In the name of god

Topic: Separation of facial movements in botoxed and normal people based on electromyography signal using artificial neural network

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Abstract

Using electromyography (EMG), muscle behavior can be measured and analyzed. The aim of the present study is to distinguish between three states: frown, surprise, and rest. The study was conducted in two parts: the first part based on the three states in both normal and Botox-treated individuals, and the second part specifically distinguishing between the frown and surprise states in normal and Botox-treated individuals. The participants of this study were 16 women with an average age of 45±15, six of whom had undergone Botox treatment. EMG signal acquisition was performed using a module and Arduino. Subsequently, the signal features were extracted, and then an artificial neural network was used for data classification. The first part achieved a 91% accuracy in distinguishing all individuals, including both normal and Botox-treated, which can be useful in various applications such as robot design for recognizing and modeling facial movements. In the second part, Botox-treated individuals could be distinguished from normal individuals with 96% accuracy during frown and surprise movements. Finally, we concluded that this research could facilitate and improve the Botox injection process and also determine a more precise timing for re-injection to minimize side effects.

Keywords: Electromyography, Botox, Neural Network, Facial Expressions

1. Introduction

Electromyography (EMG) is used to measure muscle behavior and provides information about muscle contractions during an exercise or task. EMG is widely used in various research fields. EMG can be performed using either surface or needle methods, with surface EMG being the most commonly used due to its less invasive nature compared to the needle method [1]. Two common methods for interpreting EMG signals are signal intensity recording and pattern recognition. EMG signals can be affected and altered by many factors, including interference from adjacent muscle signals, muscle force variations, power line noise, and other noise sources [2]. Researchers have made significant efforts to reproduce the brain's system for human face recognition, resulting in numerous algorithms for facial recognition. In this study, we use EMG for signal acquisition. Based on studies, there are three fundamental approaches to face recognition: biometric signal-based methods, facial geometry-based methods, and appearance-based methods. The three main stages for face recognition are biological data acquisition (including signals or images), feature extraction, and result presentation [3]. This paper proposes a deep learning model for multimodal emotion recognition based on the fusion of electroencephalogram (EEG) signals and facial expressions to achieve an excellent classification effect [14].The anatomy of the face is divided into three main regions: the upper face, the midface, and the lower face. The surface anatomy of the face includes the skin that covers the entire surface, while the deep anatomy includes muscles, fat pads, nerves, blood vessels, and bones.The upper face starts from the hairline and extends down to just below the lower eyelid. The midface starts from the lower eyelid and extends down to the top of the upper lip. The lower face starts from the upper lip and extends to the bottom edge of the chin. Previous studies have commonly used EMG signals to study emotions from the occipitofrontalis, temporalis, procerus, corrugator, zygomaticus major, zygomaticus minor, and masseter muscles [4]. In the study conducted by the researchers in this article, they examined six facial expressions among 19 women and 17 men, all of whom were healthy and had no cosmetic procedures performed on their faces. From the EMG analysis of various expressions, they concluded that the anger and disgust expressions exhibited the highest muscular activity, while the surprise and sadness expressions showed the least activity. In the end, they concluded that muscle activity is greater in the upper part of the face compared to the lower part[16].Facial expressions do not always reflect our true emotions, making it crucial and challenging to assess facial expressions to determine if they are intentional, voluntary, or deceptive [5]. For recognizing various facial expressions like happiness, anger, disgust, etc., a wireless two-channel data collection system is used, recording signals from the zygomatic and corrugator facial muscles in four stages: feature extraction, feature selection, classification, and emotion recognition [6].

Studies have shown that recognizing and interpreting emotions in older faces is more difficult than in younger faces. The main reason for this is not clear, but it may be due to age-related changes such as wrinkles or the decreased flexibility of facial muscles. The facial muscles involved in expressing emotions lose their flexibility with age, which reduces the accuracy of displaying facial expressions. [7 Facial aging is a multifactorial process that involves changes in all facial tissues, including the skin, muscles, fat, and ligaments. This study aims to investigate the potential action of facial muscles using non-invasive surface-derived EMG in healthy young and old volunteers. The results of this study may help better understand facial aging and appropriate treatment and prevention methods [8]. All facial muscles function as a unit and are interconnected, so injections should only be made into the muscle responsible for the cosmetic effect and not adjacent muscles, as this could have harmful or even opposite effects. Using new research methods and techniques in injections can provide a better understanding of the functional anatomy of facial muscles, leading to more accurate injections by physicians for optimal results with minimal side effects [9].

Figure 1 - Electrode location on the face according to the article[8]

Botulinum toxin (Botox) consists of 7 types of neurotoxins used to reduce facial wrinkles. Botox works by preventing the release of acetylcholine, leading to localized muscle paralysis and skin tightening, typically occurring 24 hours to two weeks after injection [10, 11]. In this study, 150 people aged 18 to 70 were studied. There was a total of 62.7% postinjection side effects, with varying degrees of severity[15].

In this study, we aim to examine facial expressions and their various positions using EMG signals and to facilitate treatment methods and reduce facial aging, specifically focusing on Botox treatments, to achieve the highest efficiency with the least error, as shown in Figure 1.

References	method (features)	moods	Classification
[8]	Using the facial movement mask (FMG), which focuses on the movement of the facial muscles.	multiple	**MMI, PEN, GAN**
[10]	This article summarizes the advances in facial expression and reviews nearly 30 detection methods.	multiple	**MMI, SVP, 3D**
[11]	Real images of facial expressions were used in this study, and the original images look younger or older.	Angry, scared, disgusted, and sad	**(GAN)**
[10]	In this article, facial electromyography of nine facial muscles has been investigated bilaterally.	multiple	**SNR**
[14]	Using electrodiagnostics, electroneurography, electromyography and transcranial magnetic stimulation, facial conditions and nerves have been examined.	multiple	**nEMG sEMG TMS**

Table . 1 - Examination of facial expression detection methods in other articles

The method presented in this article is non-invasive compared to the methods used in other studies in this field, such as needle electromyography, and has no side effects for the test subjects. The targeted area, which includes the muscles, has been precisely examined and compared to facial imaging methods. Given the high accuracy and precision obtained with this method, it consumes less time and cost. This method can be utilized to develop a device for facial analysis to treat aging and minimize its effects.

Accuracy and Precision: The method used in the present article shows high accuracy (91% and 96%), making it superior in terms of precise classification of facial states and Botox detection compared to the other studies, which do not specify accuracy.

Invasiveness: The present method is non-invasive, which is a significant advantage over more invasive techniques like those used by Chen, Wang et al.

Applicability: The method's precision and non-invasive nature make it particularly suitable for cosmetic applications such as Botox treatment, whereas the methods in other studies might be more suited for broader diagnostic purposes.

Article/Study	Method Used	Data Type	Features Extracted	Classification Technique	Accuracy	Unique Aspects
Present Article	EMG signals from the forehead muscle	EMG signals from 16 female volunteers (average age 45 ± 15)	Time, frequency, and nonlinear features (e.g., RMS, maximum, minimum, Shannon entropy)	Neural Network with a hidden layer	91% for facial states, 96% for Botox detection	Non-invasive, precise electrode placement, high accuracy, useful for Botox treatment
[8]	Facial Movement Mask (FMG)	Facial muscle movements	Various mask features	Multiple methods (e.g., GAN)	–	Focus on muscle movement detection
[12]	Electrodiagnostics, electroneurography, electromyography, transcranial magnetic stimulation	Facial conditions and nerves	Multiple features from diagnostics	Multiple methods	–	Comprehensive facial condition analysis

Table .2 -Comparison Table and Explanation of Methods Used in the Article

2. Materials and Methods

The subjects of this study were 16 female volunteers with an average age of 45 ± 15, six of whom had received Botox injections. In an introductory session, the experimental procedure was explained to them. We aimed to examine the lines formed on the forehead during three expressions: frowning, surprise, and rest To collect data. the forehead surface was first moistened with water-soaked cotton to ensure it was completely clean for minimal resistance. Then, the electrodes were placed in designated positions. Three single-channel bipolar surface electrodes were used to record EMG signals. Two electrodes were placed further apart, with a reference electrode in the middle, as shown in Figure 2, recorded in 20-second intervals for each expression.

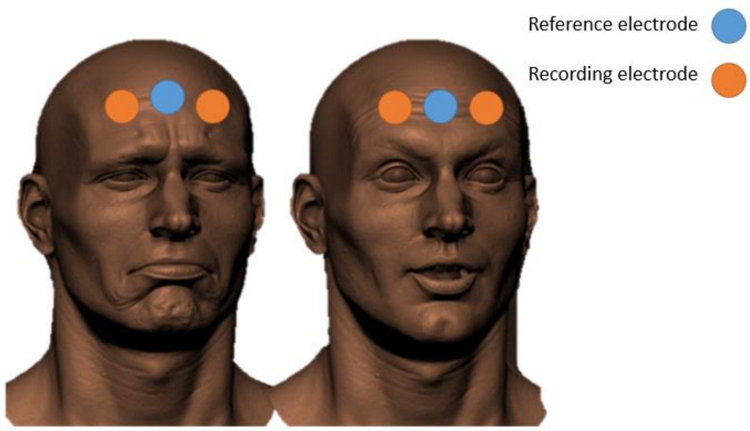

Figure 2 - The place of electrode placement to record the signal in different facial states

Three shielded cables were used to transmit biological data from the body to the EMG module. The leads were connected to the EMG module. The cables were kept as short as possible to minimize noise interference with the main signal.

A 6-pin module was used for data collection, with the first three pins connected to the body and the second three pins connected to the Arduino board, as shown in Figure 3. An Arduino UNO was used for hardware implementation. The Arduino, equipped with an ATMEGA microcontroller and several analog input pins, received analog data with voltages between 0 and 5 volts and converted them to digital values. A serial oscilloscope was used to display and save the data. During the experiment, the power supply was disconnected to eliminate power line noise.

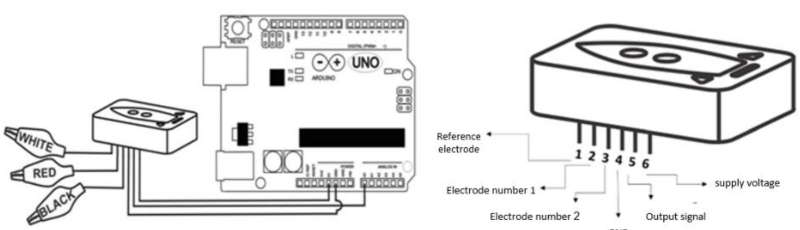

Figure 3_ Module and Arduino UNO (connecting cables)

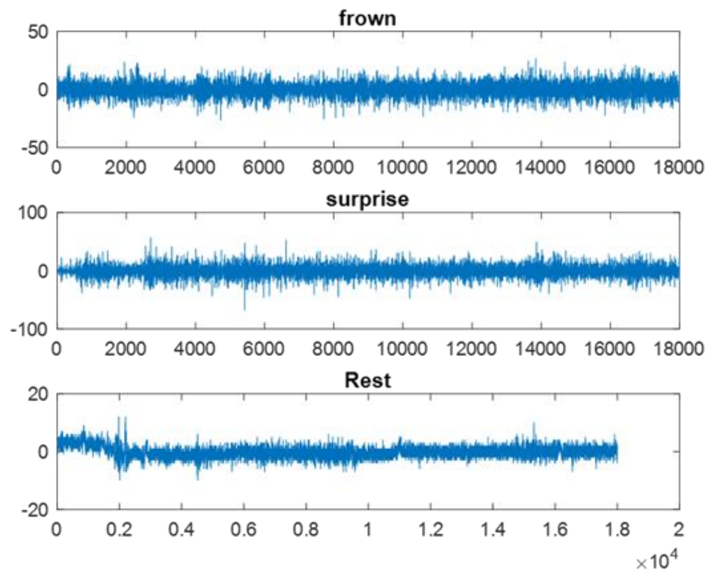

Figure 4_ A data sample of the three states of frown, surprise and rest from the face without Botox of a 23-year-old woman

In the pre-processing stage, we used a series of Butterworth and Savitsky-Glay filters. Butterworth filters have many applications and are widely used in many signal processing circuits. It is used to select or exclude selected frequency signals in a complete spectrum of the given input. Therefore, the filter is used to pass selected frequency signals through it or remove selected frequency signals from it. This filter is used to shape the frequency spectrum of a signal. Among the features of this filter, we can mention these things, this filter is based on R-C op amp (operational amplifier). This is an active filter, so if necessary, its gain can be adjusted. The main characteristic of the Butterworth is that it has a flat crossover and a flat band stop. This is why it is usually called a flat flat filter. The type of Butterworth filter we used here is a 20 Hz to 450 Hz bandpass filter. If we consider a general equation representing a Butterworth filter of order n, then the frequency response is written as formula 1-2 below.

$$H(jw) = \frac{1}{\sqrt{1+\epsilon^2(\frac{\omega}{\omega p})^{2n}}} \qquad (2\text{-}1)$$

In the above relation, n represents the order of the filter, ω is equal to 2πf and ∈ is equal to the maximum gain of the passband (Amax).

The Savitzky-Golay filter is a digital filter that can be used to smooth a set of digital data points. This is done by processing successive subsets of adjacent data points with a lowdegree polynomial using the method of least squares. When the data points are evenly spaced, an analytical solution to the least squares equations can be found, which takes the form of a set of filter coefficients that can be applied to all subsets of data to produce estimates of the smoothed signal at the central point of each subset., based on the mathematical equation (1 -2) to be done.

$$Y_j = \sum_{i=\frac{1-m}{2}}^{\frac{m-1}{2}} C_i y_j + i \qquad \frac{m+1}{2} \le j \le n - \frac{m-1}{2} \tag{2-2}$$

In this formula,the data includes a set of points {xj, yj}, j = 1, ..., n,where xj is an independent variable and yj is an observed value. They are Ci with a set of twist coefficients m. After filtering, we converted the data into 2-second windows. MATLAB R2017a software was used for data processing. From each received signal, 8 features were extracted as follows.

Average: It is one of the characteristics of the data obtained according to formula 2-3.

$$Mean = \frac{\sum_{i=1}^{n} xi}{N} \tag{2-3}$$

In this relationship, N is the number of data, xi is the value of each data in location i.
Curvature means an arcuate curve that describes a particular aspect of the probability distribution that is obtained according to equation 2-4 .

$$Kurt(X) = E[(\frac{X-\mu}{\sigma})^4] = \frac{\mu^4}{\sigma^4} \tag{2-4}$$

In this relationship μ is the mean and σ is the standard deviation of the random variable X. E is meant by Omid-mathematical random variable. Skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable around its mean., which is obtained from formula 2-5.

$$\tilde{\mu}_3 = \frac{\sum_i^N (X_i - \bar{X})^3}{(N-1)*\sigma^3} \tag{2-5}$$

In this relation, N is the number of variables in the distribution, Xi is the data points, X is the mean of the distribution, σ is the standard deviation, degree 3.

The effective voltage, which is the root mean square, is a statistical measure of the variable quantity. It is obtained according to equation 2-6.

$$RMS = \sqrt{\frac{1}{n}\sum_i x_i^2} \qquad (2\text{-}6)$$

In this regard, n is the number of measured data, xin is the data points. Standard deviation in statistics is a measure of the amount of variation or dispersion of a set of values. which is obtained according to equation 2-7.

$$\sigma = \sqrt{\frac{\sum(x_{i-\mu})^2}{N}} \qquad (2\text{-}7)$$

In this relationship, N is the size of the population, xi is the data points, and μ is the mean of the population.

The median is the value that separates the upper half from the lower half of a data sample, a population or a probability distribution, obtained according to equation 2-8.

$$Med(X) = \begin{cases} X_{\left[\frac{n+1}{2}\right]} & n = 2i + 1 \\ \frac{X_{\left[\frac{n}{2}\right]} + X_{\left[\frac{n}{2}+1\right]}}{2} & n = 2i \end{cases} \qquad (2\text{-}8)$$

In this relation, X is the sorted list of values in the dataset, n is the number of values in the dataset. We used Shannon's entropy to extract the feature that indicates the irregularity of the signal.

Fft is the decomposition of a string of values into components with different frequencies. If we know the spectrum of the signal, we can calculate the signal itself. We use discrete Fourier transform and inverse discrete transform, which are calculated according to formulas 2-9 and 2-10.

$$X(k) = \sum_{n=0}^{N-1} x(n) \cdot e^{-j\frac{2\pi nk}{N}} \qquad (2\text{-}9)$$

$$x(n) = \frac{1}{N}\sum_{k=0}^{N-1} X(k) \cdot e^{-j\frac{2\pi kn}{N}} \qquad (2\text{-}10)$$

In this relation, the counter x and n are the number of data.

3. Results

In this study, After filtering the data and performing feature extraction, we extracted eight features from the data and presented each in Table 2. This table specifically shows eight different features in the domains of time, frequency, and nonlinear characteristics. The table has three rows indicating the mean, maximum, and minimum values of the features. This table demonstrates that there are differences in the EMG feature values between different facial expressions and between Botox and non-Botox individuals. Given these values, it can be inferred that specific features such as RMS, maximum and minimum values, and other nonlinear and linear features can effectively distinguish these states and individuals. Ultimately, utilizing these features can improve the accuracy of models for analyzing facial movements and identifying Botox and non-Botox individuals.

Shannon entropy	middle fft	average fft	standard deviation	rms	multiple	Elongation	Average	The name of the feature
-8309.9	0.27806	1.390389	7.7698	473.06711	0.35000	18.4162	472.21	The median value
-2.0531	0.27806	1.390389	147.903	491.4224	53.6767	2.8977e+03	490.02115	The maximum value
-8787.5	0.27806	1.390389	0.7932	11.2009	-1.29025	2.3174	-0.016178	Minimum amount

Table 3 - average, maximum and minimum features

After extracting the features, an artificial neural network with a hidden layer according to Figure 5 was used to classify the data.

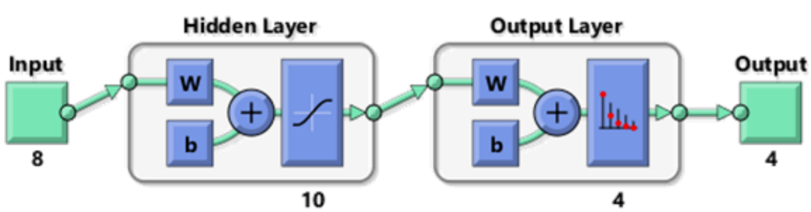

Figure5 - Neural network with 10 hidden layers for classification of the second part

We used a neural network for data classification and comparison. This task was performed in two parts. In the first part, we classified all the data to examine the three states of frown, surprise, and rest according to Figure 6. In the second part, we compared the states of surprise and frown in individuals who had Botox and those who were normal, as shown in Figure 7.

Figure 6 - The figure examine the three states of frowning, surprise and rest

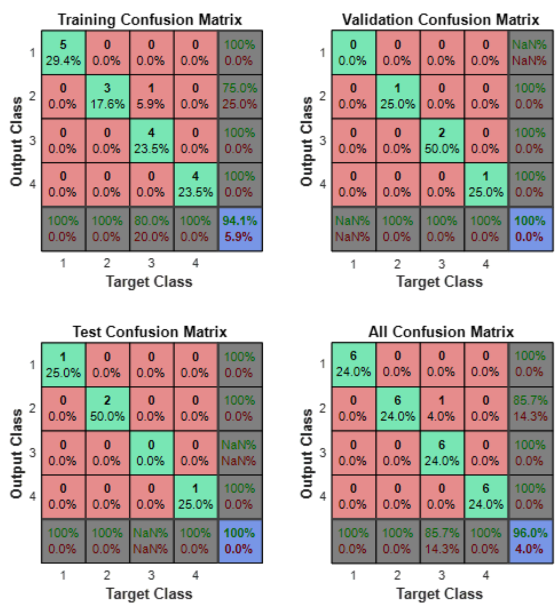

Figure 7 - the figure on the left to compare normal and botoxed people

Neural Network Analysis:

(Training Confusion Matrix)

In these matrices, the accuracy of the predictions in the training phase is displayed. It is observed that the prediction accuracy in this phase is usually high because the model is evaluated with data it has seen and been trained on.

(Validation Confusion Matrix)

These matrices are used to evaluate the model with data that was not used during training. The prediction accuracy in this phase is slightly lower than in the training phase, indicating the model's actual performance on unseen data.

(Comparison of Results Between Different States (Frown, Rest, Surprise)

The matrices show that the model can effectively distinguish these states, but some states may be identified with higher accuracy than others. For example, in the training phase, the accuracy of detecting the frown state is very high.

(Botox and Non-Botox)The matrices indicate that the model also performs well in distinguishing between Botox and non-Botox individuals. For instance, in the testing phase, the accuracy of identifying non-Botox individuals is very high (93.1%).The presented confusion matrices demonstrate the good performance of the neural network model in distinguishing various facial states (frown, rest, surprise) as well as identifying Botox and non-Botox individuals. Overall, the model's accuracy is high in the training phase and slightly decreases in the validation and testing phases, indicating the model's good generalization ability. The model can be effectively used for analyzing and identifying different facial states and distinguishing between Botox and non-Botox individuals.

4. Conclusion

The present article, with the study and experiments conducted using the electromyography signal from the selected forehead muscle on the three states of frowning, surprise and rest after feature extraction in three domains of time-frequency and non-linear features, identified the mentioned facial states through the network. A hidden neural layer can be distinguished with 91% accuracy in all subjects, whether normal or botoxed. Also, in another part of that research, it was found that botoxed people can be distinguished and identified from normal people with 96% accuracy during the two movements of frowning and surprise. This study is related to the results obtained in previous articles [4, 5, 6] and confirms the results of these articles. The subject of recognizing facial movements by this method can be used in many cases, such as making robots that can recognize facial movements and model them. In the second part, which compared normal people and Botox, we came to the conclusion that with this work, we can help facilitate and improve the Botox injection process. By examining these signals, we can determine a more accurate time for re-injection of Botox and determine the appropriate place for injection to have the least side effects. In future studies, it is suggested to combine electromyography and electroencephalography data in order to increase the accuracy and also separate movements with more classification classes.

5. References

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