean             | 0.995| 0.714| 0.485| 0.228| 0.077| 0 | 0.067| 0.257| 0.464| 0.656| 1.01 |
| S.D              | 0.281395| 0.170111| 0.129207| 0.15683| 0.011595| 0 | 0.006749| 0.174423| 0.132933| 0.226087| 0.318119|
Average deviations among FCSs over all 20 images of each rotation axis (A) for every rotation angle are given in Table 1. It is obvious in case of all axes, error increases with rotation angle. Figure 6 illustrates average deviation over all axes and subjects versus rotation angle which is an inverse-bell shaped. The value of Mean±SD of the deviation varies in the range 0.06±0.006° to 1.01±0.318°. It is obvious in case of all axes, the variabilities between the FCSs were introduced due to variation of bone morphology among the specimens. Translation errors of the origins between FCSs (before and after rotation back to original position) of all 20 images of each rotation axis for every rotation angle were also calculated. Origins as being coordinate points were rounded to the nearest integer and hence no translation error was observed for all arbitrary axes in any subject but some errors might exist in the fraction level which is not significant. The possible reason for the deviation (rotational error) of FCSs could be introduced due to interpolation (cubic interpolation was used in this work) during shape reconstruction back to original form after the rotation.

Figure 6. Average deviation versus rotation angles between the constructed automated FCSs before and after the rotation, by taking account of all arbitrary axes. Horizontal and vertical axes are in degree and average error in degree (°), respectively. Mean deviation increases with respect to rotation angle.

4.2. Statistical shape model

The SSM was constructed by the signed distance images of 20 aligned subject images as described in the previous Section 3.2. In this experiment, original feature space was 256 × 256 × 256. Figure 7 shows the signed distance of original image and reconstructed shape from SSM using PC scores of a subject. In these images, the signed distances are described by yellow-red-black color scale corresponding to positive-zero-negative distance. After that PCA was applied to the obtained shape vector as shown in Equation (5).

Figure 7. Multiplanar reconstruction view of signed distance image. Original (Left) and reconstructed (right) image by SSM, of a distal femur.

The performance of the shape model was evaluated by generalization ability [21,22] followed by leave-one-out cross validation (LOOCV) procedure. The purpose of this assessment is to indicate how well the modeling process has been able to embed the original data into a lower dimensional space, valid shape representation as well as new shape generation abilities. Generalization ability measures the ability of the model to generate unseen instances of the class of object which is not utilized during training implementation. It is performed using LOOCV reconstruction experiments. For every left-out instance, a new SSM is computed from the remaining training instances. The parameters of the left-out instance are computed to reconstruct the instance. The errors between original and reconstructed images were measured in terms of Jaccard Index (J.I.). It is also dependent on the number of modes of variation (parameters used in the reconstruction process).

To demonstrate the ability of representing femoral shape using the constructed SSM, individual shape variety synthesized by using PC score is shown in Figure 8. The PC scores were corresponding to SD along each Eigenvector. The images show that various shapes can be synthesized with changing PC scores. First and second dimensions seem to represent shape variation along medial-lateral and proximal-distal direction, respectively. Center image is mean shape, and other images are added or subtracted by one SD along corresponding direction from the mean shape. The model population included a variety of shapes from all ethnicity during training, and a variation in the synthesized shapes was observed. Fur-
thermore, Figure 9 shows the performance of the model which shows how the cumulative average J.I. changes as the number of principal components increases. We see that 7 principal components explain over 95% of the data variability in the training set. Further, for > 7 components, the increase in generalization ability is very slight, which suggests a limited benefit to select more components. Finally, for > 7 components, the error for shape validity will increase, which means the model represents plausible shape of distal femur. We therefore choose dimensionality 7 for the model.

Figure 8. Shape variation of distal femur synthesized by the constructed SSM. The center image is the mean shape, and the horizontal and the vertical axes correspond to the 1st and 2nd Eigenvectors, respectively. Each Eigenscore is the same as standard deviation along each Eigenvector.

Figure 9. Performance evaluations of the constructed shape model of distal femur in terms of generalization ability

5. Conclusion

SSM of distal femur has a wide area of applications in medical image analysis, including segmentation, morphological analysis of organ shape, etc. However, establishing correspondence across datasets is challenging as it is essential to align training subjects. This study proposes a fully-automated method for determining patient-specific FCS of the distal femur as conventional methods (manual and semi-automated) are observer-dependent and time consuming as well. The method is based on morphological analysis of distal femur in 3D MR images. Afterward an SSM has been constructed in a set of MR images by utilizing the implemented FCSs. New images were synthesized in each dimension from SSM and finally implemented model was evaluated by benchmarks model index-generalization ability. Furthermore, possible application of the implemented FCS could be in multimodal images (CT/MR) matching of distal femur, etc. In future, this study will be exploited to segment the distal femur aiming to implement fully-automated computer-aided ACL knee surgical planning [4].

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