Surface Electromyography Signal Classification for the Detection of Temporomandibular Joint Disorder using Spectral Mapping Method

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Abstract—Temporomandibular joint Disorder (TMD) is with multifaceted and complex signs and symptoms which makes day to day activities of an individual uneasy. Electromyographic (EMG) processing of related muscles recordings could provide an early and immediate detection of TMD. To detect the TMD using surface electromyography (SEMG) of Masseter and Temporalis muscle with discrete wavelet transform (DWT) using spectral coding. To analyze the data, a new feature selection approach in the spectral domain is proposed. For statistical analyses, SPSS version 24 is employed. The results of the study revealed that the proposed approach was able to improve the accuracy of the classification by implementing a combination of DWT and the Support Vector Machine (SVM). The proposed method also exhibited a significant improvement in its performance in terms of its accuracy with 93%. In addition, the statistical analysis revealed that the model was able to improve the mean rank of the experimental and control group.

Keywords—*Temporomandibular joint (TMJ); temporomandibular joint disorder (TMD); surface electromyography (sEMG); spectral mapping; discrete wavelet transform (DWT)*

I. INTRODUCTION

TMD is an orofacial disorder, which is characterized by joint noises and limitations in the range of motion. Complex and multidisciplinary symptoms related to the Temporomandibular joints (TMJ) are known to affect different parts of the body. Understanding the pathogenesis and possible reasons of these conditions can be challenging. The most common methods of diagnosing and management of TMD is with clinical evaluation followed by radiographic evaluation of images from, X ray, Magnetic resonance Imaging (MRI), cone beam computed tomography (CBCT) and Orthopantomogram (OPG). sEMG is a complementary tool that can be used to evaluate the efficiency and function of muscles by directly analyzing their electrical potentials. This technique has been widely used to diagnose and monitor the TMD as it is a noninvasive technique [1]. In recent development, EMG were processed using spectral coding where multi resolution signals are decomposed and entropy features are used in decision making of bruxism [2]. Various approaches of detection of TMD were developed in the recent research. The significance of usage of sEMG for the reliable detection of TMD is presented in this paper. For the analysis of a superimposed motor unit action a sEMG application for muscle function and its detection efficiency is outlined in [3]. In [4] the signal represents a weighted sum of various temporal and spatial motions of different electrical muscle activities. The analysis is developed as a set of different muscular movement of variation with course of observing time. A muscle imbalance detection based on muscle activity monitoring for TMD is presented in [5, 6]. The outlined approach in [7, 8] aims in developing the effect of temporary splint usage on the masticatory muscle using surface electromyography. The analysis of masticatory muscle activity after an orthodontic treatment using sEMG is discussed. In observing the deviation of masticatory muscle usage for TMD diagnosis an analysis for varying age group is presented in [9]. EMG signals are used in processing masseter and temporalis muscle using duty factors for different age group, and genders of patients having pain and pain free TMD is outlined in [10]. The analysis of TMD a short term observation of transcutaneous electrical nerve stimulation (TENS) observing pain concentration, pressure pain threshold (PPT) and EMG is outlined in [11]. The analysis of sEMG on the behavior of neck, trunk and masticatory muscle for different groups under rest and maximal voluntary clenching (MVC). Variation to sEMG activity for myofacial pain and non-pain condition is presented in [13, 14]. The variation in sEMG for Temporomandibular joint hypermobility (TMJH) for healthy and effective with mild and severe TMJH is presented in [15, 16, 17]. A discrete wavelet transform approach is proposed to analyze sEMG using Auto regression and the Shannon Entropies [18]. The proposed method with new energy-based spectral coding has advantages over the conventional approach and can provide better diagnosis.

The paper is divided into four sections. The first section introduces the concepts of TMD and EMG processing. The second section outlines the materials and methods. Third section describes the proposed approach for detecting disorder with results and discussion, and at the end section four concludes the study.

II. Materials and Methods

A. SEMG Signal Acquisition

This Experimental Analysis was conducted on 100 individuals with an age between 18 to 60 years. The subjects were notified about the procedure and a written informed consent is taken in accordance with the declaration of Helsinki [6]. Many people were omitted from the research because they had a history of orthodontic treatment, lip negligence, or prior tooth restoration [19]. The subjects underwent a complete dental history followed by radiographic evaluation using an Orthopantomography (OPG) by the Dental Practitioner. Based on the Doctors assessment, subjects were divided into two groups. The first group was healthy subjects called control and the second group was subjects with TMD called experimental group. Masseter and Temporalis Muscles of both groups were analyzed by recording the sEMG . The subjects were seated in a comfortable position before the recording was carried out. Since their jaw muscles reacted to changes in head position, no movement was allowed. They were next shown how to hold the mandible relaxed and intercuspal. They were also shown how to utilize cotton rolls to aid in clenching. Signals from the surface of the muscles were collected using a 2-channel electromyography machine. At the beginning of the sEMG recording, volunteer's skin is cleaned with 70% alcohol before the electrodes are placed on it. The participants were monitored for 10 seconds during which they were subjected to rest and clenching activities of 5 seconds each. Both scenarios were recorded using simultaneous electromyographic signals. The recordings were then processed using a 12-bit A/D converter. They are also subjected to a cut-off frequency of 10Hz to 1500Hz.After recording, the signal is filtered through a digital filter with a pass-band of 10Hz to 500Hz. The data were then analyzed using a computer algorithm known as MATLAB 2019. Processing of sEMG is carried out using time frequency analysis with wavelets.

B. SEMG Signal Processing

The proposed system architecture for EMG processing in TMD detection is shown in Fig. 1. The process involves in successive filtration of signal using high pass and low pass filters for a given scale levels. The wavelet function can be performed using two different algorithms: the Haar wavelet algorithm and the Daubechies algorithm (3). The goal of the wavelet function is to match the signal to the wavelet function that's being processed.

In this study Daubechies-4 wavelets with five levels of scaling is applied after comparing and getting better results with other wavelets and the decomposition is developed as a separation of finer spectral bands and residual elements given by

$$B[t] = \sum_{t=1}^{n} \xi[t] + \gamma[t] \tag{1}$$

Where, B[t] represent the spectral bands for a given scale level of 't' processed over a period of t=1..n, which is observed to be sum of spectral bands ξ and residual decomposed band γ. The spectral bands are derived from a set of filter blocks which are cascaded to develop a hierarchical decomposition of given signal, which results in filter spectral bands and residual components.
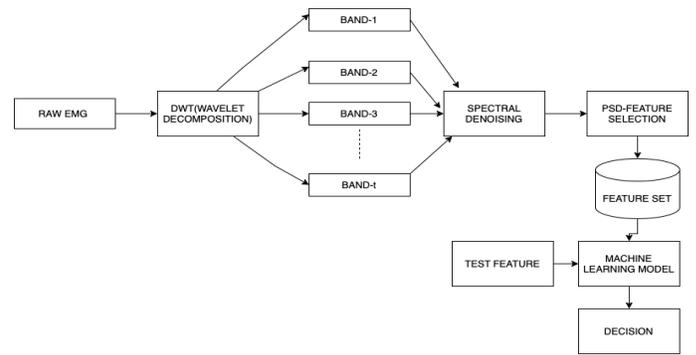

Fig. 1. Framework for Proposed Approach of TMD Detection: Raw EMG is Decomposed using DWT with Multiresolution Approach using Daubichew-4 Filter with Five Levels of Scaling for Denoising and the Reconstructed Signal is extracted with Features and Selected Feature.

The decomposed bands for the EMG signal represent a set of sub-spectral bands $\{\chi_0, \chi_1, \chi_3 \ldots \ldots \chi_n\}$ which are derived by the signal filtrations of successive residual component of previous scale. The decomposed bands are defined as a set υ which are the subset of processing signal S given by,

$$\upsilon = \{\chi_0, \chi_1, \chi_3 \ldots \ldots \chi_n\} \in S \tag{2}$$

In filtration, the maximum spectral band of each of the decomposed band is computed and average value is considered as filtering coefficients defined as,

$$f_i = \max(\chi_i)_{i=1 \text{ to } t} \tag{3}$$

$$F = \{f_1, f_2, f_3 \ldots \ldots f_t\} \tag{4}$$

$$F_{coeff} = avg(F) \tag{5}$$

The average over all decomposed band defines the distribution of varying peaks for each band. Maximum peaks of each band reflect the maximum spectral limit of the processing band. The filtration process performs a convolution operation of the decomposed band using computed filter coefficients for distortion removal. The filtration is performed as,

$$D_i = conv(\chi_i, F_{coeff}) \tag{6}$$

The denoised signal (Di) is processed for feature selection where the spectral densities of the filtered bands are computed. Spectral density illustrates the spectral energy concentric on a band. The spectral density is defined as the power spectral density (PSD) given as,

$$PSD \ (P_i) = \frac{1}{n} \left(\sum_{i=1}^{n} D_I \right) \tag{7}$$

Where, 'n' is the total number of coefficients in the band. For 't' scale bands the PSD are a set of PSD's given as {P_1, P_2, P_3 …… P_t}. In selecting features the computed spectral density is correlated and bands with PSD above the limiting value is considered as feature. The selection of feature vector is outlined in below algorithm.

Proposed Algorithm for Feature Selection:

Input: Denoised spectral bands of EMG signal (Di)

Output: Selected features

Process

Compute PSD (P_i) for obtained denoised band Di,

$$PSD\ (P_i) = \frac{1}{n}\left(\sum_{i=1}^{n} D_i\right)$$

Compute limiting threshold (L) given as,

$$= \frac{1}{4}\max(P_i)$$

Select feature using correlative method defined as,

$$Ft = \begin{cases} P_i,\ if\ P_i > L, \\ \\ 0\ else \end{cases}$$

End process

Features were selected for a limiting threshold value of 25%. Because most of the dominant values will be above this threshold. Lower values may be considered but might contain noise. The selected feature sets are trained for sparsely disturbed EMG signals of different test cases and a training process is performed to create a learning feature table. The learning feature sets is used for training a support vector machine (SVM) and testing is performed using the multi class model of SVM classifier. The processing system operates for training and testing operation, where a training process is an offline process and testing is developed as an online process. The simulation result and observations for the proposed system is presented in following section.

III. Results

A. Results of Signal Processing and Classification Model

The signal processing window of 300 coefficients is considered in processing the EMG signal. The processing window signals is iteratively processed to minimize the processing overhead and reflects a finer multi resolution details for processing signal. The EMG signal is processed for distortions with additive Gaussian noise, which are observed in the signaling domain generated due to surrounding environment and processing units. Multi resolution spectral bands using wavelet transformation is shown in Fig. 2. The decomposed bands reflect the variation of signal under different frequency resolutions.

The decomposed bands illustrate a magnitude variation under different frequency resolution [16]. These finer details give more selective characteristic of processing signal. The spectral energy density of each isolated band computed as PSD. A test of 10 iterations with varying Variance value from 0 to 1 is performed. The denoising efficiency is measured by an average Means square error (MSE), Peak signal to noise ratio (PSNR) and Root mean square error (RMSE) values.

The MSE is given by,
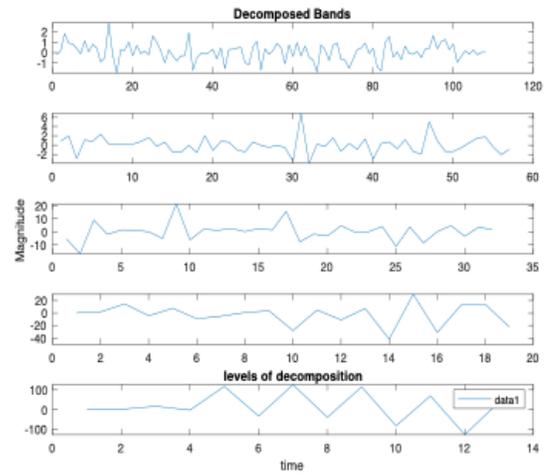
$$MSE = \frac{\sum_{i=1}^{n}(x-x')^2}{n} \qquad (8)$$

Fig. 2. Decomposed Spectral Bands for the Surface EMG Signal for Level 5 and Db4 Wavelet.

Where x is the actual signal of processing coefficients and x^' is the de-noised signal coefficients.

PSNR is given by,

$$PSNR = log_{10} \frac{peak(x')}{peak(x)} \qquad (9)$$

and RMSE is given by,

RMSE= $\sqrt{\text{MSE}}$ (10)

Observations for the developed approach spectral mapped approach (SMAP) is compared with the existing approach of soft thresholding and auto regression model (AR) [18] for denoising performance. The observation of the developed approaches for denoising for different test samples is presented in Table I.

TABLE I.   DENOISING FOR DIFFERENT TEST SAMPLE

Test sample	Method	PSNR (dB)	RMSE	Time (Sec)
S1	Soft threshold	34.9088	2.5115	0.156
	AR	45.4041	1.1643	0.031
	SMAP	50.8703	1.1756	0.015
S2	Soft threshold	34.4641	2.5064	0.175
	AR	45.4121	1.1642	0.029
	SMAP	50.8703	1.1756	0.019

The spectral coding of signal denoising eliminate distortion using a period of observation, wherein a discrete observation generate filtration for observing coefficients only which has lower filtration performance. More effective denoising results into an accurate signal representation. This result to improve the accuracy of detection.

The peak signal to noise ratio (PSNR) [18] value defines the signal strength to distortion in the processing signal. A higher PSNR defines higher signal strength in retrieved signal in reference to distortion level. The proposed method attained 51dB of PSNR which is 20dB and 8dB higher than the existing soft threshold and auto regression model respectively. Root

mean square error (RMSE) defines the standard deviation of the predicted signal compared to the original signal. The RMSE of the proposed method is 1.9 times lower than auto regression model and 2.1 time lower compared to soft threshold method.

The spectral peak values of the denoised signals are considered as a relative feature for EMG signal analysis. Detected peak levels of the processing signal is shown in Fig. 3. The spectral features are used for training the SVM model and classification of the test signal is performed for the developed multi class model [18]. Testing of developed approach is made over a sparse dataset of captured EMG samples under various postures. A k-fold test is performed where 1/kth part of the database is used for training and remaining is used for testing. The approach presented is outlined in MATLAB tool and validated for the retrieval Accuracy, sensitivity, specificity, Recall Rate, precision and computation time parameter [6]. Processing sEMG signal is captured at 5mv/sec for a period of 2 msec period.

The validation of the developed approach is performed using retrieval Accuracy, sensitivity, specificity, Recall Rate, precision and computation time parameter.

The observation for the developed system is computed for different test cases measuring the evaluating parameters. The observation for the developed approach for different classifier models, k-fold tests and varying interference levels are presented. The developed approach of Spectral mapped based classification is compared with the existing approach of Quadrant discriminant analysis and Naïve Bayes method [19]. Observation for different K-fold test for K=2 and 3 is given in Table II.

The classification performance of the proposed approach using spectral mapping method has 93% of accuracy with increases of noise variance the accuracy marginally reduced due to spectral domain processing compared to existing Quadrant discriminant analysis, KNN and Naïve Bayes classifier [19].

B. Statistical Data Analysis

Data was collected from a total of 100 respondents, who were divided into two groups: control (healthy) and experimental (patients). Of the 50 respondents in the control group, 29 were female and 21 were male. In the experimental group, there are 26 females and 24 males out of a total of 50 responses. Descriptive statistics were used to analyse the various variables within the group and sex. Two-way factorial analyses were performed to compare the mean values. The mean maximum amplitude of the subjects during rest and MVC was also estimated. The features were selected for the groups of female and male.

For all of the features, descriptive statistics were first calculated. The kolmogorov Smirnov test is used to check for normalcy, followed by a retest using the nomal Q- Q plot. We discovered that the data is not normally distributed and that the Kolmogorov-Smirnov P-value (.000) is less than.050. Furthermore, the largest observation is away from the primary diagonal in the Q-Q graph, indicating that the data is not regularly distributed. The data was then corrected for normality using log transformation, reciprocal transformation, and square root transformation. However, this method failed to convert the data into normal distribution. The results are presented in Table III. The non-parametric Mann-Whitney U test was used to investigate the significant difference between left temporalis and right temporalis rest and MVC among the participants.
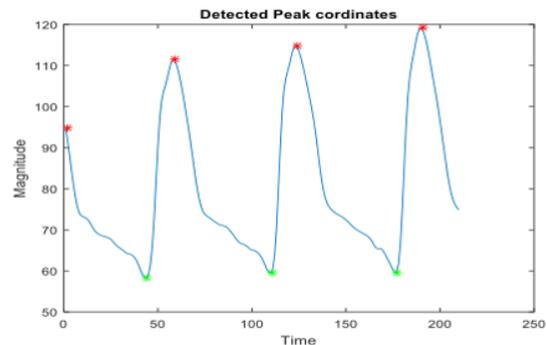

Fig. 3. Peak Detected Energy Coefficients which are the Proposed Features for the Classification.

TABLE II. DENOISING METHODS FOR DEVELOPED SPECTRAL MAPPED APPROACH (SMAP)

K-fold	Method	Accuracy	Sensitivity	Specificity	Precision	Processing Time (sec)
K=2	Quadrant discriminant analysis	41.09	0.85	0.12	0.38	2.03
	KNN	79.07	0.89	0.20	0.89	0.69
	Naïve Bayes	88.09	0.94	0.233	0.92	0.17
	Spectral mapped approach	92.9	0.96	0.253	0.94	0.041
K=3	Quadrant discriminant analysis	43.87	0.86	0.09	0.43	2.05
	KNN	80.03	0.89	0.21	0.87	0.70
	Naïve Bayes	87.39	0.94	0.238	0.91	0.17
	Spectral mapped approach	92.63	0.96	0.251	0.93	0.043

TABLE III.   MANN-WHITNEY TEST STATISTIC

Group		Right Temporalis Rest	Left Temporalis Rest	Right Temporalis MVC	Left Temporalis MVC
Control	Mann-Whitney U	51.000	53.000	23.000	77.500
	Wilcoxon W	486.000	488.000	458.000	512.500
	Z	-5.500	-5.464	-5.970	-5.050
	Asymp. Sig. (2-tailed)	.000	.000	.000	.000
Experimental	Mann-Whitney U	15.500	25.500	19.000	116.000
	Wilcoxon W	246.500	256.500	250.000	347.000
	Z	-5.381	-5.155	-5.302	-3.095
	Asymp. Sig. (2-tailed)	.000	.000	.000	.002

IV. DISCUSSION

In this study, we evaluated the effectiveness of surface electromyography in detecting the temporomandibular disorders (TMD) with the help of time-frequency domain analysis using discrete wavelet transform. The novel approach for this study is to take out the spectral peak features after denoising the EMG signal for further classification and detection. The feature representation for diagnosis using entropy based approach outlined in [18] is constraint with the magnitude variation. The proposed approach offers an integral advantage of filtration and feature selection as single processing unit. Discrete wavelet transformation has shown a significant advantage in frequency domain decomposition because of the property multi resolution coding.

The study was limited due to the small number of subjects and the heterogeneous group. Since this disorder has complex signs and symptoms, we have considered only masseter and temporalis muscle activity. Other than muscle activity, Temporomandibular Joint sounds could be analyzed. Although the results of the study indicated that surface electromyography can identify patients with TMD, Surface electromyography is noninvasive and easier to operate but during recording possibility of noises due to surrounding or sensors is accumulated which needs to be preprocessed before the analysis. Intramuscular electromyogram (EMG) may help in pattern recognition. However, the individual will experience discomfort as a result of the intrusive electrodes. The goal of the study was to determine if a complex disease can be represented through a phenotype that allows for a straightforward clinical assessment. It also wanted to know how much of the variation in the development of the neuromuscular system can be reduced through the use of morphologies.

V. CONCLUSION

The purpose of this study was to devise a new method for decomposing and classifying surface EMG signals using spectral coding approach in order to extract useful information. The proposed method is based on spectral domain signal denoising, which highlights the lowest distortion and allows the system to retrieve the smallest signal feasible. The resulting technology can greatly enhance signal retrieval accuracy. Spectral energy peaks as feature sets when applied to multiclass machine learning models performed better with accuracy and other parameters. Support Vector Machine enhanced performance and it can help with the accurate diagnosis. The subjects with TMD exhibited significant different muscle activity at than those with the control group. The theme of the study also highlighted the importance of having a comprehensive understanding of the complex disease. This is because the lack of a descriptive taxonomy can hinder the development of effective treatments. Our understanding of TMJ issues lags behind that of pain disorders. The various themes of the study also highlighted the importance of having a comprehensive understanding of the complex disease. This is because the lack of a descriptive taxonomy can hinder the development of effective treatments. The multiple approaches that are currently utilized in the research and development of TMD should be combined with a systematic strategy.

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