A Deep Recurrent Neural Network for Predicting Subject-specific Facial Soft Tissue Interaction

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ABSTRACT

Predicting biological soft tissue interaction is of great interest for developing computer-aided decision systems. This study aims to develop and evaluate a novel deep-learning approach based on the recurrent neural network for predicting facial soft tissue impact with a rubber ball. A computational workflow was established including a subject-specific finite element model of the facial soft tissue under interaction with the rubber ball. A series of simulations under different ball velocities was performed to build the learning database. We implemented a long-short-term memory (LSTM) model and then evaluated its performance using root mean square error (RMSE) and regression coefficient metrics. The obtained results showed a RMSE of 3.13 mm and a Pearson correlation coefficient of 0.98 for soft tissue displacement prediction. A RMSE of 0.001 MPa and a Pearson correlation coefficient of 0.94 was also obtained for soft tissue von Mises stress prediction. The present study showed the robustness and accuracy of the recurrent neural network for predicting complex soft tissue interaction behaviours. Our findings open new avenues for deploying novel deep learning workflow for human-facial soft

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tissue interaction. As perspective, this workflow will be integrated into our interactive facial analysis and rehabilitation system.

Keywords: *Deep Recurrent Neural Network (DRNN), Facial Soft Tissue Interaction, Subject-Specific Modeling, Long-Short Term Memory (LSTM) Network, MRI Images*

Introduction

Human soft tissue is the main actor in the dynamic movements of the human body. Soft tissue exhibits commonly a large deformation behavior during movements, tissue-tissue, and tissue-device interactions [1]-[2]. Soft tissue injuries usually occur in contact-intensive sports (e.g. football, ruby). In particular, facial soft tissue injuries are common in football [3]-[4]. Thus, a better understanding of the facial soft tissue behavior underlying impact condition is of great scientific and clinical interest. In particular, objective and quantitative indicators of the soft tissue interaction behavior such as tissue deformation and stress could be used for a better diagnosis of the injury as well as performing preventive actions [5]-[6].

The experimental characterization of the human soft tissue behavior in in vivo and non-invasive manner is a current challenging issue in the field of biomechanics. Various medical imaging modalities like computed tomography (CT) magnetic resonance imaging (MRI) or elastography (MRE) could be used to get 3D anatomical characteristics and local material properties [7-8]. However, the soft tissue dynamics under impact remain a challenge due to its complex non-linear nature and interaction with the surrounding environment. The finite element method has been used to provide an approximative solution to describe and predict soft tissue behaviour. Tissue stress behaviour under complex mechanical loadings (i.e. internal and external loadings) is also of great interest in using this approach [9]. Moreover, a mesh configuration is commonly required. Thus, the resolution of this problem leads usually to a high computational cost [10]. In particular, the study of human soft tissue behavior under impact conditions is more challenging with complex contact formulation and convergence issues [11]-[15]. Guo et al. [16] proposed an augmented Lagrangian method for tackling the sliding contact issue. Courtecuisse et al. [11] developed a new preconditioning technique coupled with an implicit time integration to study the soft tissue responses undergoing cutting, contact, and associated topological changes. Despite many efforts, a solution for a stable impact simulation in the framework of numerical modeling is still challenging for human soft tissue.

To develop another alternative solution to the numerical methods, artificial intelligence has been recently used to approximate soft tissue behavior with new AI-driven models and decision supports [17]-[19]. From a general perspective, AI technologies were developed and used to augment the computational speed and perform data interpolation or assimilation. Moreover, these technologies could be used for achieving physics or biology augmentation capacities such as synthetic data, in silico trials, or hybrid modeling. From a methodological point of view, different methodologies such as the single-AI approach or combination-AI approach have been commonly proposed. In particular, a hybrid Physics-AI approach (Physics-Informed, Physics-Augmented, AI-embedded) has been also studied. Within this context, different deep learning approaches (e.g. recurrent deep neural networks (RNNs) or convolutional neural networks (CNNs) have been coupled with other learning strategies (e.g. transfer learning) or physics-based learning to improve the predictive accuracy and performance of the soft tissue behavior and functions [20]-[24]. More precisely, Dao [21] used the coupling between the RNN and transfer learning to enhance the predictive performance of the skeletal muscle force. Zhang et al. [22] developed a novel approach to deal with nonstationary scenarios of the electromyography (EMG) signals and then to predict the EMG-based muscle forces and joint angle relationship. This study allows for strengthening the robustness and generalization aspects, and then reducing the computational cost of the model training. Hajian and Morin [24] used two streams of CNN, named TS-CNN, to describe and learn relevant features from the raw EMG signals using a multi-scale perspective. This study proposed an effective solution for the estimation of the generated elbow flexion and extension motions. Recently, Nguyen-Le et al. [10] applied the long-short term memory (LSTM) and its variant, called bidirectional LSTM, and then coupled it with a principal component analysis (PCA)-based data reduction strategy to predict the pelvis soft tissue dynamics during the complex childbirth process. According to classical machine learning models, the RNN has some advantages such as the ability to model temporal and sequential data and to deal with complex approximations of the arbitrary nonlinear dynamic system behaviors. In particular, the recurrent neural network has shown its robustness and high accuracy for time series data with high-frequency oscillations.

In summary, the use of deep learning approaches opens new perspectives for the online and offline simulation of complex musculoskeletal tissues and their interaction behavior. Thus, this study aims to develop a novel deep recurrent neural network to predict the facial soft tissue dynamics under impact conditions to simulate the football impact. The accurate finite element modeling was used for building the learning database and then fed into the r long-short-term memory network for predicting the tissue-ball interaction behaviour.

The present study focused on the predictive capacity of the long-short-term memory network for predicting facial soft tissue interaction behaviour. Then, the Materials and Methods section described the developed prediction workflow and associated simulation cases. Obtained results are synthesized and reported in the Results section. Discussion on the relevance and complexity of the proposed approach is provided in the Discussion section. The conclusions and perspectives summarize the study and address some future directions.

Materials and Methods

Soft tissue interaction prediction workflow using the deep recurrent neural network

A computational workflow was developed as illustrated in Figure 1 to predict the subject-specific facial soft tissue interaction behavior. MRI data was used to reconstruct the 3D facial soft tissue model. Then, a series of finite element models and associated simulations of the tissue-ball interaction were performed using the reconstructed model to build the learning database. The implementation of the LSTM network was performed and evaluated by using the learning database.

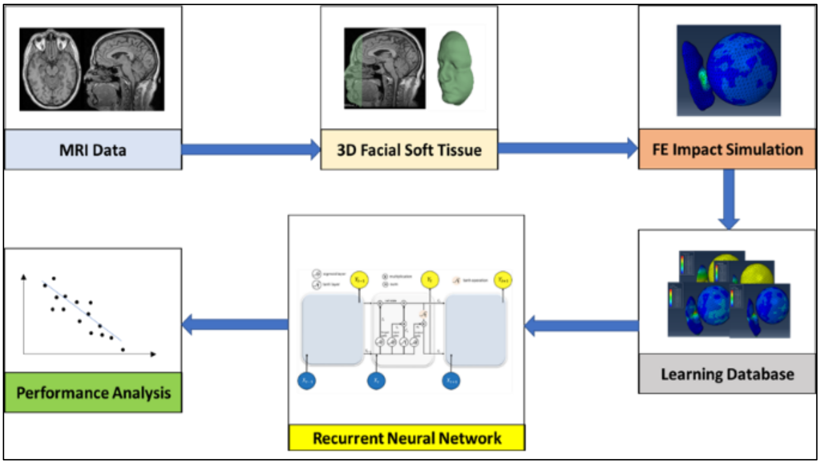


Figure 1: Overview of our computational workflow to predict the subject-specific facial soft tissue interaction behavior

3D model reconstruction using MRI

An MRI dataset of the human head was retrieved from an open-access database [25]. A semi-automatic segmentation approach was applied to segment the facial soft tissue from the raw MRI images. Thresholding ranging from 11 to 279 was used to extract the face skin envelope (Figure 2). Finally, the solid model of the facial soft tissue was generated using FreeCAD software. The MRI images are shown in Figure 2(a) while segmented images and associated 3D models are shown in Figure 2(b) and Figure 2(c), respectively.

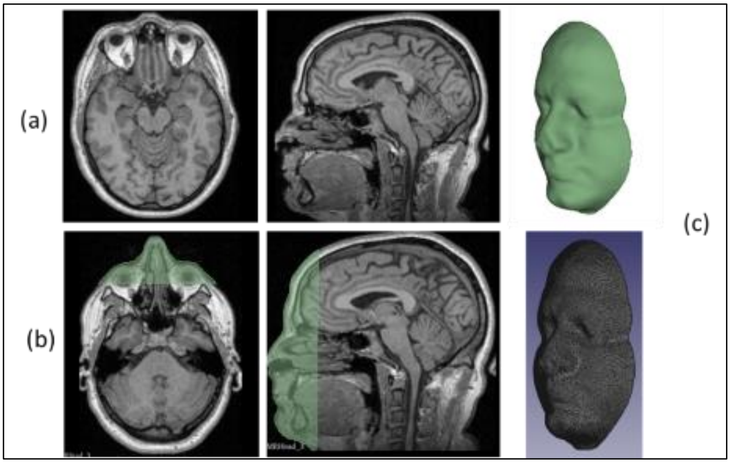


Figure 2: 3D model of the human facial soft tissue: (a) MRI images, (b) segmented images, (c) and 3D solid models

Meshing, constitutive behavior, boundary, and loading conditions

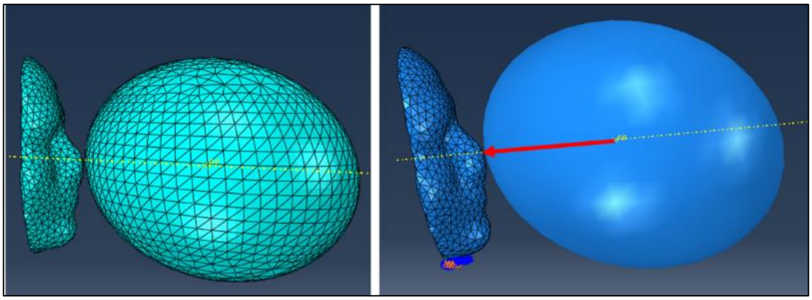
The facial soft tissue model was meshed using the Abaqus meshing function. C3D10 tetrahedral elements with explicit and quadratic formulations were applied. The facial soft tissue was modeled as an inactive material with an elastoplastic constitutive behavior (Young's modulus E = 15 kPa, $\nu = 0.49$) [26]-[27]. The yield stress and plastic strain relationship was reported in Table 1.

A rubber ball (football size 5) was also generated. C3D10 tetrahedral elements with explicit and quadratic formulations were also used to generate the meshed model. An elastoplastic constitutive law (E = 0.38 MPa, $\nu = 0.39$) was also applied. The yield stress and plastic strain relationship was also reported in Table 1.

Table 1: Minimum values of spacing and edge and end distances

Rubber ball		**Inactive face soft tissues**	
Yield stress	**Plastic strain**	**Yield stress**	**Plastic strain**
34	0	15	0
35	0.03	20	0.03
36	0.032	25	0.032
37	0.05	28	0.05
38	0.06	30	0.06
39	0.07	31	0.07

The lower part of the facial soft tissue model was fixed. An imposed velocity of 30 mm/s in the horizontal direction with uniform distribution was applied to the rubber ball model to simulate the soft tissue and rubber ball interaction (Figure 3).



(a) (b)

Figure 3: (a) 3D meshed models and (b) imposed velocity for simulating the impact: a mesh convergence study was performed leading to select 20695 C3D10 tetrahedral elements for the rubber ball and 9871 C3D10 tetrahedral elements for the inactive soft tissue model

Learning database generation

A series of finite element simulations of the soft tissue and rubber ball impact with different imposed velocity patterns ranging from 20 mm/s to 50 mm/s was conducted using the Abaqus software. The contact between soft tissue and rubber ball during the impact simulation was modeled using a general contact with explicit formulation. A penalty formulation was used for describing the tangential behavior while a hard contact formulation was applied for normal behavior. Note that a friction coefficient of 0.2 was used. The full-field displacement and von Mises stress were retrieved. The learning database includes 592260 items: 450000 items were used for the training step and the remaining part was used for the testing purpose.

Long short-term memory (LSTM) network implementation and performance evaluation

An LSTM network model was implemented and used for predicting the displacement and related stress fields of the facial soft tissue during the interaction with the rubber ball. To overcome the limitation of the feedback (recurrent) neural networks and to process time-varying information, the LSTM provides specific memory abilities for incorporating the time-varying information in the learning process [28] (Figure 4). Please refer to previous studies [10], [20] for more detailed information on the LSTM model. Briefly, the cell state n plays an essential role in the LSTM network. The information on the cell state needs to be updated by three gating structures (i.e. input, output, and forget gates). In particular, the forget gate determines the information to be updated while the input gate decides which relevant value is removed or added.

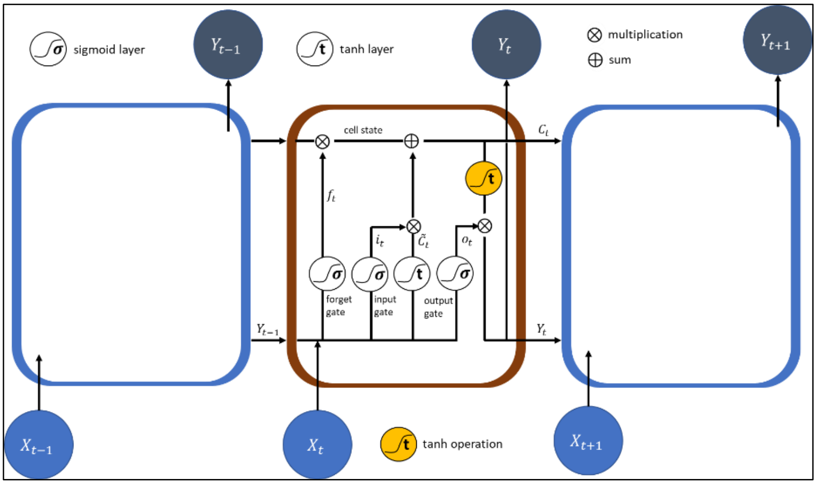


Figure 4: The overview of the used LSTM network architecture

At each repeating LSTM module, the output (o_t) is computed as follows:

$$\begin{cases} o_t = \sigma(W_0 X_t + V_0 Y_{t-1} + W_c C_t + b_0) \\ Y_t = o_t * tanh(C_t) \end{cases} \quad (1)$$

where W_0, V_0 are weighting matrices and b_0 is a bias vector. σ is the sigmoid function. Then, the $\tilde{C}_t$ is obtained at a *tanh* layer by using the following equations:

$$i_t = \sigma(W_i X_t + V_i Y_{t-1} + W_c C_{t-1} + b_i) \quad (2)$$

$$\tilde{C}_t = tanh(W_c X_t + V_c Y_{t-1} + b_c) \quad (3)$$

$$C_t = f_t * C_{t-1} + i_t \tilde{C}_t \quad (4)$$

where W_i, V_i, W_c are weighting matrices and b_i, b_c are bias vectors. Note that i_t is the output of the current input gate. It is important to note that at the forget gate, a sigmoid layer estimates a 0-1 function. The “0” value means to remove the information and "1" value means to keep the information. This function is mathematically expressed as follows:

$$f_t = \sigma\left(W_f X_t + V_f Y_{t-1} + W_c C_{t-1} + b_f\right) \quad (5)$$

where W_f, V_f, W_c are weighting matrices and b_f is a bias vector. C_{t-1} denotes the state of the memory cells at a time $(t-1)$.

The LSTM network model was implemented by using the Google Colab engine (https://colab.research.google.com). Keras application programming interface (API) was used. The LSTM network includes 1 neuron in the output layer and 5 neurons in the hidden layer. The number of batch sizes is 10000 and we used the mean absolute error (MAE) loss function. Note that the advantage of the use of the MAE is the capacity to deal robustly with the outliers. The efficient Adam stochastic gradient descent method was implemented and used for the optimization process.

The root-mean-square error (RMSE) and Pearson correlation coefficient were used as comparison metrics between the FE-based displacement or stress profiles and DRNN-based predicted ones. The RMSE of the predictor $(\hat{y})$ and the ground truth (y) is mathematically expressed as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y} - y)}{n}} \quad (6)$$

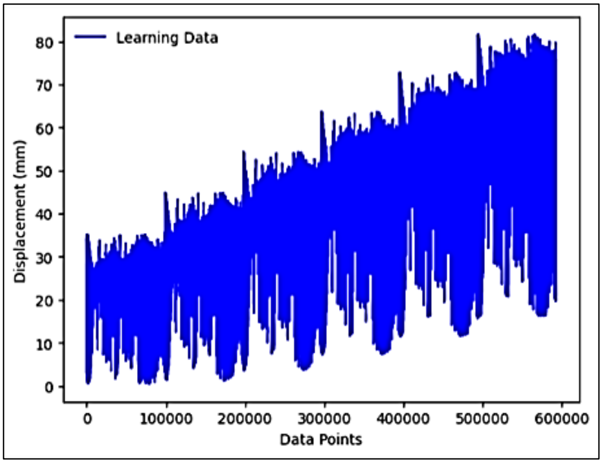
Computational Results

Learning database outcomes

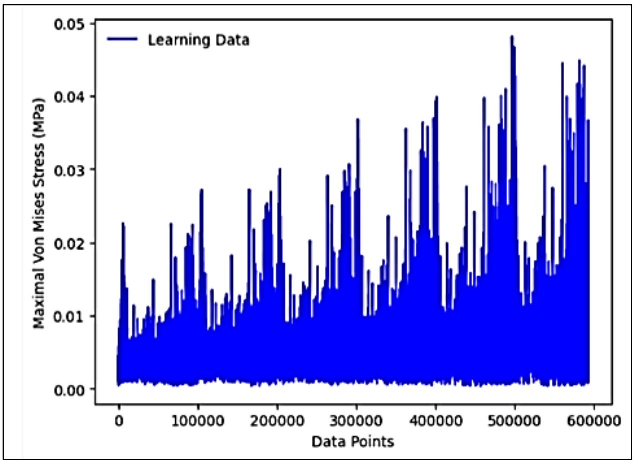
The distribution of the displacement and stress fields in the learning database is shown in Figure 5. The maximal displacement ranges from 35.2 mm to 90.2 mm while the maximal von Mises stress ranges from 0.02259 MPa to 0.05968 MPa. Displacement and von Mises stress fields of the deformed state of the facial soft tissue with ball interaction are shown in Figure 6. The displacement and von Mises stress fields on the facial soft tissue model with six different imposed ball velocities are shown. Maximal von Mises stress is found in the nose region. The computation time of a FE run is around 45 seconds.

Deep recurrent neural network prediction outcomes

The prediction of the displacement profile using the implemented LSTM model reached an RMSE of 3.13 mm and a Pearson correlation coefficient of 0.98. The prediction of the von Mises stress profile leads to an RMSE of 0.001 MPa and a Pearson correlation coefficient of 0.94 (Figure 7). The training time is around 3 hours.



(a)



(b)

Figure 5: (a) Displacement and (b) von Mises stress distribution profiles in the learning database generated from six different imposed ball velocities

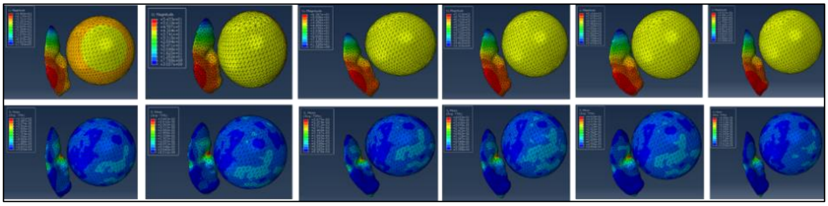
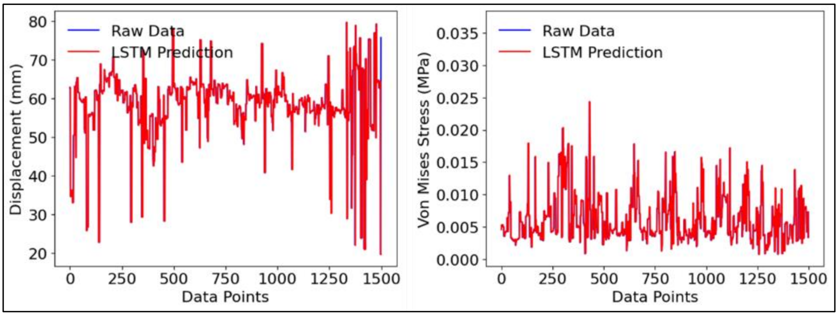


Figure 6: Illustration of the displacement and von Mises stress fields on the facial soft tissue model with six different imposed ball velocities



(a) (b)

Figure 7: Illustration of the (a) predictions of the displacement and (b) von Mises stress fields on the facial soft tissue

Discussion

Human soft tissue has been considered a complex material. To model this tissue, different constitutive laws range from simple linear elastic law, and hyperelastic law to complex multi-physics and multi-scale laws [29]-[30]. Moreover, when integrating the impact behavior, plastic behavior should be taken into consideration. The use of different deep learning approaches allows us to give an approximative solution to soft tissue dynamics with classical hyperelastic law [10], [20], [31]. However, the predictive accuracy and performance of the deep learning approaches for the case of plastic behavior are still misunderstood. The present study developed and evaluated an efficient deep-learning approach using the LSTM network to predict facial soft tissue under impact conditions within the elastic and plastic regimes. Our obtained results confirmed the robustness and accuracy (Pearson correlation coefficient ranges from 0.94 to 0.98) of the RNN architecture to predict the facial soft tissue behavior with such complex material properties and an explicit integration scheme. This accuracy level is in the ranges of accuracy of the

LSTM network for predicting other bio-signals in the literature [10], [20]-[24]. Thus, this opens new avenues to predict the facial soft tissue with complex topological changes by using such a deep learning approach.

Artificial Intelligence (AI) has metamorphosed many fields with different relevant applications in the computer vision or precision medicine fields. Within this perspective, new applications have been also studied in the Biomechanics field by using new AI-driven models and associated decision supports. Especially, deep learning has been considered as a potential approach to give an approximative solution to solve the partial differential equations (PDE) which are commonly used to describe the behavior of complex physical systems and model behavior. The use of the long-short-term memory (LSTM) model has shown its robustness and high accuracy level for different bio-signals with nonlinear and high-frequency oscillation nature [10], [20], [28]. To enhance the predictive capacity, the quality of the learning database plays an important role in ensuring a high prediction accuracy. The use of experimental data for the learning process is an ideal case. However, due to the lack of non-invasive and *in vivo* experimental techniques and protocols to measure the soft tissue stress in *in vivo* conditions. Numerical approximative approaches such as mass-spring system modeling or finite element modeling have been considered as alternative solutions to give an approximative estimation of the soft tissue stress under complex boundary and loading conditions. In our study, the accurate finite element modeling approach was used leading to optimizing the prediction accuracy. Further study should be investigated to integrate more relevant data in the learning process to scope with different loading scenarios [32].

The complexity of our present study remains, firstly, in the development of a realistic facial model system and associated simulations. Secondly, the prediction accuracy depends on the learning database and the choice of an appropriate prediction model. The development of subject-specific human body models becomes a customized approach in the field of biomechanics. The use of different medical imaging modalities such as CT scans or MRI allows 3D personalized geometries to be reconstructed in a straightforward manner [8]. In our study, we used MRI modality, which is non-invasive and then can be used for a large panel of subjects. However, the reconstruction process of the finite element model and associated simulations is still time-consuming and requires complex data processing skills and experiences. In the future, an automatic process to generate finite element models and simulations should be of great interest, especially in the context of the generation of a large-size learning database. Moreover, other model behaviors (e.g. ablation, failure) will be analysed and used to enhance the facial soft tissue interaction and associated prediction.

Regarding the limitations of the developed face finite element model, the first limitation relates to the simplified FE model integrating only a layer of soft tissue. Further study should be investigated to include a full head model with bone structures, brain, and isolated muscle to give a more realistic impact simulation. Moreover, only inactive soft tissue was modeled. Active facial muscle behavior should be incorporated in the future to better describe the loading sharing of the facial soft tissues under impact conditions. Note that some recent works on soft tissue [33]-[35] can provide more relevant data for enhancing the training and predicting processes. Furthermore, other performance evaluation metrics (e.g. R-squared or weighted mean absolute percentage error) will be also investigated in future works. Finally, the real-time efficiency of our proposed approach will be carefully analysed in the future before deploying our solution in the real monitoring system.

Conclusions and Perspectives

The present work studied the predictive capacity of the recurrent neural network, especially the LSTM network for the prediction of facial soft tissue interaction. The obtained results showed the robustness and accuracy of the LSTM network for predicting time-series bio-signals with complex interaction behavior. We showed a high prediction level of the displacement and von Mises stress fields by using the LSTM model. Our findings open new avenues for deploying novel deep learning workflow for complex human facial soft tissue interaction. As a perspective, this workflow will be integrated into our interactive facial analysis and rehabilitation system to give real-time feedback on soft tissue interactions with other tissues or with medical devices.

Contributions of Authors

All authors confirmed the equal contributions in each part of this work. All authors reviewed and approved the final version of the present work.

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Conflict of Interests

All authors declare that they have no conflicts of interest.

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