Learning Neuromuscular Control for the Biomechanical Simulation of the Neck-Head-Face Complex

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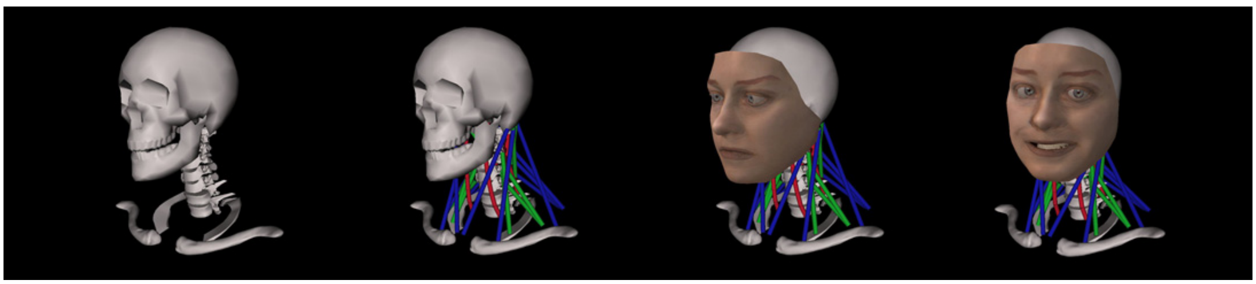

Figure 1: Our biomechanical system comprises a skeleton, muscles, neural control system, and an expressive face.

Introduction

The neck has a complex anatomical structure and it plays an important role in supporting the head atop the cervical spine, balanced in gravity, while generating the controlled head movements that are essential to so many aspects of human behavior. We have developed a biomechanical model of the human head-neck system that emulates the relevant anatomy. Our model is characterized by appropriate kinematic redundancy (7 cervical vertebrae coupled by 3-DOF joints) and muscle actuator redundancy (72 neck muscles arranged in 3 muscle layers). This model presents a challenging motor control problem, even for the relatively simple task of balancing the mass of the head atop the cervical column. We describe a neuromuscular control model for the neck that emulates the relevant biological motor control mechanisms. Incorporating low-level reflex and high-level voluntary sub-controllers, our hierarchical controller provides input motor signals to the numerous muscle actuators. In addition to head pose and movement, it controls the coactivation of mutually opposed neck muscles to regulate the stiffness of the head-neck multibody system. Taking a machine learning approach, the neural networks within our neuromuscular controller are trained offline to efficiently generate the online pose and tone control signals necessary to synthesize a variety of autonomous movements for the behavioral animation of the human head and face.

Biomechanical Model

Fig. 2 shows the overall architecture of our head-neck system model, which comprises the skeleton, muscles, and hierarchical controller. The voluntary sub-controller generates feedforward and setpoint control signals: The feedforward signal is generated to attain the desired pose and tone. The setpoint signal specifies the desired strain and strain rate of each muscle, as well as the magnitude of the feedback gain. Comparing the strain and strain rate against their desired values, the reflex controller generates a feedback signal and adds it to the feedforward signal, thus determining

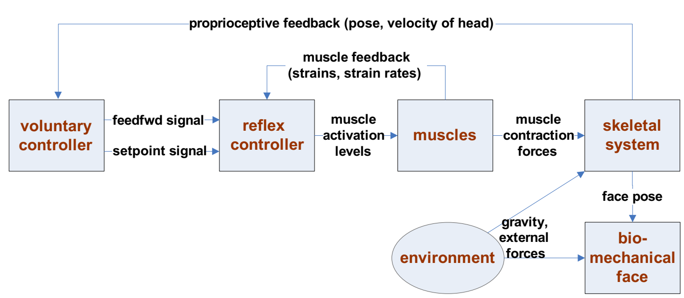

Figure 2: Face-Head-Neck System Architecture.

the activation level of each muscle. Given an input activation signal, each muscle generates a contraction force depending on its length and velocity. Finally, the skeleton produces articulated motion in response to the internal muscle forces and external environmental forces, such as gravity and applied forces. Physics-based animation is achieved by numerically integrating the equations of motion of the biomechanical model through time. We have augmented the realism of our biomechanical neck-head model by coupling a biomechanical face model (the lower right box in Fig. 2) to the front of the skull as shown in Fig. 1. Including control computations, our simulation runs about 10 times slower than real time on a PC with a 3.2 GHz Mobile Intel Pentium 4 CPU and 1 GB of RAM.

The relevant skeletal structure is modeled as an articulated multibody system. It includes a base link, seven cervical bones, C1–C7, and a skull. In the human spine, disks are sandwiched between adjacent vertebrae, allowing 6-DOF motion. To each joint angle, we attach a rotational damped spring in order to model the stiffness of the ligaments and disks. Consulting references on anatomy, we incorporated 72 individual muscles into the musculoskeletal model. The neck muscles are arranged in three layers—deep, intermediate, and superficial. In the deep layer, there are a total of 48 muscles, which improve controllability. Six muscles are attached across each cervical joint, such that they cover the 3 DOFs of the joint. This increases, if not guarantees, controllability and affords greater freedom to model the major muscles of the intermediate and superficial layers, each of which include 12 muscles. Each muscle actuator is also modeled biomechanically as a simplified Hill-type muscle model, which is frequently used in biomechanics research.

Learning Neuromuscular Control

The complexity of the musculoskeletal model, especially its kinematic and muscular redundancy, which imitates that of its biological counterpart, confronts us with a challenging control problem. We believe that the best way to tackle this problem is via an approach inspired by biological motor control mechanisms, all the more so because our long-term goal is to create lifelike characters that are able to synthesize a broad range of human motions.

The computational mechanisms underlying the implementation of the voluntary controller are artificial neural networks sustained by machine learning techniques. Neural networks are trained to generate the appropriate pose and tone control signals necessary for the musculoskeletal system model to synthesize a variety of autonomous humanlike movements for the behavioral animation of the head and face. The training data are precomputed by solving repeated optimal control problems. It takes less than 10 hours to train each neural network on our 3.2 GHz CPU PC. Once trained, the neural network can approximate suitable outputs for particular inputs orders of magnitude faster than one can hope to do by solving the associated optimization problem. This makes the trained neural network suitable for online use, especially for interactive animation.

We use 3-layer networks with two hidden layers of sizes 20 and 40 neurons. The dimension of the network output vector is 72, the total number of muscles. The trainable parameters of the network are the weights and bias terms associated with the neurons, and they are computed using the backpropagation learning algorithm. To train the pose controller neural network, we randomly sample the head pose space. For the i-th sample pose $\mathbf{h}_d^i$, the desired pose signal $\mathbf{a}_p^i$ is the solution of a constrained optimization problem to achieve the desired pose while minimizing weighted muscle contraction forces. On the order of $20,000 \approx N$ training pairs $\{\mathbf{h}_d^i, \mathbf{a}_p^i\}_{i=1}^N$ are generated offline to train the neural network using backpropagation. Given a desired head pose $\mathbf{h}_d$, the trained pose controller network efficiently computes a feedforward signal online to maintain $\mathbf{h}_d$ with minimal muscle contraction forces $\mathbf{f}_C$. Due to muscle redundancy, there are usually many combinations of muscle coactivations that can increase tone. The tone neural network is similarly trained offline with on the order of $20,000 \approx N$ training pairs $\{\mathbf{h}_d, \mathbf{a}_t\}_{i=1}^N$, where the maximum tone signal $\mathbf{a}_t^i$ is obtained by solving a constrained optimization problem

Results

As Fig. 3 shows, our biomechanical model can synthesize coordinated head-eye movements that emulate at least the primary head-eye movement phenomena reported in the literature. When we present a moving visual target (the doll) to the model, the eyes are directed to make a saccadic ocular rotation (with maximum angular velocity of 200 degrees/sec) to point in the direction of the visual target relative to the head. Simultaneously, the head motion subcontroller of the neck neuromuscular controller issues a high-level command to rotate the head in the direction of the gaze. As the head executes the desired rotation via the low-level physical simulation, the eyes make a continuous compensatory movement such that they remain directed at the visual target. Fig. 3 shows the head gazing at the target in two different directions. Employing a rule-based behavior routine, the biomechanical face automatically synthesizes

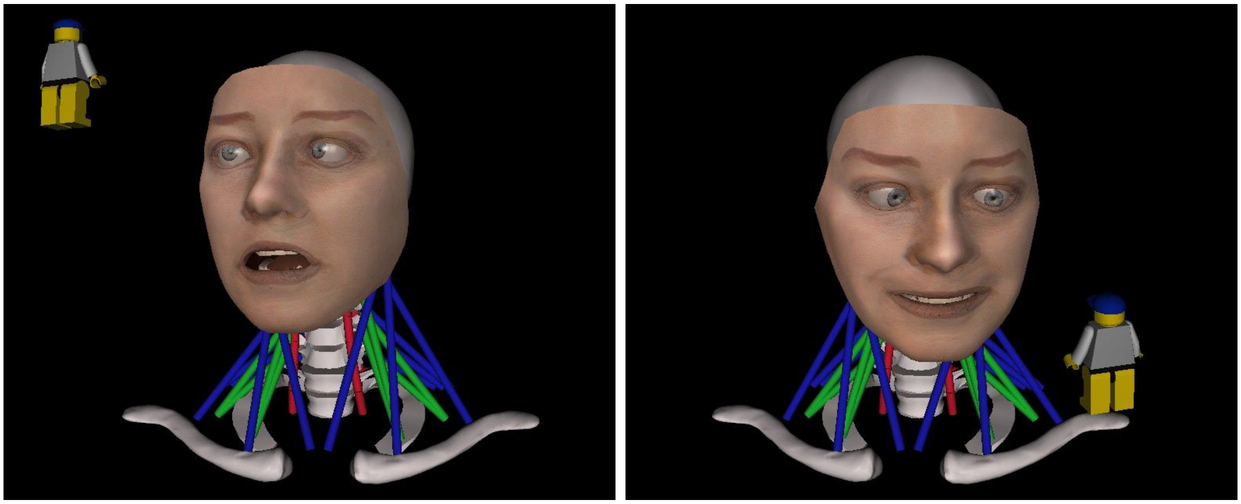

Figure 3: Head-Eye gaze behavior. Snapshots of the model gazing at a target in different directions.

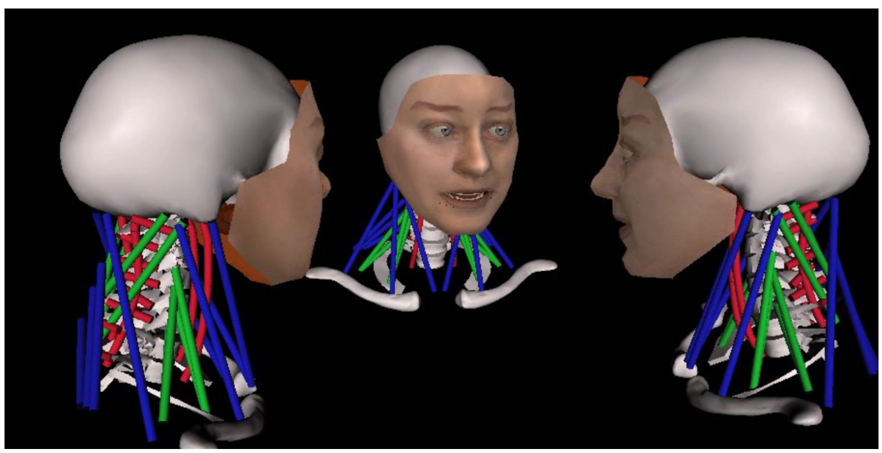

Figure 4: Autonomous behavioral-based interaction between three face-head-neck systems.

baby-like facial expressions as the eyes and head track the target. It appears awed when the doll is situated above the head, pleased when the doll is around eye level and held still, and angry when the doll is shaken.

Fig. 4 illustrates three autonomous face-head-neck systems interacting in a multi-way behavioral facial animation scenario. Each of the faces is supported by our head-neck musculoskeletal system, which automatically synthesizes all of the head motions necessary to sustain a highly dynamic multi-way interaction. As in the above demonstration, the synthesized head movements must cooperate with eye movements in order to direct the gaze at visual targets in a natural manner. The middle head in the figure acts as a "leader" synthesizing random expressions and alternating its attention between the other two heads, which act as "followers". Once a follower has the leader's attention, the follower will observe the leader's expression and engage in expression mimicking behavior. However, excessive mimicking will lead to behavior fatigue—the follower will lose interest in the leader and attend to its fellow follower.

References

[1] Sung-Hee Lee, Demetri Terzopoulos. Heads Up! Biomechanical modeling and neuromuscular control of the neck. *ACM Transactions on Graphics,* **25**(3), August, 2006, 1188–1198. *Proc. ACM SIGGRAPH 06 Conference,* Boston, MA, August, 2006.