Simulating Skin Deformation Using Anatomical Structure, Muscle Dynamics, and Soft Tissue Dynamics

Abstract

Movement of skin and muscle is essential for bringing a character to life. This movement is difficult to animate in a realistic fashion using traditional techniques because of the subtle details required. In this paper, we present an algorithm that generates natural, dynamic, and detailed skin deformation from standard motion capture joint angle data. The algorithm consists of two steps: identification of a muscle deformation model and simulation of the skin deformation.

In the identification step, we use a musculoskeletal model to identify muscle deformation parameters that relate the muscle shape to its length and tension. The muscle shape is measured using a large number of motion capture markers from a few trials. The simulation step first uses the identified muscle deformation model to obtain the quasi-static muscle shape at each frame of a given motion sequence. The skin deformation is then computed by simulating the passive muscle and soft tissue dynamics as a mass-spring-damper system. We demonstrate our method using joint angle motion capture data of performances with muscle contraction and external impacts. Experimental results show that the simulated skin deformations are qualitatively similar to high-speed camera observations of actual skin deformations.

CR Categories: I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism—Animation

Keywords: Skin Deformation, Musculoskeletal Model, Motion Capture, Muscle Deformation Model, Soft Tissue Dynamics.

1 Introduction

As has been demonstrated in recent theatrical releases, skin deformation of animated characters must be natural, dynamic, and detailed if the characters are to appear realistic and lifelike. This level of realism is particularly important in scenes of rich natural environments such as those seen in Avatar and realistic special-effect shots such as those in The Curious Case of Benjamin Button. These deformations are essential for conveying a sense of life: the tension in the muscles and the jiggle of the underlying muscle and soft tissue convey the exertion of the character and the dynamics of the motion.

A number of algorithms have been created for generating plausible skin deformation [Maya Alias/Wavefront 2011; Lewis et al. 2000; Zhang et al. 2002]. Most of these approaches drive the skin motion from the skeletal structure and add the passive dynamics of the skin as a secondary step. Linear blending, spring-damper systems and volumetric models have been used to create natural skin deformations. These approaches, however, do not accurately represent the complex underlying structure of bones, tendons, muscles, and interstitial tissue that are present in the human body. Recently, more effort has been expended in making anatomically grounded models. For example, Lee and colleagues [2009] use an anatomically correct human musculoskeletal model to simulate quasi-static skin deformation for the upper body based on detailed geometry and deformation models of the muscles.

In this paper, we present an algorithm that generates detailed skin deformation from a skeleton animation based on, for example, standard motion capture joint angle data. Our approach consists of two main steps: 1) identification of muscle model parameters and 2) simulation of skin deformation. In the identification step, we use a musculoskeletal model with a muscle deformation model to identify subject-specific muscle shape parameters. Although this step requires skin geometry data captured with densely placed markers [Park and Hodgins 2006], it is performed only once for each subject using a short motion sequence. The muscle model relates the quasi-static muscle shape to muscle length and tension, which can be obtained by computing the inverse kinematics and dynamics using a musculoskeletal model and joint angle data. The simulation step first uses the muscle model to obtain the quasi-static muscle shape for the given motion sequence. It then computes the skin deformation by simulating the passive muscle and soft tissue dynamics as a mass-spring-damper system.

The rest of this paper is organized as follows. In Section 2, we review existing skinning techniques for character animation. Section 3 describes the two main steps of our approach: identification of the muscle model and simulation of skin deformation. In Section 4, we present the experimental results, including a comparison between simulated and real skin deformation. We conclude the paper in Section 6.
1.1 Contributions

We are the first to realize skin deformation that has anatomical and physical consistency for human arm and leg motion. We accomplish this goal by using prerecorded data to identify model parameters and then using those parameters in a detailed anatomical simulation. Using explicit knowledge of the underlying internal structure allows us to realize a level of detail that would be difficult to obtain with a purely data-driven approach. Conversely, having a muscle model with parameters identified from data allows us to simulate a detailed anatomical model without the time-consuming hand tuning or the stability issues that often arise in simulations of this complexity.

2 Related Work

Skin deformation and dynamics are required for a realistic and natural-looking character, and many approaches have been developed for skin animation. One of the most common approaches is a linear-blend skinning method in which each skin vertex position is computed using a weighted sum of the positions of nearby joints. However, when linear-blend skinning is applied to a human character, he/she often lacks realism because of artifacts such as the candy wrapper and the collapsing joint effects [Lewis et al. 2000] and lack of small scale details in skin deformation.

More realistic models fall into two broad classes: simulated and data-driven. To model human-like creatures, researchers have proposed a layered approach in which the skin is driven by interactions between multiple underlying layers with different properties that are based on anatomy. Chadwick and colleagues [1989] introduced a deformable layer between the rigid skeleton and the skin surface to represent muscles and soft tissues. Various parts of the human body have been modeled in detail, such as the face [Lee et al. 1995], torso [Zordan et al. 2004; DiLorenzo et al. 2008], hand [Sueda et al. 2008], and upper body [Lee et al. 2009]. With this approach, the research focus has been on modeling the shape and deformation of muscles to reduce artifacts and express details in skin deformation.

The muscle shape has been approximated as ellipsoids [Scheepers et al. 1997; Pratscher et al. 2005] and cylinders [Wilhelms and Gelder 1997], or learned from anatomical data such as Visual Human [Dong et al. 2002]. Deformation of muscles and soft tissues is often simulated by physics-based models including mass-spring-damper models [Lee et al. 1995; Nedel and Thalmann 2000; Zordan et al. 2004] and volumetric models such as the finite element method [Sifakis et al. 2005; Lee et al. 2009] or the finite volume method [Teran et al. 2003].

To avoid issues with stability and computation, data-driven approaches model skin deformation directly from data rather than simulating the behavior of each layer in the musculoskeletal structure. Anguelov and colleagues [2005] used SCAPE to build a pose deformation model and a body shape variation model from three-dimensional scan data and generate skin deformation for a new posture. Park and Hodgins [2006] used motion capture to collect data, and then trained the parameters of a mass-spring model from motion captured data to generate skin deformation from skeletal motion capture data [Park and Hodgins 2008]. Their mass-spring model treated body part as a homogeneous medium rather than having separate models for muscles, fat, and interstitial tissue as we do. Shi and colleagues [2008] trained parameters of a skin deformation model from user-provided examples.

In biomechanics and robotics, many musculoskeletal models have been developed for simulation and analysis of human body dynamics [Delp et al. 2007; Rasmussen et al. 2001; Forster et al. 2004; Nakamura et al. 2005] with applications for rehabilitation [Komura et al. 2005], prosthetics [Geyer and Herr 2010], and sports science [Murai et al. 2010]. We use one of the musculoskeletal models developed in this field to obtain muscle pathways and tension. However, these models focus on accurate simulation and analysis of human motion and do not include computation of the skin or muscle shape.

3 Method

In this paper, we describe a new algorithm for simulating skin deformation in novel motion sequences that is based on an anatomical model of the musculoskeletal system and a passive dynamics model of the muscles and soft tissue. Our goal is to replicate the skin deformation observed on the human body during dynamic activities. The human body consists primarily of bones, muscles, fat, organs, and skin. During dynamic activities, actuated muscles cause bone motions as well as muscle bulging due to tension and length changes. Additionally, muscles and soft tissue, including skin, fat, and organs, deform passively in response to the bone and muscle movement as well as external forces from the environment.

Our skin deformation model consists of three sub-models (Figure 2):

1. A muscle model that relates the muscle length and tension to the quasi-static muscle shape. This model represents the muscle building and relaxation due to different activation levels.

2. A muscle dynamics model that describes the passive dynamics of muscles using a mass-spring-damper system. The model consists of point masses placed at the vertices of the muscle polygon model and connected by springs and dampers. The quasi-static muscle shape generated by the previous model determines the rest length of the springs at each time step.

3. A soft tissue dynamics model that describes the passive dynamics of the skin and subcutaneous fat using a mass-spring-damper system. The model consists of point masses placed at the vertices of the skin surface polygon model that are connected by springs and dampers, as well as additional springs and dampers connecting them to the point masses on the muscle or bone surfaces.

The muscle model includes a number of parameters that can be tedious to adjust by hand. We therefore provide a method to identify the muscle model parameters from a sequence of measured skin geometry data. Although this method requires skin deformation data measured with dense markers, the identification process is performed only once for each subject or body type using a short motion sequence. Once the parameters are identified, our system can simulate the skin deformation from novel motion data captured using standard marker sets. We describe the details of modeling and identification processes in Section 3.2.

Figure 3 shows the block diagrams of the identification and simulation processes, where the blocks with red borders are the new components developed in this work. The details of each process are explained in the following subsections. In Section 3.1, we review the skin deformation data collection process [Park and Hodgins 2006] and the musculoskeletal model [Yamane et al. 2005; Nakamura et al. 2005; Nakamura et al. 2006]. We then present the muscle model and the parameter identification process in Section 3.2. In Section 3.3, we describe the algorithm to simulate the dynamic skin deformation using the muscle and soft tissue dynamics models.
3.1 Skin Deformation Data and Musculoskeletal Model

Identifying the muscle model parameters requires sample skin deformation data. We use the data recorded by Park and Hodgins using an optical motion capture system with 400–450 reflective markers [Park and Hodgins 2006]. The marker trajectories were recorded by 16 near-infrared Vicon MX-40 cameras at a rate of 120 fps. In our work, we use a slow jump motion that is approximately 300 frames in length. We select a slow sequence in which the soft tissue dynamics does not play a big role in the skin deformation.

In order to obtain the input data for the muscle model, we apply the inverse kinematics and dynamics algorithms of a musculoskeletal model [Nakamura et al. 2005] using the trajectories of 60 markers manually chosen from the full set of 400. The musculoskeletal model used in our work [Nakamura et al. 2006] consists of a skeleton and musculo-tendon network models. The skeleton model has 155 degrees of freedom (DOF), and the inertial parameters (mass, inertia, and local center of mass) of the bone segments are computed from an average human model [AIST 1998]. The musculo-tendon network model includes 989 muscles to drive the skeleton, as well as 50 tendons, 177 ligaments, and 34 cartilages to passively constrain the skeleton. Each of the muscles, tendons, and ligaments is represented by two end points (origin and insertion points), any number of via points, and straight pathways between them. Each origin, insertion, or via point is fixed with respect to a bone, and their locations are computed by solving the forward kinematics (Figure 4).

We first obtain the joint angles of the skeleton model at each frame with an iterative inverse kinematics algorithm using the positions of the 60 markers as soft constraints [Yamane and Nakamura 2003]. Then, the joint torques required to execute the measured motion are computed by applying a recursive inverse dynamics algorithm for articulated rigid bodies [Luh et al. 1980]. Finally, we compute the muscle tensions required to produce the joint torques [Nakamura et al. 2005]. The number of muscle is much larger than the dimension of joint torques and this redundancy is solved by mathematical optimization. If electromyograph (EMG) data are recorded at the same time, we can obtain physiologically plausible muscle tensions for actions that are not observable by the motion, such as co-contraction [Yamane et al. 2005].

Although using actual skin deformation data will result in a more accurate estimate of the muscle deformation parameters, it is not always reasonable to assume that such data are available. As an alternative, a modeler can provide the skin shapes at a few frames in a motion sequence either captured using a standard marker set or created by an animator. The identification process described in the next subsection can proceed in exactly the same way, except that we only have skin deformation data for selected frames.

3.2 Modeling and Identification of Muscle Model

We next develop a muscle model that gives the quasi-static muscle surface shape from the muscle length and tension. Because most skeletal muscles have spindle-like shapes, we approximate the quasi-static muscle surface with a spindle whose cross-section perpendicular to the pathway is an ellipse, the size of which varies along the pathway according to a sigmoid function (Figure 4). The sigmoid parameters and the eccentricity are represented as functions of the muscle length and tension. In addition, we divide a muscle at a center point into two parts (parts 1 and 2) with different sets of sigmoid function parameters to represent asymmetric muscles such as the Soleus. In the following equations, we omit the muscle index for clarity because the muscle model parameters of a muscle do not affect other muscles.

We represent the quasi-static muscle surface shape in a cylindrical polar coordinate system for each part whose longitudinal axis is the muscle pathway (Figure 4). For a point on the $m$-th ($m = 1, 2$) part of a muscle, the distance from the pathway, $r_m$, is described by the location along the pathway $x$, the angle from the polar axis $\theta$, and the current frame number $t$ ($t = 1, 2, \ldots, T$) as

$$r_m(x, \theta, t) = \left(\frac{k_{m,3}(t)}{1 + e^{k_{m,4}(t)-k_{m,2}(t)x}} + k_{m,4}(t)\right) \times \sqrt{1 - \varepsilon^2(t) \sin^2 \theta}$$

(1)

where sigmoid function parameters $k_{m,n}(t)$ ($m = 1, 2, n = 1, 2, 3, 4$) and the eccentricity $\varepsilon(t)$ are functions of the muscle...
length \( l(t) \) and tension \( \tau(t) \):

\[
k_{m,n}(t) = \alpha_{m,n} l(t) + \beta_{m,n} \tau(t) + \gamma_{m,n} \quad (n = 1, 2, 3, 4) \\
\varepsilon(t) = \alpha_{s} l(t) + \beta_{s} \tau(t) + \gamma_{s}
\]  

(2)  

(3)

In our implementation, the \( x \) axis is normalized for each part so that \( x = 0 \) represents the origin or insertion of a muscle and \( x = 1 \) represents the center point.

In this model, the eccentricity common to the whole muscle and four sigmoid parameters for each part have three coefficients. The total number of parameters to identify is therefore 27 for each muscle. We determine these parameters at each muscle independently so that the muscle shape fits the skin deformation around the muscle during the motion capture sequence, as described in the following paragraph.

Let us define a muscle segment as a section of a muscle between two neighboring origin, insertion or via points along the pathway and denote the number of segments in a muscle by \( L \). At each motion capture frame \( t \), we find a user-defined number of markers closest to the pathway that belongs to each segment and represent their positions in the local cylindrical polar coordinate system of the muscle as \((\hat{r}_{k,t}, \theta_{k,t}, \hat{x}_{k,t})\) \((k = 1, 2, \ldots, L)\). The closest marker of a segment may be different among frames.

We then solve an optimization problem to adjust the model parameters so that the total distance between the muscle surface and the positions of the closest markers is minimized. The cost function has a quadratic form with four terms and is described as

\[
Z = \frac{1}{2} \left( Z_r + a_1 Z_v + a_2 Z_t + a_3 Z_s \right)
\]  

(4)

where \( a_x \) are user-defined positive weights. Details of each term are given below.

The first term \( Z_r \) represents the total squared distance between the muscle surface and measured marker data and is formulated as

\[
Z_r = \sum_{t=1}^{T} \sum_{k=1}^{L} \Delta r_{k,t}^T \Delta r_{k,t} \quad (5)
\]

\[
\Delta r_{k,t} = \hat{r}_{k,t} - r_m(\hat{x}_{k,t}, \hat{\theta}_{k,t}, t)
\]  

(6)

where \( m \) represents the part that segment \( k \) belongs to.

The second term \( Z_v \) represents the variance of the muscle volume across the entire motion sequence and can be formulated by

\[
Z_v = \sum_{t=1}^{T} \left( V_1(t) + V_2(t) - \bar{V} \right)^2
\]  

(7)

where \( V_m(t) \) is the volume of part \( m \) at frame \( t \) computed by

\[
V_m(t) = l_i(t) \int_0^1 r_m^2(x, 0, t) \pi \sqrt{1 - \varepsilon^2(t)} dx
\]

(8)

and \( \bar{V} \) is the average of the total volume during the whole motion sequence. This term is added to represent the muscle volume conservation [Kardel 1990].

The third term \( Z_t \) is added to constrain the radius at origin and insertion so that the muscle is smoothly connected to the tendons at the ends. Using a manually chosen tendon radius \( w \), \( Z_t \) is formulated as

\[
Z_t = \sum_{t=1}^{T} \left( (w - r_1(0, 0, t))^2 + (w - r_2(0, 0, t))^2 \right).
\]

(9)

The last term \( Z_s \) represents the difference between the radii at the end of two parts and is formulated as

\[
Z_s = \sum_{t=1}^{T} (r_1(0, 1, t) - r_2(0, 1, t))^2.
\]

(10)

This term is added to ensure that the two parts are connected smoothly at the boundary.

### 3.3 Muscle and Soft Tissue Dynamic Deformation

In this section, we describe the deformation simulation method used for both the muscles and the soft tissue including skin and subcutaneous fat. Our method models the bones, the muscles, and the skin surface as polygonal surfaces. Let \( P^s \) denote the set of skin vertices, \( P^m \) the set of vertices on muscle surfaces, and \( P^b \) the set of vertices on bone surfaces. In the soft tissue dynamics model (Figure 6, top), each skin vertex \( p_s \in P^s \) is connected to:

1. adjacent skin vertices,
2. a set of nearby muscle vertices, which includes the vertices within the hemisphere whose center is at \( p_s \) and the radius is \( \alpha + r \), where \( r \) is the distance between \( p_s \) and its nearest vertex in \( P^m \cup P^b \) and \( \alpha(>0) \) is the offset, and
3. the bone vertices included in the hemisphere defined above.

Note that skin vertices may be connected to multiple muscles. Furthermore, these connections allow the skin to slide over the muscle surface to the extent allowed by the spring stiffness. In the muscle dynamics model (Figure 6, bottom), each muscle vertex \( p_m \in P^m \) is connected to:

1. adjacent muscle vertices,
2. skin vertices that have been connected to \( p_m \) by the procedure above, and
3. the closest point on the muscle pathway.

We incorporate the quasi-static muscle shape into the muscle passive dynamics by updating \( l_{ij} \), the natural length of the spring between \( p_i \in P^m \) and \( p_j \in P^m \), to match the distance between corresponding vertices on the quasi-static muscle shape at each frame. As a result, the muscle deforms not only subject to the skeleton motion but also to the change in the quasi-static muscle shape according to the muscle activation.
We model the muscle and soft tissue dynamics model with a mass-spring-damper system. This mass-spring-damper system is based on the realistic skin shape created by a modeller, and the simple spindle-like muscle shape is only used to indicate how the detailed skin shape should deform. Although in principle Finite Element Method (FEM) may be applied, we chose to use mass-spring-damper system models because FEM would require significant simplification of the boundary and loading conditions for layered system such as skin and muscles, and therefore do not significantly improve the results compared to mass-spring-damper model due to the simplifications.

If $p_i$ is connected to $p_j$ via a pair of spring and damper, the force applied to vertex $p_i$ from $p_j$, $f_{ij}$, is computed by

$$f_{ij} = k_{ij} \left( \frac{|x_{ij}| - l_{ij}}{|x_{ij}|} \right) \frac{x_{ij}}{|x_{ij}|} + c_{ij} \left( \frac{v_{ij}}{|v_{ij}|} \right) \frac{v_{ij}}{|v_{ij}|}$$

where $x_i$ and $v_i$ are the position and velocity of vertex $p_i$, $x_{ij} = x_j - x_i$, $v_{ij} = v_j - v_i$, and $k_{ij}$ and $c_{ij}$ are the stiffness and damping coefficients of the spring connecting vertices $p_i$ and $p_j$. We add all the forces for each vertex in $\mathcal{P}^s \cup \mathcal{P}^m$, and compute its acceleration.

We need a numerical integration method to update the positions and velocities of the skin and muscle surface vertices. Although some methods, such as the implicit integration method [Baraff and Witkin 1998], allow a larger time step than the explicit integration algorithm would, they are not suitable for our application because they add an extra damping effect that may diminish jiggling. We use the Velocity Verlet integration method [Swope et al. 1982] that allows us to achieve high stability at no significant computational cost over the explicit Euler method.

Spring and damper coefficients have to be chosen so that the simulation results become stable and realistic. We use different spring and damper coefficients for the springs between skin vertices, between muscle vertices, and between skin and muscle vertices because they have different material properties. The first is barely stretchable with high stiffness whereas the latter two represent the soft tissue that moves more dynamically.

To keep the number of parameters manageable, the individual spring coefficients are determined based on a few manually-selected global spring parameters. The spring coefficients between a pair of skin vertices are computed by dividing the global skin-skin spring parameter $K_{ss}$ by the size of the polygon which the vertices belong to. We use the same method for the springs between muscle vertices using another global parameter $K_{mm}$. The spring coefficient between a muscle vertex and the corresponding pathway vertex, $K_{mp}$, is also chosen by a user. For the springs between a skin and a muscle/bone vertex, we determine the total spring coefficient for each skin vertex by multiplying the global skin-muscle/bone spring parameter $K_{smb}$ by the total area of the polygons which the vertex belong to. The total spring coefficient is then distributed to individual springs so that the coefficients become inversely proportional to the nominal spring lengths. This relationship is motivated by the observation that the part of skin close to the bones, such as near elbow and ankle, shows stiff movements, while the part farther from the bones shows more dynamic movements due to the thick soft tissue and muscle layers. Finally, the damper coefficient is determined by $d = \sqrt{K}/50$ for a connection with a spring coefficient of $K$.

4 Results

The sample skin deformation data used for muscle model identification are recorded with 400–450 reflective markers using 16 near-infrared Vicon MX-40 cameras at a rate of 120 fps [Park and Hodgins 2006]. The motion data used for the simulations are recorded with 60 reflective markers using the same motion capture system. We also record the contact force between the subject and the ground using two AMTI AccuSWay PLUS force plates, each of which can measure the six-axis contact force and momentum at a rate of 1 kHz, as well as electromyography (EMG) using Aurion ZeroWire system with 16 pairs of electrodes at a rate of 5 kHz. The EMG data are processed by mean subtraction, rectification, and a Butterworth bandpass filter with a cut-off frequency of 10–1000 Hz. A high-speed video camera is also used for some of the motions to capture the dynamic skin deformation at 1 kHz.

The parameters used in all simulations are $\alpha = 2$ cm, $K_{ss} = 10^4$, $K_{mm} = 10^5$, $K_{mp} = 10^5$, and $K_{smb} = 10^7$.

4.1 Evaluation of Identified Muscle Model

We first demonstrate the advantage of using musculoskeletal and muscle deformation models to obtain the underlying muscle shapes. As we mentioned in Section 3, we use the skin deformation data captured by markers densely placed on the skin. The distance between a marker and the closest point on the simulated skin surface indicates how well the muscle deformation model describes the skin deformation.

We compare the distances when the quasi-static muscle deformation is considered and not considered using two motion sequences: the slow jump motion used for identification and a slow walk mo-
Table 1: Means and standard deviations of the distances between measured markers and their closest points on the skin surface when muscle deformation is considered and not considered in the two motions.

<table>
<thead>
<tr>
<th>motion</th>
<th>with deformation</th>
<th>no deformation</th>
</tr>
</thead>
<tbody>
<tr>
<td>slow jump</td>
<td>14.2 [mm]</td>
<td>14.3 [mm]</td>
</tr>
<tr>
<td>slow walk</td>
<td>14.4 [mm]</td>
<td>15.0 [mm]</td>
</tr>
</tbody>
</table>

Figure 7: Skin deformation simulation with muscle co-contraction. The top row shows the skin deformation simulation and the middle row shows the increase in the upper arm perimeter. Yellow and red colors indicate the amount of muscle bulging. The bottom graph shows the activities of the Biceps Brachii and Triceps Brachii measured by EMG.

4.2 Simulation Results

We now show simulated deformation of different parts of the skin for various motions to demonstrate our method. These motions are measured from a subject different from the one used for identifying the muscle model using a standard marker set, force plates, EMG, and a high-speed camera recording for reference. The video clips of the simulated and recorded skin deformation are shown in the supplemental movie.

Figure 7 shows a body building pose with bulging of the upper arm muscles. The top row represents the simulated skin deformation, the middle row represents the increase in the upper arm perimeter from the initial state, where the color changes from yellow to red gradually as the perimeter increases, and the bottom row represents the corresponding snapshots from the high-speed video camera. The bottom graph shows normalized activities of the Biceps Brachii and Triceps Brachii obtained by post-processing the EMG data. The result shows that our method effectively simulates the bulging of the muscles during co-contraction, which is mainly detected by the EMG data because co-contraction of antagonistic muscles does not appear as joint motion.

Figures 8 and 9 represent the simulation results for a jump motion. In this motion capture session, we attached several markers in a mesh pattern to quantitatively compare the actual and simulated skin deformations.

Figure 8 shows the snapshots from the simulations and high-speed camera recording. The top row represents the simulated skin deformation without passive dynamics of muscles and skin, the second row represents the simulated skin deformation with our algorithm, and the bottom row represents the corresponding snapshots from the high-speed camera recording. The motion simulated by our algorithm includes muscle jiggles similar to the one observed in the high-speed camera recording.

Figure 9 plots the trajectories of selected markers from the measured and simulated skin deformations. The blue and red lines represent the measured and simulated trajectories of four randomly-selected markers. And the green dotted lines represent the marker trajectories that are simulated without muscle or soft tissue dynamics. The horizontal axes represent the time [sec], and the vertical axes represent the position [m], where x, y, and z axes are defined as shown in the upper-left corner. The amplitude, frequency, and duration of the jiggles in the simulated skin deformation are similar to those in the measurement, especially in the y direction just after the landing, which would not be realized without muscle or soft tissue dynamics.

In Figure 10, the subject hits an object with his arm. The top row represents the simulated skin deformation, and the middle row represents the corresponding snapshots from the high-speed camera recording. The high-speed camera video shows the skin wrinkle...
The three axes are defined as shown in the upper-left corner. The graphs only show four randomly-selected markers for clarity, but all other markers show similar trajectories. The three axes are defined as shown in the upper-left corner.

Figure 9: Trajectories of the measured and simulated markers during the jump motion. The graphs only show four randomly-selected markers for clarity, but all other markers show similar trajectories. The three axes are defined as shown in the upper-left corner.

around the elbow caused by the impact, which is also seen in our simulation.

We additionally consider a parameter that determines the average relative thickness of muscles with respect to soft tissue to emulate different body types. The third row of Figure 10 shows the skin deformation when this parameter is selected so that the model is 25% less muscular than the one in the top row. The amplitude of the skin jiggles becomes larger than that observed in the muscular model, which is qualitatively correct in the actual human body.

Figure 10: Skin deformation simulation of the arm with the external impact. The bottom row shows a simulation result with a less muscular model.

5 Discussion

In this paper, we developed a new algorithm for simulating skin deformation in novel motion sequences based on an anatomical model of the musculoskeletal system and a passive dynamics model of the soft tissue. This algorithm directly generates the skin deformation from motion data, and has many advantages.

First, the muscle model allows us to compute the quasi-static muscle shape from muscle length and tension information for a wide range of motions. The resulting muscle shape is consistent with the dynamics of the motion because it is based on the muscle pathway and tension data obtained by inverse kinematics and dynamics algorithms for a musculoskeletal model.

Also, this algorithm can simulate physiologically realistic skin deformations that are difficult to estimate only from standard motion capture data if EMG data are recorded along with the motion data. An example is muscle co-contraction, which cannot be estimated only from motion data because the activations of antagonistic muscles do not cause a joint motion. The muscle bulging due to the co-contraction changes the impression of behavior dramatically.

Moreover, the passive dynamics of the soft tissue effectively describes the interaction between the skin and internal bones and muscles. Our model can simulate the skin deformations depending on the underlying structure, such as different jiggling patterns when the skin hits the tibia side and the calf side of the lower leg.

Finally, the model can easily be generalized to a variety of body types by applying our identification method. The rigid, internal structure may also stabilize the soft tissue dynamics simulation.

Our method has several assumptions that will be addressed in future work.

For example, we identified the muscle model parameters assuming that the measured skin deformation data are not affected by the soft tissue dynamics. We then manually adjusted the passive dynamics model parameters (spring constants) to obtain desirable skin deformations. We will develop an algorithm for simultaneously identifying two sets of parameters using dynamic skin deformation data.

Additionally, we approximated the muscle shape by a parameterized spindle. We can apply the same identification and simulation method to any muscle shape if we can determine the pathway of every muscle. Simulation results will be improved by considering the real muscle shape.

References


Maya Alias/Wavefront, 2011.


