Neuromuscular Disease Detection Employing 1D-Local Binary Pattern of Electromyography Signals

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***Abstract*—In this contribution, a novel technique for the detection of neuromuscular disorders is proposed employing a 1D-local binary pattern of electromyography signals. 1D-LBP is a local feature descriptor that is capable of identifying localized and sudden fluctuations present in EMG signals due to irregular firing patterns of motor neurons which is rooted in the physiology of the neuromuscular diseases. In the present contribution, initially, the 1D-LBP technique was applied on healthy, myopathy and amyotrophic lateral sclerosis EMG signals to obtain their respective LBP codes. The histogram of occurrence of LBP codes of different types of EMG signals was subsequently used as features to classify EMG signals using support vector machines (SVM) classifier. To reduce the size of the feature dimension, the performance of the proposed method was further evaluated using uniform 1D-LBP. Two binary classification problems were performed and investigations revealed that both conventional and uniform 1D-LBP returned very high detection accuracies for both problems, which can be potentially implemented for real-time neuromuscular disease detection.**

Keywords—Classification, electromyography signals, local binary pattern and support vector machines.

I. INTRODUCTION

Electromyography (EMG) signals are aperiodic, complex and non-stationary time series, which measure the electrical activities produced by the muscle contractions inside the human body, which are controlled by the central nervous system. EMG signals contain significant information about the origin and firing patterns of different motor neurons associated with the muscle tissues. In clinics, EMG signals are used to diagnose several neuromuscular and neurodegenerative disorders like myopathy, neuropathy, ALS, etc. Myopathy is one kind of neuromuscular disease which is caused due to abnormal functioning of skeletal muscle fibres. Amyotrophic lateral sclerosis (ALS) is another fatal neurodegenerative disorder that causes rapid impairment of nerve tissues eventually leading to the death of the motor neurons [1]. In pathology labs detection of such diseases is usually done by expert neurologists based on visual inspection of EMG signals, which are time-consuming and prone to human error. Therefore, considering the abovementioned issue, various advanced signal processing methods have been proposed by the researchers in the past few years for fast and accurate computer-aided detection of neuromuscular disorders.

In the existing literature, various feature extraction techniques from EMG signals have been implemented for the detection of neuromuscular diseases. Time domain-based methods including cross-correlation technique [2] have been implemented for identifying neuromuscular disorders. Frequency domain-based analysis of EMG signals using fast Fourier transform (FFT) [3], Mel-frequency analysis of cepstral coefficients [4] etc. have been reported in the existing literature. Since EMG signals exhibit non-stationary properties, joint time-frequency domain based techniques including short-time Fourier transform (STFT) [5], continuous wavelet transform (CWT) [6], discrete wavelet transform (DWT) [7] Stockwell transform [8], modified Stockwell transform [9] empirical mode decomposition [10], etc. have been reported for classification of EMG signals. Non-linear features such as multiscale entropy, approximate entropy, Hurst exponent and largest Lyapunov exponent etc. extracted from EMG signals for detection of neuromuscular disorders have been reported in [11]. The application of chaos theory employing multifractal detrended fluctuation analysis (MDFA) has been reported in [12]. Recently, the application of visbility graph for detection of neuromuscular disorders has been reported in [13].

Although several methods have been implemented by the researchers for the detection of neuromuscular disorders, yet one limitation of the existing methods is that they generally analyze EMG signals on a global scale without adequately tracing the local variations present within a signal. Since EMG signals manifest localized discharge patterns of motor neurons within short durations, therefore a local variation of EMG signals contains more significant information about the characteristics of different neuromuscular diseases. Considering the aforesaid fact, in this study, a 1-dimensional local binary pattern (1D-LBP) technique is proposed for the detection and classification of healthy, myopathy and ALS EMG signals. LBP is mainly a type of visual descriptor, widely used in the domain of computer vision for image texture classification [14]. In this study, we implement 1D-LBP which is derived from 2D-LBP, for analysis of 1D signal. Applications of the 1D-LBP technique have also been reported in recent literature for speech recognition purposes [15], EEG signal analysis [16] etc. In this study, we investigate the feasibility of using 1D-LBP to investigate the localized patterns of motor neurons present in EMG signals. Apart from being an effective pattern recognition tool to retrieve underlying repetitive patterns in a non-linear time series, one major advantage of LBP technique is that it is very much sensitive to the local fluctuations present in a non-stationary time signal thereby making it particularly suitable for analyzing the local firing patterns of the motor units (MUs) present in the EMG signals. Hence, the 1D-LBP method was chosen in this work to extract meaningful features from the EMG signals.

To this end, healthy, myopathy and amyotrophic lateral sclerosis (ALS) EMG signals were acquired from an online existing database and the 1D-LBP technique was applied to the respective EMG signals to compute their corresponding LBP codes. From the LBP transformed EMG signals, the histogram of the number of occurrences of the different

LBP codes was computed and considered as a distinctive feature parameter in this study for the classification of different categories of EMG signals. Here, the classification of EMG signals was done using support vector machines (SVM) classifier. Two binary classifications were performed and it was observed that the proposed methodology yielded high very high classification accuracies in discriminating healthy from myopathy and ALS EMG signals. A flowchart of the proposed method is presented in Fig. 1.

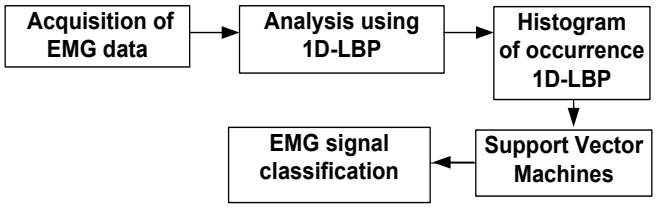

Fig. 1. Flowchart of the proposed technique

II. Data Acquisiition

In this work, EMG signals were acquired from the online available EMGLAB database [17]. The dataset consists of EMG recording corresponding to 10 healthy patients, 7 myopathy patients and 8 patients diagnosed with ALS disorder. The recording of the EMG signals was done by placing concentric needle electrodes on five different positions on the brachial biceps muscle and the medial vastus muscles, positioning them at three distinct insertion levels mentioned as high, medium and low. The EMG recording was done using an audio-visual feedback system, under the supervision of expert neurologists. The duration for recording for each EMG signal was measured as 11.184 seconds and the signals were digitized at a sampling frequency of 23.438 kHz, resulting in 262134 data points per signal. The EMG signals were subsequently fed to high and low-pass filters with cut-off frequencies set at 2 Hz and 10 kHz respectively. Fig. 2(a-c) shows the sample healthy, myopathy and ALS signals. After data acquisition, each signal was partitioned into 64 segments, with each fragment containing 4096 data points. Out of these 64 segments, the 25 middle steady regions (ranging from 31st to 55th segment) were used for signal analysis as reported in [18].

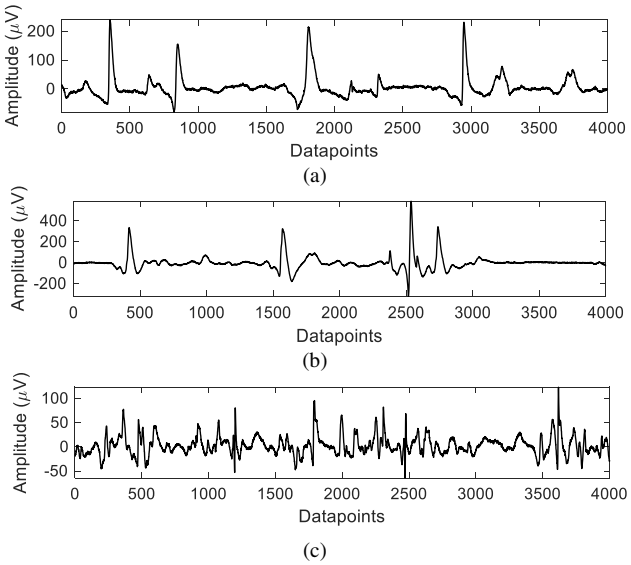

Fig. 2. EMG signals of (a) healthy (b) myopathy and (c) ALS category

III. Methodology

A. 1D-Local binary pattern (1D-LBP)

The concept of 1D-local binary pattern was derived from the basic concept of 2D-local binary pattern, which is popularly used for image and texture classification [13]. The basic idea of 1-D LBP is quite similar to the texture descriptor, which sequentially evaluates all the neighborhood pixels with respect to a center pixel to compute its equivalent LBP code. The operation of 1D-LBP technique requires selection of a window of length N, where N must be an odd number. For N number of data points lying within the selected window, a central element P_c is chosen in such way that it has $\left(\frac{N-1}{2}\right)$ number of neighborhood samples on either side of it. The LBP code for the center element P_c is computed by comparing the amplitude difference between P_c with each neighborhood element P_i in a sequential manner using (1)

$$LBP = \sum_{i=1}^{N} f(P_i - P_c).2^{i-1} \quad (1)$$

where, $f(P_i - P_c) = 1$, if $P_i \geq P_c$ else 0, if $P_i < P_c$. The process is repeated by sliding the window iteratively along the entire length of the signal to obtain the LBP code of the entire time series. The LBP codes can vary between 0-2^{N-1}, where N is the size of the selected window. Fig. 3 shows the computation of 1D-LBP code of a portion of the random time series with center element P_c and window length N=9. The LBP value of a particular signal can range from 0-255 (for N=9).

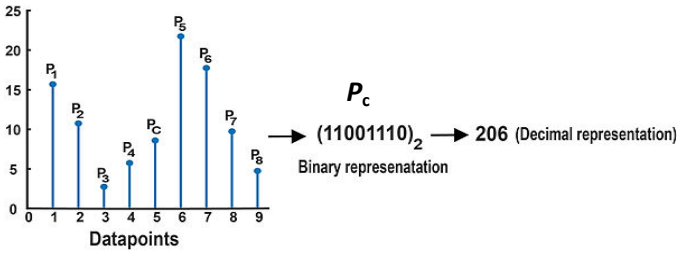

Fig. 3. LBP code generation of the centre element of a random time series

B. Concept of uniform 1D-LBP

Although 1D-LBP acts as a promising tool for time series analysis yet one limitation of conventional 1D- LBP is the size of the feature vector. After obtaining a binary pattern for a particular signal, the 1D-LBP histogram is computed which indicates the number of occurrence different binary patterns for a given signal. The obtained 1D-LBP histogram is generally used as features to the machine learning classifiers for the purpose of classification. Since the LBP codes vary from 0-2^{N-1}, it is evident that the maximum dimension of the histogram features can be 256 for N=9. For N=11, the maximum feature dimension is 1024 and for N=13, it can be 4096, which makes 1D-LBP computationally expensive. To address this problem, the concept of uniform patterns was developed.

The uniform 1D-LBP can be considered to be a subset of conventional 1D-LBP, containing at most two transitions bitwise (i.e. from 0-1 or from 1-0) in its binary representation. For e.g., if we consider two binary

representations 0000100 (2 transitions) and 10000101 (4 transitions), the former is a uniform pattern, but the latter is a non-uniform pattern. The use of only uniform patterns can reduce the feature dimension substantially. For e.g., using uniform patterns the size of the feature vector for N=9 can be reduced from 256 to 59. Thus, uniform LBP is computationally superior to conventional 1D-LBP.

C. *Support vector machines (SVM) classifier*

In this study, the SVM classifier was employed to discriminate between healthy and different categories of neuromuscular disease EMG signals. SVM is a popular machine learning algorithm primarily proposed to solve binary classification problems. A detailed description of the theory of SVM has been reported in [19]. Since this study, two binary classifications were done, so SVM was chosen for this work. SVM utilizes a fitting technique to map the training samples to an optimum separating hyperplane (OSH) satisfying Mercer's theorem. According to the operating principle of SVM, the theory of structural risk of minimization (SRM) is incorporated to maximize the class margin between different types of samples. The mapping of training samples onto the OSH is done with the help of different mapping functions known as kernel functions such as linear, polynomial, Gaussian, or radial basis functions (RBFs), etc. In this paper, the RBF kernel was found to yield the best classification performance for both the classification problems.

IV. RESULT AND DISCUSSION

A. *EMG signal analysis using 1D-LBP*

In this study, 7500 EMG signals (2500 per class) were considered for analysis. The 1D-LBP technique was implemented to analyze the healthy, myopathy and ALS signals for the detection and classification of neuromuscular disorders. For this purpose, the EMG signals were first transformed from the time domain to the LBP domain by computing their respective LBP codes using (1). In this study, the window size N=9 is chosen for the analysis of EMG signals. The size of the selected window is an important parameter in 1D-LBP. If the size of the selected window is too small, then the local variations will not be properly captured by 1D-LBP due to the presence of an insufficient number of neighborhood data points surrounding the center element. On the other hand, if the selected window is too large, then the size of the feature dimension will increase, which leads to an increase in the computational complexity of 1D-LBP. Moreover, increasing the size of the selected window may provide more information about the global variation rather than the local variation present in a signal. Thus, the selection of optimal window length is an open problem and a particular solution to this window size selection problem is non-existent. In the present case, N=9 was chosen since it was observed that the local fluctuations present in an EMG signal can be better captured using N=9. The variation of the 1D-LBP transformed healthy, myopathy and ALS signals for N=9 is shown in Fig.4 (a-c). In Fig.5 (a-c), the corresponding histograms of occurrences for three EMG signals are shown for conventional 1D-LBP. From Fig.4 (a-c) and Fig.5 (a-c), it is evident that the 1D-LBP transformed signals, as well as their respective histogram of occurrences of binary patterns, are different from one another. The highest number of occurrences is observed for myopathy signal followed by ALS and healthy signals, respectively.

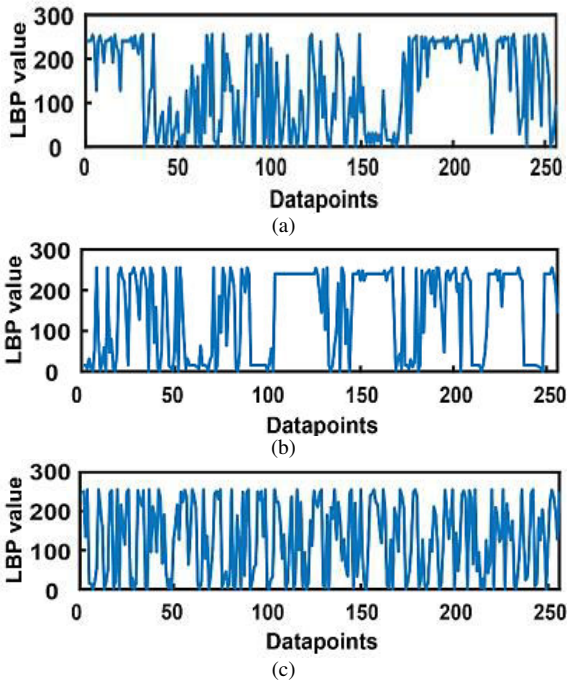

Fig. 4. LBP transformed EMG signals (a) healthy (b) myopathy (c) ALS

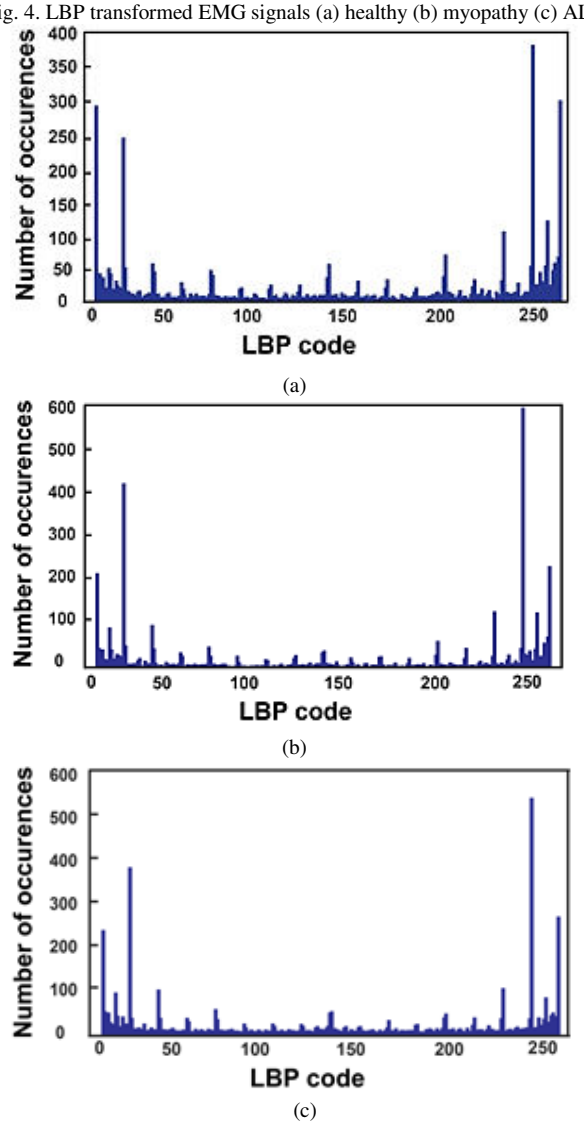

Fig. 5. Histogram of number of occurence of conventional 1D-LBP codes (a) healthy (b) myopathy (c) ALS

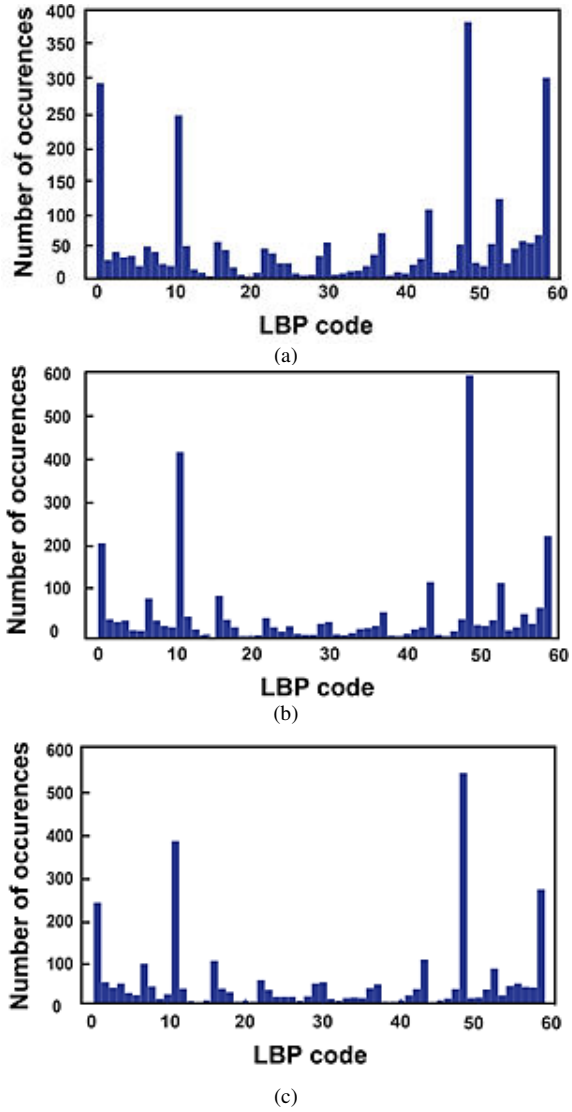

Fig. 6. Histogram of number of occurence of uniforml 1D-LBP codes (a) healthy (b) myopathy (c) ALS

In Fig. 6 (a-c), the variation of the histogram of occurrences of uniform 1D-LBP is shown for healthy, myopathy and ALS signals, respectively. Like conventional 1D-LBP, significant differences in the histogram of occurrences of uniform LBP codes are observed for three classes of EMG signals. Hence, the histograms of occurrences of both conventional and uniform 1D-LBP are used as features in this study to classify different EMG signals.

B. Performance assesment of the SVM classifier

In the present work, two binary classifications i.e. healthy vs. myopathy and healthy vs. ALS have been addressed to verify the practicability of the proposed method. The performance of the SVM classifier has been evaluated using three statistical performance parameters namely accuracy, sensitivity and specificity. Since, 2500 EMG signals corresponding to each class i.e. healthy, myopathy and ALS category were considered in this study, the dimension of the resultant feature input to the classifier was 2500×256 matrix for conventional 1D-LBP and 2500×59 matrix for uniform 1D-LBP. To overcome the issue of overfitting and at the same time to improve the reliability of the classifier's performance in this study, a 10-fold cross-validation method was also adopted. The performance analysis is reported in terms of percentage of the mean and standard deviation values of the above-mentioned performance parameters after iteratively performing the classification process for 10 times. The performance of the SVM classifier evaluated using conventional 1D-LBP as well as uniform 1D-LBP histogram features is reported in Table I and Table II, respectively.

From the performance analysis of the SVM classifier reported in Table. I and II, it is observed the proposed methodology has yielded a reasonably high degree of classification accuracies in discriminating healthy signals from the myopathy and ALS signals.

TABLE I. CLASSIFICATION PERFORMANCE OF SVM CLASSIFER USING CONVENTIONAL 1D-LBP FEATURES

Classification	Accuracy (%)	Sensitivity (%)	Specificity (%)
Healthy vs. myopathy	95.43±1.02	98.24±1.35	96.34±2.05
Healthy vs. ALS	96.45±0.75	100±0	95.74±1.58

TABLE II. CLASSIFICATION PERFORMANCE OF SVM CLASSIFER USING UNIFORM 1D- LBP FEATURES

Classification	Accuracy (%)	Sensitivity (%)	Specificity (%)
Healthy vs. myopathy	96.20±1.14	98.60±1.85	94.58±2.31
Healthy vs. ALS	97.25±1.25	100±0	96.45±1.40

The standard deviations (indicated in brackets) obtained for each parameter are also very small which further indicates the robustness of the proposed method. From Table I, it can be observed that compared to healthy vs. myopathy classification, better classification accuracy, sensitivity and specificity are obtained for healthy vs. ALS classification using conventional 1D-LBP features. A similar observation is also true for uniform1D-LBP features as shown in Table II. Between conventional and uniform 1D-LBP, better performance was observed using uniform 1D-LBP features for both classification problems. Nevertheless, the overall classification performance of both conventional and uniform 1D-LBP was found to be satisfactory for two binary classification tasks which validate the efficacy of the proposed method for neuromuscular disease detection.

C. Comparative performance analysis with existing methods

The performance of the proposed method was also compared with some existing literatures and the results are displayed in Table III. From the comparative study, it can be seen that the proposed methodology employing 1-D LBP technique to detect neuromuscular disorders has performed better than the existing literature. This may be explained by the fact that since the proposed method used local features, therefore the differences in the dynamics of motor neuron

TABLE III. COMPARATIVE ANALYSIS WITH EXISTING METHODS

Task	Reference	Accuracy (%)
H vs ALS	[3]	92.8
	[10]	95
	[21]	89.16
	This work	97.25±1.25
H vs M	[20]	91.67
	[21]	82.41
	This work	96.20±1.04

firing patterns for different classes have been better captured by 1D-LBP compared to other methods.

V. CONCLUSION

In this study, a novel technique employing the 1D-LBP technique is proposed to discriminate healthy from myopathy and ALS signals. The acquired EMG signals were analyzed using 1D-LBP to observe their respective local variations in time scale. The LBP codes for three classes of EMG signals were computed and the histogram of occurrence of each LBP code for three categories of EMG signals was selected as features. A significant difference in the histogram features was observed indicating that local patterns vary widely among three classes of EMG signals. These extracted histogram features were used as inputs to the SVM classifier for classification. To reduce the feature dimension, uniform 1D-LBP was also used to evaluate the performance of the SVM classifier. Investigations revealed that the proposed approach employing 1D-LBP based feature extraction delivered reasonably accurate results in classifying EMG signals. Further, it was also observed that the uniform 1D-LBP has performed better than conventional 1D-LBP. In comparison with the existing literature, the proposed method was found to deliver better performance. Hence, it can be concluded that the proposed method can be practically applied to develop a computer-aided neuromuscular disease detection system.

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