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Research paper

Classification of sEMG Signals for Diagnosis of Unilateral Posterior Crossbite in Primary Dentition using Fast Fourier Transform and Logistic Regression

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Abstract

Posterior crossbite is a common malocclusion disorder in the primary dentition that strongly affects the masticatory function. To the best of the author’s knowledge, for the first time, this article presents a reasonable and computationally efficient diagnostic system for detecting the characteristics between the children with and without unilateral posterior crossbite (UPCB) in the primary dentition from the surface electromyography (sEMG) activity of masticatory muscles. In this work, 40 children (4–6y) are selected and divided into the UPCB (n = 20) and normal occlusion (NOccl; n = 20) groups. The preferred chewing side is determined using a visual spot-checking method. The chewing rate is determined as the average of two chewing cycles. The sEMG activity of the bilateral masticatory muscles is recorded during two 20-s gum-chewing sequences. The data of the subjects is diagnosed by the dentist. In this work, the fast Fourier transform (FFT) analysis is applied to the sEMG signals recorded from the subjects. The number of FFT coefficients is selected using the logistic regression (LR) methodology. Then the ability of a multi-layer perceptron artificial neural network (MLPANN) in the diagnosis of neuromuscular disorders is investigated. In order to find the best neuron weights and structures for MLPANN, particle swarm optimization (PSO) is utilized. The results obtained show the proficiency of the suggested diagnostic system for the classification of the EMG signals. The proposed method can be utilized in clinical applications for the diagnosis of unilateral posterior crossbite.

1. Introduction

Unilateral posterior crossbite (UPCB) is generally accompanied by a lateral movement of the jaw from maximal opening to centric occlusion [1]. In 80–97% of cases, posterior crossbite in the growing individuals results in functional crossbite [2]. Some efforts have confirmed that UPCB produces morphological and positional asymmetries of the mandible in the children [3, 4]. The changes in muscle activity as a result of the presence of crossbite have been shown in various studies [5-7]. The sEMG can be utilized for a key objective valuation of changes in the electrical activity of the masticatory muscles. In the children, sEMG is commonly executed, as it provides a non-invasive and easy way to monitor muscle activity through the use of surface electrodes. Generally, sEMG has been employed as information about muscle activation in order to classify the differences in chewing patterns among the individuals [8]. Moreover, the researchers have used sEMG for an early diagnosis of the malfunction of muscles and joints that play a role in the chewing process [9, 10]. The studies indicate that the presence of crossbite can affect the sEMG activity of masticatory muscles [11-15]. Therefore, the aim of this work was to detect the possible differences in the sEMG activity of masticatory muscles and the characteristics of chewing cycles in the children with and without UPCB in the primary dentition.

Many studies have used the sEMG signals in the signal clinical practice and the rehabilitation field. They have shown that there is a hidden valuable information in the sEMG signals, which is a powerful tool used to assist the diagnosis of neuromuscular disorders [16, 17]. They have used different techniques for signal classification including the fast Fourier transform (FFT) [16], neuro-fuzzy methods [17], artificial neural networks [18-22], Laguerre estimation technique [23], SVMs [24], parallel cascade identification (PCI) [25], and fast orthogonal search (FOS)[26]. Guller and Kocer [16] have applied FFT to the sEMG signals recorded from ulnar nerves of 59 patients to interpret data. Then they have used the principal component analysis (PCA) in order to reduce the amount of FFT signals. Next, they have applied the PCA coefficients as the inputs of MLPANN and SVM. They have compared the ability of these mentioned methods in the diagnosis of neuromuscular disorders. Kocer [17] has also utilized the neuro-fuzzy system (NFS) and auto-regressive (AR) analysis in order to produce a new and reliable classification system for a rapid diagnosis. Barmpakos *et al*. [27] have introduced a method for detecting the possible neuropathy or myopathy cases of a subject based on the sEMG signals. They extracted the features in the wavelet domain, and used the K-NN algorithm and the k-folds method for the classification. They showed robustness of their approach in the clinical dataset. Wu *et al*. [28] have proposed a hybrid method in order to improve the accuracy of the fuzzy support vector classification machine (FSVCM). They used the hybrid bacterial foraging (BF) and particle swarm optimization (PSO) in order to optimize the unknown parameters of the classifier. They applied their methods to identify the fatigue status of the sEMG signal. Subasi [29] has proposed a novel PSO-SVM method in order to improve the EMG signal classification accuracy. He used a discrete wavelet transform (DWT) and a set of statistical features from the sEMG signals. He compared the superiority of his method to the conventional machine learning ones such as k-NN and the RBF classifiers. He showed that PSO-SVM may be an efficient tool for the diagnosis of neuromuscular disorders.

Figure 1 presents the overall framework of the proposed method, which encompasses feature extraction, feature selection, and classification. In the first step, four bipolar sEMG electrodes recorded the electrical activities of the masseter and temporalis muscles of the volunteers. Then the raw signals were segmented into a fixed 512-point window with and overlap 256 points. Next, the FFT method was applied to each filtered signal, and the frequencies and amplitudes of the first n peaks were determined. Then a matrix containing the features of the training and test set was constructed. Next, ten best frequencies domain features were selected (determined based on LR). Finally, the reduced feature matrix was fed to the MLPANN classifier as the input vectors. In order to find the best neuron weights and structure for MLPANN, particle swarm optimization (PSO) was utilized.

This paper is organized as what follows. Data acquisition and experimental protocol are prepared in Section 2. Moreover, the feature selection and classifier are presented in Section 2.4. The results and discussion are shown in Sections 3. Finally, the conclusion is presented in Section 4.

2. Materials and Methods

2.1. Subjects

A cross-sectional study design was used, with recruitment of a convenience sample of 40 children aged 4–6 years who were to start dental treatment at the Department of Paediatric Dentistry, Mashhad Dental School, Mashhad, Iran. The Research Ethics Committee of the dental school approved the project. The children were divided into two groups: the UPCB group, which consisted of 20 children with UPCB, and the control group, which consisted of 20 children with normal occlusion (NOccl). The children and their parents received oral and written explanations of the research aims and methodology. The written informed consent was obtained from all parents. The inclusion criteria were being in the primary dentition period (4–6 years), absence of caries and pain, and NOccl or UPCB involving two or more teeth (functional crossbite). The exclusion criteria were a record of previous orthodontic therapy, missing or carious teeth, any sign or symptom of a craniomandibular disorder or parafunctional habit (e.g. clenching, bruxism, oral breathing), and a record of previous dental or orofacial trauma.

2.2. Data acquisition and experimental protocol

Two 20-s sequences of chewing the sugar-free gum were performed by each child. The average number of cycles in these two sequences was then divided by 20 in order to establish each subject's automatic habitual chewing rate (cycles/s). In addition, the mean cycle duration during the 20-s sequence was calculated (Figure 2). In order to record the electrical activity of the muscles, an eight-channel sEMG amplifier was used. In order to perform A/D data conversion, the data acquisition cards (sampling rate of 1000 Hz) were utilized. Advantech PCI-1730U USB data acquisition module was used to gather and digitize the signals for storage, analysis, and presentation on a PC.

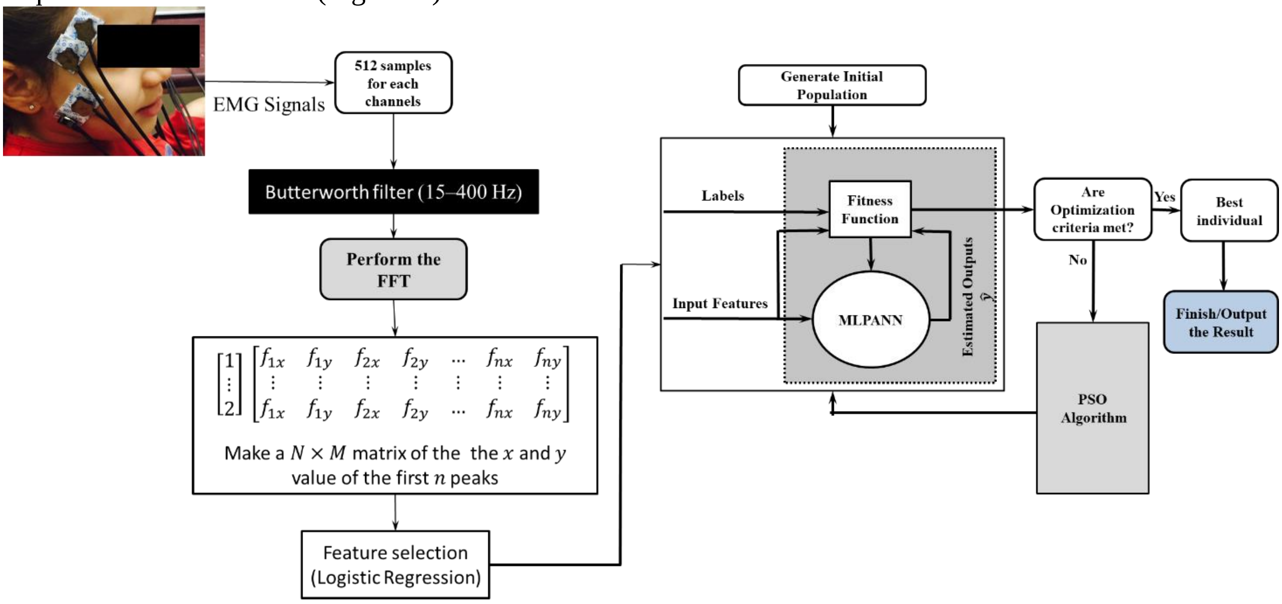

Figure 1. A block diagram of the proposed technique.

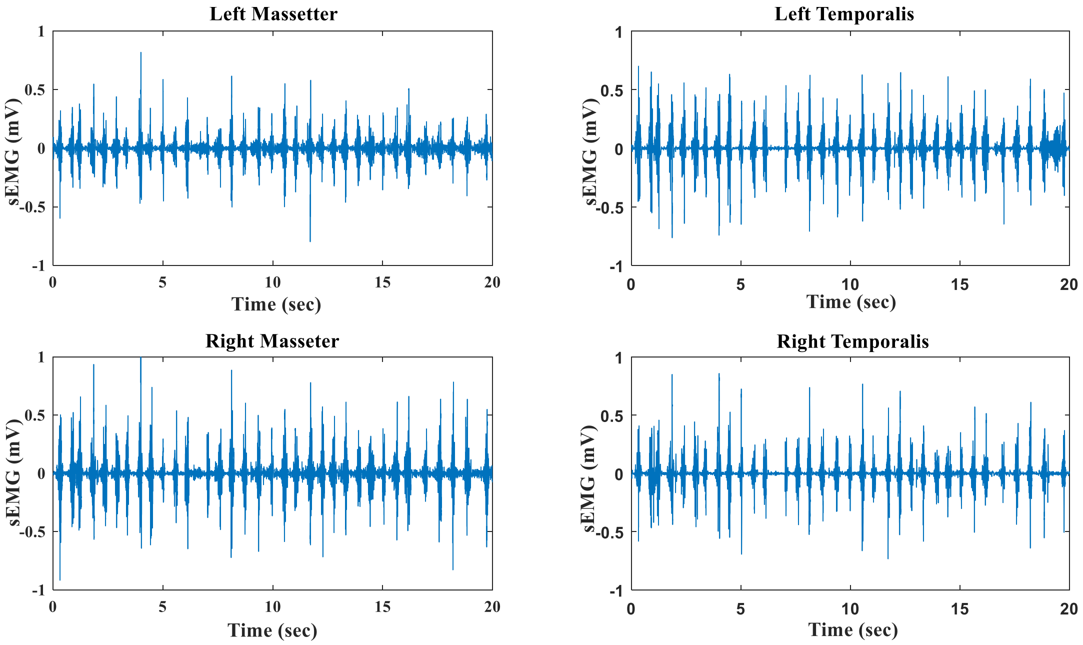

Figure 2. Sample raw data recorded from subject 2.

For each subject, the sEMG signals from four muscles–the right and left masseter and temporalis–were recorded (Figure 3). The surface electrodes were placed ~2 cm apart on the masseter and anterior temporalis in the following orientations: for the masseter, the level halfway between the zygomatic arch and the gonial angle, close to the level of the occlusal plane; and for the anterior portion of the temporalis muscle, anterior to the anterior border of the hairline. The evaluation was performed in a quiet and comfortable environment. During the procedure, the child remained seated comfortably, with a straight back and with the head oriented in the Frankfort plane, parallel to the floor. The skin and the electrodes were cleaned with 70% ethyl alcohol for grease or pollution residue. The ground electrode was placed over the subject's occipital protuberance. The muscle activity was recorded during two 20-s chewing sequences (in which the subject chewed sugar-free Trident gum).

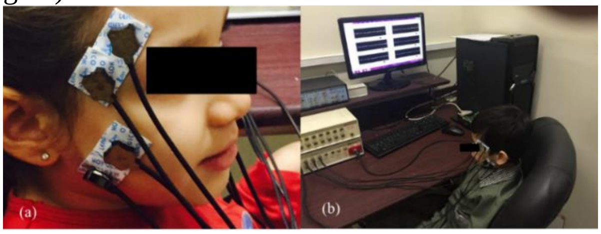

Figure 3. (a) Position of sEMG electrodes (b) experimental setup.

2.3. sEMG feature extraction

The sEMG signals contained key hidden information about the neuromuscular disorders and motion of limbs. Feature extraction that is known as a significant methodology for extracting valuable information from sEMG can significantly improve the pattern recognition accuracy. In order to extract the frequency features from the sEMG signal, spectral analysis should be applied to the sEMG signal. The recorded raw sEMG signals were passed through a band-pass (15–400 Hz) third-order Butterworth filter. After filtering out the noise, the signals were cut in fixed-width windows of 0.512 s with an overlap of 0.256 s. This rectangular windowing technique was utilized to estimate the frequency spectrum for the corresponding frame. Then FFT was applied to each windows, and the value of the frequencies at which the oscillations occurred and the corresponding amplitudes were obtained. Next, the frequencies and amplitudes of the first n peaks were chosen, and a matrix containing these values was constructed. In this work, $n = 20$. This matrix had 160 columns as the frequency features (4 muscles × 20 peaks × 2 values).

2.4. Feature selection and classification

Eliminating the redundant features of the sEMG signals is a vital step in the classification scheme [19] Since the FFT analysis produces a large number of coefficients (i.e. number of feature is 160). Therefore, the amount of FFT coefficients has to be reduced. We used a LR model in order to select independent features. The maximum likelihood estimation was employed to train the LR model. In this work, ten optimum frequency features were selected and fed to MLPANN. MLPANN is the significant method in the pattern classification problems [18, 22]. This methodology is well-known as universal approximates for non-linear input-output mapping. A MLPANN consists of three layers: an input layer, an output layer, and an intermediate or hidden layer. Figure 4 shows a scheme of a common MLPANN with four layers: input, two hidden and output layers. Mathematically, a four-layer MLPANN comprising $m_1$input nodes, m_2 first hidden layer nodes, m_3 first hidden layer nodes and m_4 output layer nodes is expressed as:

$$y_0 = \varphi^{(3)}\left(\sum_{h_2=0}^{m_3} W_{h_2.o}^{(3)} \cdot \varphi^{(2)}\left(\sum_{h_1=0}^{m_2} W_{h_1.h_2}^{(2)} \cdot \varphi^{(1)}\left(\sum_{i=0}^{m_1} W_{i.h_1}^{(1)} \cdot x_i\right)\right)\right) \quad o \in [1, m_4] \tag{1}$$

where the functions $\varphi^{(3)}$, $\varphi^{(2)}$, and $\varphi^{(1)}$ are the activation functions, and $W_{h_2.o}^{(3)}$, $W_{h_1.h_2}^{(2)}$ and $W_{i.h_1}^{(1)}$ are the weight set connecting the 2nd hidden layer to the output layer, the 1st hidden layer to the 2nd hidden layer, and the input layer to the 1st hidden layer, respectively; Moreover, y_o indicates the network outputs.

Commonly standard back-propagation (BP) was employed to train the networks [30]. However, in this work, the PSO methodology was employed to obtain the optimal neuron weights in the neural networks and optimum structures. PSO has the ability to explore the solution space of a given problem in order to obtain the best answers given to a particular objective function. This method is inspired by the natural social behavior and movement of insects, birds, and fishes [31]. The role of PSO is to find the best reference value for the prediction process, while MLPANN searches for the best mapping function to predict the targets based on the scheme provided by PSO. The optimization parameter structure of MLPANN consists of the number of hidden layers (one or two), the number of neurons in each hidden layer (between 5 to 25), and the activation function in each hidden layer (log-sigmoid function and tan-sigmoid function). All algorithms are coded in Python using Scipy, Numpy, and scikit-learn.

3. Results and Discussion

Many studies have investigated the sEMG activity of the masseter muscles in patients with UPCB but few have evaluated the activity of the masticatory muscles in patients with primary dentition [1, 11, 32-35]. The results from different studies are discrepant, possibly due to the differences in the samples, the measurement point locations, and/or the sEMG quantification techniques [36, 37]. In the current work, we employed MLPANN in order to detect this malocclusion on the masticatory muscle activity to provide information on the necessity of early treatment in patients with primary dentition.

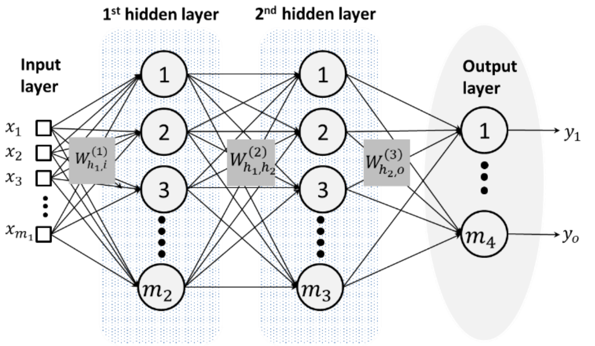

Figure 4. Structure of multi-layer perceptron.

In contrast, the previous researchers have mainly used RMSs for the quantitative analysis of the sEMG signals to provide further insight into the characteristic changes in muscle composition and structure due to the presence of crossbite, and the FFT methodology has been used. A comparison between the performance of BP and PSO shows that there is no statistically significant difference between them, when they are used for updating the neural network weight parameters. However, the main advantage of PSO is to find the best structure of MLPANN simultaneously. Thus the PSO method was employed for training and finding the optimal structure of MLPANN. The optimum MLPANN architecture is the 10-5-2 topology. The result obtained indicates that the feature reduction using the LR method has a small impact on the overall network feature performance, and the error of the classification accuracy rate is maintained within 1–3%. Since the classification accuracy rate is reasonable, the feature reduction can reduce the storage and calculation cost. Moreover, the results obtained show that the percentage of a correct classification is 84.2%. For comparison of the diagnostic accuracy of the mentioned MLPANN, linear kernel support vector machine (LSVM), radial kernel support vector machine (RSVM), and linear discriminant analysis (LDA), the concept of receiver operating characteristic (ROC) analysis was used. The ROC analysis is an appropriate way to visualize the performance of a classifier. In order to represent the classifier's performance as a single value, the area under the ROC curve (AUC) value is determined. In fact, this value expresses how much the model is capable of distinguishing between the classes, and the higher the AUC, the better the model is at distinguishing between UPCB and NOccl. As shown in Figure 5, MLPANN with an area of 0.866 has a more diagnostic ability than the other methods. Generally, the result obtained show that an optimum MLPANN has a superior performance than the mentioned methodologies to classify people with and without disease in a clinical application.

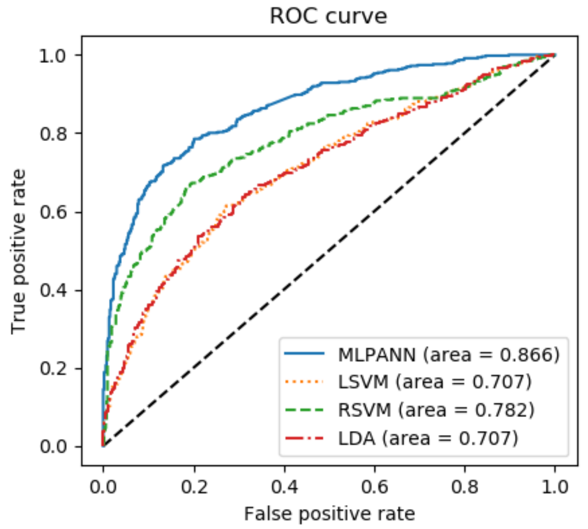

Figure 5. ROC curves of MLPANN, LSVM, RSVM, and LDA methods.

It should be noted that to find the reason for errors in classification, root mean square (RMS) and median frequencies (MDFs) are used. These parameters revealed the possible variations in muscle characteristics and muscle fibre composition.

Figure 6 illustrates the MDF and RMS values from sEMG signals for the left and right chewing sides in the two groups. Neither feature different significantly according to chewing side or group. Moreover, the global difference between chewing sides was not significant. The same results were obtained for the masseter and temporalis muscles. Mean RMS values for the masticatory muscles as well as mean MDF values for the masseter muscles on both sides had large standard deviations (Figure 6). Given the lack of a significant difference between the sides in both groups, the mean values of the features corresponding to the left and right temporalis and masseter muscles were calculated for a further inter-group comparison (Figure 7). The mean MDF for the temporalis muscles was significantly larger in the NOccl group than in the UPCB group ($p < 0.05$). No such difference was observed for the masseter muscles. Moreover, RMSs for the masseter and temporalis muscles did not differ significantly.

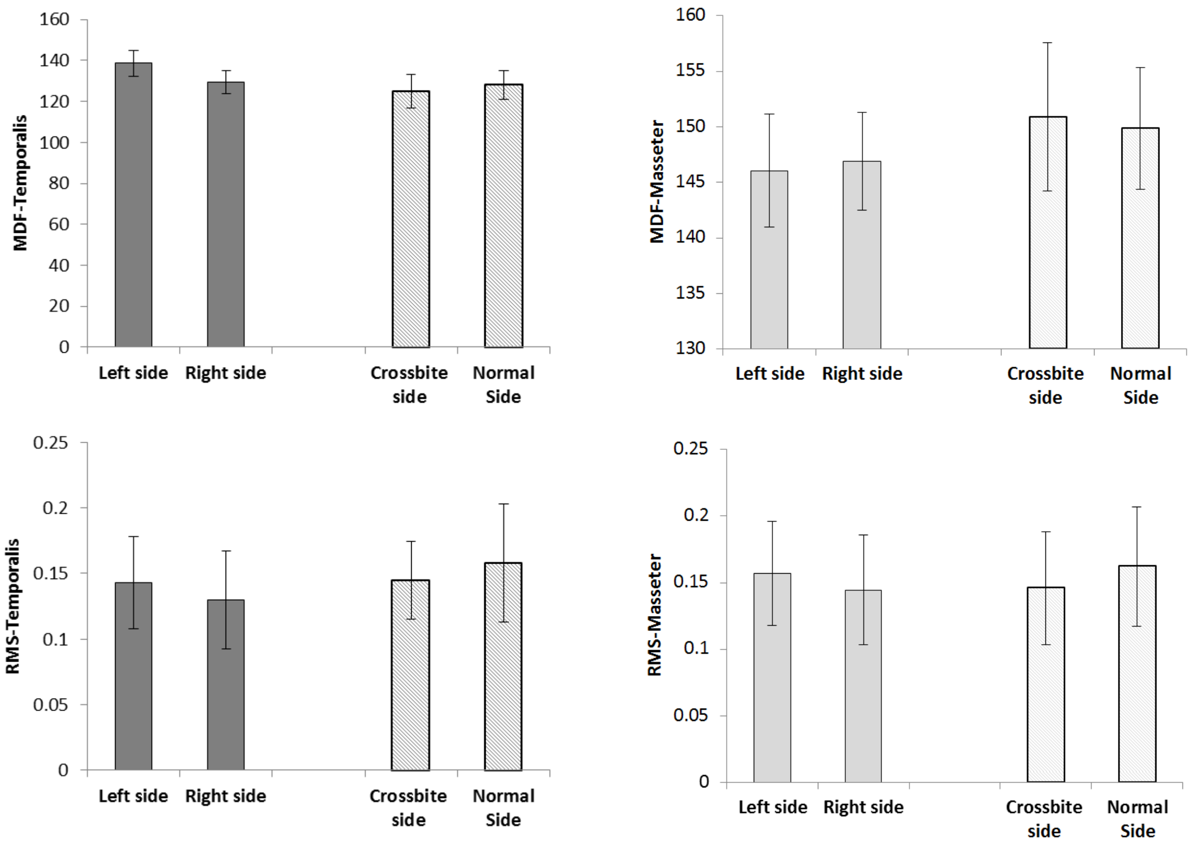

Figure 6. RMS and MDF values for the masseter and temporalis muscles on both sides in the UPCB and NOccl groups.

Therefore, the mean MDF for the temporalis muscles was significantly larger in the NOccl group than in the UPCB group. Comparison of the MDF and RMS values from the masseter and temporalis muscles revealed no significant difference for chewing side or group. These results indicate that both muscles play symmetric roles in the two studied groups. Thus despite this similarity of the two groups, we could conclude that the proposed methods were able to classify both groups with reasonable accuracies.

Due to the ethical considerations, we only employed the sEMG electrodes in this work, and thus monitored the average estimated electrical activity of the muscles located at the hearing site of the electrodes. The use of needle electrodes may provide further insight into the variations in the muscle fibre characteristics due to the presence of crossbite and the chance for a more discriminative investigation.

4. Conclusion

In the current work, we employed MLPANN and FFT in order to detect the unilateral posterior crossbite on the masticatory muscle activity to provide the main information on the necessity of early treatment in the patients with primary dentition. The frequency features from the sEMG signals were extracted by FFT. Then in order to enable the diagnosis to become faster and easier, the LR method was employed to select the best features as the input parameter MLPANN. Moreover, the PSO method was used to find the optimum MLPANN. The optimum MLPANN architecture was the 10-5-2 topology. The results showed that in spite of RMSs and MDFs not differing between the chewing sides or groups, the optimized MLPANN had a reasonable accuracy (84.2%). The results of evaluation of the ROC curve clearly show the viability of the proposed automated system in the clinical applications.

The main contributions of this paper include proposing a method that can be used to diagnose unilateral posterior crossbite (UPCB) from the sEMG signals. This paper contributes by (1) using FFT to extract the frequency features from the sEMG signals, (2) employing the LR method to choose the important features, and (3) finally, PSO-MLPANN employed to estimate the problem during the gum-chewing sequences.

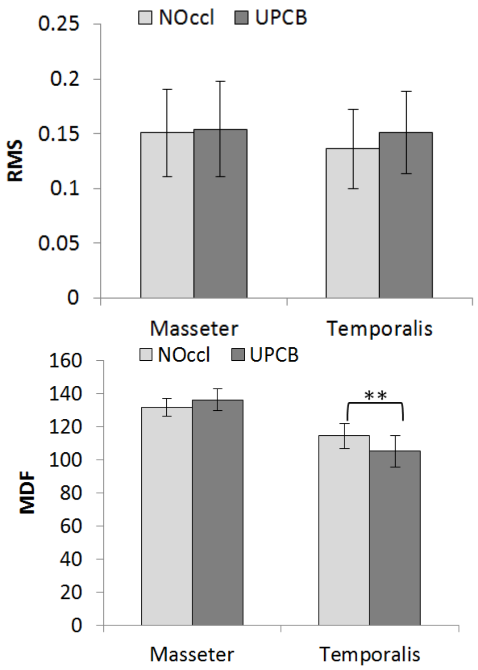

Figure 7. Mean RMS and MDF for left and right temporalis and masseter muscles in UPCB and NOccl groups. **p < 0.05.

References

[1] C. Maspero, L. Giannini, G. Galbiati, L. Kairyte and G. Farronato, G, "Neuromuscular evaluation in young patients with unilateral posterior crossbite before and after rapid maxillary expansion," *Stomatologija*, vol.17 (3), pp. 84-88, 2015.

[2] B. Thilander, S. Wahlund, and B. Lennartsson, "The effect of early interceptive treatment in children with posterior crossbite," Eur. *J. Orthod.*, vol. 6(1), pp. 25-34, 1984.

[3] A. S. Andrade, G. H. Gameiro, M. DeRossi and M. B. D. "Posterior Crossbite and Functional Changes: A Systematic Review," *Angle Orthod.*, vol. 79(1), pp. 380-386, 2009.

[4] A. S. Pinto, P. H. Buschang, G. S. Throckmorton, P. Chen, "Morphological and positional asymmetries of young children with functional unilateral posterior cross-bite," *Am. J. Orthod. Dentofacial Orthop.*, vol 120(5), pp. 513-520, 2001.

[5] K. Woźniak, L. Szyszka-Sommerfeld, and D. Lichota, "The electrical activity of the temporal and masseter muscles in patients with TMD and unilateral posterior crossbite" *Biomed Res. Int.*, 2015.

[6] M. Wieckiewicz, M. Zietek, D. Nowakowska, W. Wieckiewicz, "Comparison of selected kinematic facebows applied to mandibular tracing," *Biomed Res. Int.*, 2014.

[7] I. Veli, T. Uysal, T. Ozer, F. I. Ucar, M. Eruz, "Mandibular asymmetry in unilateral and bilateral posterior cross-bite patients using cone-beam computed tomography," *Angle Orthod.*, vol. 81(6), pp. 966-974, 2011.

[8] D. Braxton, C. Dauchel, and W. Brown, "Association between chewing efficiency and mastication patterns for meat, and influence on tenderness perception", *Food. Qual. Prefer.*, vol. 7, pp. 217-223, 1996.

[9] W. E. Brown, K. R. Langley, L. Mioche, S. Marie, S. Gérault, D. Braxton, "Individuality of understanding and assessment of sensory attributes of foods, in particular, tenderness of meat," *Food. Qual. Prefer.*, vol. 7, pp. 205-216, 1996.

[10] A. Monaco, F. Sgolastra, I. Ciarrocchi, R. Cattaneo, "Effects of transcutaneous electrical nervous stimulation on electromyographic and kinesiographic activity of patients with temporomandibular disorders: a placebo-controlled study," *J. Electromyogr. Kinesiol.*, vol. 22(3), pp. 463-468, 2012.

[11] A. D. S. Andrade, M. B. D. Gavião, G. H. Gameiro, M. D. Rossi, "Characteristics of masticatory muscles in children with unilateral posterior crossbite", *Braz. Oral Res.*, vol. 24, pp. 204-210, 2010.

[12] M. G. Piancino, D. Farina, F. Talpone, A. Merlo, and P. Bracco, P., "Muscular activation during reverse and non-reverse chewing cycles in unilateral posterior crossbite", *Eur. J. Oral Sci*, vol. 117, pp. 122-128, 2009.

[13] S. Tecco, S. Tetè, and F. Festa, "Electromyographic evaluation of masticatory, neck, and trunk muscle activity in patients with posterior cross-bites", *Eur. J. Orthod.*, vol. 32, pp. 747-752, 2010.

[14] S. G. Farias Gomes, W. Custodio, J. S. Moura Jufer, A. A. Del Bel Cury, R. C. M. Rodrigues Garcia, "Correlation of mastication and masticatory movements and effect of chewing side preference," *Braz. Dent. J.*, vol. 21, pp. 351-355, 2010.

[15] G. Iodice, G. Danzi, R. Cimino, S. Paduano, A. Michelotti, " Association between posterior crossbite, skeletal, and muscle asymmetry: a systematic review," *Eur. J. Orthod.*, vol. 38, pp. 638-651, 2016.

[16] N. F. Güler, and S. Koçer, " Classification of EMG signals using PCA and FFT" *J. Med. Syst.*, vol. 29, pp. 241-250, 2005.

[17] S. Koçer, "Classification of EMG signals using neuro-fuzzy system and diagnosis of neuromuscular diseases," *J. Med. Syst.*, vol. 34, pp. 321-329, 2010.

[18] H. Kalani, , S. Moghimi, and A. Akbarzadeh, "Towards an SEMG-based tele-operated robot for masticatory rehabilitation," *Comput. Biol. Med.*, vol. 75, pp. 243-256, 2016.

[19] H. Kalani, , S. Moghimi, and A. Akbarzadeh, "Toward a bio-inspired rehabilitation aid: sEMG-CPG approach for online generation of jaw trajectories for a chewing robot," *Biomed. Signal Process. Control*, vol. 51, pp. 285-295, 2019.

[20] N. Goharian, , S. Moghimi, and H. Kalani, "Application of an ANN-GA method for predicting the Biting force using electromyogram signals" *Signal and Data Processing*, vol. 14, pp. 41-52, 2017.

[21] M. Asefi, S. Moghimi, H. Kalani, A.Moghimi, "Dynamic modeling of SEMG–force relation in the presence of muscle fatigue during isometric contractions," *Biomed. Signal Process. Control,* vol .28, pp. 41-49, 2016.

[22] h. Kalani, S. Moghimi, and A. Akbarzadeh, "SEMG-based prediction of masticatory kinematics in rhythmic clenching movements" *Biomed. Signal Process. Control*, vol 20, pp. 24-34, 2015.

[23] N. Goharian, S. Moghimi, and H. Kalani, "Estimation biting force based using EMG signals and Laguerre estimation technique, " *in Proceedings of 2015 23rd Iranian Conference on Electrical Engineering*, Available: IEEE Xplore, http://www.ieee.org. [Accessed: 02 July 2015].

[24] H. Kalani, S. M. Tahamipour-Z, I. Kardan, A. Akbarzadeh, A. Ebrahimi, R. Sede, "SVM for Decoding the Human Activity Mode from sEMG Signals" *in Proceedings of 2019 7th International Conference on Robotics and Mechatronics (ICRoM)*, Available: IEEE Xplore, http://www.ieee.org. [Accessed: 20 April 2020].

[25] N. Goharian, H. Kalani, and S. Moghimi, "A time-delay parallel cascade identification system for predicting jaw movements" *in Proceedings of 2014 21st Iranian Conference on Biomedical Engineering (ICBME)I,* Available: IEEE Xplore, http://www.ieee.org. [Accessed: 19 February 2015].

[26] H. Kalani, A. Akbarzadeh, and S. Moghimi, "Prediction of clenching jaw movements based on EMG signals using fast orthogonal search" *in Proceedings of 2015 23rd Iranian Conference on Electrical Engineering*, Available: IEEE Xplore, http://www.ieee.org. [Accessed: 02 July 2015].

[27] D. Barmpakos, P. Kaplanis, S. A. Karkanis, C. Pattichis, "Classification of neuromuscular disorders using features extracted in the wavelet domain of sEMG signals: a case study", *Health Technol*., vol. 7, pp. 33-39, 2017.

[28] Wu, Qi, J. F. Mao, C. F. Wei, Shan Fu, Rob Law, Lu Ding, Bi-Ting Yu, B. Jia, and C. H. Yang., "Hybrid BF–PSO and fuzzy support vector machine for diagnosis of fatigue status using EMG signal features" *Neurocomputing*, vol. 173, pp. 483-500, 2016.

[29] A. Subasi, "Classification of EMG signals using PSO-optimized SVM for diagnosis of neuromuscular disorders" *Comput. Biol. Med*., vol. 43, pp. 576-586, 2013.

[30] V. Khoshdel; A. R Akbarzadeh, " Application of statistical techniques and artificial neural network to estimate force from sEMG signals" *J. AI Data Min.* vol. 4, pp. 135-141, 2016.

[31] H. Kalani, M. Sardarabadi, and M. Passandideh-Fard, "Using artificial neural network models and particle swarm optimization for manner prediction of a photovoltaic thermal nanofluid based collector" *Appl. Therm. Eng.*, vol. 113, pp. 1170-1177, 2017.

[32] A. S. Andrade, M. B. Gavião, M. Derossi, and G. H. Gameiro, "Electromyographic activity and thickness of masticatory muscles in children with unilateral posterior cross-bite," *Clinical Anatomy: The Official Journal of the American Association of Clinical Anatomists and the British Association of Clinical Anatomists*, vol 22, pp. 200-206, 2009.

[33] N. Tsanidis, G. Antonarakis, and S. Kiliaridis, "Functional changes after early treatment of unilateral posterior cross-bite associated with mandibular shift: a systematic review," *J. Oral Rehabil*., vol. 43, pp. 59-68, 2016.

[34] B. Lucas, T. de S. Barbosa, L. J. Pereira, M. B. D. Gavião, and P. M. Castelo, "Electromyographic evaluation of masticatory muscles at rest and maximal intercuspal positions of the mandible in children with sleep bruxism," *Eur. Arch. Paediatr. Dent.*, vol. 15, pp. 269-274, 2014.

[35] E. M. A. Ibraheem, and M. Z. Nassani, " The effect of flexible acrylic resin on masticatory muscle activity in implant-supported mandibular overdentures: a controlled clinical trial" *Electronic physician*., vol. 8, pp. 1752, 2016.

[36] K. H. L. Turcio, P. R. J. Zuim, A. M. Guiotti, D. M. Dos Santos, M. C. Goiato, D. A. Brandini, "Does the habitual mastication side impact jaw muscle activity?" *Arch. Oral Biol*., vol. 67, pp0 34-38, 2016.

[37] G. S. Throckmorton, P. H. Buschang, H. Hayasaki, A. S. Pinto, "Changes in the masticatory cycle following treatment of posterior unilateral crossbite in children" *Am. J. Orthod. Dentofacial. Orthop.*, vol. 120, pp. 521-529, 2001.

طبقه بندی سیگنال‌های الکترومایوگرافی برای تشخیص بیماری کراس بایت خلفی با استفاده از آنالیز تبدیل فوریه سریع و رگرسیون لجستیک

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چکیده:

بیماری کراس بایت خلفی یکی از اختلالات شایع در دندان های شیری است که بر عملکرد جویدن تاثیر بسزایی دارد. در این مقاله قصد داریم با استفاده از سیگنال‌های الکترومایوگرافی (sEMG) عضلات اصلی در عمل جویدن، یک سیستم برای تشخیص کراس بایت خلفی در دندان های شیری پیشنهاد دهیم. در این پژوهش چهل کودک (بین چهار تا شش سال) برگزیده شده‌اند که بیست نفر از آنها دارای این مشکل هستند. فعالیت الکترومایوگرافی عضلات صورت این کودکان دو مرتبه و در هر مرتبه به مدت بیست ثانیه جویدن آدامس ثبت شده است. در این مقاله، در ابتدا آنالیز تبدیل فوریه سریع (FFT) به سیگنال‌های حیاتی sEMG ثبت‌شده از افراد اعمال می‌شود. تعداد ضرایب FFT با استفاده از روش رگرسیون لجستیک (LR) انتخاب می‌شوند. سپس توانایی شبکه عصبی مصنوعی پرسپترون چند لایه (MLPANN) در تشخیص اختلالات عصبی عضلانی مودر ارزیابی قرار می‌گیرد. به منظور یافتن بهترین وزن‌ها برای نرون های شبکه عصبی و همچنین ساختار بهینه برای این شبکه، از بهینه‌سازی ازدحام ذرات (PSO) استفاده می‌شود. نتایج به‌دست‌آمده نشان‌دهنده توانایی منطقی و قابل قبول سیستم پیشنهادی برای طبقه‌بندی سیگنال‌های sEMG می‌باشد. روش پیشنهادی می‌تواند در کاربردهای بالینی برای تشخیص کراس بایت خلفی مورد استفاده قرار گیرد.

کلمات کلیدی: کراس بایت خلفی، سیگنال‌های الکترومایوگرافی، آنالیز تبدیل فوریه سریع، شبکه عصبی مصنوعی پرسپترون چند لایه.