Estimating Skeleton from Skin Data for Designing Subject-Specific Knee Braces

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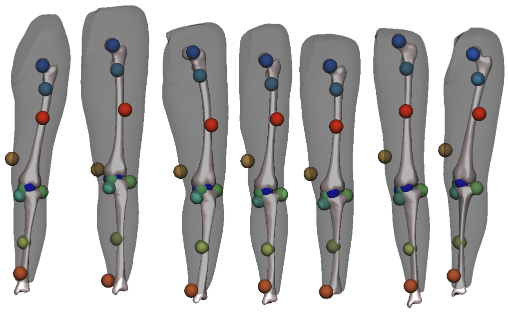
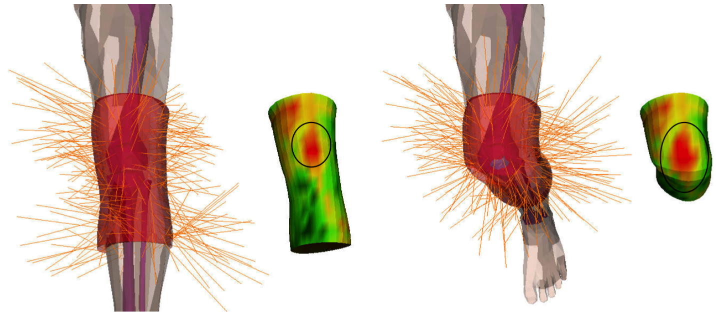


(a)



(b)

Figure 1: *(a). The skin and anatomical bone from CT scan data is registered with a template model to share the same mesh structure. (b) Our virtual knee brace model is fitted to subject specific skin and restitution force is computed. Left image shows force vectors on each vertex and right image shows color visualization of force with red as a larger force and blue as a lesser force.*

Keywords: character modeling, shape analysis

Concepts: •**Computing methodologies** → **Mesh models;**

1 Introduction

Knee brace is a sports product or medical equipment that increases the stability in the dynamics of the knee. The proper design of a subject-specific knee brace should take her anatomical characteristics into account since they are influential to the knee dynamics. However, anatomical information is hidden under the skin, and obtaining such information is restricted to expensive equipments such as Magnetic Resonance Imaging (MRI) device or Computed Tomography (CT) scan device.

In this paper, we develop a predictive model to estimate subject specific anatomical bones from the skin data, learned with training data of the leg skin data and the leg bone data as an input-output pair. We then examine the restitution force generated by virtual knee brace as the subject flexes her knee.

2 Our Approach

In order to construct a prediction model with CT scan data, the data structure should share the same mesh structure. We convert the image data of CT to 3D triangulated meshes using a simple thresholding based on intensity values by using a Slicer software package [Pieper et al. 2004]. Obtained mesh data have huge number of vertices with many problems (e.g., self intersection, non-manifold pieces), thus we clean and reduce the number of vertices by using Poisson resampling. We then register a template mesh to these data. Our generic template is obtained from Ultimate Human Model [Lee et al. 2009], from which we used only the skin mesh of the leg and the anatomical bones of femur and tibia. CT data is obtained from Digital Korean (http://dk.kisti.re.kr/) and we used 20 subjects with 10 males and 10 females with various ages. Fig.1(a) shows result of some of the registered meshes.

After registering all the CT data with template mesh, we train the radial basis function network (RBFN) to predict new anatomical bones corresponding to a given new input shape of the skin. RBFN is one of the most powerful interpolation methods to learn the best weight values between source and target data pairs. For our experiments, we employ Gaussian function for the basis function. In order to capture the spatial relationship between the skin and the bone, we represent the coordinates of the bone with the Mean Value Coordinate (MVC) [Ju et al. 2005] with respect to the skin. Thus, given the vertex positions of the input skin mesh, the MVC of the bone mesh is estimated by RBFN. Multiplying newly obtained MVC to the absolute coordinates of the skin surface gives the absolute coordinates of the new bones. Fig.2 shows result of some of the estimated skeleton. Errors are measured as the mean of Euclidean distance between normalized object of ground truth and estimated skeleton.

To match a given virtual knee brace to the subject, we first manually align the knee brace near the position of knee and register the inner vertices of knee brace to the skin using nonrigid ICP. We then project the deformed vertices of knee brace to the nearest face of the skin and compute the barycentric coordinates of each projected face.

We employ the Finite Element Method (FEM) to simulate the dynamics of the body and knee brace. We simulate a skeleton with articulated rigid body dynamics and skin with soft body dynamics. By fixing boundary nodes between the skin and bone, we can couple soft body dynamics with rigid body dynamics. The knee brace is simulated with soft body dynamics by inducing contact forces with skin surface as external forces. After computing the deformed position using the soft body simulation, we compute the restitution force of each node by examining stress-strain relation. Fig.1(b) shows visualization of restitution force on knee brace.

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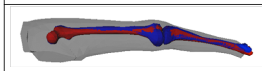
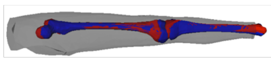
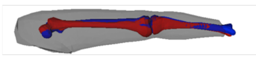
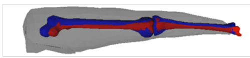
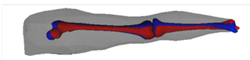
	0.0727
	0.0513
	0.0981
	0.1254
	0.0990

Figure 2: *Result of estimated skeleton (red) and ground truth (blue). Right column shows the measured error.*

3 Conclusions and Future Work

We have successfully estimated anatomical bone configuration with less than 10% of error with a leave-one-out test. The estimated subject-specific anatomy allows for predicting restitution force given by the knee brace. In future work, we will investigate the effect of the shape parameters of knee brace on the dynamics of the knee.

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