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Multi-scale AM–FM analysis for the classification of surface electromyographic signals

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ABSTRACT

In this work, multi-scale amplitude modulation–frequency modulation (AM–FM) features are extracted from surface electromyographic (SEMG) signals and they are used for the classification of neuromuscular disorders. The method is validated on SEMG signals recorded from a total of 40 subjects: 20 normal and 20 abnormal cases (11 myopathy, and 9 neuropathy cases), at 10%, 30%, 50%, 70% and 100% of maximum voluntary contraction (MVC), from the biceps brachii muscle. For the classification, three classifiers are used: (i) the statistical K-nearest neighbor (KNN), (ii) the self-organizing map (SOM) and (iii) the support vector machine (SVM). For all classifiers, the leave-one-out methodology is used to validate the classification of the SEMG signals into normal or abnormal (myopathy or neuropathy). A classification success rate of 78% for the AM–FM features and SVM models was achieved. These results also show that SEMG can be used as a non-invasive alternative to needle EMG for differentiating between normal and abnormal (myopathy, or neuropathy) cases.

1. Introduction

The electromyographic (EMG) examination provides important information for the assessment of neuromuscular disorders and is generally carried out using needle electrodes. However needle electrodes put the patients under considerable pain and discomfort, as well as the risk of infection. In addition, constant expert supervision is necessary, which renders the whole process quite lengthy. In paediatric examinations and tests in particular, there are even more difficulties in using needle electrodes, and long term monitoring is quite difficult [1]. Surface electrodes and the acquisition of surface EMG signals provide a non-invasive alternative to needle EMG for the detection of neuromuscular disorders. At present, a surface detected signal is preferred only for obtaining global information about the time and/or intensity of superficial muscle activation [1].

In previous work [2–7] it was shown that time and frequency domain features extracted from the EMG signals can be used successfully for the classification and the identification of neuromuscular disorders. Abel et al. [3], found a percentage of correct classifications of 75% when 12 normal subjects were compared with 18 myopathy and 15 neuropathy patients examined with needle EMG. Turns analysis and small segments analysis were used. A turn was counted if the amplitude difference between adjacent turning points was at least 100 μV, whereas a small segment was defined when the time interval between turns was equal or less than 1.5 ms in duration. However authors concluded that the classification methods used, did not offer better results than the interference pattern analysis and could not by any means match the diagnostic success of an experienced clinician. Christodoulou et al. [4] developed a modular neural networks system where multiple features extracted from needle EMG signals were fed into multiple classifiers for the assessment of 12 normal subjects, 13 subjects suffering with myopathy and 15 subjects suffering with motor neuron disease, reaching a diagnostic yield of 87.5%. Abou-Chadi et al. [5] used three versions of neural networks to facilitate automatic classification of SEMG. With unsupervised techniques, the correct classification score reached 80%, when five normal subjects and five myopathy subjects were selected from a pool of 14 normal subjects and 14 patients. Recordings were performed for 5 s at 50% MVC. Abou-Chadi et al. [5] reached the conclusion that when SEMG is properly processed, it may provide the physician with a diagnostic assisting tool. In another SEMG study, Kaplanis [6] reached a correct classifications score of 82.9%, when 91 control subjects and 20 pathogenic cases were placed in a pool of subjects (results were normalized based on the number of subjects for each group). In a recent work Istenič et al. [7] used multiscale entropy of recorded SEMG and support vector classification on a similar database. In

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three-class classification with 9 subjects per class, they reached an accuracy of 70.4%, whereas in two class-classification with 9 normal vs 18 abnormal subjects they achieved 81.5%.

In this work, we investigate the use of new feature sets extracted using multi-scale amplitude–modulation frequency-modulation (AM–FM) representations [8–10]. Our motivation for pursuing AM–FM features comes from the fact that they can capture local (instantaneous) variations in amplitude, frequency, and phase. Here, three sets of AM–FM features are estimated from the SEMG signals at various scales and force levels: (i) the instantaneous amplitude, (ii) the instantaneous frequency, and (iii) the instantaneous phase. We use the term scale to refer to a collection of bandpass filters [10]. Within each scale, a single AM–FM component is estimated. We also use the term multi-scale AM–FM analysis to refer to AM–FM components extracted from the combination of different scales. A significant distinction of the AM–FM analysis proposed in the current paper over prior work is the relaxation of the requirement to have multi-scale analysis using band-pass filters that cover continuous-intervals in the frequency-domain. This generalized approach allows finer control over the extraction of AM–FM features. Thus, in this paper, we consider the use of different combinations of bandpass filters for generating multi-scale AM–FM components.

For each of the AM–FM components, we compute the AM–FM feature histograms and use them as inputs to the classifiers. For the classification, three classifiers are implemented: (i) the statistical K-nearest neighbor (KNN) classifier, (ii) the self-organizing map (SOM) and (iii) the support vector machine (SVM). For all classifiers the leave-one-out methodology is used to validate the classification of the SEMG signals into two classes, i.e. normal or pathogenic.

We provide a description of the data acquisition process in Section II. In Section III we describe the extraction algorithms for the time and frequency features and the AM–FM features. In Section IV, we present results using the three different classifiers. We give the results in Section V and provide concluding remarks in Section VI.

2. Material and data acquisition

Surface EMG recordings were acquired from 20 control subjects (NOR) and 20 subjects suffering from neuromuscular disorders (11 myopathy and 9 neuropathy cases). Patients referred were first examined and diagnosed by their physician and were divided according to the general type of neuromuscular disorder (myopathy or neuropathy). It should be emphasized that patients selected and referred for SEMG in this study were randomly selected and did not present a homogeneous group, i.e. these patients were at different stages of the disease and did not have the same Medical Research Council (MRC) score. The data were collected at the Department of Clinical Neurophysiology at the Cyprus Institute of Neurology and Genetics, Nicosia, Cyprus [6]. The Nicolet Viking IV electromyography two-channel amplifier unit was used. Through the system, the low and high frequency values for recording were set at 20 and 500 Hz respectively, and the amplifier input impedance was in excess of 1000 MΩ.

A calibrated force measurement system, with a total weight of 40 kg was placed at the foot end of a couch, used for the subjects to lie down. The weights were lifted via a strap placed at the subjects' wrist and connected to the system through a force transducer, which was connected directly to a calibration circuit. The subject was required to pull at maximum voluntary contraction (MVC) three times with an interval of 2 min in between to avoid fatigue. The MVC was marked on the oscilloscope and was used as a reference for monitoring the percentage force level. Recordings were made at five different force levels, i.e. at 10%, 30%, 50%, 70% and 100% of MVC from the biceps brachii muscle carried out under isometric voluntary contraction (IVC).

3. AM–FM feature extraction

For the purposes of this paper, we consider the use of new, multiscale AM–FM representations that can be efficiently used to describe non-stationary signal behaviour [10,11]. Here, we express each input signal using:

$$f(k) = \sum_{n=1}^{M} a_n(k) \cos \varphi_n(k) \tag{1}$$

where $n = 1, 2, \ldots, M$ indexes the AM–FM components, a_n represents the nth instantaneous amplitude, and φ_n represents the nth instantaneous phase. Here, AM–FM components are extracted over a dyadic filter bank (see [10] for 2-D examples). In what follows, we provide a step by step description of feature extraction.

First, we use the 1-D FFT to estimate the analytic signal f_{AS} [10]. This is accomplished by zeroing out all the negative frequency components and then multiplying by 2 all remaining FFT frequency components. The AM–FM signal is then filtered through a dyadic filter bank. For example, for the 2-scale dyadic filterbank we have bandpass filters with pass-bands of 0–125 Hz, 125–250 Hz, 250–500 Hz. For 3-scale filterbanks, we sub-divide the low-frequency band. Thus, for 3-scale filterbanks we have bandpass filters with pass-bands of 0–62.5 Hz, 62.5–125 Hz, 125–250 Hz, 250–500 Hz, whereas for 4-scale filterbanks we have 0–31.25 Hz, 31.25–62.5 Hz, 62.5–125 Hz, 125–250 Hz, 250–500 Hz. Over each channel filter, we estimate the instantaneous amplitude (IA), the instantaneous phase (IP) and the instantaneous frequency (IF) of the signal using

$$a(k) = \left| f_{AS}(k) \right|, \tag{2}$$

$$\phi(k) = \arctan\left(\frac{imag(f_{AS}(k))}{real(f_{AS}(k))} \right) \tag{3}$$

$$\frac{d\phi(k)}{dt} \cong \frac{1}{n} \arccos\left(\frac{f_{AS}(k+n) + f_{AS}(k-n)}{2 f_{AS}(k)} \right). \tag{4}$$

where in (4), n is a variable displacement that can vary from 1 to 4, based on the argument that provides the minimum condition number to arccos(·) function.

Over all of the resulting estimates, we also apply dominant component analysis by only selecting the IA, IF, and IP estimates with the maximum value of IA (see [10] for details). Here, it is important to note that the extracted features are functions of the selected channel filters. In our multi-scale AM–FM analysis example, we consider different combinations of band-pass filters (channels) from different filters. At each time-domain sample, we extract a single set of AM–FM features, based on the channel that gives the largest IA at each sample. We then compute 32-bin histograms for the IA, IF, and the IP.

From the generated AM–FM features, the histograms for 32 equal width bins were computed and were used as input feature sets for classification. The histograms were further normalized by division of the histogram with the number of SEMG signal points in order to alleviate any bias due to different signals lengths. Fig. 1 shows an SEMG signal from a normal subject (only shown 1000 samples points for visibility) and its corresponding AM–FM histograms.

4. Classification

The three 32 bins AM–FM histograms (i.e. 96 bins in total) were used as input into the three different classifiers investigated. The

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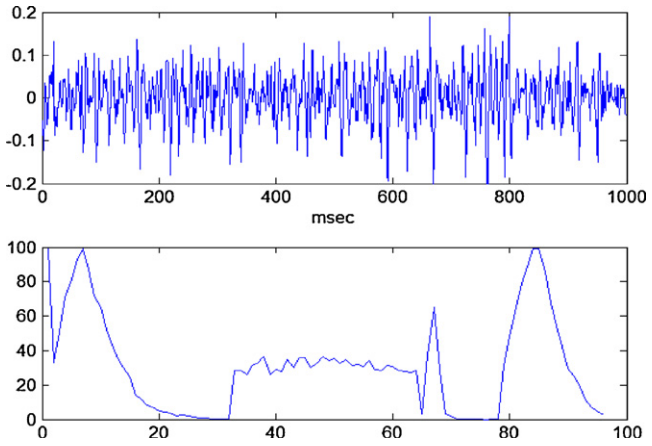

Fig. 1. Sample of SEMG signal (in mV) from a normal subject at 100% force level (top row) and its corresponding AM–FM histograms (bottom row, where the *y*-axis represents the percentage frequency of occurrence of the corresponding components). The first 32 samples represent the histogram of the instantaneous amplitude. This is followed by the histogram of the instantaneous phase and the histogram of the instantaneous frequency.

leave-one-out methodology was applied where for each input pattern to be classified all the remaining patterns were used as the training set. The average of all classifications scores was the final score. This made the classification procedure independent of bootstrap sets and the results more robust and reliable.

We consider the following classifiers [9]:

- The statistical *k*-nearest neighbor (KNN) classifier for several values of k ($k = 1, 3, 5, 7, 9, 11, 13$ and 15).
- The self-organizing map (SOM) classifier as an unsupervised method [12].
- The support vector machine (SVM) classifier using Gaussian Radial Basis Functions [13].

From each subject, five feature vectors were calculated one for each force level and inputted to the classifiers. Furthermore the five classification outputs per subject were combined using majority voting, i.e. the subject was assigned to the class where the majority of the five individual SEMG signals per force level were assigned. This was done in order to get a final and more reliable estimate of the classification result, since as it was shown in [4] modular neural networks system enhanced the diagnostic performance of the individual classifiers making the whole system more robust and reliable.

5. Results

Surface EMG recordings from 20 control subjects (NOR) and 20 neuromuscular subjects (11 myopathy and 9 neuropathy) were recorded at 10%, 30%, 50%, 70% and 100% of maximum voluntary contraction (MVC), from the biceps brachii muscle. For each SEMG recording the AM–FM histogram features were extracted from the instantaneous amplitude (IA), instantaneous phase (IP), and the instantaneous frequency (IF). The IA, IP, and IF were normalized by the signal length in order to alleviate any biases due to different signals lengths and their histograms were used as input to the three classifiers.

For extracting the multi-scale AM–FM features, we consider the use of 3, 4 and 5 channel filterbanks. For comparison, we performed multi-scale AM–FM analysis using both the entire collection of band-pass filters as well as using selected subsets of band-pass filter combinations. In considering subsets, we were particularly interested in combinations that included both low and high-frequency bands that avoided the common middle-bands. High-scale frequency bands tend to follow short-term changes in the EMG signal and thus tend to describe subtle differences. On the other hand, low-scale frequency bands tend to follow long-term changes and thus describe long-term trends in the signal. It should be noted that all possible combinations with the middle frequency bands were also investigated but gave poorer results in differentiating between normal and abnormal cases. The combination of AM–FM features from the low- and high- frequency scales was found to better differentiate between normal and abnormal cases. The combination of low- and high-frequency scales for 4 scales gave the best results. In what follows, we provide more details on the most promising AM–FM features.

Fig. 2 displays boxplots of the instantaneous amplitude (IA) and of the instantaneous frequency (IF) histograms for the normal and abnormal classes. All figures are at 100% force level of maximum voluntary contraction. In this example, we can see the lack of any IF components that belong in the middle bands (e.g., no IFs in the 100–200 Hz range). In Fig. 2, it is interesting to note the larger number of outliers in the abnormal case. It is also interesting to note that the most significant differences appear in the higher frequencies. In what follows, we provide a more detailed analysis of the AM–FM features that gave the most significant differences.

Table 1 tabulates the results of the Wilcoxon statistical analysis test between normal and abnormal cases for IA and IF. As shown in Table 1, there is a shift towards higher frequencies in the IF spectrum with increasing force level.

Table 2 tabulates the AM–FM correct classifications success rate for the three classifiers KNN, SOM and SVM and for the five force levels. In addition, the five force level scores per subject were combined with majority voting and the results are also given in Table 2. For the KNN classifier the values provided in Table 2 are for $k = 11$ which gave the best results and for the SOM for a 7×7 map matrix and an evaluation neighborhood window 3×3 for the same reason.

All models were trained with the 32 bin histograms of IA, IP, and IF (i.e. 96 bins in total) as shown in Fig. 1, and the best classifier was by far the SVM followed by the SOM and the KNN classifiers. The SVM models trained with the 30% and 100% MVC signals gave the highest percentage of correct classifications score (%CC = 75%, Sensitivity = 65%, and Specificity = 85%). Combining the five force level scores per subject with majority voting improved the average success rate, reaching in the case of the SVM classifier 78%.

The last column of Table 2 tabulates the percentage of correct classifications score of SVM models trained with the corresponding AM–FM IA and IF histogram bins that demonstrated significant statistical difference (as given in Table 1). It is clearly shown that these models gave better performance, with the models trained with the 30%, 10%, and 100% MVC signals, achieving a %CC score of 78%, 75%, and 75%, respectively. For the 30% MVC model, that achieved the highest %CC score, the Sensitivity was 70%, and the Specificity was 85%. Combining the five force level scores per subject with majority voting improved the average success rate, reaching a score of 78%.

A close inspection of Tables 1 and 2 reveals that force levels that had a larger number of features with significant differences also gave better classification results. For example, at 70% force level, we had the lowest number of features with significant differences and the lowest classification scores. On the other hand, at both 30% and 100% force levels, we have five, the largest number of significantly different results, and these are associated with the best classification scores. Yet, the combination of all force levels did not improve over what we obtained with just the significantly different features associated with the 30% force level. Both gave 78%.

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Table 1
Statistical analysis based on the Wilcoxon test of the AM–FM IA and IF histogram bins between normal and abnormal cases. The histogram bins that demonstrated significant difference at $p < 0.05$ are tabulated.

Force level (%)	IA (mV)	IF (Hz)
10	0.15–0.156, 0.169–0.175	78–109, 312–328
30	0.131–0.15, 0.156–0.187	62–78, 219–297, 312–344
50	0.031–0.044	219–297, 312–422
70	–	234–266, 312–359, 391–437, 469–484
100	0.031–0.05, 0.162–0.169, 0.193–0.2	234–250, 312–484

Table 2
Percentage of correct classifications score for KNN, SOM, and SVM models for classifying a subject as normal or abnormal (suffering from neuromuscular disease) based on AM–FM feature sets.

AM–FM feature set	32 bin histograms of: IA, IP, and IF			Statistically significant features of Table 1
Force level (%)	KNN (%)	SOM (%)	SVM (%)	SVM (%)
10	53	55	68	75
30	50	60	75	78
50	60	58	68	73
70	53	55	65	65
100	63	63	75	75
All force levels[a]	58	60	78	78

[a] The five force level scores per subject were combined with majority voting.

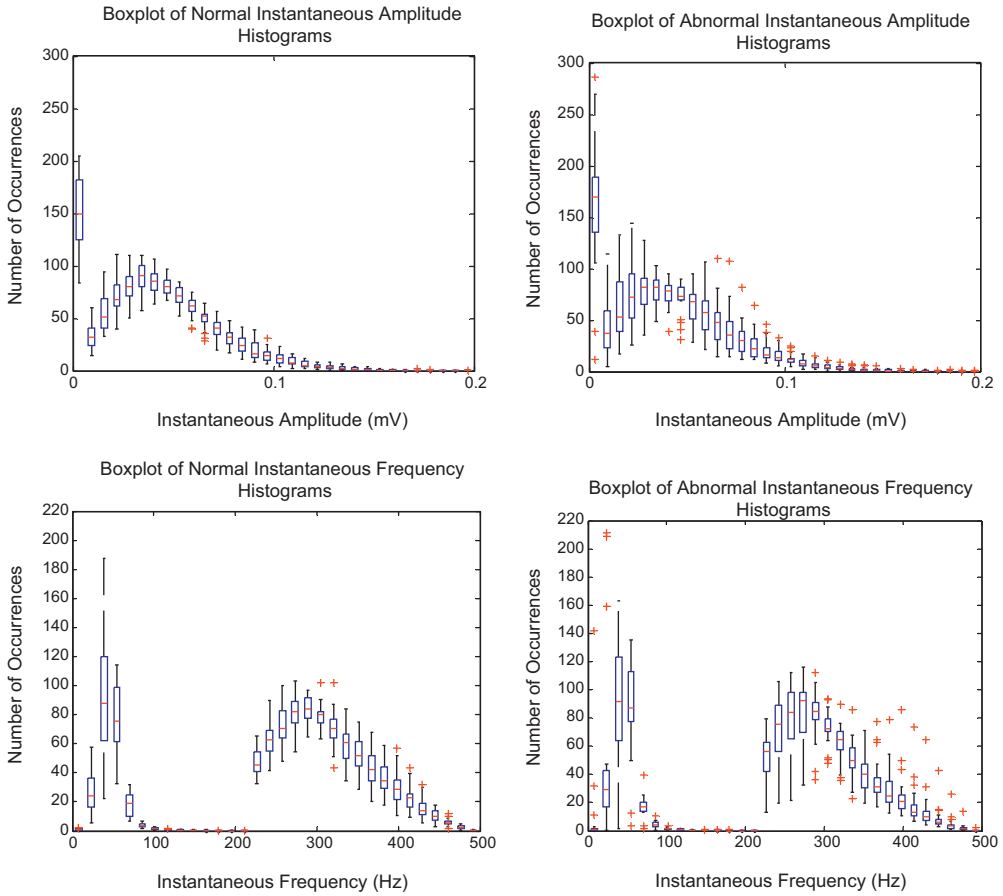

Fig. 2. Boxplots of the instantaneous amplitude and the instantaneous frequency histograms for the normal and the abnormal classes at 100% of MVC. In each plot, we display the median, lower, and upper quartiles and confidence interval around the median. Straight lines connect the nearest observations within 1.5 of the IQR (inter quartile range) of the lower and upper quartiles. Crosses indicate outliers with values beyond the ends of the 1.5 × IQR.

6. Concluding remarks

The American Association of Electrodiagnostic Medicine has published in 1999 [14] a technology review paper mentioning that there were no clinical indications for the use of surface EMG in the diagnosis and treatment of disorders of muscles and nerves, however, it may prove useful in the non-invasive monitoring of the progression of these disorders. Although SEMG is not used routinely in the clinical neurophysiology lab for the diagnosis and treatment of neuromuscular disorders, several studies investigated

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different feature sets and classification models for differentiating between normal and abnormal SEMG recordings from subjects suffering with neuromuscular disorders [2–7] (as documented in the Introduction section). These models were trained with time, frequency, and multi-scale features, and their performance varied with respect to the correct classifications score from 75 to 87.5%.

In this work it was shown that AM–FM analysis provides new feature sets, which can be used successfully for the classification of SEMG signals. The percentage of correct classifications score achieved for the statistically significant IA and IF features for the 10%, 30%, 50%, 70%, and 100% of MVC were 75%, 78%, 73%, 65%, and 75%, respectively. These results can easily be compared to a recent study by Istenič et al. [7] that investigated multiscale entropy on the same SEMG dataset where it was found that the percentage of correct classifications score achieved for 10%, 30%, 50%, 70%, and 100% of MVC was 65%, 65%, 78%, 74%, and 78% respectively. Moreover, when combining all the statistically significant IA and IF features for all force levels, the %CC was 78% versus 81.5%, 77.8%, 74.1%, and 74.1% achieved for the entropy based classification using the Haar, Morlet, Daubechies order (8), and Mexican hat mother wavelets [7], respectively. Thus, it has been clearly demonstrated that using only the AM–FM multiscale IA and IF statistically significant features and SVM modeling, the highest %CC of 78% can be used for differentiating normal vs abnormal cases. Moreover, it should be mentioned that time and frequency domain features investigated on the same SEMG dataset gave significantly lower %CC score [9]. Furthermore, it should be noted that the performance of the classification models documented should be analysed, and/or interpreted having in mind that the abnormal SEMG recordings investigated come from a very heterogeneous group of subjects suffering with neuromuscular disease.

The use of multi-scale AM–FM analysis has to be investigated on more subjects suffering with neuromuscular disorders, as well as to be investigated on longitudinal studies for monitoring the progression of disease.

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