Combining biomechanical and data-driven Body Surface Models

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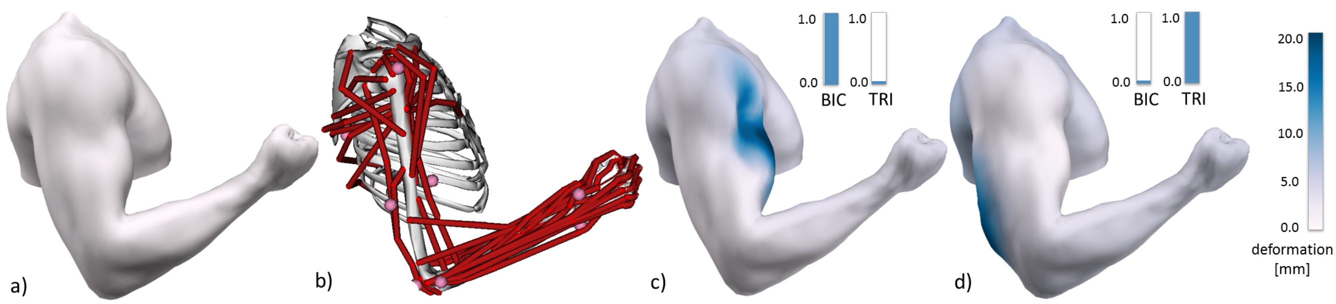

Figure 1: We combine real world surface data of an elbow flexion motion (a) with biomechanical simulation in OpenSIM (b) to a hybdrid surface model predicting the shape deformation from simulated muscle data, here shown with full biceps activation (c) and with fully activated triceps (d).

ABSTRACT

Statistical body shape modelling can be used to realistically generate complex muscle deformation effects on the skin. However, purely data-driven models still ignore the biomechanical nature of surface deformations. Reliable anatomically and biomechanically consistent predictions are barely possible. Our research aims at combining the previously separate paradigms – data-driven and simulation-driven 3D surface modeling – to a hybrid body shape model. Our first goal consists of synthesizing the skin surface from simulated biomechanical data. As a first step in this direction we show preliminary results of our model of an elbow flexion motion with separate biceps and triceps muscle bulging that exhibits believable muscular deformation effects on the skin surface while enabling singular control over specific muscle regions. Our model is separately controllable in shape and pose and extensible to a wider range of human body shapes, joint motion and muscle regions.

CCS CONCEPTS

• **Computing methodologies** → Shape representations; **Shape modeling**; *Animation*;

KEYWORDS

Data-driven Body Shape Modelling, Biomechanical simulation

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1 MOTIVATION

Deformation of the skin is caused by a complex interplay of muscles, tendons, fat and connective tissue during joint motion. Muscle shape can be affected by various conditions including external load, the person's physical constitution as well as bio-physical parameters like the muscle's moment arm, fiber length and the velocity of length change, which in turn depend on the joint angle. The biological mechanisms are well-studied in the field of Biomechanics where the simulation of muscle forces and other biomechanical data (e.g. joint reaction forces, tendon and ligament forces, damping forces etc.) is successfully achieved with the help of muscle models, the equations of motions and optimization techniques [Enoka 2015], yet without providing any notion of volume or muscle surface. The anatomically accurate modelling of the muscles' surface, however, requires computationally demanding physics-based simulation models [Lee et al. 2012]. An alternative approach is based on learning deformations from multiple subjects [Hasler et al. 2009], in multiple poses [Anguelov et al. 2005], or even from multiple external forces that result in pronounced muscle deformations [Neumann et al. 2013]. These models tend to produce very convincing, fine-scale deformation effects, yet lack bio-physical justification.

Our approach combines the advantages of statistical body shape modelling with the physical accuracy of biomechanically inspired body models by modelling the correlation between surface data and biomechanical data. Our model is able to synthesize the skin surface based on the force magnitude of specific muscle fiber strands, like for instance biceps longus or triceps medialis, and thus gives control over the muscle shape. A secondary purpose of the model encompasses assumptions about distinct muscle activation patterns without using any sensory devices for muscle activation measurements. As a result, the range of applications opens up from computer graphics to applications in therapy, rehabilitation, exoskeleton control and sports.

2 METHOD

Our proposed model extends the SCAPE model by Anguelov et al. [Anguelov et al. 2005]. According to SCAPE, it uses deformation gradients for modelling body part rotation induced (Q) and Shape induced deformation components (S) separately. First, pose-based deformation Q is learned based on twist vectors containing the body part rotations R as a prestep. Secondly, we subtract the pose model from the input data. The residuals form the shape-specific deformation component S, containing the difference in muscle shaping effects under increasing external loads. Principal Component Regression is our method of choice for relating the biomechanical data with the shape deformation, whereby an intermediate Principal Component Analysis step helps to prevent overfitting by selecting only the most meaningful PCA components for linear regression. By this means, we configure a semantic model that – provided with pose specific parameters (6 degrees of freedom for the shoulder and elbow joint) and a specific muscle activity pattern in the form of a vector of muscle activities as inputs – delivers the according deformation gradients to reconstruct the resulting surface.

For a proof of concept, we use the dataset provided by [Neumann et al. 2013] consisting of detailed surface meshes of the shoulder-arm-area in motion and concentrated on an elbow flexion motion (ranging from unflexed pose to maximum flexion and back), performed by a male subject under varied external loads. The focus was limited to biceps and triceps – the most prominent agonist-antagonist pair of muscles in the upper arm. We then feed the captured data into OpenSIM [Delp et al. 2007], an open source framework for biomechanical body modeling and simulation developed by the university of Stanford with a wide range of applications in the field of Biomechanical and clinical research [Hicks et al. 2015]. Fig. 2 shows the strong coherence between the weight curves of the First Principle Component of body surface deformation with the simulated force curves of biceps longus over all elbow flexion repetitions with barbell weights increasing from 0 to 14 kg.

3 DISCUSSION AND FUTURE WORK

The described approach facilitates the synthesis of skin shape from a given state of muscle activity and pose. In contrast to previous work in the field of statistical modelling, our model enables CG artists to animate the specific muscle activation pattern e.g. fine-scale muscle twitches. As shown in Fig. 1 as well as in the accompanying video, the results exhibit plausible muscle effects in arm shape. Our model allows for separate control over pose and shape.

With a limited training database of just one type of motion, our preliminary model remains fairly limited, resulting not just in a restricted pose model but also in some inaccuracies in the shape

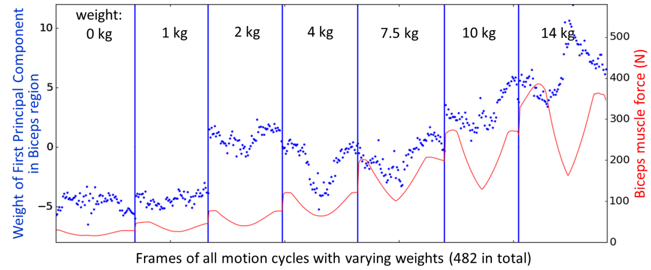

Figure 2: The deformation change in the biceps region along the axis of the First Principal Component for several sequences of elbow flexion motion with increasing weights (blue) correlates well with muscle forces simulated with OpenSIM's Static Optimization tool (red).

model's triceps region, since the triceps' activation is particulary low - just a fraction of biceps activation - during elbow flexion. As antagonistic muscle, it acts as joint stabilizer and thus co-contracts slightly with increasing biceps activation [Enoka 2015]. However, in biomechanical simulation, which relies on energy optimization, the triceps' force is estimated to decrease with increasing load. The indispensible inversion step of the triceps muscle data could be prevented by extending the model with motion data of further, more triceps intensive exercises. In general, training on a larger dataset including several subjects, more body parts and, especially, covering a wider range of human motion, will improve the generalisability, both in terms of pose and shape.

Our preliminary model was trained under the assumption of quasi-static motion. However, utilizing the muscle model's force-length-velocity curves during simulation, our approach facilitates a dynamic muscle behavior, provided that the training database is extended by motion sequences with varied timing. Future work also encompasses the replacement of the currently manual procedure for muscle region definition with an automatic process that isolates and assigns meaningful muscle regions in a data-driven way.

Other types of biomechanical data can as well be included into the shape regression model, for instance joint reaction forces, muscle moment arms or fiber length, making it a potential tool for muscle surface-based predictions of biomechanical data relevant for applications in clinical disciplines.

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