

Shape Completion and Modeling of 3D Foot Shape While Walking Using Homologous Model Fitting

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Abstract

Technologies for measuring the human body shape have been developed to aid in the design of products. Recently, several 4D measurement systems have been developed. These systems can measure the shape of a foot during motion based on computer vision technology. We have developed a 4D measurement system (consisting of 4 camera-projector units) that can measure the shape of the foot at 200Hz. Using this system, about 50 frames of shape data for one step of walking, and about 100 frames for one step of running, were captured. However, the measured data have the following problems: [1] some parts cannot be measured due to occlusion; [2] measured data do not have anatomical information; [3] there is no widely accepted methodology for analyzing a time-series of body shape data.

To solve these problems, we developed a technology for creating homologous models of foot shape data obtained by a 4D measurement system. Homologous models consist of the same number of the same topology, and each data point is defined based on the anatomical homology. In the present modeling technology, we use a homologous model using a polyhedral template. The template model consists of data points for describing the surface shape, landmarks for defining the anatomical correspondence between shapes, and internal skeletons for describing joint angles. By fitting the template model to each frame we can accomplish homologous modeling for 4D-measured data.

We show how the model can be used for shape completion and modeling ---generating a complete surface mesh and granting anatomical feature points given a limited set of captured points specifying the target shape. Using principal component analysis (PCA) and joint rotation, we can accomplish homologous modeling for 4D-measured data.

Keywords: anthropometry, homologous model, deformable model, principal component analysis skeleton model, 3D model fitting

1. Introduction

In recent years, anatomy and biomechanics have been widely used in criminological and medical applications, and in usability testing of products. They also play an important part in ergonomic design [1]. For such purposes, accurate measurement and modeling of human shape is necessary. Nowadays, 3D full body scanners are available. For example, shoes should be designed in consideration of a user's foot [2]. Ideally, the design should consider not only the static shape, but also the dynamic shape while walking, running, and so on.

The Digital Human Research Center (DHRC) developed a measurement system of anatomical feature cross-sections using multiple view stereo matching, which can measure foot shape while the subject is walking [3]. In this way, they aim at accurately measuring for the dynamic shape of the human foot in motion (i.e. walking or running). But the system could measure only feature cross sections. Therefore, the measurement of the whole 3D foot shape should be accomplished as the next step. Accordingly they have developed a 4D measurement system (consisting of 4 camera-projector units) that can measure the foot shape at 200Hz.

By using this system, about 50 frames of shape data for one step of walking, and about 100 frames for one step of running, are captured. However, measured data have several problems.

First, measured data has many deficit parts due to occlusion. Because of the pro-cam system, the light patterns have to be projected on the measured objects without any occlusions for a correct result. Second, the measured data do not have anatomical information, only have coordinate information (xyz) as point-clouds. Therefore we can't quantitatively use information about foot deformations while the subject is walking. Third, there is no widely accepted methodology for analyzing a time-series of body shape data. To make effective use of measured data, we have to complement deficit parts and add anatomical information to the measured data. In other words, we need to perform shape completion and modeling of time-series foot deformation data.

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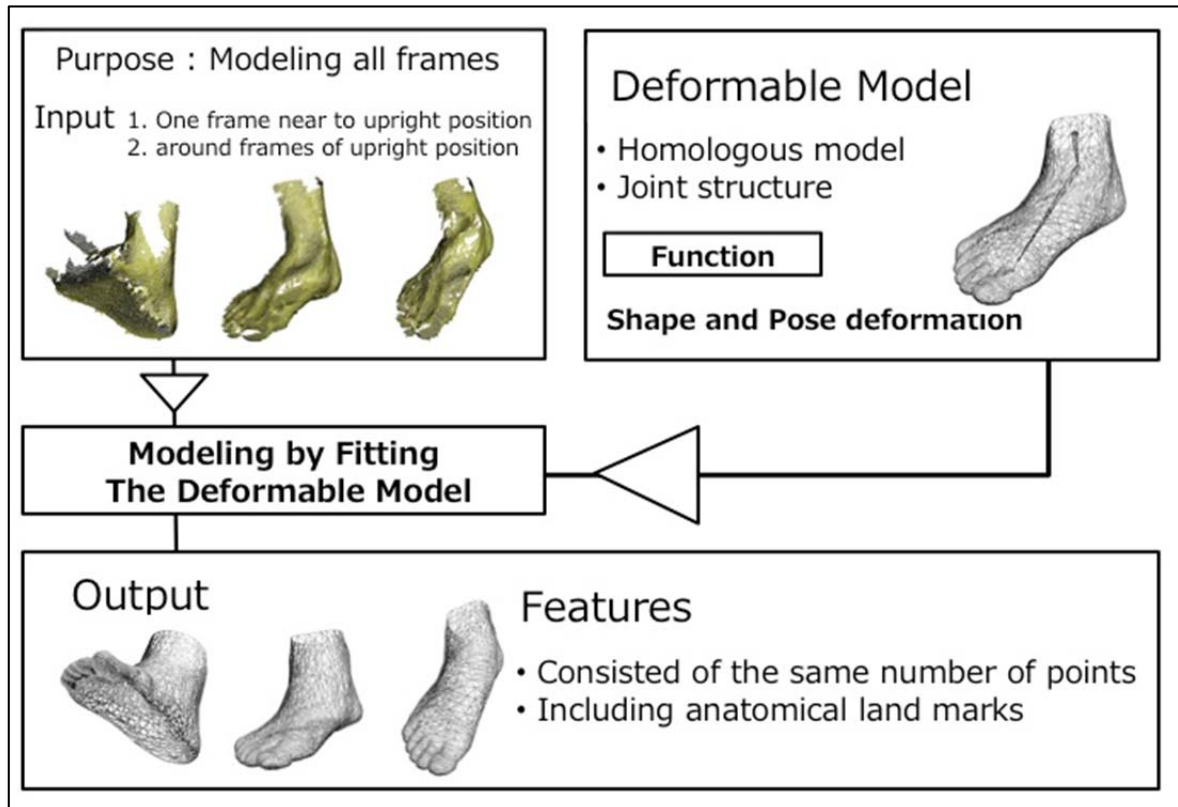


Fig. 1. Framework of the proposed method

Some different methods for shape completion of deficit shape data have already been proposed. SCAPE[5], one of these methods, is a model-based approach. The SCAPE system used a set of high resolution scans of one subject to animate the body shapes of new subjects based on a single scan and a set of marker positions. SCAPE decoupled the motion into a rigid body component and a residual deformation. The SCAPE model can complement the deficit part of measured data using a training set. This system captured joint angle-specific deformations that were present in the data but could not capture dynamic effect in the surface of the skin and the SCAPE model has no anatomical information.

In this paper, we propose a method to resolve these problems. We use a homologous model, which consists of the same number of the same topology, and each data point is defined based on the anatomical homology. We construct a foot database using homologous models. Using principal component analysis and skeleton based skin mesh deformation, we fit the deformable model to the measured data with deficit parts. Finally, we achieve homologous modeling of each frame in the gait cycle.

2. Method

In this section, model-based method which is called Active Shape Models (ASM) [5] and skeleton based skin mesh deformation (Skinning) [6] is applied for foot model to realize shape deformation and pose change for creating deformable foot model and fitting the model to each frame of 4D-measured data.

First, We prepare some homologous foot models for constructing homologous foot database and apply PCA for the database.

Second, after applying PCA, each foot shape is represented as one point in a subspace. Input data (homologous foot model) constructs a cloud in this subspace. An average of input data is center of the area. Arbitrary foot shape in the subspace is generated efficiently by translate from center position to another position in the space. In addition, hierarchical joints structure is set at homologous foot model to realize pose change.

Third, we optimize homologous foot shape for one frame which is near-upright position during in 4D-measured data. In other words, optimization of foot model for near stand position in gait-cycle is searching appropriate position in subspace.

Finally, fitting homologous model to next or back to near-upright frame one by one in sequence. We use Skinning as a pose deformation method for homologous model fitting.

2.1. Homologous Foot Model

Homologous models consist of the same number of the same topology, and each data point is defined based on the anatomical homology. The DHRC can create homologous foot models with laser 3D scanners (INFOOT), and dimensionality reduction, leaving the information in cross section and characteristic feature points from the raw scan data. This homologous model is designed for the last. There is a problem using the model for fitting because of the difference between the number of the points consisting of the homologous model and the number of the points of the measured data.

Therefore, we use homologous foot data that was generated by extracting 1946 points from full-body 3D homologous models Dhaiba (Digital Human Aided Basic Assessment system) [7] which is a visualization software platform implemented on VirTools®. In this way, we prepare 52 homologous foot data and normalized scale of foot long of 52 homologous foot models.

2.2. Shape deformation

2.2.1. Active Shape Models

In n feet database ($n = 52$), each foot is described by the same m vertices ($m = 1946$), which have been defined by anatomy specialists. A \mathbf{v}_i represents the position of i -th vertices in a 3D foot model; \mathbf{F} represents a foot shape. An i -th \mathbf{v}_i is a 3D point and consists of $(x_i \ y_i \ z_i)$. The initial 3D model as $\mathbf{F}^{\text{average}}$ is defined as the average of each foot in the database.

$$\mathbf{F} = [\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m] \quad (1)$$

$$\mathbf{F}_{\text{average}} = \frac{1}{n} \sum_{k=1}^n \mathbf{F}_k \quad (2)$$

These foot models were analyzed by PCA. We have a large matrix \mathbf{X} , including n samples' points data. Each sample has $P = 1946 \times 3 = 5838$ dimensions.

$$\mathbf{X} = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1P} \\ x_{21} & x_{22} & \dots & x_{2P} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nP} \end{pmatrix} \quad (3)$$

The covariance matrix is $n \times n$ matrix.

We represent the l -th biggest eigenvalue of the covariance matrix of the above matrix \mathbf{X} as λ_l ($l = 1, 2, \dots, n$).

In this case, the eigenvector \mathbf{w}_l in relation to the l -th biggest eigenvalue is a binding coefficient of the l -th principal component, and the l -th principal component z_l and l -th principal component score \mathbf{t}_l are represented as below.

$$z_l = \sum_{p=1}^P \omega_{pl} x_p \quad (4)$$

$$\mathbf{t}_l = \mathbf{X} \mathbf{w}_l \quad (5)$$

$$\mathbf{T} = (\mathbf{t}_1 \ \mathbf{t}_2 \ \dots \ \mathbf{t}_n) \quad (6)$$

The matrix consists of the eigenvectors \mathbf{P} (loading matrix); thus, we can describe it as below.

$$\mathbf{P} = (\mathbf{w}_1 \quad \mathbf{w}_2 \quad \cdots \quad \mathbf{w}_n) \quad (7)$$

Therefore, eq.(8) is derived from the above equations. Thus, the data matrix X is projected to the subspace.

$$\mathbf{T} = \mathbf{X}\mathbf{P} \quad (8)$$

Calculating the inversion matrix of P , we achieve foot shape deformation efficiently by changing each score of the principle component. We describe the coordinates of the new vertex below.

$$\hat{\mathbf{x}} = \sum_{k=1}^n \mathbf{t}_k \mathbf{w}_k^{-T} \quad (9)$$

We can generate a homologous foot model that has a unique body shape unlike any other model. To fit the generated homologous model's shape to the near-upright measured foot data of 4D-measured data, we have to optimize the principal component score vector \mathbf{t} .

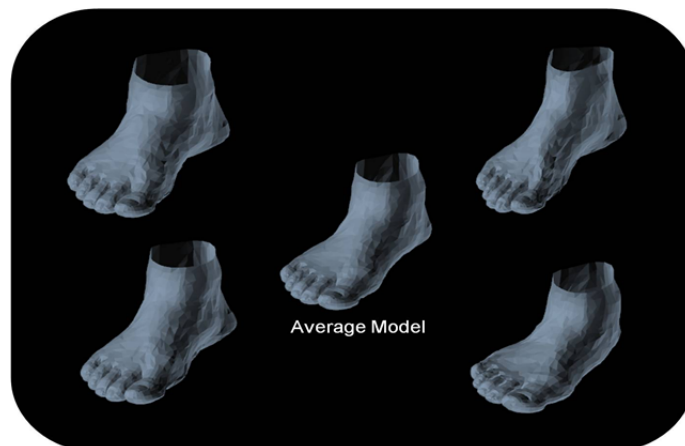


Fig. 2. The result of deformation of homologous models by changing PC scores

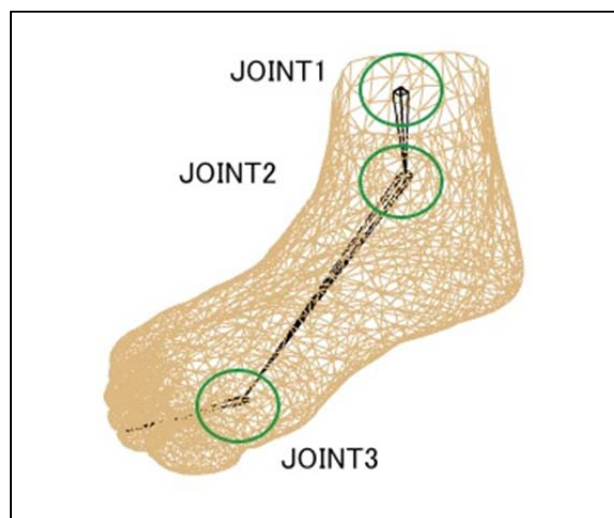


Fig. 3. Internal skeleton based on joints

2.2.2. Postural Changes

A homologous model is constructed in an upright position so we can't generate pose deformations using PCA. Therefore, due to realize pose deformation, we set hierarchical bones which consist of joint structure in a homologous foot model. However, this joint structure does not have a function to deform the surface skin connected with the joint rotation. We need to implement a surface skin deformation algorithm called skinning, that the geometry of the surface skin is deformed along with the change of the joint angles in the hierarchical structure.

First, we have to set joints to the appropriate points. The homologous model has anatomical information so we can set joints to near anatomical feature points. In this case, we set 3 joints (Link1,2, are near ankle, Link3 near ball of the big toe). We don't think that the number of joints and joint positions are the best, but this is enough to express pose deformation using joints.

First, we define \mathbf{M}_i as a homogeneous transformation matrix from a world coordinate to a certain i -th joint coordinate and \mathbf{B}_i is the i -th joint coordinate transformation such is used in translation and rotation. In fact, joints have a parent-child relation, so \mathbf{M}_i represents transformation from the world coordinate to the parent joint coordinate and ${}^i\mathbf{B}_{i+1}$ represents the transformation from i -th joint to the next joint. \mathbf{v} is the original vertex, and \mathbf{u} is the transformed vertex whose position depends on the joint. There are n joints influenced by the position of \mathbf{v} , which expresses certain vertex position in the world coordinate.

$$\mathbf{u} = \sum_{i=0}^{n-1} \omega_i \mathbf{B}_i \mathbf{M}_i^{-1} \mathbf{v}, \quad \text{where} \quad \sum_{i=0}^{n-1} \omega_i = 1, \quad \omega_i \geq 0. \quad (10)$$

The vertex \mathbf{v} is transformed by the different joints' concatenated matrices, and then blended using the weights ω_i . The weight is nonnegative and sum to 1.

Each weight is defined in Dhaiba as XML format using CG software Maya.

2.3. Shape Optimization

First of all, to a frame closing to standing state in a 4D-measured data, we manually align with homologous model position at the heel position of measured data and adjusting homologous model scale to measured data. After alignment and length adjustment, we perform shape deformation by using principal component score (PCA fitting) and skinning (Pose fitting). In case of fitting to near-stand position of measured data, we use only PCA fitting, because optimization of PCA fitting equals to finding individual shape in subspace which made by homologous models' database. In case of fitting other frames, we use only Pose fitting, because optimization of pose fitting is equal to dealing with external force for foot in gait, therefore we should not change PC score except for first phase of fitting. The principal components are linear and independent of each other. Therefore, we can optimize each principal component score in number order. First, we define the gravity point g^h to each mesh of the homologous model. The number of each mesh which constructs the homologous model is 3861; thus g^h_n means the n -th gravity point. In the same way, we define g^m which means the gravity point of the measured data.

Second, we calculate the nearest pair of each gravity point from g^h_n with g^m as the adopted point. As a result, we get d_{ave} , which means the average of the 3861 distances. Finally, $E(t)$ is defined related to d_{ave} .

$$d_{ave} = \frac{1}{n} \sum_{i=1}^n (g_i^h - g^m) \quad (11)$$

When the fitting is being performed, only g_h can be changed through PC scores optimization. Therefore we conduct sequential computation for the proper pair of gravity distances.

3. Fitting Experiments

Figure 4 shows the result of our system. First of all, we position the template model to the nearly standing position in the gait cycle. Then we optimize some of pc scores to fit the template model. Then Next step is fitting other shapes by changing the pose of the foot model. The result model is colored by

the distance between the template model and measured data. The nearer to blue the better the results we have.

Figure 5 shows the result of the template model after fitting some of measured data that is in a different posture from the standing position.

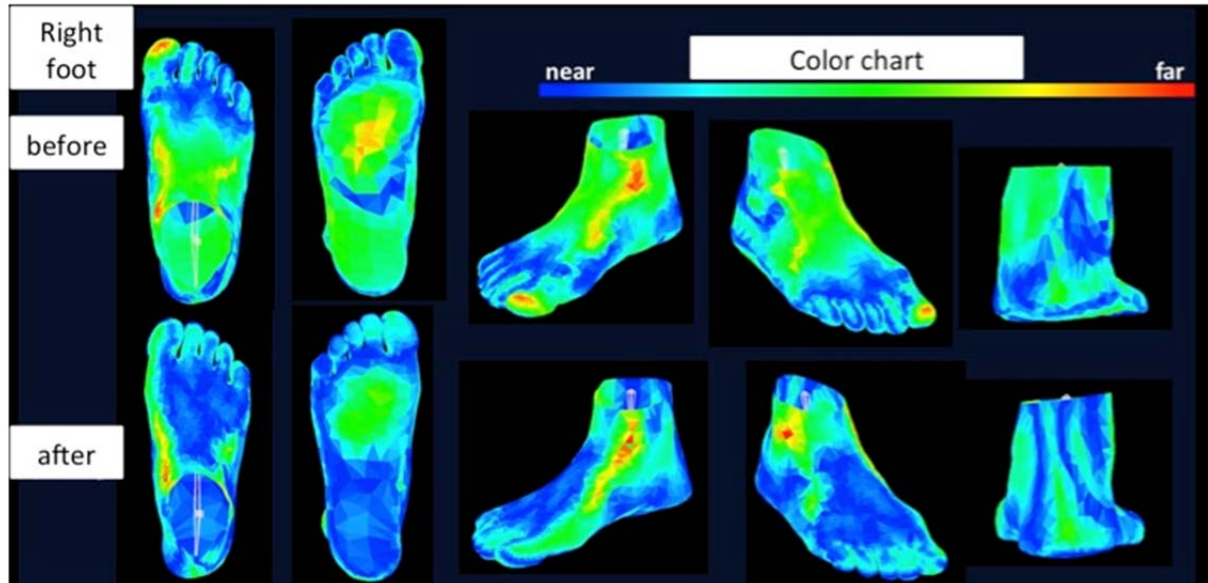


Fig. 4. Result of comparison between models before and after PCA

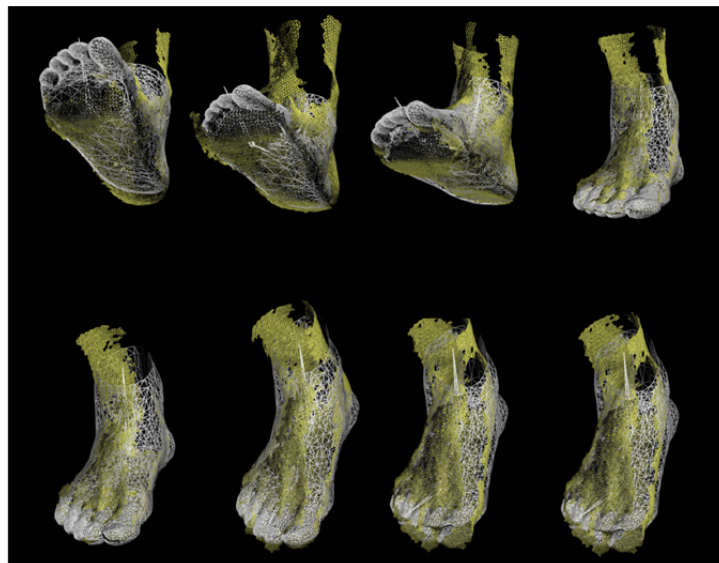


Fig. 5. Result of model fitting to measured data at various postures in a gait cycle

5. Conclusions

In this paper we proposed a model-based method of fitting a template model to 4D-measured data, which is captured using multiple cameras and projectors while walking or running. By using a homologous model as a template, the significant problem of measured data (there are a lot of deficit parts and there is no anatomical information in measured data) was solved efficiently.

In order to fitting a template model to measured data exactly, we used PCA and skeleton-based deformation.

However, to define the target model was difficult because there was no reference data on dynamic shape.

For future works, it is needed to define the correct answer and perform accurate validation of our system.

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