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ORIGINAL RESEARCH

Complexity measures, an analysis for electromyography and its possible application to spinal cord injuries

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Abstract

The objective of this paper is to propose a new method for classifying the Electromyography (EMG) signal in discriminating among neurogenic and myopathic for patients that have Spinal Cord Injuries (SCI). The method can have possible connections with physical processes and the main assumption in this approach is that the different forms of neurologic conditions have different information encoded in EMG, possibly quantifiable by EMG complexity measures. This approach is the main contribution in this paper and the results can open new possibilities to investigate the presumable connection of SCI with chaotic components in EMG signals as descriptors for neurologic type of diseases. In comparison with other methods (machine learning and deep learning), the main objective of this paper is to extract knowledge with less effort, that is, to use selection of features and neural network classifiers in a simpler manner with acceptable results. In a prospective study, the three types of EMG were used as time series in order to calculate the complexity of signals (normal, myopathic and Amyotrophic lateral sclerosis (ALS) as neuropathic type, because used database has no neuropathic EMG records as result of patients' SCI). The combinations of the most frequent measures of complexity (for biomedical signals) were used for the classification (Approximate Entropy, Sample Entropy, Reyni Entropy, Lempel Ziv Entropy and T-complexity). The classification reached 100% for both training case and discrimination of myopathy and 0.8663 accuracy for the three classes. These results suggest a possibility that the complexity can be a good indicator of type of disease using EMG with perspective study in EMG. The obtained results were in accordance with results from literature obtained by Machine Learning and Deep Learning. The prediction of SCI's evolution in time can be also investigated using coefficients of complexity, but the preliminary results showed that, due to large variability of the individual, the mathematical model is nonlinear and its analytical formula is difficult to be guessed in this stage of research. However, the classification using a simple multilayer perceptron (MLP) and Extreme Learning Machine (ELM) gives satisfactory results, comparable with the ones published in literature using Deep Learning but in a much simple manner.

Keywords

EMG; Machine learning algorithms; Time series complexity; Optimal threshold; Classification algorithm

1. Introduction

Spinal Cord Injury (SCI) impairs the ability to perform activities of daily living (ADL) including locomotion; even almost 45% of SCI patients have residual function in upper members.

According to the level of injury, the patients are classified as having paraplegia or tetraplegia [1] and the International Standards for Neurological Classification of Spinal Cord Injury (ISNCSCI) are used for determining the level and severity of the injury. The treatment and rehabilitation period for SCI patients is long, expensive and exhausting in all cases [2]. Extracted parameters from EMG were used to classify the assisted and independent standing of persons during rehabilitation procedures and further to a prediction algorithm that is ranking the effectiveness of muscle activation patterns generated for standing. The analysis of EMG and/without spinal cord epidural stimulation (scES) is complicated by involving an analysis of EMG signal including Short-Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT), Spectral power density, EMG linear envelope, and the Non-Negative Matrix Factorization (NNMF) algorithm for normalization in the dimensionality reduction process [3, 4].

The relationship between EMG and SCI is investigated in many papers, sometimes with different objectives. EMG was used after pre-processing, as input in a classifier with two classes: normal and neuropathy in [3] and spatial filtering using Principal Component Analysis (PCA) and possible investigation of statistics Z-score in neurogenic change proposed in [4]. An interesting work proposed a clustering method to classify two groups of changes, neurogenic and myopathic changes in [5]. The classification is based on values of Z-score of each subject that also calculate the complicated index based on EMG areas and a linear regression that separates the two clusters [5].

Spatial filtering [6] was used to improve the classification using group of muscles having "myopathy" or "neurogenic" changes versus normal cases in direct relationship with SCI. Patterns in EMG and sEMG are very useful in rehabilitation process and evaluation of progress in rehabilitation [7, 8]. Sophisticated predictor as artificial neural networks (ANN) can be used in prognostic using variables collected in one year (as included subjects' age at the time of injury, sex, American Spinal Injury Association Impairment Scale (ASIA) scores, *etc.*) in [9]. In [10] authors proposed an EMG score calculated for muscle contractions using a 6-point scale to assess the recovery after acute SCI in man for 12 muscles.

There are no significant papers that deal with complexity modification in EMG signals as result of SCI. However, there are efforts to analyze the EMG signals using complexity measures as fuzzy approximate entropy to detect stroke-changes effect in muscle activation [11]. In [12], the authors investigate the possible relationship between Root Mean Square (RMS) and fuzzy entropy (FuzzyEn) of EMG, also recording the possibility to use FuzzyEn that could potentially be used as indicator for spasticity. A proposal is made in [13] to use Sample Entropy (SampEn) as a biomarker in order to investigate the trend (almost horizontal) when the surface area of EMG epoch increases. Three groups are investigated by plotting logarithmic values of SampEn *vs.* area of EMG epoch: healthy subjects (control group), subacute stroke group and chronic stroke subjects [13].

An interesting application of classification of patients that have knee osteoarthritis (one of the most important lower limb disabilities) and people that are healthy is proposed in [14]. Features forming sEMG are extracted using entropy measures (SampEn, AppEn, and FuzzyEn) and multivariate analysis of variance (MANOVA) is used over 2×4 (group $\times$ muscle). The entropy-based features were clustered using Fuzzy C-Mean (FCM) algorithm and the best classification is made by FuzzyEn with 88% accuracy and 88.57% specificity.

Machine Learning (ML) algorithms can be seen as part of artificial intelligence (AI) and proved to be a successful solution for a large array of problems, including classification of biomedical signals. The signals are usually pre-processed, followed by a feature selection (as part of pattern recognition problems) used in various types of classifiers. The features selection are bases on empirical selection (as number and type) or mathematical approaches which calculate a selection of them that contribute most significant to results (PCA-principal component analysis, kernel PCA, ICA-independent component analysis, LSA-latent semantic analysis, isomap, autoencoder, PLS-partial least squares regression, *etc.*). The main advantage of this type of approach, is that, due to small number of variables used in classification, the algorithms are fast, easy to be implemented with small resources (easy to be applied to wearable devices, *e.g.*) and possibly more intuitive and related to physical processes. The main disadvantage is that the search of features cannot be exploited exhaustively in the case of signal processing (frequency analysis, spatiotemporal measures, and so on). The ability of researchers plays an important role in choosing the group of features considered the most useful to be used as inputs of classifier.

The surface electromyography (sEMG) is used in [15] to determine the neuromuscular disorders (normal, myopathy, and neuropathy). A two-stage binary classifier is used and the accuracy obtained is 86.9% [15]. In [16], the authors proposed a novel method to extract features from EMG records, Normalized Weight Vertical Visibility Algorithm (NWVVA). Three classifiers were used (k-nearest neighbor, multilaye r perceptron neural network, and support vector machine) with 98.36% accuracy [16]. Five statistic features for three classes were proposed in [17]: Autoregressive (AR), Root Mean Square (RMS), Zero Crossing (ZC), Waveform length (WL) and Mean Absolute Value (MAV), with maximum accuracy 86.3%. In [18], the authors consider the frequency domain of EMG as features using Discrete Wavelet Transform (DWT) and Multilayer Perceptron (MLP) as classifiers for diabetic and non-diabetic patients. An interesting review of ML methods is presented in [19]; however, it is not an exhaustive survey, there are algorithms not included. A complex method for feature extraction with hyperparameter optimization and Bayesian decision is proposed in [20]. The accuracy measure is given as Area Under the ROC (AUC) with a score of 81.7% (muscle-level) and 81.5% (patient-level) [20].

Deep Learning Approach [21, 22] (including LSTM-Long Short-Term Memory and CNN-Convolutional Neural Networks) gives new solutions to classification problems, having the advantage that the input vector (in the discrete 1D signals case) can be very high (vector with a size of the magnitude of thousands of elements) and the Deep Neural Networks (DNN) is able to classify these vectors using pretrained Neural Networks (NNs). The training of DNN requires many computing resources and also the practical implementation is difficult for low-cost hardware as body sensor area network (wearable application) used in biomedical applications. A summarization of few important papers in this direction is given in Table 1. High-density surface electromyography (HD-sEMG) was used as input for deep learning networks in order to classify 27 finger gestures in [23]. A connection between sEMG (surface EMG) and limb kinematics is made in [24] using a database for 65 isometric hand gestures. A deep learning approach for classification of stance/swing phases and prediction of the foot–floor-contact signal for treadmill walking is proposed in [25]. An approach EMG-based gesture recognition using ADANN (Adaptive Domain Adversarial Neural Network) for generation of features is proposed in [26]. A good start for the application of DNNs in biomedical signal processing is the review by [27].

The complexity measures of time series were successfully used for the analysis of Electroencephalogram (EEG) and Elec-

TABLE 1. Selected summary of state of the art in EMG classification.

Ref	Application	Algorithms/Techniques	Database availability	Results
[3]	2 classes: normal and neuropathy	FFT, Power spectrum	N/A	RMS (Root Mean Square) = 1.1893
[4]	3 classes: normal, myopathy and neuropathy	PCA, clustering index (CI)	N/A	HD-sEMG, classes based CI between 0 and 1
[5]	2 classes: neurogenic and myopathic	clustering index, Z-score, linear regression	N/A	95% Specificity, 92% and 61% sensitivity
[9]	patient's level of injury, 5 levels	Artificial Neural Networks	National Spinal Cord Injury Model Systems Database	85% accuracy
[11]	complexity of the generated EMG signals decreases due to muscle damage after stroke	fuzzy approximate entropy (fApEn), ANOVA, Bonferroni post hoc test	N/A	N/A validation
[12]	level of spasticity	root mean square (RMS) and fuzzy entropy (FuzzyEn)	N/A	2-D map results, no validation
[13]	three classes: healthy subjects (control group), subacute stroke group and chronic stroke subjects	logarithmic values of SampEn *vs.* area of EMG epoch;	N/A	Regression lines for separations of classes, R^2= 0.782
[14]	two classes	approximate entropy, sample entropy, and fuzzy entropy; Fuzzy C-Mean	N/A	92% of accuracy, 91.43% sensitivity and 93.33% of specificity
[15]	normal, myopathy, and neuropathy classes	42 features, random forest classifier	N/A	86.9% accuracy
[16]	healthy, myopathy, and amyotrophic lateral sclerosis (ALS) classes	normalized weight vertical visibility algorithm for feature extraction, k-nearest neighbor, multilayer perceptron neural network, and support vector machine classifiers	Physionet and EMGLAB	98.36% accuracy
[17]	normal, myopathy, and neuropathy classes	five statistic features, multilayer perceptron	EMG lab database	highest accuracy 86.3%
[18]	two classes: diabetic and non-diabetic	discrete wavelet transforms (DWT), multilayer perceptron (ML)	N/A	95.45% accuracy
[20]	two classes: normal and ALS/IBM (Amyotrophic Lateral Sclerosis/Inclusion Body Myositis	Bayesian technique	N/A	Area Under the ROC (AUC) score 81.7% (muscle-level) and 81.5% (patient-level)
[23]	27 finger gestures, 2D dataset	3D CNN Architecture	CapgMyo and CSL-HDEMG	highest accuracy 98.9%
[24]	65 isometric hand gestures	N/A	Open access	N/A
[25]	classify gait events (proper stance and swing phases) and foot-floor-contact	Multilayer NN with deep learning approach	N/A	highest accuracy 95.28 ± 0.5
[26]	eleven hand/wrist gestures	Adaptive Domain Adversarial Neural Network (ADANN): CNN, ConvNet, Grad-CAM	N/A	highest accuracy 81.38%

The notations in Table 1 are: FFT (Tast Fourier transform); N/A (not available); PCA (Principal Component Analysis); HD-sEMG (High-density surface electromyography); EMG (Electromyography); ANOVA (Analysis of variance); EMGLAB (`http://emglab.net/`); CNN (convolutional neural network); CSL-HDEMG (a database, `https://www.uni-bremen.de/en/csl/research/motion-recognition`); NN (Neural Network); Grad-CAM (Gradient-weighted Class Activation Mapping).

trocardiogram (ECG) signals. In [28], Lempel-Ziv complexity measure (LZ) was used for dichotomous classifier in focal and non-focal EEG sign. The same algorithm was used to detect arrhythmias in [29].

The major complexity measures and major entropy measures that are often used as measure complexity are identified in [30]. A non-exhaustive selection of complexity measures (used in this paper) is [31–37]: Lempel-Ziv (LZW) [31, 32], approximate entropy (AppEn) [33] Sample Entropy (SampEn) [34] and Rényi Entropy (RenyEn) [35].

The main motivation for this approach is the construction of simpler classifiers, with feature extraction related to complexity of signals. The complexity of signal can be related to EMG disorders due to SCI, and the supposition is that the different level of complexity can reveal somewhat the information coded in signal, in a different manner for normal and a different manner for abnormal, disorder that can be fused for classification of normal/type of abnormality.

The challenges for this approach are mainly the consuming time for complexity analysis and the availability of many records for database with many EMG disorders. Different muscular groups can have different EMG complexities, so a general approach for all the muscle affected by SCI is difficult to be constructed.

Our contribution refers to: (a) usage of different complexity approaches to discriminate the muscular disorders, and (b) combination of different complexity approaches in order to increase the accuracy of classification of disorder types.

The objective is to provide an alternative to other approached and a possible correlation of different types on neural disorder with complexity in EMG signal.

The results can have implications in the design of a monitoring device using a small microcontroller as wearable device.

2. Methods

The main work proposed in this paper is based on the observation from plotted graph of papers [3] and [4]. The linear regression analysis in both papers suggests that a linear discriminator is not a satisfactory classification of EMG signal for healthy subjects, for EMG collected from subjects with stroke or Spinal Cord Injury (SCI). The main idea is that the corresponding EMG signal from persons that have neurological disorder can be somewhat quantified in a coded information to the corresponding type of disorder, that has different causes—different effects in EMG coding information.

The basis for time series complexity calculus is the binarization schema, that is the real values of time series are transformed in a sequence of symbols, the most common being "0" and "1" [32]. The most used method for binarization of $X = \{X_0, X_1, \cdots, X_{n-1}\}$time series in a binary time series $S = \{S_0,\ S_1, \cdots, S_{n-1}\}$is based on threshold (one, two or more levels) [28], based on a threshold (that can be the mean value between the maximum and minimum of X):

$$s_j = \begin{cases} 1 & x_j \geq th \\ 0 & x_j < th \end{cases} \tag{1}$$

In our case, $th = \min(X) + (\max(X) - \min(X))\ /2$. The three types of EMG signals (normal, myopathy and neurogenic) are collected from literature, signals pre-processed with artifacts removed. All the sequences are analyzed from left to right. In our case, the number of symbols α = 2 (two binary values, "0" and "1").

There are few approaches that can be used for a good choice of *th* extracted from all the sequences (related to statistics): median value, average value or empirical value extracted from standard deviation. Our choice of the average values is consistent with approaches from literature. In some cases, a single threshold cannot be enough for application, thus, more thresholds can be used (3 of 4 thresholds, according to [21]).

2.1 Lempel-Ziv Complexity

P sequence of symbols of incremental length (starting with length 1) is examined from left to right in the string *S*. Each new pattern as subsequence of consecutive strings from *S* is counted by a counter *c(n)*.

Let's denote by $S = s_1, s_2 \cdots, s_n$ a finite length of symbols, and $S(i,j) = s_i,\ s_{i+1}, \cdots,\ s_j\ \epsilon\ S$, $i < j$ is one substring that starts at *i* point and end at position *j*. The null set is denoted by $S(i,\ j) = \{\}$. Let *Q* and *R* be substrings of type *QR* the concatenation of them and let's denote by *QRD* a sequence obtained after the last character of *QR* is deleted (*D* is the common notation for deleted). In a scan procedure, the string S is parsed from left to right in order to obtain distinct strings. Let's denote by *B(S)* the set of basic words. A substring *S(i,j)* is compared with the strings from *B(S)*, substrings up to *j-1*, that is *S(i,j-1)*. If *S(i,j)* is present, no new component is present, *B(S(i,j-1))* is updated to *B(S(i,j))*, and *S(i,j)* is updated to *S(i,j+1)*, and the process is repeated until the end of string. If *S(i,j)* is not present, a new component is found and a dot is placed after *S(j)*. The dots mark all the new distinct strings found in the parsing process. The process repeats until *j* = *n* (*n* is the length of string *S)*. The start process begins with *S (1,1)*, the first symbol in the string *S*.

The algorithm is constructed from two operations: comparison and accumulation. The number of symbols is denoted by α, and the superior limit of *n* is given by:

$$\lim_{n\to\infty} c(n) = b(n) = n/log_{\alpha}n \tag{2}$$

The counter of complexity *n* normalized is usually defined as:

$$C(n) = \frac{c(n)}{b(n)} \tag{3}$$

where *n* is the apparition rate for new patterns. In order to compare different time series, the length of them must be the same. The main idea is that the uncertainty is decreased, the information is increased and the dynamics of complexity is more predictable. The measure of complexity can be used to classify different levels of dynamics and a classifier based on these measures is investigated in this paper.

For example, the string 0111010100010 is parsed as 0 1 11 010 100 010 and the complexity measure is calculated for *c(n)* = 5 and *n* = 13, so *C(n)*= 1.7079.

2.2 Approximate Entropy

Approximate Entropy (ApEn) is a measure or regularity in time series data, a measure of randomness of data [33, 38]. Let's denote a series of patterns of length *p* (smallest integer for patterns that are not intersected in pairs), derived from *X(n)*.

$$ApEn\,(p,\ r,\ n) = \frac{1}{n-p+1}\sum_{i-1}^{n-p+1}\log C_i^P\ (r) - \frac{1}{n-p}\sum_{i-1}^{N-p}\log C_i^{P+1}\ (r) \tag{4}$$

where r is a parameter (tolerance of comparison and $C_i^p\ (r)$ is the correlation integral (*e.g.*, r = 0.2, p = 2). By statistical point of view, the ApEn is a method used to quantify the amount of regularity and the unpredictability of fluctuations for a given time-series data. This can be seen as to form the theory of information as a coded binary information if the data is converted in binary string and the complexity of information can be interpreted as pattern for unpredictability or randomness.

2.3 Sample Entropy

Sample Entropy (SampEn) is a measure of complexity, different from Approximate Entropy (ApEn). The main advantage of this measure is that self-similar patterns are not counted. Let's take a template vector of length m as *Xk,* $m\ =\ xk + 1,\ xk + \cdots,\ xk + m2,$ a sub-vector *X*, and *r as* a tolerance value. Sample entropy is the probability that having a distance between a set of two sub-strings lower than *r*, to also have a subset of sub-strings length *m+1* that have a distance between them lower than *r*. The matching is usually based on a Euclidean metric distance.

The calculation of SampEn, for two numbers, A (vector pairs of length *m*+1) and B (vector pairs of length *m*) is done by:

$$SampEn = -\log\left(A/B\right) \tag{5}$$

$$dc\left(X_{i,\ m},\ X_{j,\ m}\right) = \max_{k=1,\ldots,\ m}\left(x_{i+k},\ x_{j+k}\right) \tag{6}$$

$$dc\left(X_{i,\ m},\ X_{j,\ m}\right)\ < r \tag{7}$$

The main parameters are the length of window and *r* (a choice can be *r* = 2 × *std* = 6; *std*—standard deviation and length of window *m* = 2).

2.4 Rényi Entropy

Rényi Entropy generalizes the shannon entropy, and can be used as measure of complexity. Let's denote by p_i the probability for a random variable to take a given value out of *n* values, and by α, the order of entropy measure. As α increases, the measure is more sensitive to occurrence of values with higher probability, meanwhile the values occurring less are small representatives. The Rény entropy is given by:

$$H\left(\alpha\right) = \frac{1}{1-\alpha}log_2\left(\sum_{i=1}^{n}p_i^{\alpha}\right) \tag{8}$$

The entropy requires the estimation of probability and one of the most used methods is the calculus of histogram. A good choice in our case is $\alpha \in$ [2 10], interval chosen by empirical trials. In the case of α = 2 is about the collision entropy and it is a common choice for Rény entropy in applications as start point of analysis of time series.

2.5 T-code

The computation of T-complexity is approached by using T-codes, a novel method of self-synchronizing codes, which has been proposed by Tichener [39] and presented in detail in [40]. One alphabet with a set of symbols is used to construct the first level of augmentation (an essential term used in T-code). This set of symbols is memorized in this first level. The next levels of augmentation are deployed iteratively by removing a chosen T-prefix and annexing it to the list of code words [40]. T-decomposition is an inverse operation and it assays the sequence of T-prefixes having as result the total distinct prefixes with which the complexity is computed.

The T-code applies to substrings by means of a window *W* of finite length. Let *A* be an alphabet set with finite length, *uw*—the merging of two strings *u* and *w*, and *uk*—the merging of *k* copies of string *u*. The recursive formula [40]:

$$S_j = \bigcup_{i=1}^{k_j}\left\{P_j^i s \mid s\ \in S_{j-1} \setminus\ \{P_j\}\right\} \bigcup \left\{P_j^{k_j+1}\right\} \tag{9}$$

can build the series of T-code, where S_0 = *A*, P_j is a prefix, P_j is a string, k_j is a natural number and *s* is also a string. In tree theory it is usually noted by $S_{(p_1,\ \ p_2\ ,\ldots,p_n\ )}^{(k_1,\ \ k_2,\ \ \ldots,k_n\ )}$. If we have a binary alphabet, $A = \{0,\ 1\}$, for instance, a T-augmentation presented as tree is shown in Fig. 1. By means of the algorithm named T-decomposition, for a certain string, the sequence is parsed as follows:

$$s = P_n^{k_n}P_{n-1}^{k_{n-1}}\ldots P_1^{k_1}A \tag{10}$$

$$tc = \sum_{j-1}^{n}log_2(k_j+1) \tag{11}$$

The T-complexity of the string s is calculated by Eqn. 11 and used as feature in classification in the next section.

2.6 Classification using Neural Network

Classification and clustering are two methods in machine learning algorithms used in pattern identification that have some similarities. Sometimes, the clustering methods are the first step in classification in order to obtain a linear separation

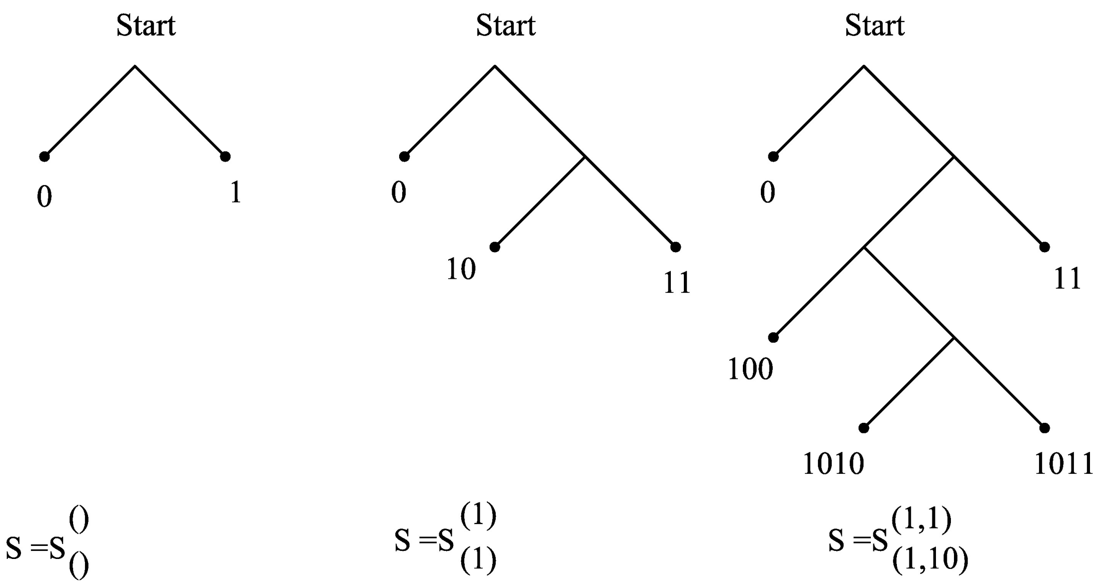

FIGURE 1. Intermediary T-code, computed for $S_{(1,\ 10)}^{(1,\ 1)} = \{0,\ \ 11,\ 1100,\ \ 1011\}$.

of the classes or a simpler mathematical form of classifier. In our case, it is about supervised classification, that is, the classes are known, so the numbers of clusters are predefined, so a known classifier is considered (excellent performances mathematically demonstrated by universal approximation theorem), neural networks (NN) [41], Multilayer Perceptron (MLP).

There are various architectures and types of NNs proposed in literature but doing a tradeoff between complexity (the simplicity of NN is preferred) and performance, a simple multilayer feedforward NN is chosen (Fig. 1).

Let's denote by $X = \{x_1, x_2, \cdots, x_n\}$ the input vector of features, $Y = \{y_1, y_2, \cdots, y_n\}$ the output vector, $T = \{t_1, t_2, \cdots, t_n\}$ the targets, the relationship input-output can be written in matrix form (for k layer):

$$y_j^k = \varphi\left(\sum_{i=1}^{n_j} w_{ji}^k \bullet x_i^{k-1} + \theta_j\right) \tag{12}$$

$$\varphi\left(x\right) = \frac{1}{1 + e^{-x+\theta}} \tag{13}$$

where ${w_{ij}}^k$ are the weight of connection between neurons i from layer k-1 and j from layer k, ${x_i}^k$ the output of neuron i in the layer k, θ_j the threshold of sigmoidal function of activation (Eqn. 10) of neuron j from layer k and ${y_j}^k$ the output of neuron j in the layer k (Fig. 2).

The usual choice of a NN feedforward classifier is represented two hidden layers with sigmoidal function and one output layer with linear function of activation in order to prevent saturation at output.

The experiments used also ELM-AE as this is presented in [42]. The hidden layer in ELM-AE network has nodes with parameters randomly generated and after that, they are made orthogonal.

The main performance metric for multiclass classifier in machine learning algorithms (computed from confusion matrix) are: Accuracy (Acc), Precision (Pr) and Recall (Re). Let's denote by True Positive (TP) the elements labeled as positive by the model and they are actually positive, False Positive (FP) the elements that have been labeled as positive by the model, but they are actually negative, True Negatives (TN) are the elements correctly classified by the model, and False Positive (FP) the elements that have been labeled as positive by the model, but they are actually negative. In order to be coherent with results from the other papers presented in state of the art, only Acc was used [43].

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{14}$$

In our case, the main interest is the correct classification, that is how performing is our classifier (the Acc measure).

2.7 Classification using clustering

The Self-Organizing Tree Algorithm (SOTA), introduced by [44] combines self-organization features maps (SOM) with hierarchical clustering in order to produce a tree (that can be a growing neural network) where the final nodes are clusters [45, 46]. The binary tree topology in SOTA algorithm selects in the first step a node that has the largest heterogeneity and splits it into two nodes (the daughter cells). The tree continues to grow until all the observations are mapped to leaf nodes [46]. An implementation in R language is provided by [47], the clValid package. An interesting new application is bioinformatics is proposed in [48] demonstrating the very good performance of SOTAs algorithm in this particular case.

In [49] the authors proposed a novel algorithm adaptive double SOM (ADSOM) that eliminated biases from the set of parameters allowing a more efficient clustering. ADSOM combines SOM and position vector (bidimensional) with parameter training. A recent approach that uses the SOM algorithms

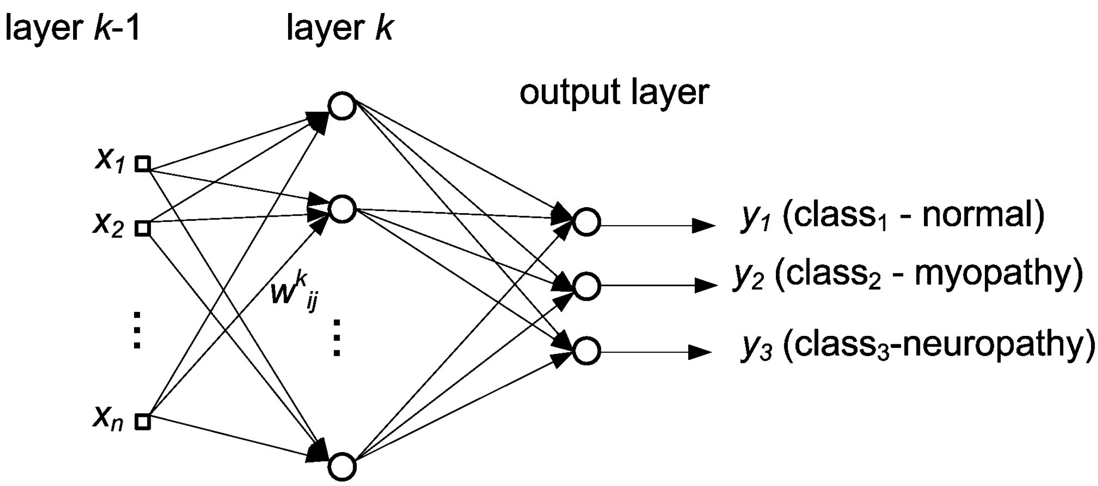

FIGURE 2. Typical architecture for MLP.

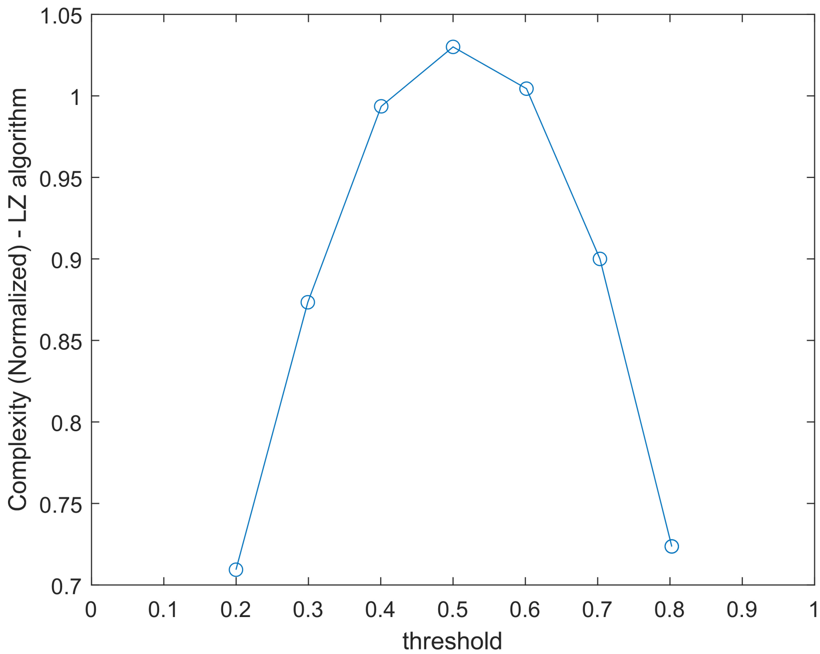

FIGURE 3. Normalized complexity *vs.* threshold level used in binarization.

and other packages for unsupervised clustering algorithms in a bioinformatic analysis is proposed in [48].

3. Results and Discussions

Even the threshold can modify the results substantially if only one complexity measure is used. In Fig. 3, the LZ algorithm is applied to a random (uniform distribution) time series of $2^{13} = 8192$ sample, a typical length number of samples for signals processing in biomedical engineering. It can be seen form Fig. 3, that a simple modification of threshold from 0.5 to 0.6 modifies the complexity value by 0.0381, in some methods being enough to overlap the classes (Fig. 3).

In this paper we used a measure of threshold (single threshold), binary alphabet of "0" and "1", based on simple statistics as 0.5.

EMG was pre-processed to remove artifacts [50–54]. A larger database is N2001 (`http://www.emglab.net/emglab/Signals/N2001/index.html`) with three types of signals: normal, myopathic and ALS (that can be considered as neuropathic).

From this data base, a selection is made taking into account only the records from Biceps Brahii muscle (BB) in order to reduce the variability due to muscle type. The data set was split in two (random normal distribution): 70% of records for train and 30% for tests (around 10 seconds each record). There are 150 records from 10 patients for normal case, 3 patients with myopathy, 53 records and 6 patients with ALS, 98 records, filtered and 60 Hz frequency removed by a Notch filter.

The approximate entropy, sample entropy and Rényi Entropy are subjects of intense and exhaustive analysis [55–59] and the short presentation of them in methodology is motivated by non-repeating approaches. The input layer in NNs has numerical values for all five complexity measures, and the output target is three classes: ALS, Myopathy and Normal.

From Figs. 4,5 it can be see that the myopathy is clearly

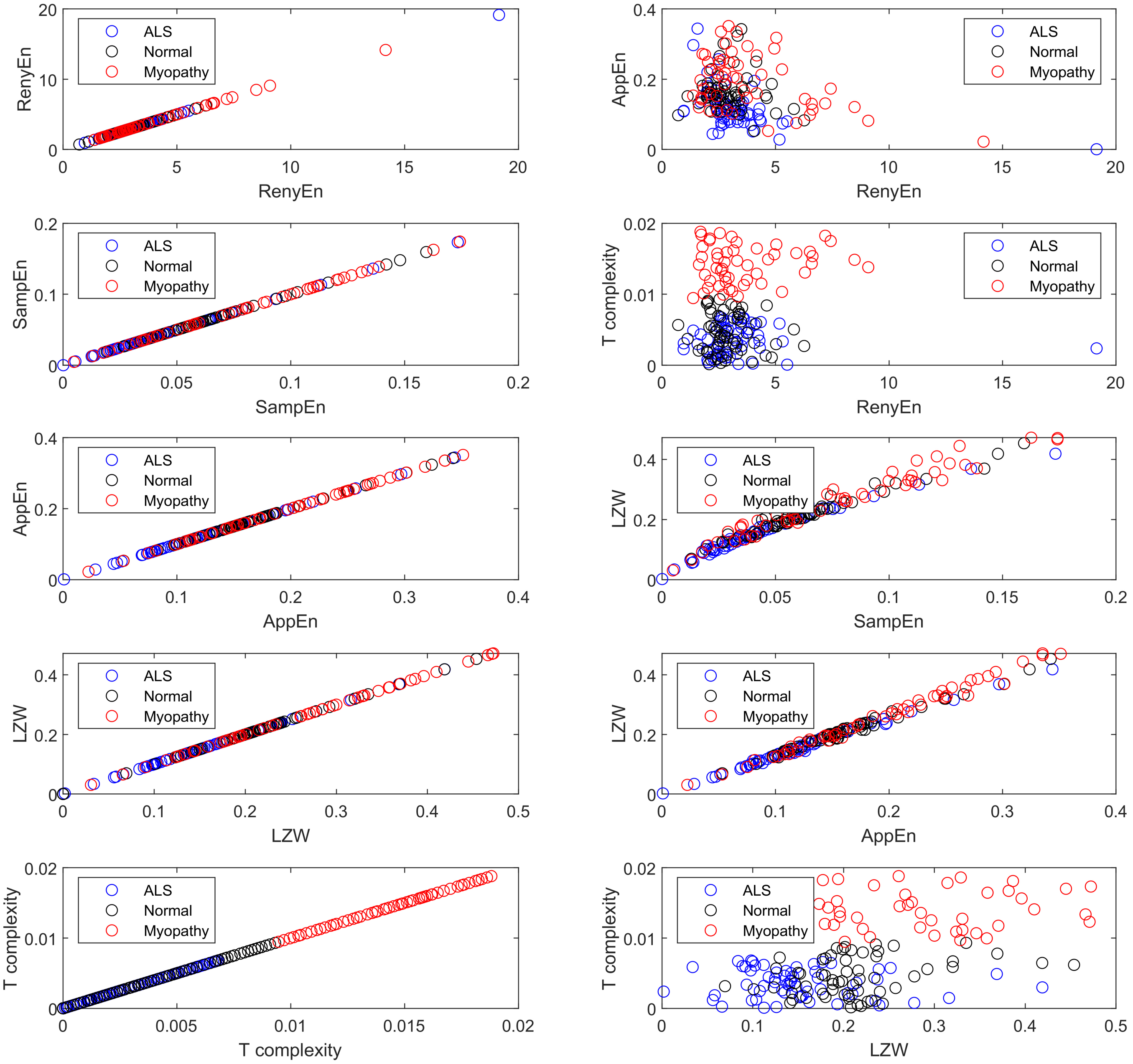

FIGURE 4. Combination of complexity measure in a 2D Map.

piecewise linear separable from the rest of the classes with 100% accuracy in both training and test cases. The problem arises from ALS and Normal separation, which in the actual stage is difficult to explain, but probably more specific records are necessary related to neuropathy and related to SCI not ALS.

The accuracy of classification for all classes, that is the correct classification, is 86.6% in training stage and 82.95% in test stage, that are acceptable results for automatic classification, in accordance with the results from literature.

It would be interesting to evaluate the rough sensitivity for each type of complexity, that is, the influence of each type of complexity to good classification (Table 2). It is clear from this table that each type of complexity contributes to a good result; the most interesting is T-Complexity that can dramatically decrease the quality of classifier.

The experiments take into account SOTA algorithm [47].

TABLE 2. Accuracy (Acc) for selection of 4 from 5 complexity measures.

Variable out	Acc
RenyiEn	0.8314
SampEn	0.7965
AppEn	0.8256
AppEn	0.8256
T-complexity	0.6337

Using N2001 database, a set of data was constructed: 60 records—normal, 60 records-myopathy, and 52 records—ALS. The SOTA clustering algorithm is an unsupervised type and 5 clusters were found using Euclidean distance [47], as in Fig. 6.

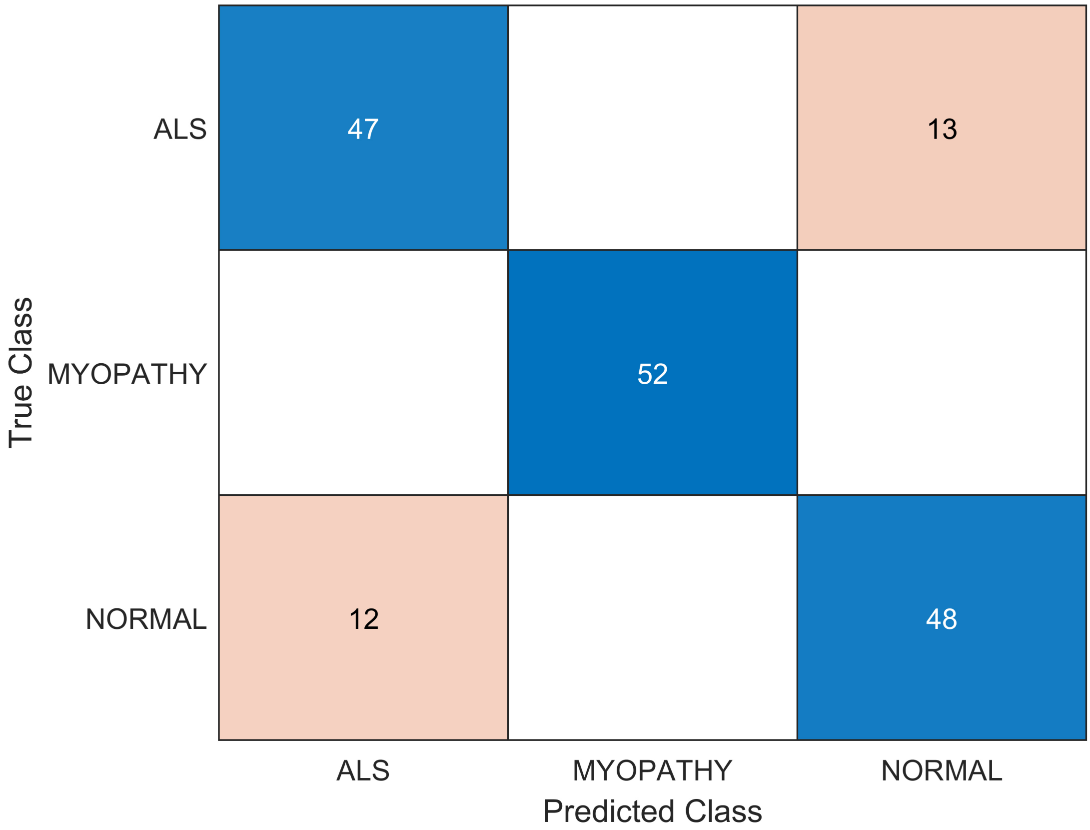

FIGURE 5. Three-class confusion matrix.

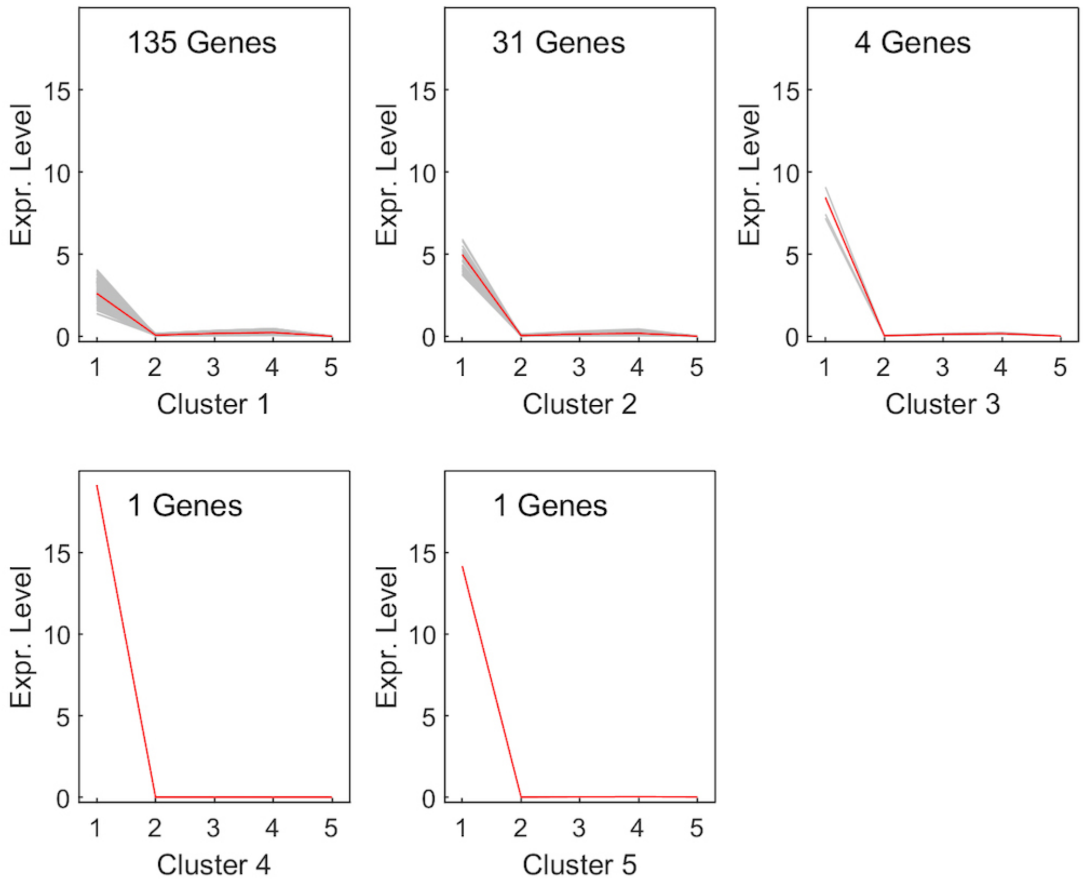

FIGURE 6. Clusters using SOTA algorithm.

It can be seen that cluster 1 has 135 records and cluster 2 has 31 records; taking into account that the maximum correct classified records, there can be 60 (as the dataset was constructed) results that the misclassification is at least 75 + 21 = 96 records, the accuracy is below (172–96)/172%, that is 44.19%, making this solution unfeasible. This means that the SOTAs algorithm is not a feasible solution, but for this selection of features of EMG signal (complexity), this solution is unfeasible.

The results are in accordance with recent approaches related to the connection between SCI and EMG [53]. This study has no taken into account the influence of age in EMG. It is known that the muscle response decreases with age but the studies related to this problem are very poor in quantitative aspects [54]. The study can be useful in developing new research in muscle activity prediction for COVID-19 and post COVID-19 patients [53], even the quantification (quantitative approach) related to COVID-19 effects over muscle model is a subject of debate.

There are some limitations of the proposed method. ApEn and SampEn are very sensitive to their input parameters [55, 56]. Optimal values are actually found by empirical methods but there is no mathematical formulation yet for this problem applied to the approach in this paper. The proposed method cannot detect the progression of neuropathy, so the records at different moments of evolution of disease can produce values of complexity that have not studied yet [57]. The previous results that use T-Complexity [58, 59] can be a solution of the problem. An inherent limitation is due to number of different patients in database used in this approach. A much larger database (in number of patients) are not available yet and the further research will be extended inasmuch such a database is available.

In the next steps of this research, other measures of complexity will be the subject of Python package, *e.g.*, Wavelet Packet Entropy [60] and also the diffusion entropy [57].

4. Conclusions

A novel method for classification of EMG is proposed in this paper. Also, a new approach was proposed to classify the EMG records that apply to SCI, the complexity measure. The application of LZW and a 2D map for fusion of different complexity values for the same signal is a new solution for EMG signals in classification problems. The method is useful for both short data sets and long datasets but some preliminary results showed that accuracy increase for short sequences of datasets and multiple thresholds (the tree thresholds produce a notable increase of accuracy, but the choice of them vas set empirically). LZW requires a more computational effort and a high time of computation in comparison with other complexity algorithms but the better results compensate this effort.

The method uses pairs of values of complexity for binarized EMG with very good result when three classes are used: normal, myopathy and neuropathy. The results are comparable with the results reported in literature, but there can be other type of complexity that have not exploited yet for EMG signals.

In the future implementation, a package for Python will be developed and its content will contain implementation for other two complexity measures: Tsallis entropy and Shannon entropy.

In the future research, a more extended EMG database will be used and more classes will be included to develop the assertion from this paper. Also, Graphic User Interface (GUI) will be developed in MATLAB in order to help the user manipulate the data and select the pairs of algorithms used for complexity calculus. Other algorithms that calculate the complexity will be taken into account and a heuristic method of efficient time series binarization is under development.

The main benefit of this approach can be considered to be a simpler approach of classification of different neural disorders and the possible discussion the content of information in EMG in each case. It is worth mentioning that the accuracy of detection between health and non-health (myopathy and ALS) is 100% in both train and test case. The accuracy decreases only in the case of classification in myopathy and ALS so a tool based on this approach to detect the existence of neural disorder can be the second benefit of this approach.

AUTHOR CONTRIBUTIONS

DA, MR, MI, MT, and AG—designed the research study; DA, MR, MT, and AG—performed the research; MI—analyzed the data; CI and IC—wrote the manuscript, all authors read and approved the final manuscript.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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