Quantification of sEMG Signals for Automated Muscle Fatigue Detection Using Nonlinear SVM

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ABSTRACT:
Fatigue is a multidimensional and subjective concept and is a complex phenomenon including various causes, mechanisms and forms of manifestation. Thus, it is crucial to delineate the different levels and to quantify self-perceived fatigue. The aim of this study was to introduce a method for automatic quantification and detection of muscle fatigue using surface EMG signals. Thus, sEMG signals from right sternocleidomastoid muscle of 9 healthy female subjects were recorded during neck flexion endurance test in Quaem hospital. Then six features in time, frequency and time- scale domains were extracted from signals. After dimensionality estimation and reduction, the SVM classifier was applied to the resulted feature vector. Then, the performance of linear SVM and nonlinear SVM with RBF kernel and the effect of σ value in RBF kernel, on the accuracy of classification were evaluated. The results show that the best accuracy is achieved using RBF kernel SVM with σ equal to 0.5 (91.16%) and also the selected features using LLE criterion, were RMS, ZC and AIF. These results suggest that the selected features contained some information that could be used by nonlinear SVM with RBF kernel to best discriminate between fatigue and nonfatigue stages.

KEYWORDS: Surface Electromyography (sEMG), SternoCleidoMastoid muscle (SCM), muscle fatigue, classification, Radial Basis Function (RBF) kernel, Support Vector Machines (SVM).

1. INTRODUCTION

Fatigue is a multidimensional and subjective concept and is a complex phenomenon including various causes, mechanisms and forms of manifestation, hence poses a complex problem for the physician [1]. Since fatigue has physiological and psychological dimensions, delineation of its different levels and quantification of self- perceived fatigue is crucial [1].

Fatigue definition is very complex, not unique and controversial but physiological fatigue is usually defined as the loss of voluntary force- producing capacity during exercise. This can be due to both central and peripheral mechanisms [1]. Fatigue has mostly been studied at peripheral level, i.e. in the muscle tissue. During peripheral fatigue, the accumulation of lactate and extracellular potassium, together with a lowering of pH, affects membrane excitability [1,2]. Surface EMG signals provide useful information about the underlying mechanisms of fatigue. In spite of the limitations of the application of sEMG method to muscles positioned directly below the skin and the problem of cross talk from neighbouring muscles, this method due to its non- invasiveness, applicability in situ, real- time monitoring of fatigue and correlation with biochemical and physiological changes of muscle during fatigue, is widely used to determine local muscle fatigue [2]. To reduce the difficulty of the problem and the number of factors affecting the EMG signal, most past researches focused on myoelectric manifestation of muscle fatigue during isometric, constant force conditions [3]. Since fatigue itself is not a physical variable, its assessment requires the definition of indices based on physical variables that can be measured, such as force, power, or variables associated to the EMG signal, such as amplitude and spectral estimates [3]. The most widely used method for estimating the spectrum of the EMG signal is Fourier transform. Fourier methods suffer from several limitations. One of them is the stationarity assumption, otherwise information about spectral changes will be lost [2,4,5]. Z.G. Zhang et al. [6] have used the time-dependent power spectral density (PSD) estimation of nonstationary surface electromyography signals for fatigue analysis during isometric muscle contraction. They have used time-varying autoregressive (TVAR) model for power spectral estimation. The need for a PSD estimation unavoidably introduces a number of factors (method for PSD estimation, implementation algorithm, order of parametric model, shape and size of the analysis window), which directly affect the estimates of the spectral variables. In our research, we have used frequency variables which do not require spectral estimation. In addition, most of the pervious researches have presented methods for muscle fatigue quantification and only a few of them have introduced methods for automated classification and prediction of muscle fatigue. M.R. Mulla et al. [7] have applied wavelet transform and genetic algorithm for classification of muscle fatigue during isometric contraction and have reached average correct classification of 88.14%. A. Subasi et al. [8], have used time- frequency, neural network and ICA methods for muscle fatigue detection and have achieved accuracy percentage of 89%. L.M. Stirling et al. [3], also have used wavelet transform and linear SVM for fatigue detection. In order to train SVM classifier, they have labeled training dataset using perceived exertion reported by subjects (Borg scale) and achieved recognition rate of more than 80% across all muscles.

In this paper, we have used new EMG variables for quantification of muscle fatigue in time, frequency and time- scale (wavelet) domains. These features not only overcome Fourier based methods limitations, but are inherently suitable for nonstationary signals. Then, since our data were nonlinearly separable, SVM classifier with RBF kernel was used for automated classification of EMG signals into fatigue and nonfatigue stages. Then, the effect of σ value in RBF kernel, was evaluated on the accuracy of classification.

2. METHODS AND MATERIALS

2.1. Subjects

Nine healthy female volunteers (age 29.77±5.58 years, mass 62.22±6.64 kg, BMI 23.53±2.32 kg/m^2) with right hand dominant participated in this study. The subjects had not specifically trained their neck and shoulder muscles, and none of them was a competing athlete. Prior to their inclusion, all subjects were aware of recording protocol and the aim of study by examiner and information on examination forms. The measurements were carried out in the department of neurology, Quaem hospital. Before participation, all subjects were evaluated by a neurologist in order to ensure the absence of neurological or musculoskeletal disorders. The measurements were done between 4 to 7 P.M. The subjects were not allowed to take any analgesics or muscle relaxants 24 hours before the examination. All volunteers signed informed consent prior to their inclusion.

2.2. Protocol

Surface EMG signals were recorded (using PowerLab/4SP-SP5638 (ADInstruments Pty Ltd. Australia), bandpass: 10-500 Hz, notch: 50Hz, sampling frequency: 2kHz) bipolarly with Ag/AgCl circular disposable surface electrodes of diameter 15mm, from sternocleidomastoid muscle during neck flexion endurance test. The electrodes were placed slightly posteriorly over the middle part of the muscle in the direction of muscle fibers, attached onto muscle at 2cm interelectrode spacing. The reference electrode was placed on the medial part of the clavicle. The leads were fixed by medical tape in order to minimize motion artifacts. To keep the interelectrode resistance low, the skin was cleaned with 70% isopropyl alcohol.

For neck flexion endurance test, the subjects lain in a supine position on the examination bed while their knees were at 60° angle. After 1 minute adaptation period, volunteers were asked to flex their neck and hold it at 20° with the aid of examiner and in this position, jut out the chin as far as possible and maintain this condition until exhaustion. During the examination, the subjects were asked to announce the time, when they have felt fatigue for the first time, i.e. when the subjects felt fatigue but still able to continue recording. This moment was marked by comment which is one of the LabChart 7.3 software facilities. Thus, primary and manually labeling of data into fatigue and nonfatigue classes became possible.

2.3. Feature Extraction

Since fatigue itself is not a physical variable, its assessment requires the definition of indices based on physical variables that can be measured, such as force, power, or variables associated to the EMG signal, such as amplitude and spectral estimates [4,9]. In order to quantify muscle fatigue, first sEMG signals were split into one second frames with 50% overlap. Then 6 features in time, frequency and time- scale domains were extracted from each frame. The features were normalized to come into a suitable scale. It should be noted that all analyses of sEMG data were performed by MATLAB R2010a software (Mathworks Inc, USA). Table 1, shows the extracted features for muscle fatigue quantification.

ZCR: The Zero Crossing Rate (ZCR) is defined as half the number of zero crossings of $x(t)$ per second. This feature indicates the number of baseline crossings of EMG signal.

$$ZCR = \frac{1}{2N}\left[\sum_{k=1}^{N-1}\left|\operatorname{sgn}[x(k)] - \operatorname{sgn}[x(k-1)]\right|\right] \quad (1)$$

Where x(k) is the time series of signal, N is the number of samples in one frame and sgn is the sign function [2,12,13].

RMS: Root Mean Square (RMS) of sEMG signal is indicative of firing frequency, duration and velocity of the myoelectric signal. The increment of this feature shows the recruitment of extra motor units to produce constant force and is an index of fatigue development.

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \quad (2)$$

Where x_i is the i^{th} sample of a signal and N is the number of samples in each frame [2,12,13].

AIF: Averaged Instantaneous Frequency (AIF) is a new frequency variable for monitoring the frequency decrement of surface EMG signals during sustained isometric contractions. AIF is based on the concept of the instantaneous frequency and overcomes the shortcomings of mean and median frequency features by avoiding the problem of spectral estimation. In addition, it does not require any quasistationarity assumptions, since it is inherently suitable for nonstationary signals. This index can be calculated by the following equation:

$$AIF = \frac{1}{t_b - t_a}\int_{t_a}^{t_b} w_i(t)dt \quad (3)$$

Where $\omega_i(t)$ is the instantaneous frequency of the signal and $[t_a, t_b]$ is the frame length (1 second) [5].

DF: Dominant Frequency (DF) finds dominant frequency within the selected frequency band (usually estimated using Welch's method). In this paper, a frequency band of 15 Hz to 45 Hz has been selected (since they have repeated most frequently) [10,13].

WIRM1M51: Wavelet Index of Ratios between Moment -1 at Maximum energy scale and Moment 5 at scale 1 (WIRMIM51) that can be described by (4):

$$WIRM1M54 = \frac{\int_{f_1}^{f_2} f^{-1} D_{\max}(f).df}{\int_{f_1}^{f_2} f^{5} D_1(f).df} \quad (4)$$

Where $D_{max}(f)$ and $D_1(f)$ are the power spectra calculated using Fourier transform of the maximum energy and first scales of the DWT (Discrete Wavelet Transform) using the wavelet sym5, respectively, and f_1= 10 Hz and f_2= 500 Hz [4,13]. Here, maximum energy scale was 4.

WIRE51: Wavelet Index of Ratios of Energies at scale 5 and 1 (WIRE51) that can be described by (5):

$$WIRE51 = \frac{\sum_{i=1}^{N} D_5^2[n]}{\sum_{i=1}^{N} D_1^2[n]} \quad (5)$$

Where $D_5(f)$ and $D_1(f)$ are the details at scales five and one, respectively of the DWT calculated using wavelet sym5 [4,13].

Table 1. Extracted features from sEMG signals.

Time Domain	Frequency Domain	Time- Scale Domain
ZCR	AIF	WIRM1M51
RMS	DF	WIRE51

2.4. Classification Using SVM

Application of support vector machine (SVM) for classification problems is a new approach which became popular in recent years. The SVM approach is that in the training phase, it tries to select the decision boundary so that its minimum distance from each of the classes becomes maximum. This selection caused decision to bear the noisy situations in practice and to have a good response. This boundary selection method is based on the points called support vectors [11].

The linear SVM problem is a two- class classification problem using linear models. In practice, however, the class conditional distributions may overlap, in which case the exact separation of the training data can lead to poor generalization. Thus there is a need to modify SVM because the solution for linearly separable data is not applicable for nonlinearly separable case [3]. One solution is to allow some of the training points to be misclassified. To do this, the slack variables, $\xi_i \geq 0$, are assigned to each training data point. Another solution is the use of nonlinear SVM. Nonlinear SVM operates in two stages: (1) nonlinear mapping of the feature vector onto a high dimensional space and (2) construct an optimal separating hyperplane in the high dimensional space [11].

Since SVM is a supervised learning method, it is necessary to label each frame before processing. Signal labelling into (0) fatigue and (1) nonfatigue classes is performed based on self- report of subjects.

2.4.1. RBF Kernel

In this study, linear and nonlinear SVM are used for EMG signal classification. To implement nonlinear SVM, the kernel function should be introduced. Here, we have used radial basis function (RBF) kernel. RBF kernel can be defined as (6):

$$k(X_i, X_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2s^2}\right) \quad (6)$$

This kernel function is basically useful for data which their class conditional probability distribution function is Gaussian. RBF kernel maps such data into another space where the data become linearly separable [11].

3. RESULTS

3.1. Changes in sEMG Indices over the Time

Manifestations of muscle fatigue in EMG signals were analyzed by monitoring the time course of the features. In order to monitor the change of features during neck flexion endurance test, as mentioned before, we performed signal framing. Feature values were calculated for each frame of data and for each subject, using equations in section 2.3 and were plotted according to the number of frames. Figure 1, 2 and 3 shows time course of ZC, RMS and AIF for subject 4. Initial value and the rise or fall rate of these variables during sustained contraction are usually calculated, since they are of physiological importance [5]. These parameters are estimated by fitting a least-square regression line to the data points (the intercept and slope of a linear regression).

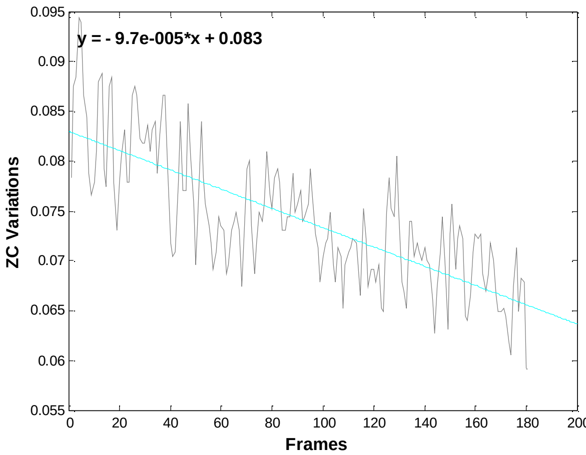

Fig. 1. Time course of ZC during neck flexion endurance test for subject 4. The frame length was 1 second. The values of the slope and intercept of the linear regression is also shown.

When muscle activity increases, the more action potential will produce which leads to the increase in the number of zero crossings. But when fatigue starts, this feature decreases because of the decrease in muscle fiber conduction. Thus, it is expected that the slope of regression line in Figure 1, be descending.

RMS of EMG signal, usually increases considerably during submaximal contractions due to the recruitment of extra motor units and an increase in firing frequency. Both are the mechanisms to cope with the declining force output. Positive slope of the regression line in Figure 2, also confirms this claim.

In this paper, we introduced a new frequency variable (AIF) for monitoring the frequency decrement of surface EMG signals during isometric contractions. This new variable, in addition to overcome the shortcomings of conventional frequency variables (mean and median frequency) by avoiding the problem of spectral estimation, also does not require any quasistationarity assumptions, since it is inherently suitable for nonstationary signals.

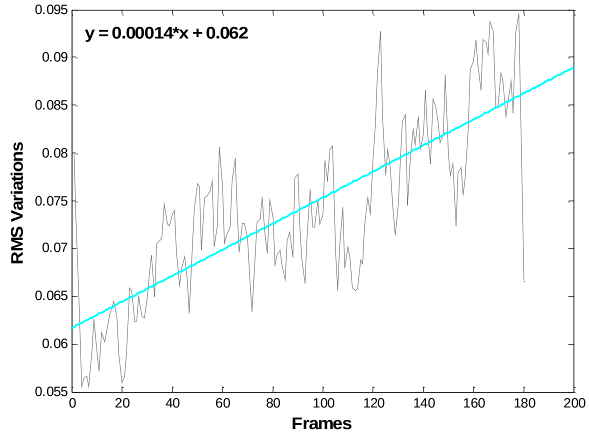

Fig. 2. Time course of RMS during neck flexion endurance test for subject 4. The frame length was 1 second. The values of the slope and intercept of the linear regression is also shown.

During isometric contractions, sEMG signals can be assumed to be locally stationary for a period of 0.5- 1.5 second. Thus, frame lengths are chosen to be 1 second, in this study. Figure 3, shows the time course of AIF index. As it was expected, the slope of linear regression line is descending.

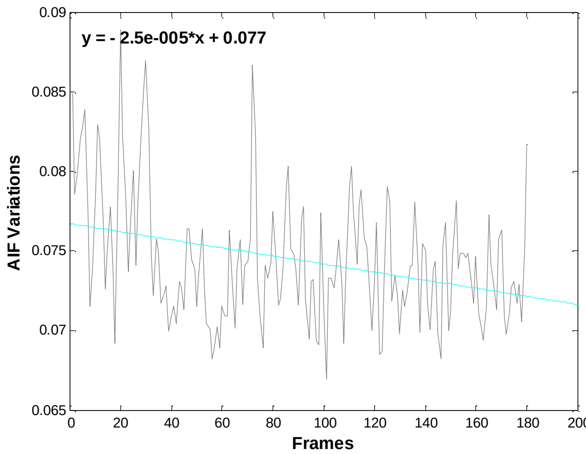

Fig. 3. Time course of AIF during neck flexion endurance test for subject 4. The frame length was 1 second. The values of the slope and intercept of the linear regression is also shown.

Figure 4, compares the values of the slope of regression lines obtained by mean frequency, median frequency and AIF methods for eight different frame lengths (from 250ms to 2000 ms). Results show that the frame length does not affect the time evolution curve of AIF, at least in the case of isometric contractions. Indeed, its effect is negligible in comparison with mean and median frequency. This figure is indicative of the stability and robustness of the estimations of the slope over different frame length when using AIF method. Similar results were obtained for all subjects.

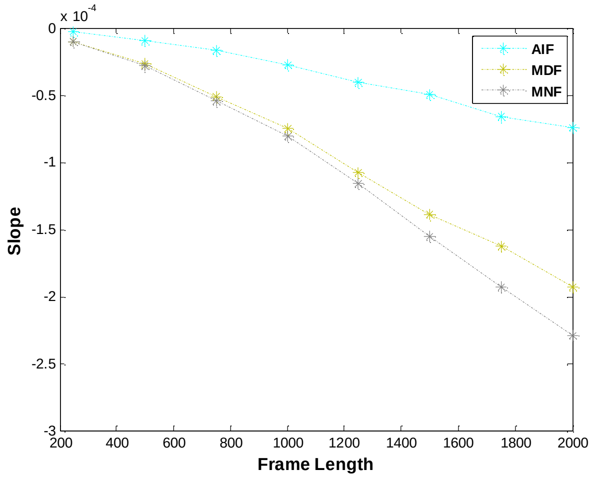

Fig. 4. The slopes of regression line for calculated AIF, mean (MNF) and median (MDF) frequency for different frame lengths for subject 4.

3.2. Dimensionality Reduction and Classification

For many learning domains, like the situation in this article, some features are defined which are potentially useful for training and classification. However, not all of these features may be relevant. In such a case, choosing a subset of the original features will often lead to better performance. For supervised learning, feature selection algorithms maximize some function of predictive accuracy. In this study, MATLAB dimensionality reduction (DR) toolbox is used for feature selection. DR is a toolbox with MATLAB implementations of 27 techniques for dimensionality reduction and 6 techniques for intrinsic dimensionality estimation. Dimensionality reduction is the transformation of high-dimensional data into a meaningful representation of reduced dimensionality. Ideally, the reduced representation has a dimensionality that corresponds to the intrinsic dimensionality of the data. The intrinsic dimensionality of data is the minimum number of parameters needed to account for the observed properties of the data. Thus, first, we used a global intrinsic dimensionality estimator named Geodesic Minimum Spanning Tree (GMST). The estimated dimensionality by this estimator, was 3. Then, Local Linear Embedding (LLE) method was used to choose appropriate features from six extracted features. Selected features using this criterion were ZC, RMS and AIF. Then this feature vector was applied to SVM classifier, in order to classify data into fatigue and nonfatigue classes. After training SVM classifier using training dataset, the performance of the classifier was evaluated for test set with linear SVM and SVM with RBF kernel. Table 2, shows the accuracy achieved by linear SVM and SVM with RBF kernel and Figure 5 indicates the result of separation using linear SVM in 2 dimensions.

Table 2. The accuracy achieved by linear and RBF kernel SVM.

Kernel Type	Linear	RBF
Test Accuracy	56.7%	91.16%

As can be seen in (6), RBF kernel function has the parameter named σ which should be defined by user. Sigma should be positive. The value of this parameter affects the accuracy of SVM classifier, considerably. The number and the value of support vectors are determined automatically. In order to evaluate the effect of sigma on the performance of SVM classifier, different σ values were used. The best accuracy was achieved with σ equal to 0.5.

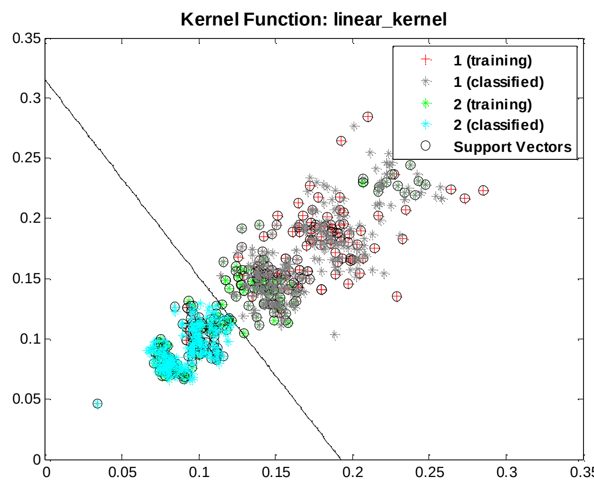

Fig. 5. The result of the classification of EMG signals into fatigue and nonfatigue stages using linear SVM.

Table 3, indicates the accuracy achieved by RBF kernel with different σ values in 3 dimensions and Figure 6 shows the effect of σ in decision surface and boundary and number of support vectors in 2 dimensions. As can be seen in Table 2 and 3, the best accuracy is achieved for σ=0.5 in RBF kernel function.

Table 3. The accuracy achieved by RBF kernel SVM for different sigma values.

Sigma	0.2	0.5	1	1.5
Test Accuracy	56.7%	91.16%	89.73%	85.74%

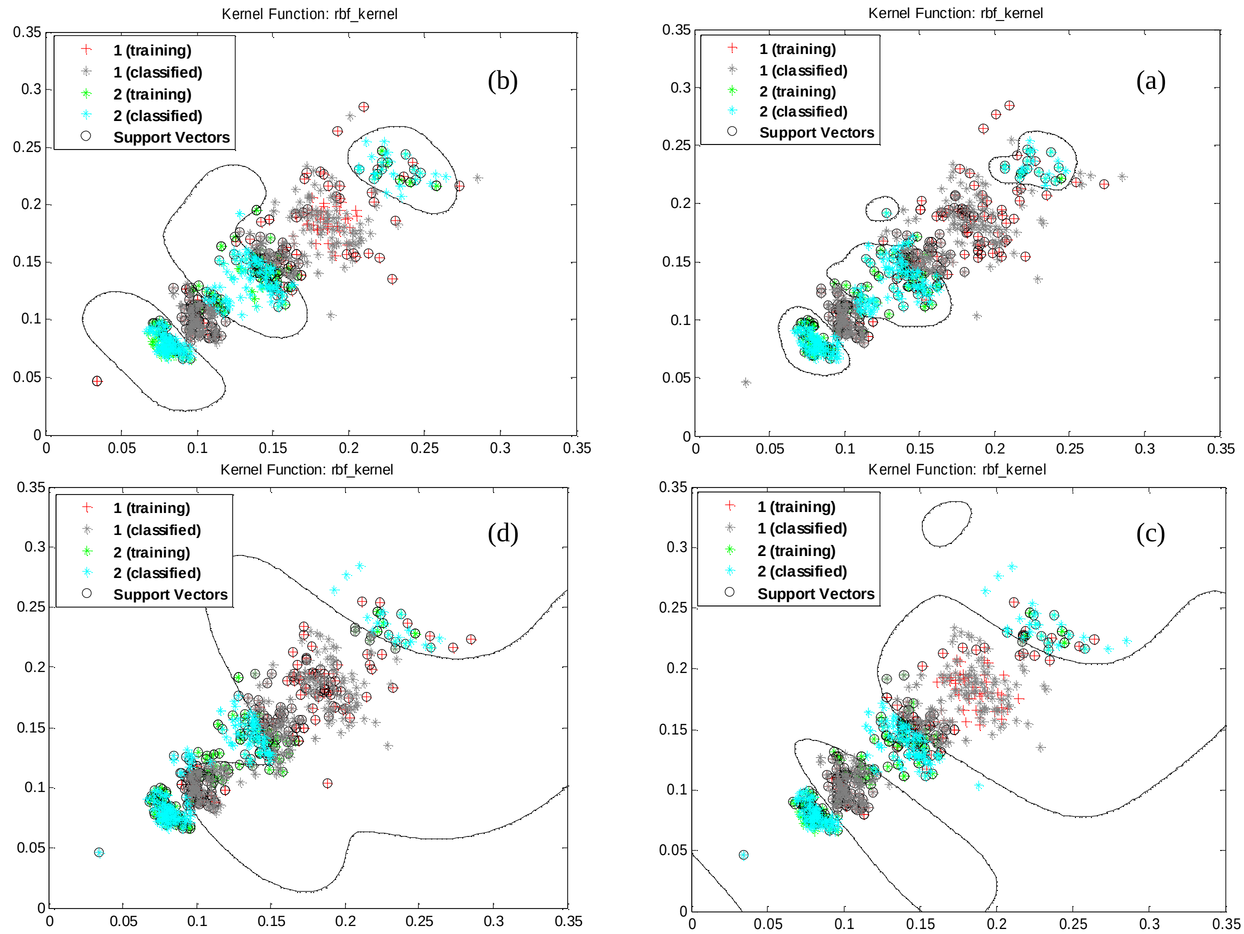

Fig. 6. The results of classification with RBF kernel and different σ values (a) σ=0.2, (b) σ=0.5, (c) σ=1, (d) σ=1.5.

4. CONCLUSION

Fatigue is a subjective concept and its definition is very complex, not unique and controversial. The detection and classification of muscle fatigue, provides useful information in many research areas. For example, in the branch of ergonomics which deals with musculoskeletal disorders, muscle fatigue may be considered as a major risk factor. Fatigue detection and classification through biofeedback system, may contribute to an awareness of a sustained muscle activation patterns. Fatigue classification also can be applied to the fields of human- computer interactions, sport injuries and performance.

During a sustained voluntary contraction, even when there is no voluntary change of muscle state, the EMG signal can be considered to be nonstationary; simply due to the inherent physiology of the organ. With the development of computer technology, spectral analysis of EMG signals has been widely used to estimate localized muscular fatigue. As a muscle fatigues, there is a concomitant change in the power spectrum derived from surface EMG signals where there is an increase in the amplitude of the low frequency band and a relative decrease in the higher frequencies. Physiologically, the frequency shift has been attributed to changes in conduction velocity, changes in intra-muscular pH, modification in the recruitment and synchronization of the motor units and the fiber type. The most commonly used frequency variables in EMG studies are central tendency measures (mean and median) and ratios of the power of high and low frequency bands. But, these features are not compatible with nonstationary nature of EMG signals. In this paper, different features in time, frequency and time- scale domain were used. Among these features, it was expected that ZC and AIF had better performance as a feature vector delivered to SVM classifier. This hypothesis was approved by selecting these features by wrapper feature selection algorithm introduced in section 3.2. Then, linear and nonlinear SVM with RBF kernel were used to classify sEMG signals into fatigue and nonfatigue classes. The kernel function or nonlinear mapping results in different kinds of support vector classifiers (SVCs) with different performance levels. But the choice of the appropriate kernel for a specific application is often a difficult task. A necessary and sufficient condition for a Kernel to be valid is that it must satisfy Mercer's Theorem, but other than that, there is really no mathematically structured approach to prefer one kernel over the other. But, if the data is known to be nonlinearly separable, we would expect that a nonlinear kernel based SVC would perform better than the one based on a linear kernel. Since the data in this study was nonlinearly separable, so it is reasonable to expect that the nonlinear SVM with RBF kernel has better performance than the linear one. The results of the classification accuracy shown in Table 2 approve this claim (56.7% for linear SVM versus 91.16% for RBF kernel). In general, the RBF kernel is a reasonable first choice. Because, first, this kernel nonlinearly maps samples into a higher dimensional space so it, unlike the linear kernel, can handle the case when the relation between class labels and attributes is nonlinear. Furthermore, the linear kernel is a special case of RBF. The second reason is the less number of hyperparameters which reduces the complexity of model selection. Finally, the RBF kernel has fewer numerical difficulties. However, this kernel is difficult to design, in the sense that it is difficult to reach an optimum σ. The fact that certain σ value makes the SVM highly sensitive to training data also contributes to the error rate of the RBF- based SVM. A larger value of σ will give a smoother decision surface and more regular decision boundary. This is because an RBF with large σ will allow a support vector to have a strong influence over a larger area. A larger σ value also increases the α value (the Lagrange multiplier) for the classifier. In this study, the best accuracy achieved with σ= 0.5. One of the advantages of the RBF kernel is that given the kernel, the α_i (the Lagrange multipliers), the number of support vectors and the support vectors are all automatically obtained as a part of the training procedure, i.e. they need not be specified by the training mechanism. At the end, we can summarize the advantages of SVM and the reasons for using it as a classifier in comparison with other classifiers as follow: (1) There are no problems with local minima, because the solution is a quadratic programming (QP) problem. (2) There are few model parameters to select. (3) The final results are stable and repeatable. (4) SVM is a minimum memory space approach. (5) SVM provides a method to control complexity independently of dimensionality. (6) SVM have been shown (theoretically and empirically) to have excellent generalization capability.

5. ACKNOWLEDGMENT

The authors would like to thank Islamic Azad University, Mashhad Branch which provides equipments needed for research and data acquisition and Mashhad University of Medical Sciences, department of neurology which allowed us to collect our data in Quaem Hospital and also a special thanks to all the participants who helped us in completing the study.

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