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Advanced Facial Rehabilitation by Coupling Reinforcement Learning and Finite Element Modeling

DP Nguyen [1], MC Ho Ba Tho [1], TT Dao [2]

[1] *Université de technologie de Compiègne, CNRS, Biomechanics and Bioengineering, France, duc-phong.nguyen@utc.fr, hobatho@utc.fr*
[2] *Université de Lille, CNRS, Centrale Lille, UMR 9013 - LaMcube - Laboratoire de Mécanique, France, tien-tuan.dao@centralelille.fr*

Résumé — This study combines reinforcement learning with finite element modeling to facial motion learning. A novel modeling workflow for learning facial motion was developed using a physically-based model of the face within the Artisynth modeling platform, reinforcement learning algorithms were used to simulate facial movements. After the training, the agent improved symmetry by approximately 89% for symmetry-oriented motion and closely matched experimental data for smile-oriented motion. This novel approach integrates finite element simulations into the reinforcement learning process, offering advanced rehabilitation programs for such patients.

Mots clefs — facial rehabilitation, finite element model, reinforcement learning.

1. Introduction

Facial palsy patients or patients under facial transplantation have facial dysfunctionalities and abnormal facial motion due to altered facial muscle functions and nerve damage [1].

Current traditional facial rehabilitation has mainly been based on a mirror approach to monitor the visual qualitative feedback from the rehabilitation exercise. Computer-aided systems based on physics-based models have also been developed to provide objective and quantitative information. However, the use of these systems in clinical routine practice still remains challenging due to several limitations : 1) the lack of building 3D information from images or depending strongly on the selected depth cameras; 2) the lack of analyzing the face in terms of expression recognition and symmetry analysis; and 3) the limitation of the predictive capacity of the facial motion patterns with emerging biomechanical properties.

The restoration of normal and symmetrical facial expressions is essential to improve the quality of life and social interactions for involved patients. Understanding of facial motion mechanism could help the involved patients in rehabilitation process. However, current solution is still limited in providing internal and external information for guiding patients. The goal of the study is to couple the reinforcement learning and the finite element modeling for better exploring facial motion learning.

Numerous finite elements models have been investigated for different clinical applications such as estimation of maxilla-facial operations, speech articulation research [2,3,4]. These finite element methods were aimed to explore the role of the facial muscle excitation, contraction and coordination during facial motion (Fig.1). Muscle excitation represents the neural control process, which contracts the face tissues and moves the skull to perform facial expressions and movements. Besides few numerical models are dedicated to subject specific data derived from medical image to ensure the potential used of the model for rehabilitation purpose [4,5].

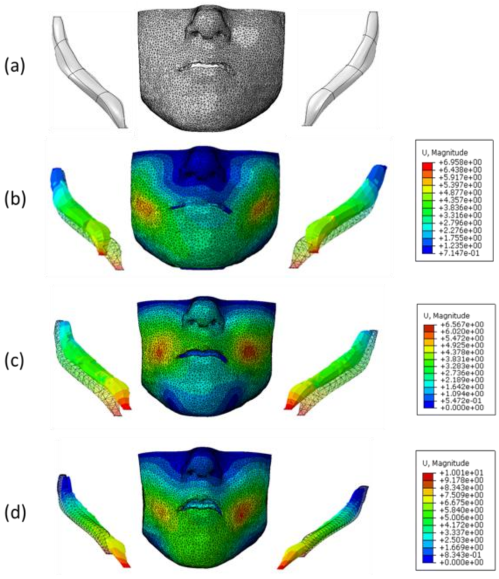

Figure 1. Fe-based displacement (u) patterns of the Zigomatic muscle and face for the neutral position (a) and the three analyzed positions: (b) smile, (c) pronunciation of sound [pou], and (d) pronunciation of sound [o]. The plotted physical quantity is the magnitude of displacement (unit: mm) [4].

Despite a detailed view on the muscle contraction mechanism and its effect on the facial motion, the physics-based approach is descriptive with a priori known input information such as muscle properties. Research are still on going on the role of different muscles and which muscles and what value of muscle excitations are to be performed for facial rehabilitation. Various numerical techniques have been pro- posed for estimating muscle excitation such as inverse dynamics, forward-dynamics tracking simulation, and optimal control strategies [6]. However, the use of this approach depends strongly on the a priori definition of input data, model properties and the targeted motion. Thus, this approach has a limited predictive capacity to explore a larger parameter space to find emerging properties during dynamic movements of the face.

The present study aims to explore the facial motion learning capacity by the coupling between the reinforcement learning and the finite element modeling. The main objective is to provide, for the first time, the modeling workflow for this complex coupling and then to evaluate different learning strategies to establish motion patterns of the face during facial expression motions. Our novel solution will explore the patient specific facial motions without a priori data from the patient and then provides a set of facial muscle activation and coordination patterns for a specific rehabilitation-oriented movement (e.g. symmetry or smile).

2. 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. 2) [7].

We used a generic face finite element (FE) model in the Artisynth modeling environment [4,9]. The face finite element model in- cludes three components such as 1) soft-tissue component with the hypodermis, dermis, and epidermis layers, 2) a cranium and maxilla component, 3) a jaw-hyoid component. To reduce computational cost and accelerate the training process, the facial model is simplified by keeping only the soft-tissue compo- nent with ten orofacial muscles (levator anguli oris (LAO), levator labii superioris alaeque nasi (LLSAN), Buccinator (BUC), Zygomati- cus (ZYG), depressor anguli oris (DAO), Risorius (RIS), depressor labii inferioris (DLI), Mentalis (MENT), orbicularis oris peripheralis (OOP), orbicularis oris marginalis (OOM)) (Fig 3) [4,9].

The soft tissue mesh comprises of 6342 brick elements and 8720 nodes. The activation for the face model results from the orofacial muscle strain and force. Ten orofacial muscles are modeled and attached in the lower face that applies muscle forces in terms of muscle excitations onto the finite element model. Muscle fibers are modeled by a set of uniaxial cable elements. As an example, the zygomatic ligaments are represented by fixing all degrees-of-freedom of soft tissue nodes that are in the region where these ligaments attach to the maxilla. Hypodermis layer was modeled using a Mooney-Rivlin hyperelastic law ($C_{10} = 0.4kPa, C_{20} = 1.4kPa, D = 50kPa$). The Fung's law was used for the epidermis and dermis layers ($c = 21.3kPa$, $\mu_a = 5.9kPa$, $\lambda_{ab} = 1kPa$, $\kappa = 250kPa$). Facial muscle was modeled as point-to-point Hill-type model ($\lambda^* = 1.4$, $\sigma_{max} = 100kPa$, $P_1 = 0.05$, $P_2 = 6.6$).

The mechanical characteristics (such as force-displacement response, pre-stress behaviors, non-linear, anisotropic, and viscoelastic constitutive laws) for the skin layer were estimated based on a combination of in vivo experiments and numerical methods. Muscles are modeled as continuous sets of cable elements, which activate in tension as point-to-point Hill-type models and are aligned along element edges. The mechanical property evolution of muscle contraction comprises muscle contractile fibres (active part), muscle body (passive part), and the stress stiffening effect. The movements of the mandible generated by muscles of mastication are not handled yet in the model. Thus, the superficial muscles, which are muscles around the lip region, involved in facial mimics are focused. Two finite element models of the face corresponding with the modeling of the symmetric face and the asymmetric face were used for facial motion learning (Fig 3.)

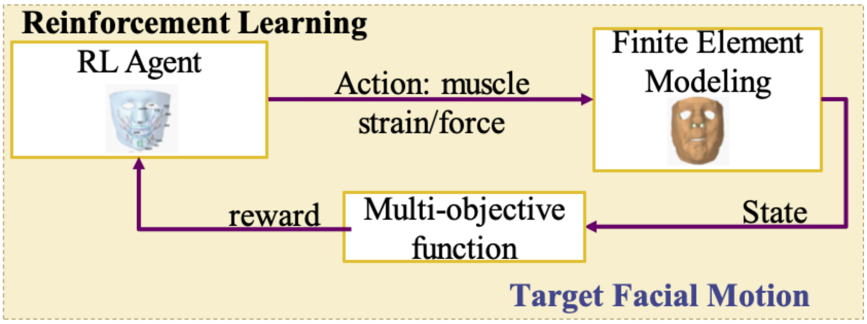

Figure 2: An overview of the innovative coupling process between FE modeling and RL.

Figure 3: Face FE modeling symmetric (left) and asymmetric(middle) and facial muscles network (right).

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 (Fig. 4,5). 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 using an open access 3D database named Bosphorus (Fig. 6). This database includes 105 subjects (44 females, 61 males) with different facial expressions (neutral, smile, surprise, fear, sadness, anger, disgust, and neutral. Happiness (smile) and neutral expressions, which are available in 130 face scans of all the subjects, were used for further validation.

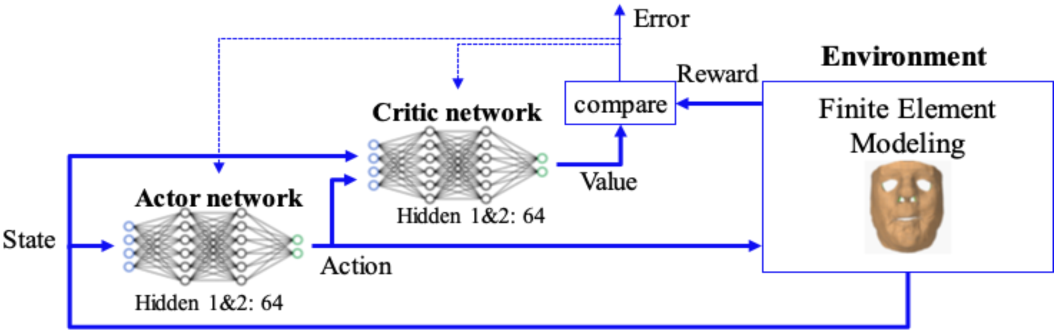

Figure 4 : The network architecture of DDPG.

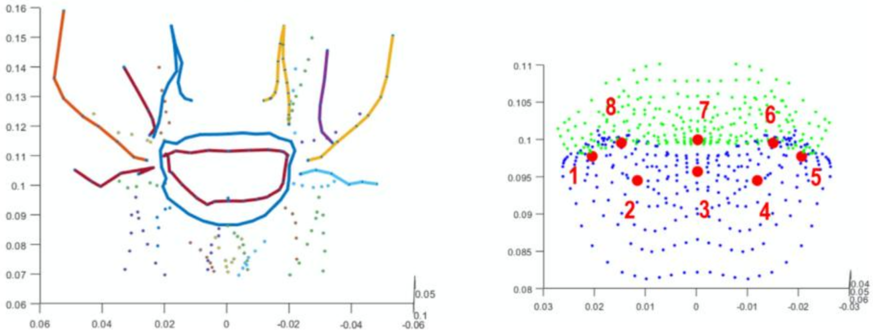

Figure 5 : Selected muscles excitations for training (left) and landmark points for the RL agent's state (right).

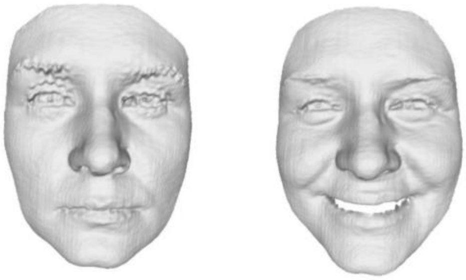

Figure 6 : Illustration from Bosphorus database with two expressions : neutral (left) and smile (right).

3. Results

As result, after spending 100 episodes of random interaction in the environment, the agent can find the optimal policy after more than 300 episodes of training. Following training the symmetry-oriented motion (Fig. 7), the predicted muscle excitations led to a significant 89% enhancement in symmetry (from R = -2.06 to R = -0.23). In the case of smile-oriented motion (Fig. 9), the predicted muscle excitations resulted in a smile, causing two points at the mouth's edges to move upward, aligning closely with the movement range found in the Bosphorus database (0.35 cm vs. 0.4±0.32 cm corresponding).

Figure 7: Face animation for symmetry-oriented motion.

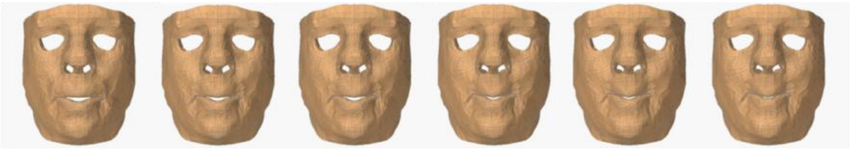

Figure 8: Face animation for smile-oriented

4. Discussion and Conclusions

The present study presented the muscle excitation patterns by coupling reinforcement learning with a finite element model of the face. We developed, for the first time, a novel coupling scheme to integrate the finite element simulation into the reinforcement learning for facial motion learning. In particular, two state-of-the- art reinforcement learning algorithms (deep deterministic policy gradient (DDPG) and Twin-delayed DDPG (TD3)) were successfully applied and implemented to drive the simulations of symmetry-oriented and smile movements.

The obtained results were in good agreement with experimental observation. A better understanding of the facial muscle activation and coordination mechanism is of great clinical interest to guide the optimal rehabilitation strategy. The present work opens new avenues to achieve this challenging objective. As perspectives, this present workflow will be applied for facial palsy and facial transplantation patients to guide and optimize the functional rehabilitation program.

5. References

1. Robinson et al. *Operative Techniques in Otolaryngology-Head and Neck Surgery* 23.4: 288-296, 2012.
2. Chabanas et al. *Med Image Anal*. 7:131–151, 2003.
3. Nazari et al. *Comput Methods Biomech Biomed Eng*. 13:469–482, 2010.
4. Flynn et al. *Comput Methods Biomech Biomed Eng.* 18: 571-582, 2015.
5. Fan et al. *Comput Methods Biomech Biomed Eng*. 20: 919-928, 2017.

6. Ho Ba Tho and Dao, *Encyclopedia of Biomedical Engineering*, 135-142, 2019.
7. Erdemir et al. *Clinical biomechanics*, 22 :131-154, 2007.
8. Nguyen et al. *Computer Methods and Programs in Biomedicine* 200 : 105846, 2022.
9. Stavness et al. *3D multiscale physiological human*. Springer, London. 253-274, 2014.

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