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Dynamic Modeling of the Electromyographic and Masticatory Force Relation Through Adaptive Neuro-Fuzzy Inference System Principal Dynamic Mode Analysis

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ABSTRACT

Introduction: Researchers have employed surface electromyography (EMG) to study the human masticatory system and the relationship between the activity of masticatory muscles and the mechanical features of mastication. This relationship has several applications in food texture analysis, control of prosthetic limbs, rehabilitation, and teleoperated robots.
Materials and Methods: In this paper, we proposed a model by combining the concept of fuzzy interface systems and principal dynamic mode analysis (PDM). We hypothesized that the proposed approach would provide nonlinear and dynamic characteristics improving the estimation results compared to those obtained by the classical PDM analysis and still having the benefits of a PDM model including the sparse presentation of the system dynamics. After developing PDM, the nonlinear polynomial function of the PDM model was replaced with adaptive neuro-fuzzy inference system (ANFIS) network architecture. After training, the relevant fuzzy rules were extracted and used for creating the fuzzy block (as the nonlinear function block) and predicting the output signal. The proposed approach was later employed to predict bite force using EMG of the temporalis and masseter muscles.
Results: Our proposed method outperformed the classical PDM analysis (in terms of our evaluation criteria) in predicting masticatory force . The inter-subject evaluation of the model performance proved that the model created using the data of one subject could be used for predicting masticatory force in other subjects.
Conclusion: The proposed model can be helpful in food analysis to predict masticatory force based on the electrical activity of the masseter and temporalis muscles.

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Introduction

In the human masticatory system, chewing is carried out by a group of interwoven muscles located on both sides of the face. The key muscles involved in this process are the masseter and temporal muscles [1]. Recording surface electromyography (sEMG) signals from chewing muscles has been an essential tool for the documentation of human masticatory system [2]. Researchers have used EMG for the early diagnosis of the malfunction of muscles and joints that play a role in the mastication process [3]. Furthermore, using the obtained data, the mechanical properties of the chewed food have been studied [4]. For instance, it has been demonstrated that increased EMG activity is observed for harder foods [5].

Food scientists have become interested in identifying the relationship between food texture, masticatory force, and the recorded EMG signals from the muscles involved in this process [6]. Creating a model to investigate the association between electrical activity and the mechanical properties of food or the created force during chewing can be of essential importance; however, some factors such as diversity in the anatomical structures of the jaws of different individuals and food texture (i.e., hardness and adhesion) can be problematic.

Investigating the link between the electrical activity of muscles and the force produced by them is of significant importance and is useful in many domains including orthopedics, rehabilitation, ergonomic design, and human machine interface [1, 7]. Several parametric and nonparametric methods have been developed for muscle force estimation using EMG signals, including artificial neural networks [7-11], parallel cascade identification [12], fast orthogonal

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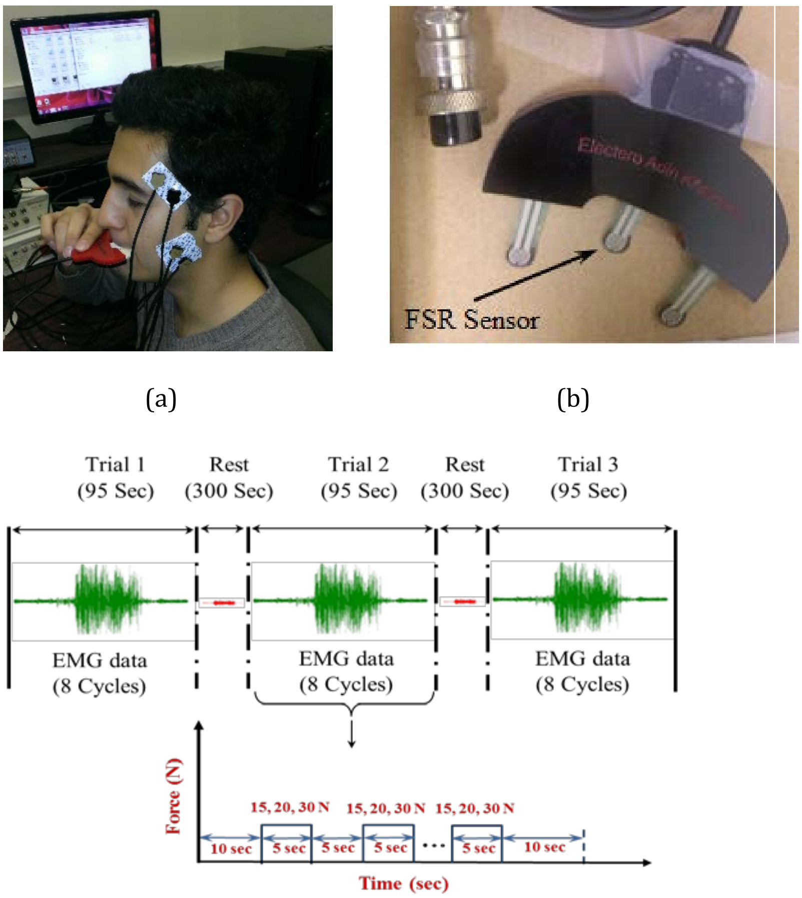
search [13], and Laguerre expansion technique (LET) [14, 15]. Moreover, applying a hybrid technique, which is a combination of physical modeling of the system and identification approaches, Wang and Buchanan estimated joint torque using EMG signals [16].

This paper proposes a new EMG-based model for estimating masticatory force. In doing so, we exploited the concepts of fuzzy interface system (FIS) and principal dynamic mode analysis (PDM) to introduce an ANFIS-PDM model. PDM has been employed for characterizing nonlinear physiological systems [14]. The PDM modeling approach separates the representation of system dynamics (PDMs) from its nonlinearities. The PDMs are obtained by utilizing Volterra-Wiener kernels based on the expansion of Laguerre polynomials [14]. We modified the PDM technique by replacing the concept of FIS for creating nonlinear mapping with output signals. We hypothesized that the proposed approach would provide nonlinear and dynamic characteristics that would improve estimation results compared to those obtained from the classical PDM analysis and still have the benefits of a PDM model including the sparse presentation of system dynamics. The proposed model was employed to predict masticatory force based on EMG signals from the masseter and temporalis muscles.

Materials and Methods

The Experimental Protocol

We recruited six healthy male volunteers (mean age: 22±2 years). All the subjects were free of any muscular pain and had no past history of orthopedic and neurological disorders. Ethical approval was obtained from Ferdowsi University of Mashhad, Mashhad, Iran. Time-locked EMG and force signals were recorded during the biting tasks with a frequency of 1000 Hz. The positioning of EMG electrodes is shown in Figure 1a. To record the electrical activity of muscles, a 16-channel EMG system was employed [6]. For each subject, EMG signals were recorded from four muscles, namely the right and left masseter and the right and left temporalis [12]. In addition, to measure mastication force, a device was designed and manufactured (Figure 1b).



(c)

Figure 1. (a)The experimental setup and electrode positioning on a subject's face, (b) Force-sensing resistor (FSR) sensors, and (c) the experimental protocol

This device is made of three Force-sensing resistor (FSR) sensors that are able to record forces up to 100 N. Moreover, the shape of this device was designed based on the jaw of the volunteers with the goal of allowing a natural masticatory process. During the recording sessions, the sensors were covered by sterile disposable wooden tongue depressors. The subjects were seated in a comfortable chair and asked to sit still during the recording sessions. They were able to see the computer screen by which a visual feedback was provided to facilitate control of timing during the masticatory task.

EMG and force signals were recorded synchronously. After placing the sensors in the mouths of the volunteers, they were requested to exert pressure on the wooden sticks at three different levels (15, 20, and 30 N) and hold the applied pressure for 5 seconds. Then, they were requested to relax the sensor slightly and again exert the same pressure after 5 seconds. This process was repeated eight times with 10 seconds of relaxation at the end (Figure 1c). For each pressure level, every volunteer was tested three times. To rule out the role of muscle fatigue, the nine (3 levels of pressure×3 repetitions) trials were ordered randomly. Although force signals were recorded from three sensors, in this paper, only the force signal recorded from the right premolars was considered for the identification and validation of our proposed model.

Figure 2 presents the recorded EMG signals from the left and right sides of the face and the force signal of one of the volunteers. The volunteer was requested to exert a force on the sensors located between her right premolars at the level of 30 N at specific times cued visually on the computer screen.

Raw EMG signals were passed through a bandpass (15–400 Hz) third order Butterworth filter [15]. In this paper, the EMG signal processing method described by Assefi et al [15] was utilized. To pre-process the force signal, first, a moving average window of size 200 was applied to the raw signal. Next, the signal was normalized to the corresponding maximum voluntary contraction (MVC). The sampling rates of both SEMG and force signals were reduced to 250 Hz to reduce the computational load.

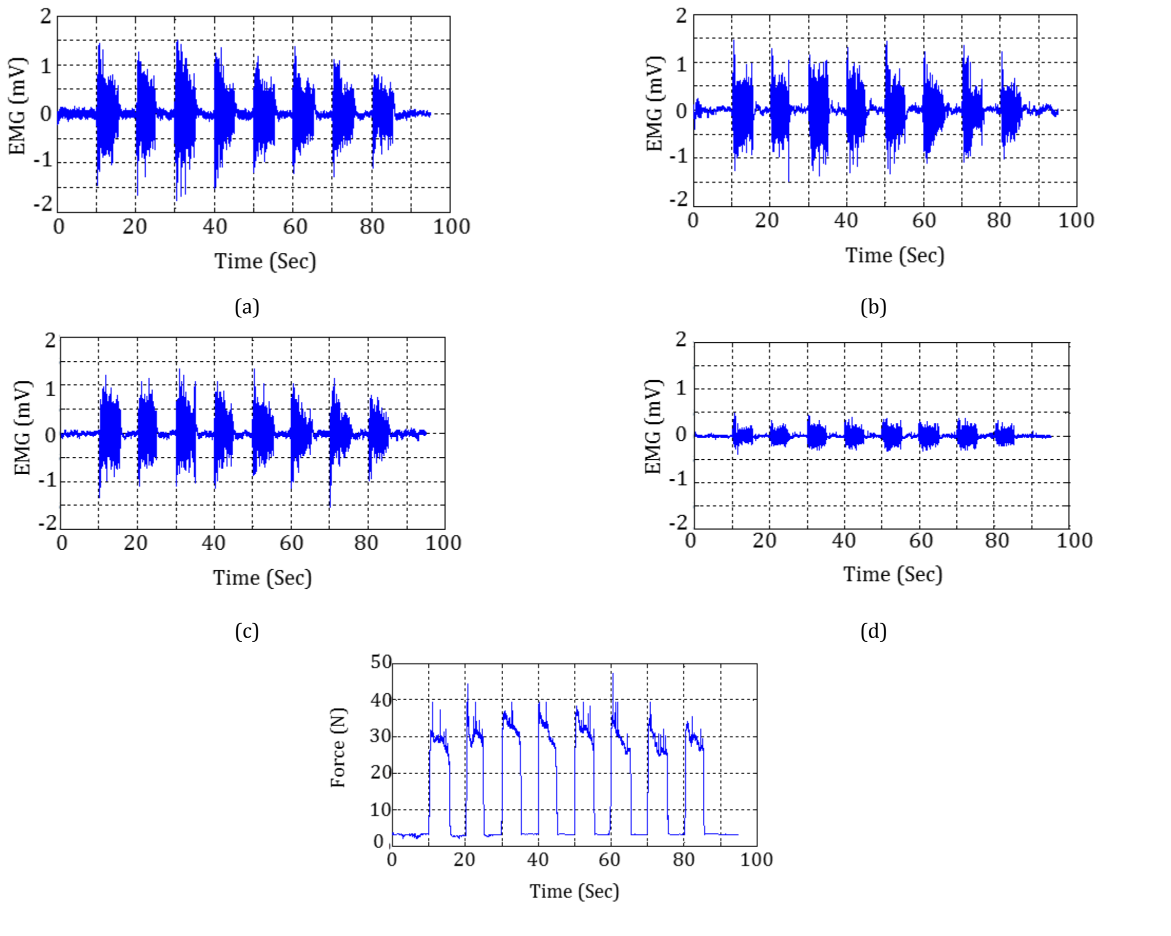


Figure 2. Electromyography and force signals recorded when the sensor was placed between the right premolar teeth. (a) The right masseter muscle, (b) the left masseter muscle, (c) the right temporalis muscle, (d) the left temporalis muscle, and (e) the force signal

Methods

In this paper, an ANFIS-PDM model is proposed. PDMs were introduced through the pursuit of parsimony in presenting the dynamics of a nonlinear system [14]. In our proposed method, the polynomial nonlinear function of the PDM model, $f[.]$ in Figure 3 was replaced with an ANFIS network architecture [17]. There are many benefits to the use of ANFIS instead of the ordinary polynomial function. These benefits are based on the fact that ANFIS exploits the capabilities of both neural networks and fuzzy systems in learning nonlinearities [17-20].

In the following sections, a brief review of the PDM analysis and ANFIS network is presented, which will later lead to the introduction of our proposed approach. This section only provides a brief introduction. Readers may refer to the previously published articles for more detailed description of the methods [15, 19, 21].

PDMs

PDM method is a nonparametric method proposed to improve the LET [22, 23]. From the viewpoint of optimal presentation of the model, LET could not be considered as the most efficient approach. In other words, if it is desired to find the most efficient model in the sense of parsimony of system representation, the minimum number of linear filters that can present a proper approximation of the system output should be determined. The aforementioned combinations of linear filters are called the fundamental modes of the system. The output signal of the system could be expressed as below:

$$\mathbf{y}(n) = \mathbf{v}'(n)\mathbf{C}\mathbf{v}(n) \tag{1}$$

where $\mathbf{v}(n)$ is the adjoined vector of filter bank and $\mathbf{C}$ denotes a symmetric matrix called the matrix of coefficients and calculated using least-squares estimation of the unknown expansion coefficients of LET. Since $\mathbf{C}$ is a symmetric matrix, there always exists an orthogonal matrix $\mathbf{R}$ whose columns are eigenvectors of the matrix $\mathbf{C}$, therefore, the output signal of the system could be expressed as

$$y(n) = \mathbf{v}'(n)\mathbf{R}'\mathbf{\Lambda}\mathbf{R}\mathbf{v}(n) = \mathbf{u}'(n)\mathbf{\Lambda}\mathbf{u}(n) = \sum_{i=0}^{L} \lambda_i u_i^2(n) \tag{2}$$

where $\mathbf{\Lambda}$ is a diagonal matrix whose diagonal elements, λ_i, are eigenvalues of the matrix $\mathbf{C}$. Analysis of the amplitude of eigenvalues sorted based on their absolute value helps distinguish the components of $u_i(n)$, which play important roles in generating the system output. Once $u_i(n)$ is determined, it can be utilized to calculate the system PDMs [22, 23].

ANFIS

Fuzzy inference systems (FIS) represent a knowledge-based method, where each fuzzy rule describes a local behavior of the system [18, 20]. The learning algorithm for ANFIS is a hybrid algorithm, which is a combination of the gradient descent and the least-squares methods. As can be noted in Figure 3, ANFIS consists of five layers. Layer 0 is the input layer and state variables are nodes in this layer. Layer 1 in schematic ANFIS performs fuzzy formation. This layer consists of input variable membership functions. The purpose of this layer is to supply the input values to the next layer. In layer 2, membership degrees of input signals of each node are multiplied by a rule firing strength ($\boldsymbol{\omega}_1$). In layer 3, the normalized firing strengths are obtained ($\bar{\boldsymbol{\omega}}_1$). Layer 4 is the conclusive part of the fuzzy rule. For instance, we have:

$$O_i^4 = \bar{\boldsymbol{\omega}}_1 f_i, \quad i = 1, 2,3,4 \tag{3}$$

where O_i^4 is i^{th} node output in the fourth layer and f_i represents the outputs of the first order Sugeno fuzzy inference system. In layer 5, rule outputs are added to create the ANFIS output:

$$O_i^5 = \sum_i \bar{\omega}_i f_i \, , i = 1,2,3,4 \tag{4}$$

Where O_i^5 is the i^{th} node output in the fifth layer.

The Proposed Algorithm

In this paper, an ANFIS-PDM model is proposed for the improvement of the masticatory force prediction accuracy. In the proposed method, a neuro-fuzzy block is used instead of a nonlinear polynomial block of the PDM. Since neuro-fuzzy models usually perform well in presenting the performance of nonlinear systems, replacing the polynomial block by them leads to better model functionality. The neuro-fuzzy block, which was applied in this paper, is an ANFIS-based block. The proposed algorithm works as follows. First, using the identification data, a PDM model was developed based on the algorithm described in the previous sections. In this step, the nonlinear function consisted of a polynomial function. Next, the constructed PDMs were extracted. The convolution of the input data with PDMs was calculated to obtain the PDM outputs that were later employed to develop the ANFIS. The ANFIS, which can be considered as a replacement for the nonlinear polynomial function, aimed at constructing a nonlinear map between the PDM outputs and the model output (the force signal). As an example, for two PDMs and four inputs from the EMG signals, the ANFIS processed eight inputs (4 inputs×2 PDMs) to create one output (the force signal). The numbers of membership functions and ANFIS parameters were determined through an error minimization process using trial and error. The gradient descent method was applied for training. After training, the relevant fuzzy rules were extracted and used for creating the fuzzy block (as the nonlinear function block $f[.]$). Since the parameters of the fuzzy system are adjusted using the adaptation law, we hypothesized that the proposed model will outperform models in which the nonlinear map is created using a predetermined structure. The block diagram of the ANFIS-PDM algorithm is presented in Figure 3.

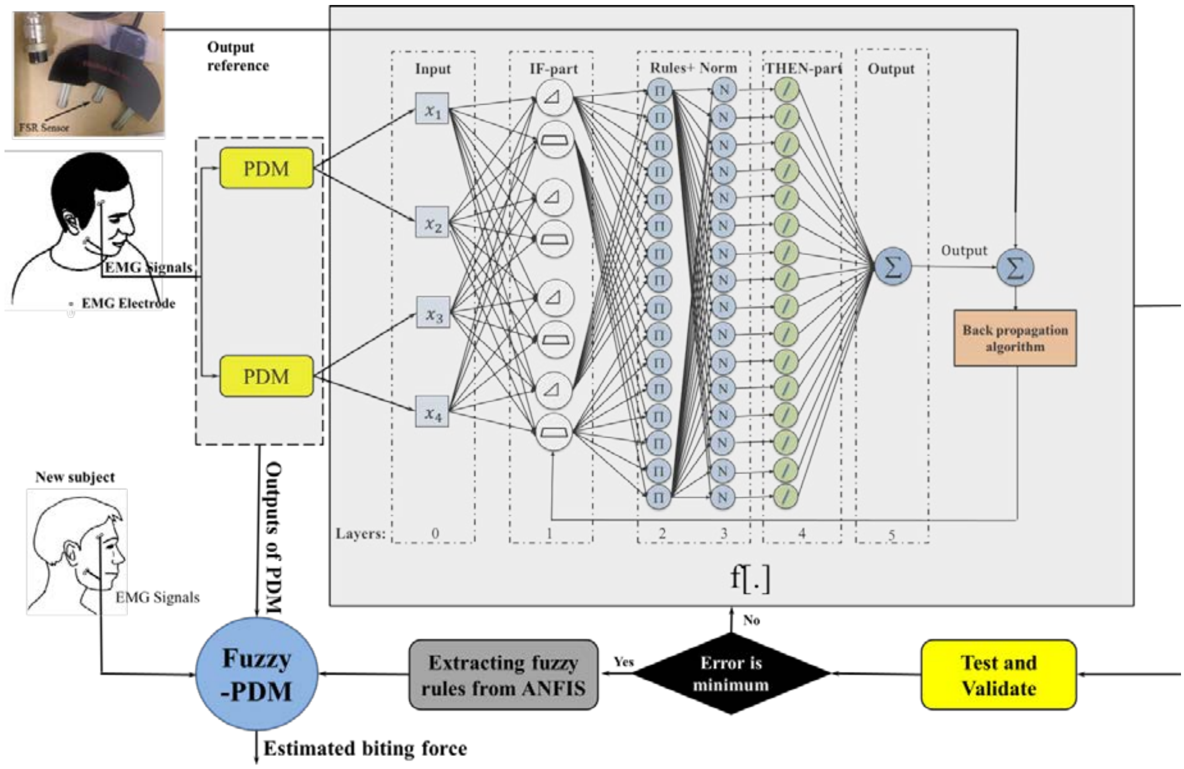


Figure 3. The block diagram of the proposed adaptive neuro-fuzzy inference system-principal dynamic mode modeling approach for two inputs and two principal dynamic modes

To validate the proposed methodology, three criteria were utilized, namely cross-correlation (CC), relative mean square error (RMSE), and average absolute error (AAE).

$$\%RMSE = 100 \times \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i)^2} \quad (5)$$

$$\%CC = 100 \times \frac{\sum_i (y_i * \hat{y}_i)}{\sqrt{\sum_i (y_i)^2}\ \sqrt{\sum_i (\hat{y}_i)^2}} \quad (6)$$

$$AAE = \frac{\sum_i |y_i - \hat{y}_i|}{N} \quad (7)$$

where N is the number of data points and CC presents the similarity between y_i and $\hat{y}_i$. Moreover, y_i and $\hat{y}_i$ indicate the real and estimated outputs, respectively [15].

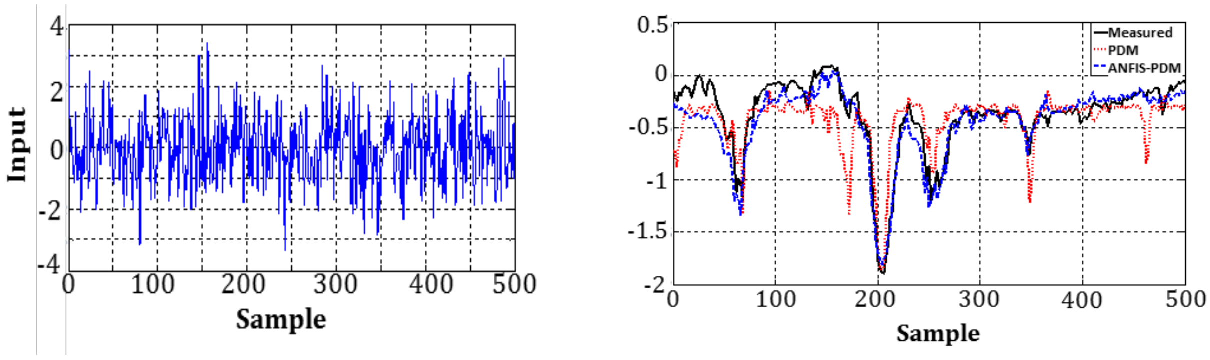
Results

Simulation Results

The first step of the validation process was allocated to checking the performance of the proposed model in a simulation scenario. We considered a second-order single-input and single output system. The functional characteristics of the simulated system were defined by the first- and second-order Volterra kernels, which were created to resemble the ones that have been experimentally observed. The output signal was created using the following equation.

$$y(n) = K_0 + \sum_{m=0}^{M} K_1(m)x(n-m) + \sum_{m_1=0}^{M}\sum_{m_2=0}^{M} K_2(m_1,m_2)x(n-m_1)x(n-m_2) \quad (8)$$

The system was simulated for a band-limited Gaussian white noise input of 5000 data points. Figure 4a presents 500 samples of the input and output data along with the prediction results for two PDMs. Figure 4b shows that the ANFIS-PDM model performance is superior to the PDM model in terms of prediction accuracy. In addition, Table 1 demonstrates the evaluation criteria for the two models in the identification and validation phases. As predicted, employing two PDMs improved model performance, however, in all cases, the ANFIS-PDM model provided better estimation results in terms of the evaluation criteria.



(a) (b)

Figure 4. (a) Gaussian noise input signal and (b) estimates of the output signal using simulated data for adaptive neuro-fuzzy inference system-principal dynamic mode (ANFIS-PDM) and PDM models using only two PDMs

Table 1. Comparing adaptive neuro-fuzzy inference system-principal dynamic mode (ANFIS-PDM) and PDM on the simulated data using one and two PDMs

	Phase	%RMSE		%CC		AAE	
		PDM	ANFIS-PDM	PDM	ANFIS-PDM	PDM	ANFIS-PDM
1 PDM	Identification	37.54	10.12	73.22	93.23	0.42	0.23
	Validation	24.35	7.51	76.12	96.56	0.39	0.19
2 PDMs	Identification	23.31	6.46	80.98	97.87	0.35	0.18
	Validation	11.34	3.32	91.54	98.99	0.27	0.14

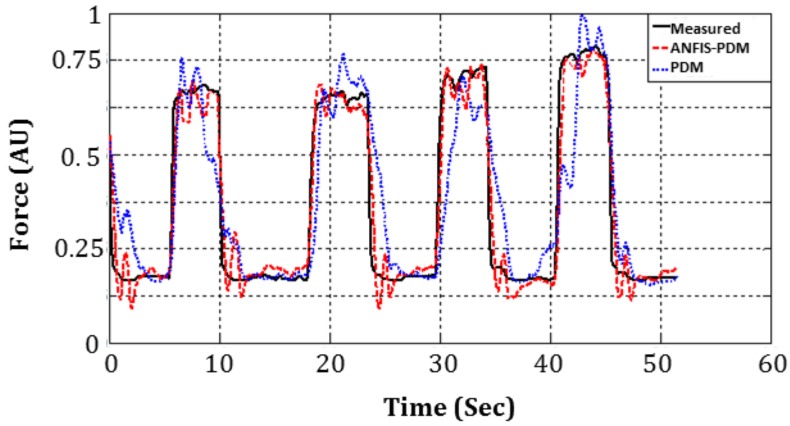


Figure 5. Comparison between principal dynamic mode (PDM) and adaptive neuro-fuzzy inference system- (ANFIS)-PDM model using only two PDMs in the validation phase

Table 2. Identification and validation results in terms of mean (standard deviation) averaged over all the subjects and force levels for ANFIS-PDM and PDM models

		%RMSE		%CC		AAE	
		PDM	ANFIS-PDM	PDM	ANFIS-PDM	PDM	ANFIS-PDM
1 PDM	Identification	45.6(5.11)	12.71(3.22)	66.18(4.23)	90.67(2.14)	0.52(0.05)	0.27(0.05)
	Validation	87.74(4.56)	13.23(2.31)	58.01(3.45)	89.89(1.98)	0.63(0.04)	0.27(0.02)
2 PDMs	Identification	14.22(4.41)	4.55(2.45)	89.42(3.56)	98.62(1.88)	0.28(0.03)	0.15(0.02)
	Validation	23.54(5.45)	6.78(1.33)	79.11(4.14)	97.61(0.54)	0.37(0.54)	0.18(0.01)

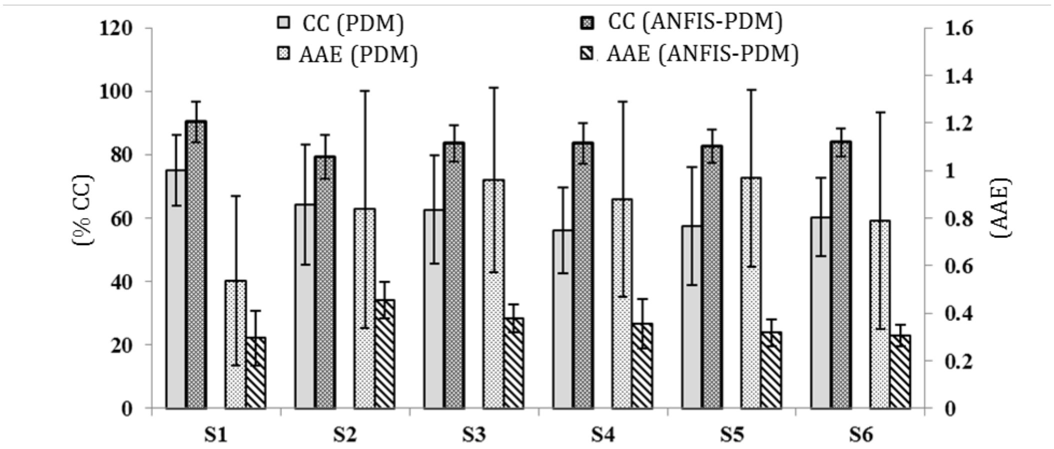


Figure 6. Results of inter-subject evaluation of the identified principal dynamic mode (PDM) and adaptive neuro-fuzzy inference system (ANFIS)-PDM models for all the subjects; the results are averaged over all force levels

Validation results

Figure 5 exhibits the ability of the PDM and ANFIS-PDM models in predicting bite force according to the EMG recordings obtained from one of the subjects. Two PDMs were employed for both models. In general, the validation results demonstrated that ANFIS-PDM outperformed the PDM model in predicting bite force. Table 2 presents the evaluation criteria for both identification and validation phases averaged over all the subjects and force levels in predicting bite force. For both one and two PDMs, the RMSE and AAE/CC corresponding to the employment of ANFIS-PDM were smaller/larger compared to those corresponding to cases where PDM was used.

Two-way ANOVA with factors model (ANFIS-PDM with one and two PDMs, one PDM and two PDMs) and force level (15, 20, and 30 N) followed by multiple comparisons was performed for all the subjects to compare the performance of ANFIS-PDM, one PDM, and two PDMs. P-value less than 0.05 was considered statistically significant. In general, our results showed that ANFIS-PDM provided lower %RMSE ($P<0.05$) and AAE ($P<0.05$) and higher %CC ($P<0.05$) compared to the PDM method (for both one and two PDMs). Moreover, the above-mentioned criteria significantly improved from ANFIS-PDM (with one PDM) to ANFIS-PDM (with two PDMs; $P<0.05$). The effect of model×force level was not significant, demonstrating that the improved performance of ANFIS-PDM in comparison to PDM was not dependent on the force level.

We also investigated the efficiency of the PDM and ANFIS-PDM models (both with two PDMs) identified using signals obtained from one subject in predicting the output signals for another subject. Figure 6 indicates the evaluation results for the validation phase. Each bar in the figure represents the mean CC/AAE for predicting bite force across all the subjects and averaged for the three force levels, with the vertical bar indicating standard deviation. Overall, the performance of ANFIS-PDM was superior to that of the PDM in all the subjects. Moreover, it can be concluded that the models identified using the data obtained from one subject can be generalized to the other subjects.

Next, we compared the ability of PDM and ANFIS-PDM techniques with fast orthogonal search (FOS) and parallel cascade identification (PCI) to estimate the EMG-force relation during biting. In doing so, we sought to compare the successful employment of the aforementioned techniques in estimating the EMG-force relation [15, 16]. RMSE of each method was compared to those of others.

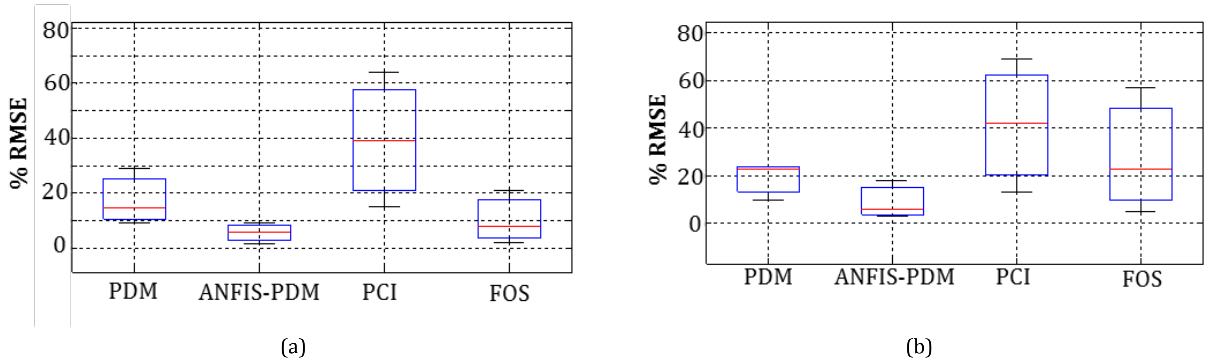


Figure 7. Comparison of four methods using a box plot graph (a) in the identification phase and (b) in the validation phase

Figure 7 presents the obtained results for each method. These results were attained by implementing the identification and validation phases. Overall, ANFIS-PDM had a better performance. The input to the cascade structure was chosen similar to what was previously selected [15, 24, 25]. RSME tends to be larger for FOS during the validation phase compared to ANFIS-PDM. In this method, a set of candidate functions (e.g., polynomial, sigmoid, and trigonometric functions) are used to predict force. Selecting the appropriate functions has a direct impact on the accuracy of estimation. In this paper, the pool of basic functions for FOS was similar to that of [15], although the terms related to the joint angle were omitted since this value was not measured during the experimental protocol.

Discussion

Compared to the conventional PDM, FOS, and PCI techniques, we found that our proposed method, ANFIS-PDM, performed better in predicting masticatory force. The benefits of the proposed approach is based on the more complex nonlinear map provided by the fuzzy block that replaced the nonlinear polynomial function. The number of PDMs was set to either one or two. The chosen number of PDMs provided force predictions with reasonable accuracy. The reason behind this observation was the overlap of the frequency content of PDMs. For systems with PDMs of non-overlapping frequency contents, more PDMs will be required for efficient model using both PDM and ANFIS-PDM approaches.

Generalization is one of the characteristics required for the developed model to be applicable in real scenarios. It was suggested [6, 7] that the identified model for one subject may not be valid for another. In Figure 6, we evaluated that the models trained on the data recorded from one subject can be reasonably generalized to the other subjects. This confirmed that these models are more comprehensive than the previous ones. The improvement may be due to our use of a fuzzy block to provide the nonlinear behavior of the system under study.

In this paper, estimations were made for three different force levels. Although visual feedback was provided during the experiments, regulating the force level at its desired value was a challenging task for the participants. For this reason, implementing the experiments with a large number of levels was not feasible. Once it is demonstrated that the proposed approach can be used for predictions at different force levels, it can be employed for predicting masticatory force for different food textures in real masticatory tasks.

Conclusion

We demonstrated that the recorded EMG signals from the masseter and temporalis muscles are sufficient for predicting masticatory force. It could also be concluded from the obtained results that the proposed ANFIS-PDM approach could predict the nonlinear dynamic relationship between the electrical activity of masticatory muscles and the produced force. The improved nonlinear mapping between the PDM outputs and the force signal resulted in more accurate predictions of the force signal.

Biomechanical modeling of the human masticatory system performance has been of special interest in recent years. Studies on biomechanical modeling have been carried out with different goals including the evaluation of variations in the mechanical properties and structure of food during chewing. This has been performed by studying jaw movements and measuring the produced force. Considering these facts, the proposed model will be helpful in the field of food analysis, using which the created force during chewing can be predicted based on the electrical activity of the masseter and temporalis muscles.

The proposed approach can be employed for predicting masticatory force for different food textures in real masticatory tasks.

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