LEARNING FACIAL MOTION USING DEEP REINFORCEMENT LEARNING AND FINITE ELEMENT MODELING

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Introduction

Due to altered facial muscle mechanism and nerve damage, patients with facial palsy or those who have undergone a facial transplant have an asymmetrical face and irregular facial movements [1]. A complex rehabilitation process is needed to restore a symmetrical face with balanced functionality. Thus, a better understanding of the facial motion mechanism plays an essential role in the recovery of symmetrical motions and typical facial expressions of the affected individuals. To provide feedbacks for decision support, computer-aided systems and physics-based models have been developed [2]. However, the predictive capacity of current solutions is still limited to explore the facial motion patterns with emerging properties. The objective of the present study is to develop a novel methodology using reinforcement learning and finite element modeling for the learning and prediction of face motion without a priori input motion patterns.

Materials and Methods

The developed methodology relates to a coupling between a reinforcement learning (RL) agent, a human finite element face model and associated simulation environments (Fig. 1).

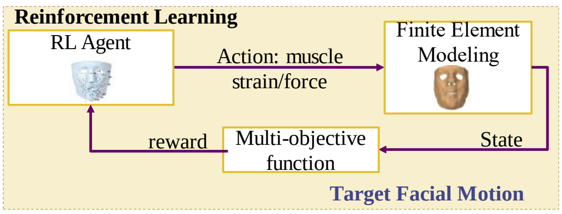

Figure 1: An overview of the innovative coupling process between FE modeling and RL.

Within the Artisynth modeling environment, a generic face FE model was used [3]. The soft tissue mesh consists of 6342 brick elements and 8720 nodes. Hypodermis layer was modeled using a Mooney-Rivlin hyperelastic law ($C_{10} = 0.4\,kPa, C_{20} = 1.4\,kPa, D = 50\,kPa$). The Fung's law was used for the epidermis and dermis layers ($c = 21.3\,kPa,\ \mu_a = 5.9\,kPa,\ \lambda_{ab} = 1\,kPa,\ \kappa = 250\,kPa$). Facial muscle was modeled as point-to-point Hill-type model ($\lambda^* = 1.4,\ \sigma_{max} = 100\,kPa,\ P_1 = 0.05,\ P_2 = 6.6$). To perform the facial learning using deep RL, an information exchange protocol was developed to transfer action and state of the face between the PyTorch RL platform and the Artisynth FE platform. Deep deterministic policy gradient (DDPG) and Twin-delayed DDPG (TD3) algorithms were implemented to drive the simulations of symmetry-oriented and smile movements. Using the Euclidean distance and angle derived from 8 landmark sites around the mouth, different reward functions were developed. For evaluation and validation purposes, numerical results were also compared with experimental observations (Bosphorus database).

Results

As a result, the reinforcement learning agent encountered 100 episodes of random behavior in the environment before discovering the best course of action after more than 300 training episodes. When it comes to symmetry-oriented motion, the expected muscle excitations assist in raising the reward value from R = -2.06 to R = -0.23, which accounts for an 89% improvement in the face's symmetry value. Two spots at the mouth's edge move up 0.35 cm when the facial model smiles (Fig. 2), which is within the Bosphorus database's expected range of motions (0.4–0.32 cm).

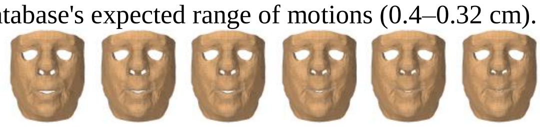

Figure 2: The animation of the face for smile motion

Discussion and Conclusions

Reinforcement learning allows performing facial motion learning without a priori input motion data. The use of this approach leads to explore the facial muscle activation and contraction patterns for a specific movement. This opens new avenues for patients-specific face rehabilitation. As perspective, our novel methodology will be applied with image-based patient-specific model of the human face of the facial palsy and facial transplantation patients.

References

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2. Nguyen et al. *Computer Methods and Programs in Biomedicine* 200: 105846, 2021.
3. Stavness et al. *3D multiscale physiological human*: 253-274, 2014.

Acknowledgements

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