Analysis of Neuromuscular Disorders Using Statistical and Entropy Metrics on Surface EMG

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Abstract: - This paper introduces the surface electromyogram (EMG) classification system based on statistical and entropy metrics. The system is intended for diagnostic use and enables classification of examined subject as normal, myopathic or neuropathic, regarding to the acquired EMG signals. 39 subjects in total participated in the experiment, 19 normal, 11 myopathic and 9 neuropathic. Surface EMG was recorded using 4-channel surface electrodes on the biceps brachii muscle at isometric voluntary contractions. The recording time was only 5 seconds long to avoid muscle fatigue, and contractions at five force levels were performed, i.e. 10, 30, 50, 70 and 100 % of maximal voluntary contraction. The feature extraction routine deployed the wavelet transform and calculation of the Shannon entropy across all the scales in order to obtain a feature set for each subject. Subjects were classified regarding the extracted features using three machine learning techniques, i.e. decision trees, support vector machines and ensembles of support vector machines. Four 2-class classifications and a 3-class classification were performed. The scored classification rates were the following: 64±11% for normal/abnormal, 74±7% for normal/myopathic, 79±8% for normal/neuropathic, 49±20% for myopathic/neuropathic, and 63±8% for normal/myopathic/neuropathic.

Key-Words: - surface electromyography, neuromuscular disorders, neuropathy, myopathy, isometric voluntary contraction, entropy, wavelet transform

1 Introduction

Electromyography (EMG) plays an important role in clinical neurological diagnosis and can confirm or exclude clinical diagnoses, indicate the site and type of an abnormality or expose disorders that are clinically uncertain [1]. In clinical practice, needle EMG evaluation, in combination with nerve conduction studies, is the standard method for assessing neurophysiologic characteristics of neuromuscular diseases [2]. Surface EMG (sEMG) is not used extensively, because analysis of sEMG made by various research groups aiming to discriminate normal from abnormal subjects have produced poor results and have hence been generally neglected or approached with suspicion [3].

The motivation for our study came from paper [7], where entropy of sEMG was used to distinguish subjects with low-back pain from those without pain. Recorded sEMG signals were first low-pass filtered using moving average by non-overlapping windows having width of 10 samples. The mean was subtracted from signals and the Shannon entropy was calculated on 1000 partitions and used as a measure of the signal complexity. The analysis of entropy values from subjects with and without low-back pain showed significant difference.

After the features of the sEMG signals are obtained, they can be classified. Various classification systems for differentiation of neuromuscular disorders were introduced, applying mainly neural networks [4] and support vector machines (SVM) [8]. The most common classifications are two-class (normal/abnormal), where myopathic and neuropathic patients are joined in one abnormal group, and three-class (normal/myopathic/ neuropathic) [4], [8].

In this paper, we present our approach based on wavelet transform of sEMG and the entropy. A subject classification was performed using decision trees, SVM and SVM ensembles. The method performance was evaluated on real sEMG signals obtained from 19 normal subjects and 20 patients, 11 of them myopathic and 9 neuropathic.

The work is organized as follows. In Section 2, main characteristics of the neuromuscular diseases are introduced and previous work in the field is overviewed. Section 3 describes methods used in our experiment, namely the data acquisition, feature extraction and classification techniques. In Section 4, the experimental results are shown, while the last section discusses and concludes the paper.

2 Overview of the field

2.1 Main characteristics of the neuromuscular diseases

Myopathies are neuromuscular disorders in which the primary symptom is muscle weakness due to dysfunction of muscle fibres [12]. Other symptoms of myopathies can include muscle cramps, stiffness, and spasm. Different types of myopathies exist, i.e. congenital myopathies, muscular dystrophies, mitochondrial myopathies, glycogen storage diseases of muscle, myoglobinurias, dermatomyositis, myositis ossificans, familial periodic paralysis, polymyositis, including body myositis and related myopathies, neuromyotonia, etc [12].

Neuropathies describe damage to the peripheral nervous system which transmits information from the brain and spinal cord to every other part of the body. More than 100 types of neuropathies have been identified [12]. The impaired function and symptoms depend on the type of nerves (motor, sensory, or autonomic) that are damaged. Some people may experience temporary numbness, tingling, and pricking sensations, sensitivity to touch, or muscle weakness. Others may suffer more extreme symptoms, including burning pain (especially at night), muscle wasting, paralysis, or organ or gland dysfunction.

2.2 Previous work

In the diagnosis of neuromuscular disorders the needle EMG techniques are dominant, but attempts to use sEMG for the diagnostic purposes are appearing as well [4], [8], [10]. Because of the vast differences between sEMG and conventional electrodiagnostic techniques, the American Association of Electrodiagnostic Medicine published a review of clinical utility of sEMG [3]. They compared conventional techniques that are used in needle EMG examination and tried to find their sEMG equivalents. Procedures that can be conducted using both EMG techniques include: single MUAP analysis (amplitude, duration and configuration) and studies of muscle fibre conduction velocity. The procedures that cannot be done using sEMG include: measuring an insertional activity of the needle, fibrillation potentials and precise localization of the lesion.

Regardless to the type of EMG used, the relationship between various kinds of pathological changes of the motor units and the shape of the EMG signal is difficult to establish [11]. This is affecting computer-based diagnosis the most, because in order to obtain good classification results each group should have distinct features that would enable to distinguish among them easily. In a search for such features, various sEMG parameters have been investigated.

Many studies relied only on one group of patients, i.e. only myopathic or neuropathic, but in order to make a complete method evaluation, both groups as well as a control group should be included, like in [4] and [8].

An overview and comparison of different EMG methods for the myopathy evaluation are presented in [1]. Different EMG methods can be helpful when diagnosing myopathies, whereas the most useful are: manual analysis of the individual motor unit action potentials (MUAPs) and turns–amplitude analyses. Analysis of the firing rate of motor units, power spectrum analysis, as well as multi-channel surface EMG may also be used in the diagnostics, but are not so common [1].

In the muscles of patients with myopathy, both the degeneration and regeneration of muscle fibres are reflected by short-duration, low-amplitude and polyphasic shape of individual MUAPs [1]. Another parameter to be analysed is the motor unit firing rate. With myopathy, early recruitment may be seen, i.e. too many MUAPs are present for the level of muscle contraction compared to normal subjects, due to the weakness of the muscle. The frequency spectrum of EMG can also be used, but it was shown the analysis of individual MUAPs was more sensitive for detecting myopathy than the analysis of the EMG signal frequency spectrum [1].

In [10], the MU size parameter was investigated. It was hypothesised that the size of a MU, defined as the number of muscle fibres innervated by a single motor neuron, is an important parameter in differentiating neuropathic from myopathic properties. Multi-channel sEMG was used to asses the MU size. Single MUAPs were extracted from sEMG signal with the help of a decomposition technique, and the properties of individual MUAPs were compared. They found out the

MUAP amplitude is significantly higher in neuropathic patients.

The next parameter studied for sEMG was muscle fibre conduction velocity. It was shown that myopathic patients can be separated from healthy subjects using mean muscle fibre conduction velocity and propagation of MUAPs [9]. Signals of myopathic patients didn't show propagation behaviour of MUAPs. Also the centre of the innervation zone couldn't be delimited as distinctly as in the normal case. Another study reported disturbance of MUAP propagation at myopathy [13].

In [4], the authors tried to discriminate between normal, myopathic and neuropathic subjects using sEMG signals of biceps brachii muscle. Five parameters were obtained, two from the time domain (turns and zero crossings per second), two from the frequency domain (median frequency and total power per second) and one from the bi-frequency domain (bispectrum peak amplitude). The k-nearest neighbour classifier with the leave-one-out method was used for classification. Results have shown a separation of normal subjects from neuromuscular diseased patients is possible with a success rate of 83%, whereas the separation of myopathic and neuropathic patients is obtained at 77%.

The complete system for the classification of neuromuscular disorders was presented also in [8]. The fast Fourier transform (FFT) was applied to sEMG signals of biceps brachii muscle. The amount of FFT coefficients was further reduced with principle component analysis (PCA). PCA coefficients were then applied to multilayer perceptron and SVM. It was shown that SVM has high anticipation level in the diagnosis of neuromuscular disorders, i.e. 85 % of correct classification.

Let us summarize the most important features that enable the discrimination of different pathologies. A neuropathic pattern is characterized by EMG activity at rest, with elongated duration and high MUAP amplitudes, increased polyphasicity and weakened interference pattern. A myopathic pattern is characterized by short duration and low MUAP amplitude, increased polyphasicity, and enriched interference pattern, the so called pathological interference.

3 Methods

3.1 Data acquisition

SEMG signals were recorded from the biceps brachii (BB) muscle of 19 non-diseased subjects and 20 patients (11 myopathic and 9 neuropathic).

Recordings were taken using a four-bar sEMG active probe with an interelectrode distance of 10 mm and a bar width of 1 mm. The electrode block was placed on the BB (see Fig. 1), in such a way that the second electrode was at a distance equal with 1/3 of the BB length towards the shoulder.

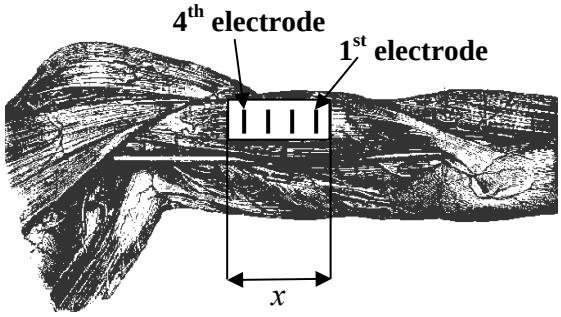

Fig. 1: Positioning of the sEMG electrodes on the BB muscle: x stands for the total electrode length, which was 45 mm.

A bar configuration was preferred from the well-accepted circular configuration, because the former intersects with more fibres than the latter. By intersecting more fibres higher amplitudes will be recorded. From the four bars of the electrode, the second was used as an allocation index. Its predefined placement ensures that all four electrodes lay between the innervation zone of the motor unit and the tendon. The single differential (SD) recordings were recorded simultaneously one from each pair of the electrode bars. Recordings were performed for 5 seconds at 10%, 30%, 50%, 70% and 100% of the maximum voluntary contraction (MVC). Band-pass filer [20÷500Hz] was applied on the recorded signals, which were then sampled with a sampling frequency of 1000 Hz at a 12-digitization resolution.

3.2 Data analysis

At the beginning, all recorded signals were inspected visually for the presence of various artefacts, such as inadequate skin-electrode contacts. The channels with loose contacts were removed from the subsequent analysis. Visual signal inspection showed also the significant difference in amplitudes between the two SD channels of each person, therefore only the channel with higher amplitude was taken into consideration. In most cases, that was the channel located further away from the muscle innervation zone.

As the first step of signal processing, the mean value was subtracted from all signals to eliminate the offset, $s(t) = s(t) - \mu$, where $s(t)$ stands for the recorded sEMG signal and μ for its mean value. Fig. 2, Fig. 3 and

Fig. 4 depict time plots of typical representatives of normal, myopathic and neuropathic groups.

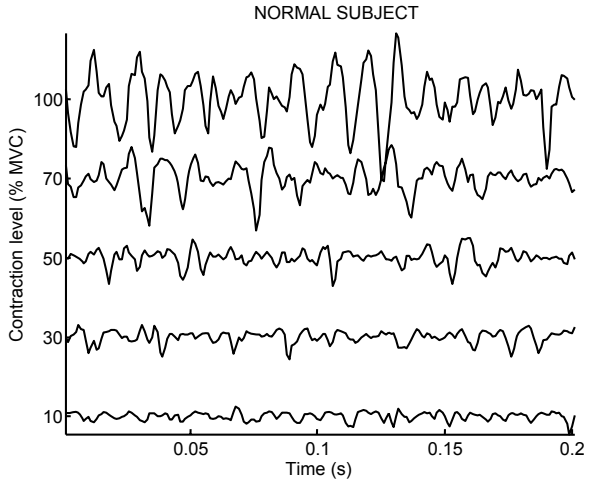

Fig. 2: Recorded sEMG signals at 5 force levels for a typical representative of normal group.

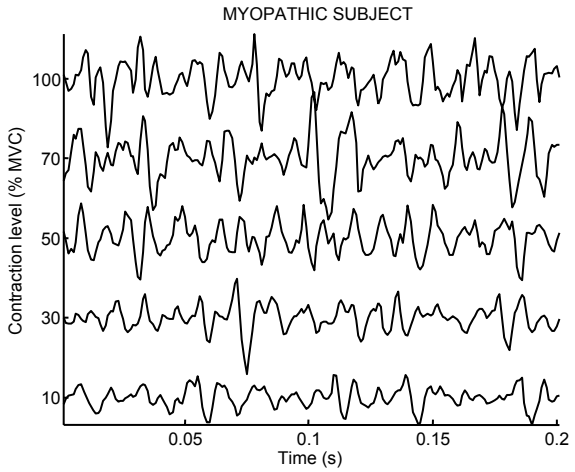

Fig. 3: Recorded sEMG signals at 5 force levels for a typical representative of myopathic group. Early recruitment is obvious at all force levels.

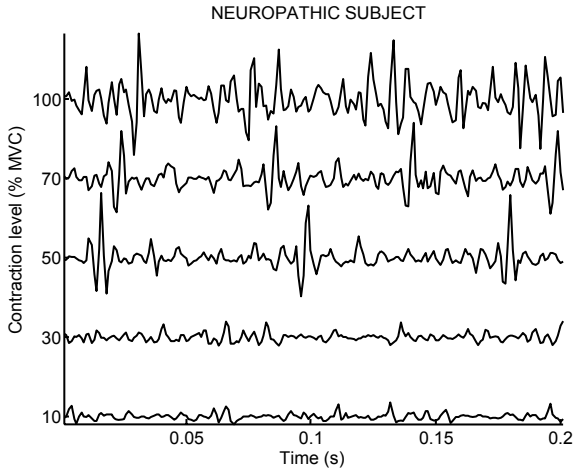

Fig. 4: Recorded sEMG signals at 5 force levels for a typical representative of neuropathic group. Large MUAPs can be seen, in particular at higher force levels.

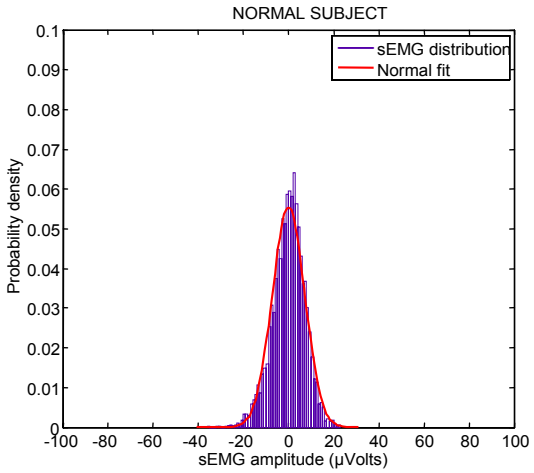

Fig. 5: Amplitude distribution for a typical representative of normal group (Fig. 2).

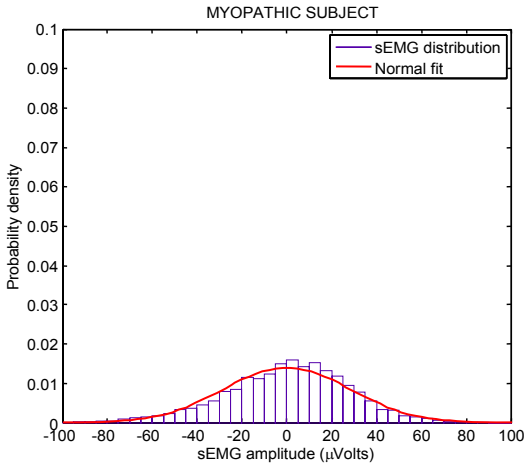

Fig. 6: Amplitude distribution for a typical representative of myopathic group (Fig. 3).

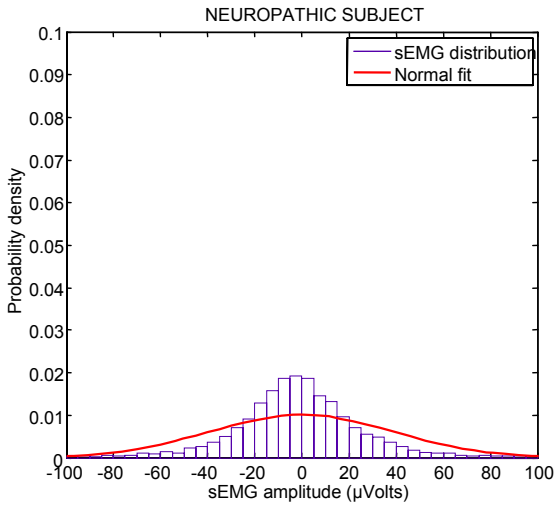

Fig. 7: Amplitude distribution of typical representative of neuropathic group (Fig. 4).

The amplitude distributions of all recorded sEMG signals were fitted by normal distribution using the 'dfittool' in Matlab. Since all sEMG signals are zero mean, only the standard deviation (σ) parameter of the normal distribution is averaged for all groups in Fig. 8. Examples of fitted distributions for typical signal representatives are depicted in Fig. 5, Fig. 6 and Fig. 7.

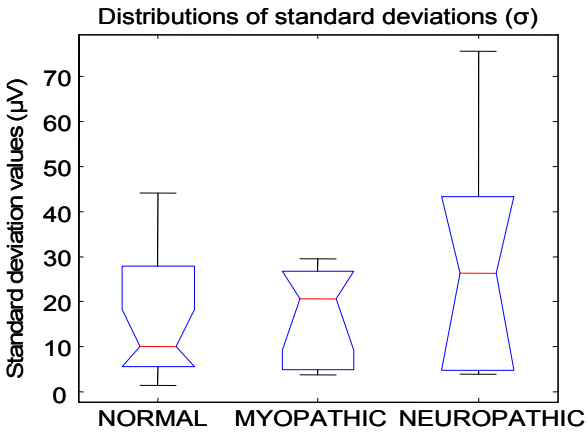

Fig. 8: Distribution of standard deviations (σ) for the three groups: normal, myopathic, and neuropathic. The lower and upper line of the box represent upper and lower quartile, the notch represents median. The lines extending out of the box represent other data.

3.3 Feature extraction technique

For each subject we used one single differential sEMG channel and 5 different force levels (10 %, 30 %, 50 %, 70 % and 100 % MVC), obtained as described in Subsection 3.1), i.e. 5 signals per person in total (see Fig. 2, Fig. 3 and Fig. 4). The signals were further processed in order to extract some important features. Each of the signals was first transformed using continuous wavelet transform (CWT) [6].

Let $s(t)$ be the signal and ψ the mother wavelet. The wavelet coefficient $C_{a,b}$ of $s(t)$ at scale a and translation b is defined by Eq. (1):

$$C_{a,b} = \int_{-\infty}^{+\infty} s(t) \frac{1}{\sqrt{a}} \overline{\psi\left(\frac{t-b}{a}\right)} \cdot dt, \qquad (1)$$

where $\overline{\psi}$ is the complex conjugate of ψ and b = 1,..., length of $s(t)$. In our experiment, the Haar wavelet was chosen and each signal was transformed at 8 dyadic scales ($2^j, j = 1,2,\ldots,8$) (see Fig. 9). At lower scales, signals have higher frequencies, while higher scales pose lower frequencies (smoothed signals).

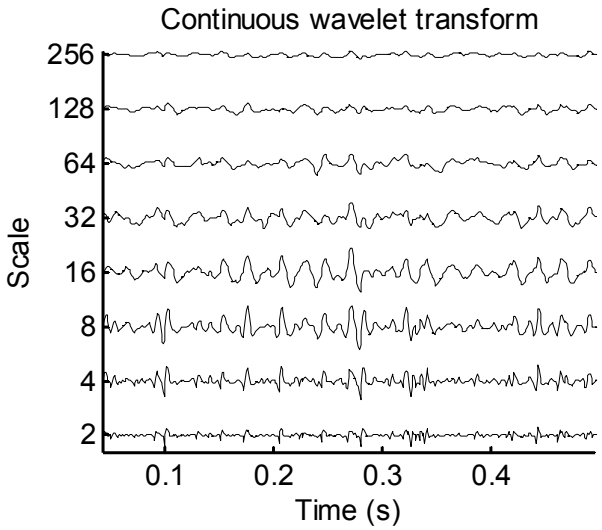

Fig. 9: Time-scale representation: a sEMG signal at 30% MVC contraction transformed by CWT.

At each scale, the transformed signal is further used to calculate the Shannon entropy:

$$H(X) = -\sum_{i=1}^{M} P(X = x_i) \log_2 P(X = x_i), \qquad (2)$$

where $H(X)$ is the entropy for random variable X, where X takes discrete values x_i with probability $p_i = P(X = x_i)$, and M is the number of partitions of peak-to-peak amplitude interval. In our case the logarithm with base 2 was used. The range of entropy values depends on the number of partitions and the base of the logarithm used. The lowest entropy (H=0) is scored when the random variable has one certain outcome, and all other outcomes have zero probability. The maximum entropy ($H = \log M$) is achieved, when all outcomes of the random variable have equal probability. We implemented M = 1000 partitions and the base 2 logarithm, so the maximum possible entropy in our case is 9.97.

After the feature extraction, a set of 40 features per subject was formed, i.e. 5 sEMG signals were transformed at 8 scales totalling in 40 signals on which the entropies were calculated, yielding finally 40 scalar values. The classification of subjects was based on the obtained feature set. Fig. 10 depicts average feature set for normal group with standard deviation.

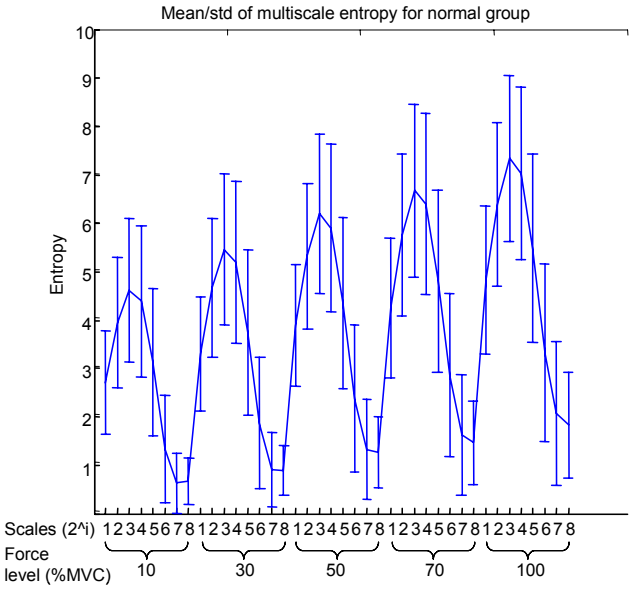

Fig. 10: A feature set is depicted for the normal group; solid line represents the average value for the group, while error bars delineate standard deviation.

4 Experimental results

From the feature set calculated by the proposed technique (40 features per person) we created five datasets, where subjects were labelled based on their type as:

- normal / abnormal (myopathic and neuropathic),
- normal / myopathic,
- normal / neuropathic,
- myopathic / neuropathic,
- normal / myopathic / neuropathic.

To obtain best classification results, we used three different techniques from the WEKA machine learning package [5], i.e. decision trees, support vector machines (SVM) and SVM ensembles. We resorted to 3-fold cross-validation using 50 iterations for each machine learning technique. 3-fold cross-validation was performed, so that the complete database was divided into 3 equal parts, two of them then used as learning sets and one as testing set. In our example with a total of 39 subjects, one part consisted of 13 subjects. For the learning purposes, 26 subjects were used, and 13 for testing the classification.

Classification correctness and deviation of 150 classifiers for each dataset and machine learning technique are shown in Table 1, where cells with the highest classification score for given dataset are shaded. It can be seen that two classification methods performed the best, i.e. SVM and SVM ensemble, although the decision trees with human readable knowledge representation were only slightly less accurate then SVMs. Since datasets decision classes are biased, we applied Receiver Operator Characteristic (ROC) as the classifier quality measure. From Table 2, it is clearly visible that the best results were obtained by SVM (highest ROC).

The highest success was scored by normal/neuropathic classification, so this indicates that normal and neuropathic groups are the most distinguishable, while myopathic and neuropathic groups are hardly distinguished.

Table 1: Classification results obtained on real sEMG signals

Classification of subjects as	Number of subjects per class	No. of classes	Classification rate ± standard deviation [%]		
			Decision trees	SVM	SVM ensemble
normal / abnormal	19 / 20	2	56.36± 8.80	63.90±11.02	63.18±10.22
normal / myopathic	19 / 11	2	68.69±11.20	73.33± 6.60	71.85± 9.71
normal / neuropathic	19 / 9	2	73.52±11.19	79.03± 7.71	78.09±10.08
myopathic / neuropathic	11 / 9	2	48.67±19.17	47.47±19.94	43.07±19.90
normal / myopathic / neuropathic	19 / 11 / 9	3	51.69±11.06	62.50± 7.42	60.26± 8.89

Table 2: ROC of classifications

Classification of subjects as	Number of subjects per class	No. of classes	ROC ± standard deviation		
			Decision trees	SVM	SVM ensemble
normal / abnormal	19 / 20	2	0.59±0.13	0.72±0.11	0.64±0.11
normal / myopathic	19 / 11	2	0.52±0.13	0.67±0.16	0.60±0.14
normal / neuropathic	19 / 9	2	0.48±0.09	0.76±0.15	0.60±0.11
myopathic / neuropathic	11 / 9	2	0.50±0.16	0.43±0.19	0.40±0.13
normal / myopathic / neuropathic	19 / 11 / 9	3	0.58±0.13	0.69±0.12	0.63±0.11

In the next experiment, we tried out whether an individual force level exist that yield better classification rates as other levels. Instead of using all five force levels, we tested classification by using only the signals at 10 % MVC, then only at 30 % MVC, etc. 2-class normal/abnormal classification was performed. No greater differences were detected between the average of all the force levels together and only one level, but better classification is obtained at lower contractions (10% MVC) for all classification techniques. The results are presented in Table 3.

Table 3: Classification results for individual force levels.

Force level % MVC	Classification rate ± standard deviation [%]		
	Decision trees	SVM	SVM ensemble
10	64.18±9.90	57.27±12.68	65.67±11.08
30	61.42±10.57	49.73±7.66	62.03±12.41
50	50.21±14.04	47.30±7.08	51.42±13.88
70	46.97±9.75	45.76±6.85	50.18±11.64
100	45.24±13.47	46.06±4.58	46.45±14.06

We also investigated dependencies of classification rates on different scales. Again, we ran 3 classification techniques, but this time only on the entropies for single scales. 2-class normal/abnormal classification was performed. Results are shown in Table 4. They indicate the classification results do not depend on the scale. However, better results are obtained if averages across all the scales are used.

Table 4: Classification results for individual scales.

Scale	Classification rate ± standard deviation [%]		
	Decision trees	SVM	SVM ensemble
2	54.42±11.80	53.24±8.69	57.70±10.86
4	50.97±11.19	55.30±11.43	59.52±10.52
8	50.97±6.65	56.45±10.42	57.30±9.64
16	50.09±6.55	55.52±11.07	58.64±12.98
32	55.09±11.42	60.00±11.84	61.24±11.66
64	49.15±5.64	58.97±12.56	63.27±12.94
128	49.45±5.68	58.70±11.49	59.64±13.78
256	49.79±6.00	60.30±13.86	61.85±12.70

5 Conclusion

A major drawback of all the sEMG electrodes used nowadays is that only the electrical activity of superficial muscles is accessible. Moreover, the sEMG electrodes cannot record positive sharp waves, fibrillation potentials or other abnormal spontaneous activities that can be measured using needle electrodes. These are the issues that are limiting the use of sEMG in the clinical diagnosis. But sEMG can provide other useful information, only the right features must be found.

Our experiments show that the amplitudes of recorded sEMG signals vary over a large range for both the normal and ill subjects. This is probably owing to the different thickness of the individual fat layers, which acts like a low-pass filter. The sEMGs of patients show higher average amplitudes than those of normal subjects. This could be attributed to the suboptimal electrical properties of the muscles [14].

The sEMG signals in patients with the neuromuscular diseases can vary evidently depending on the stage of the disease. In the beginning stages of the disease the changes in sEMG can hardly be detected, while at an advanced stage the symptoms of disease are easily detectable. To correctly classify all the patients regardless to the stage of their disease, sEMG recording and processing is not enough. Other tests, such as muscle biopsies, blood tests, genetic testing, etc., should be carried out to determine the disease.

Another important issue, in particular when tracking myopathic changes in muscles, is that myopathy can affect only individual muscles, while the properties of other muscles can remain unchanged. Therefore, it is also important to measure sEMG of the muscle which is affected by the disease. In the case of myopathy only some of the MUs can be affected by the disease, while other MUs remain unchanged. Since sEMG measures the integrated electrical activity of all MUs within the surface-electrode uptake volume, deviating MUs can be hidden among healthy ones. But this problem cannot be resolved only with sEMG amplitude processing. Another step has to be performed prior to classification of subjects, i.e., the extraction of individual MUAPs form the sEMG, which is attainable by using suitable decomposition techniques.

The decomposed MUAPs give a better insight in the muscle and also the conventional classification methods based on the MUAP duration and amplitude can perform well in such a case. But also it has to be taken into account that the superficial MUs contribute to the sEMG much more than others, so deeper MUs cannot be detected easily and their changes are hardly detectable.

As it was mentioned in Section 2, some investigations have been performed on the diagnostic use of sEMG [4], [8]. A direct comparison of these methods can be done as follows. The authors in [8] focused on the frequency domain parameters only, as they were using FFT, but they did not report any typical values for the groups, so it is not clear how the frequency content was changing between the groups. They only reported detailed classification results, which are 84.16 % using

multilayer perceptron and 85.42 % using SVM for 3-class classification.

Another work [4] addresses the same topic in the time (turns and zero crossings per second), frequency (median frequency and total power per second), and bi-frequency (bispectrum peak amplitude) domains. They reported typical parameter values and their changes versus force levels. All 5 reported parameters were used in classification obtaining the following results: 69 % for 2-class and 61% for 3-class classification using k-nearest neighbours. These results are very similar to our findings, which can be explained by the fact that we experimented with the same signal set as the authors of [4]. The signals in [8] were taken from different subjects in different circumstances not known to us in details. This fact can be considered crucial for different classification results. At the same time, it is evident that the orthogonalisation used in [8] improved the class separability significantly; therefore it is worthwhile to consider it.

At the end we would like to point out the open issues to be investigated in order to estimate additional classification improvements. This includes the use of other types of entropy, such as Tsallis, and the use of other types of wavelets, such as Gaussian, Daubechies, etc.

Acknowledgement

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