# The Application of Machine Learning Algorithms to the Analysis of Electromyographic Patterns from Arthritic Patients

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***Abstract*— The main aim of our study was to investigate the possibility of applying machine learning techniques to the analysis of electromyographic patterns (EMG) collected from arthritic patients during gait. The EMG recordings were collected from the lower limbs of patients with arthritis and compared with those of healthy subjects (CO) with no musculoskeletal disorder. The study involved subjects suffering from two forms of arthritis, viz, rheumatoid arthritis (RA) and hip osteoarthritis (OA). The analysis of the data was plagued by two problems which frequently render the analysis of this type of data extremely difficult. One was the small number of human subjects that could be included in the investigation based on the terms specified in the inclusion and exclusion criteria for the study. The other was the high intra- and inter-subject variability present in EMG data. We identified some of the muscles differently employed by the arthritic patients by using machine learning techniques to classify the two groups and then identified the muscles that were critical for the classification. For the classification we employed least-squares kernel (LSK) algorithms, neural network algorithms like the Kohonen self organizing map, learning vector quantification and the multilayer perceptron. Finally we also tested the more classical technique of linear discriminant analysis (LDA). The performance of the different algorithms was compared. The LSK algorithm showed the highest capacity for classification. Our study demonstrates that the newly developed LSK algorithm is adept for the treatment of biological data. The muscles that were most important for distinguishing the RA from the CO subjects were the soleus and biceps femoris. For separating the OA and CO subjects however, it was the gluteus medialis muscle. Our study demonstrates how classification with EMG data can be used in the clinical setting. While such procedures are unnecessary for the diagnosis of the type of arthritis present, an understanding of the muscles which are responsible for the classification can help to better identify targets for rehabilitative measures.**

***Index Terms*— EMG, gait data, kernel methods, 3D locomotion analysis, neural networks, osteoarthritis, rheumatoid arthritis.**

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## I. Introduction

Arthritis is a disease in which there is damage present in the joints. It has been estimated that more than 21% of US adults (46.4 million persons) have had doctor-diagnosed arthritis [1]. Our patients consisted of subjects suffering from two common forms of arthritis: hip osteoarthritis and rheumatoid arthritis. In osteoarthritis (OA) low grade inflammation results in pain in the joints caused by the wearing of the cartilage that covers and acts as a cushion inside the joints. Rheumatoid arthritis (RA) on the other hand is a chronic inflammatory autoimmune disorder. It affects the distal extremities. All arthritis in the lower limbs therefore affects gait and impinges on the capacity of a patient to lead an independant life.

Currently in the clinical setting, gait disorders are primarily studied using kinematics as opposed to electromyographic data. Kinematics is the study of the limb displacement in space. Electromyographic (EMG) activity is the electrical activity of muscles. The use of EMG recordings in order to classify and understand neuromuscular disorders is however promising for many reasons. In the first place, EMG data in many situations has been found to vary significantly based on the type of gait being examined, while the kinematic data was found to be relatively invariant. This was found to be true when studying the EMG and kinematic recordings of backward versus forward locomotion [2], the changes in gait following spinal cord injuries [3] and the locomotion in reduced gravity [4]. Secondly, the EMG is a physiological measure which brings us closer to understanding the neuromuscular adaptations to such joint disorders. One of the major reasons for the current underutilization of EMG data is the difficulty in treating such data. Compared to kinematic data, it shows a much greater inter-individual and inter-cycle variability [5] and [6]. Electromyographic activity is also subject to several sources of noise such as electrical noise, motion artefacts and cross talk [7]. Cross talk refers to the influence that the electrical signals from one muscle could have on another.

Concerning research, another difficulty with such studies can be the limited number of subjects. Despite the wide prevalence of arthritis in an ageing population, a proper understanding of the effects of joint disorders on gait requires strict exclusion criteria. This is due to the fact that the vast majority of arthritis patients and the accompanying control subjects are more advanced in age and also suffer from other problems that significantly affect gait such as diabetes and non stabilised hypertension. The exclusion of subjects with

these disorders, limited the number of subjects that could be included in the study. The controls were required to be from an age group matching those of controls. The same criteria for exclusion as applied to patients were also applied to controls. In addition, for the latter group, any sign of arthritis was a reason for exclusion from the study. A more detailed description of the exclusion and inclusion criteria can be found in the Methods section.

It is important to identify the differences in the muscular activity during the gait of patients suffering from arthritis. This would lead to improvements in the rehabilitative measures that are currently used for such patients such as physical activity. Several studies have now demonstrated the positive effects of physical activity in the case of arthritis patients [8], [9] and [10]. Techniques such as electro muscle stimulation for muscular strengthening are being developed for rehabilitation [11]. These measures are currently undertaken in a general fashion without a proper understanding of the muscles which are functioning in a manner which is significantly different from that of healthy subjects. In the best of conditions, a kinematic gait analysis might be conducted [12] and [13]. However, even if a kinematic change is detected, it could be due to many different patterns of altered muscular activity. Physical activity for rehabilitation is best undertaken with an understanding of the muscles which are involved. Once the muscles which are the most altered are identified, they could also be used to objectively follow the evolution of a patient following some treatment.

In this study we explore the potential of several machine learning techniques for the analysis of EMG data recorded during gait. From all the problems mentioned in the paragraph above, it is clear that EMG studies would benefit greatly from analyses that are fault tolerant. We therefore applied several neural network and kernel method analyses to the problem. These more recently developed methods were also compared to the more classical LDA technique. The problem was approached as a classification task to distinguish control subjects from arthritic patients. Identifying the muscles that are critical for the classification would then help us to differentiate the muscular activity between the two groups. Another purpose of the study was to test the capacity of the LSK algorithms, that were recently developed by Dodd et al. [14] and Nair [15]. Biological data can be very difficult to analyze due to problems of high dimensionality and noise. Here, we test the capacity of this newly developed kernel methods for treating biological data.

The machine learning techniques explored in the study were neural networks, the kernel methods and LDA. As opposed to neural networks and the kernel methods, LDA as the name suggests is a linear technique that finds linear transformations of the dependent variables that would provide for a better classification than the individual variables. Neural networks and the kernel methods represent two more recent developments in the history of machine learning. Neural networks borrow some concepts from neuronal processing. The neural network methods tested in this study were a Kohonen self organizing map (SOM), learning vector quantization (LVQ) and the multi layer perceptron (MLP). The kernel methods are a class of algorithms that use a kernel function in order to transform a nonlinear learning problem into a linear one. Kernel methods can be divided into different types depending upon the loss function that is used [16]. Some examples of kernel algorithms are support vector machines which are based on statistical learning theory, gaussian processes which were developed using a Bayesian/probabilistic approach and finally, regularization networks, which make use of functional analysis concepts. The LSK kernel methods described in this paper belong to the category of regularization networks.

The LSK algorithms use the reproducing kernel Hilbert space (RKHS) theory and Tikhonov regularization principle for data modeling and the conjugate gradient (CG) algorithm for finding the solution of the model. Four different variations of LSK algorithms, viz, CGF, CGPI, CGPII and CGPIII were discussed in [14] and [15]. (The differences between these four subtypes are described in the Section II-B and Appendix). The capacity of these algorithms for treating biological data however has never been explored. In this paper we investigated the potential of these algorithms for extracting information from highly complex data like EMG recordings.

Several nonlinear machine learning methods have been applied previously to the study of kinetic, kinematic and EMG data gathered from gait studies. Kinetic data comes from foot pressure measurements while kinematic data comes from the study of limb displacements in space. Several kinds of neural networks have been used for classifying kinematics and kinetic data with various degrees of success. A good review on the subject can be found in work by Chau [17] and [18]. The EMG data in these studies were mostly used for the nonlinear mapping between EMG and kinematic or kinetic variables. The EMG data has therefore been used to predict tendon forces [19] and [20], basic gait parameters such as velocity and cadence [21] and elevation angles of the lower limbs [22]. In the realm of kernel methods, there has been an application of support vector machines to the study of kinematic data in order to classify kinematic patterns in cerebral palsy patients [23] as well as for categorizing the gait of old and young subjects [24] and [25]. All these studies indicate that these techniques hold much promise in understanding arthritis. Our research is original in comparing neural networks and some kernel methods for the classification of EMG data. These signals are more complicated and show a greater intra- and inter-subject variability than kinetic or kinematic signals. Since gait is a function that is frequently affected in arthritis, we carry out an investigation of the effectiveness of these different methods of machine learning in studying EMG data from arthritic patients. We demonstrated in this study that despite the difficulties involved in analyzing EMG data, that they can be exploited by machine learning techniques for further understanding of the disorder.

## II. METHODS

In this section we provide a description of the methods used to carry out the study. We first describe how the EMG data was collected. Information concerning some aspects of these experiments has already been published [26]. Concerning

the theoretical techniques only a brief description of LDA, SOM, LVQ and MLP are given as these are relatively old, well published techniques. As the LSK is a new variant of the kernel method a more elaborate explanation has been provided both in the Methods section and the Appendix. This is followed by an explanation of the measures that are used to evaluate the different machine learning techniques. Finally we explain how we identified the muscles that were critical for the classification.

### A. EMG Data Gathering

The raw material for our study was the EMG data collected from CO, RA and OA subjects. The RA group consisted of eight outpatients, while ten outpatients were in the OA group. Patients were defined as suffering from rheumatoid arthritis based on the criteria established by the American Rheumatism Association or as suffering from hip osteoarthritis based on the criteria established by the American College of Rheumatology. The age of the members of the CO, RA and OA groups were $60 \pm 7$ years (mean age $\pm$ std deviation). All subjects in the RA and OA groups were assessed by an experienced rheumatologist. Exclusion criteria applied to the RA and OA patients were other musculoskeletal disorders, Alzheimer disease, Parkinson disease, motor neuron disorders, non-stabilized diabetes mellitus, blood hypertension, respiratory insufficiency, pregnancy and lactation. For control subjects, these criteria and in addition, the presence of any arthritis, were reason for exclusion from the study. All participants gave their informed consent for participation in the study, which was approved by the local ethic committee and conformed with the declaration of Helsinki.

The EMG data were recorded at a rate of 2000 Hz by means of bipolar surface electrodes (1 cm diameter, electrode separation of 1 cm) which were placed over six muscular groups of each leg of the RA patients. The muscles recorded from were the soleus, gactrocnemius medialis, peroneus brevis, tibialis anterior, vastus lateralis, and biceps femoris. For the OA patients, the muscles recorded from were the soleus, gactrocnemius medialis, gluteus medialis, tibialis anterior, vastus lateralis, and biceps femoris. Electromyographic recordings were obtained from seven muscles of each leg for the control subjects. These muscles were the soleus, gactrocnemius medialis, peroneus brevis, tibialis anterior, vastus lateralis, biceps femoris and gluteus medialis. The appropriate muscles were then used from the CO muscle pool for each type of classification. A ground electrode was placed on the wrist. Signals were preamplified (x100), digitized, and transmitted to the remote amplifier via telemetry. The EMG data from each trial were first filtered with zero-phase 5th order band-pass Butterworth filter at 20-400 Hz and full-wave rectified. The resulting EMG signal was normalized with respect to the mean EMG activity measured during the whole gait cycles. Finally, EMG recordings were time interpolated over individual gait cycles to fit a normalized 200-point time base. An illustration of the EMG data collected from the right gluteus of an RA subject is given in Figure 1.

### B. LSK methods

The LSK methods were developed using RKHS theory [27] and the Tikhonov regularization principle [28]. The theoretical background of the functional & parametric learning models and CGF are discussed below. In the appendix we have provided a description of CGPI, CGPII and CGPIII.

Consider a two category classification problem, $\{(x_1, z_1), (x_2, z_2), \ldots, (x_N, z_N)\}$, $x_i \in \mathcal{X} \subseteq \mathbb{R}^m$, $z_i \in \mathbb{R}, i = 1, 2, \ldots N$, and $\mathcal{X}$ is a normed space. Let $z_i \geq 0$ if $x_i \in C_1$ and $z_i < 0$ if $x_i \in C_2$ where, $C_1 \subset \mathbb{R}^m$ and $C_2 \subset \mathbb{R}^m$ are the two given classes. Assume there exists an unknown function $f$ that generates the given data. Hence

$$f(x) \begin{cases} \geq 0, \ x \in C_1 \\ < 0, \ x \in C_2 \end{cases}$$

Let $f$ belong to a RKHS $\mathcal{F}$, defined on $\mathcal{X}$. (By [42] a RKHS, $\mathcal{F}$, is a Hilbert space of real valued functions on some set $\mathcal{X}$ in which all the point evaluations are bounded linear functionals). Then the given learning problem can be represented in functional and parametric forms [14] and [15]. The functional representation of the learning problem is

$$z = Lf = \sum_{i=1}^{N} (L_i f) e_i \tag{1}$$

where $L : \mathcal{F} \rightarrow \mathbb{R}^N$ is a bounded linear operator, $z = [z_1, z_2, \ldots z_N]^T$, $L_i : \mathcal{F} \rightarrow \mathbb{R}$ is a bounded linear operator such that $L_i f = z_i$ and $e_i \in \mathbb{R}^N$ is the $i$th standard basis vector. Since $f = L^* c$, where $L^*$ is the Hilbert adjoint of $L$ [29], (1) can be represented as

$$z = LL^* c = \sum_{i=1}^{N} (L_i f) e_i \tag{2}$$

For the finite dimensional case, $LL^* = K$, where $K = [k(x_i, x_j)]_{ij}$ is the kernel matrix [29]. Here, $k$ is the reproducing kernel of $\mathcal{F}$. Now (2) can be written as

$$z = Kc = \sum_{i=1}^{N} (L_i f) e_i \tag{3}$$

Equation (3) is the parametric representation of the learning problem.

For practical reasons, a regularized cost function has to be used in order to solve the above linear models. This is because (1) and (3) suffer from numerical instabilities and hence the solution is not insensitive to noise. Using the Tikhonov regularization with a suitable regularizing operator, stable approximations for inverse problems can be found.

The Tikhonov functional corresponding to (1) is

$$J_{reg}(f) = ||Lf - z||^2_{\mathcal{F}} + \mu ||f||^2_{\mathcal{F}} \tag{4}$$

where, $\mu > 0$ is the regularisation parameter. The solution $f_{reg}$ that minimizes $J_{reg}(f)$ is called the regularized solution of (1). Finding a function that minimizes (4) is equivalent to solving its normal equation [30]. The normal equation of a cost function is obtained by taking its gradient and equating it to zero [31]. The normal equation corresponding to (4) is

$$(L^* L + \mu I) f = L^* z \tag{5}$$

The CG algorithm derived for solving (5) is named as CGF [14] and [15]. A more complete description of the development of the LSK algorithms can be seen in studies done by Dodd et al [14] and Nair [15].

### C. LDA

LDA is a classical, supervised method that makes use of statistical approaches for dimensionality reduction and classification. It maps high dimensional data to a low dimensional space using a transformation matrix. The optimal transformation matrix is determined by minimizing the inter-class distance and maximizing the intra-class distance of the classes of objects under study [32].

### D. SOM and LVQ

Kohonen's self organizing map (SOM) is an unsupervised method that maps high dimensional data to a low dimensional space. The topological and metric properties of the data are preserved in the Kohonen mapping. The network has nodes that are arranged linearly or in a grid pattern. The nodes are fully connected to the input layer, which means associated with each node there exists a weight vector having dimension equal to the input space. During the training phase, the Euclidian distance is calculated between the input training vector and the nodes of the network. The node corresponding to the smallest distance becomes the winner. Weight changes are then made for the winning node and for its closest neighbours. The weights during the training phase (t) are updated according to the following equation

$$\delta w_{ki} = \eta(t) \exp -[d(k,c)^2 \frac{1}{2(\sigma(t))^2}][x_{ki}(t) - w_{ki}(t)]^2 \quad (6)$$

where $w_{ki}$ is the weight vector associated with input vector $x_i$ and the node $k$. The term $\delta w_{ki}$ is the change in $w_{ki}$, $\eta(t)$ is the learning rate, $\sigma(t)$ is the learning radius, $d(k,c)$ is the distance from the winning node $c$ to the $k$th node and $x_{ki}$ is the $k$th component of the input vector $x_i$. The factors controlling $\eta(t)$ and $\sigma(t)$ were not constant but decreased gradually according to the following equation

$$\eta(t) = \eta_i(\eta_f/\eta_i)^{t/T} \quad (7)$$

where $\eta_i$, $\eta_f$ are pre-defined constants, $t$ is the epoch and $T$ is the total number of epochs. A similar equation was also used for decreasing $\sigma(t)$. A complete desciption of the Kohonen network can be found in [33] and [34].

Learning vector quantization is a supervised version of SOM. The network architecture of LVQ is same as that of SOM, except that it uses labeled nodes. The weight change equation for LVQ is the same as that for the Kohonen SOM except that it is multiplied by a factor +1 for correct classifications and -1 for incorrect classification [33].

### E. MLP

We compared the LSK methods to a standard MLP network. The MLP is trained using a feedforward-backpropagation (FFBP) algorithm [35]. The network was constructed using the typical three-layer architecture with an input layer, a so-called "hidden" layer and an output layer. Inputs to the network were arranged to be bipolar. There was also a "bias" node on input, which provided an output threshold.

The $tanh$ squashing function was used instead of a sigmoid function in order to avoid a slow convergence. Another measure taken to avoid this problem was the use of the Fahlman offset [36] and [33]. A momentum term is also added to the weight change value. This is a fraction of the previous weight change for that node and ensures a smoother convergence trajectory.

### F. Input data preparation and testing protocol for the algorithms

The inputs for the classification consisted of vectors of dimension $2400$. This corresponds to the EMG recordings of twelve muscles sampled at 200 points in one locomotion cycle placed end to end. As for each subject, the EMG data was recorded for several cycles. Each subject was therefore associated with several EMG vectors each of dimension $2400$. The mean number of EMG vectors associated with each subject of the CO class was 11. For the RA class it was 13 and finally for the OA class it was 18.

The EMG data from the RA patients contained missing values and artifacts (7.86%). Those values were imputed with the regularized expectation maximization (EM) algorithm [37] and [38]. The EM algorithm is an iterative method for computing the maximum likelihood estimates of the parameters from incomplete data [38]. In the regularized EM algorithm Tikhonov regularization principles [28] are also used for obtaining a unique solution.

The data was normalized using the linear method, i.e., for each muscle its maximum activity was set to be one and its minimum activity was set to zero. Such a normalization procedure was adopted to give an equal importance to all the muscles and also to preserve information concerning differences in EMG amplitude between patients and control. Experiments were done by applying CGF, CGPI, CGPII, CGPIII, SOM, LVQ, MLP and LDA. A cross validation procedure was used for the training and testing. For each question investigated, a total of 30 trials were conducted. For each investigation, eighty percent of the subjects (with all the cycles associated with that subject) from each class was chosen randomly by the algorithm for training. The remaining subjects were then used for testing. At no point was data from the same subject used for training and testing. Differences were determined to be significant by using ANOVAs and a Tukey HSD *posthoc* test. This method of sampling the data for training and testing was successfully used for analyzing neural activity in the inferior temporal cortex with the Kohonen network [39] and by French when studying the problem of catastrophic forgetting in neural networks [40] and [41].

### G. Performance Measures

The performance of the classifiers was determined using accuracy, sensitivity, specificity and the speed of convergence. For the LSK method, we also computed the values for the

receiver operating characteristic (ROC) curves. The following are the definitions of accuracy, sensitivity and specificity

$$\text{Accuracy} = \frac{ar_s + co_s}{ar_s + ar_f + co_s + co_f} \tag{8}$$

$$\text{Sensitivity} = \frac{ar_s}{ar_s + ar_f} \tag{9}$$

and

$$\text{Specificity} = \frac{co_s}{co_s + co_f}. \tag{10}$$

Here $ar_s$ and $co_s$ are respectively the number of arthritis and control test vectors that the classifier identifies correctly and $ar_f$ and $co_f$ are respectively the number of arthritis and control test vectors that the classifier identifies incorrectly.

Sensitivity can be seen as the probability that the test is positive given that the subject is a patient. Specificity can be interpreted as the probability that the test is negative, given that the subject is not a patient.

The performance of the LSK algorithms was also evaluated using the receiver operating characteristic (ROC) curve. The ROC curve of a continuous binary classifier consists of points with (1- specificity) as the x co-ordinate and sensitivity as the y co-ordinate. The points are obtained using different threshold values [43]. The accuracy of the test is higher if the ROC plot bulges towards the upper left corner.

Also evaluated for the study were the number of epochs taken for each algorithm to converge. In the case of MLP, LVQ and SOM the number of epochs for training was chosen in the following fashion: it was the maximum number of epochs following which the performance of the network was not found to improve. The weights in the networks were also not found to change beyond 0.05 units. The CG algorithm converges in at most $N$ steps and hence the stopping criteria for the LSK algorithms was: stop the algorithm when $||J_{reg}(f^{n+1}) - J_{reg}(f^n)|| < 10^{-5}$, where $n < N$ and $f^n$ was the function obtained at the $n$th iteration.

### *H. Identifying the muscles that function differently between patients and controls*

We used the LSK method, viz, the CGF for identifying the muscular differences between controls and patients. This was done by analyzing the classification success showed by LSK after deleting one muscle at a time from the classes under study.

### *I. Hyper parameters*

For applying the LSK algorithms, the RKHS space generated by the Gaussian kernel, $k(x, x^{'}) = exp(-\beta||x - x^{'}||^2)$, where $\beta \in \mathbb{R}$ is the kernel width, was taken as the hypothesis space. The hyper parameters, kernel width $\beta$ and regularization parameter $\mu$ were determined using cross validation [42]. For applying cross validation an initial estimate of the hyper parameter was calculated. Then a search for the hyper parameter was done around the estimated value. The parameters that need to be initialized in the algorithms were always set to 0 which always satisfied the given conditions. The value of $\mu$ for the CO vs RA class was 0.8 while it was 0.03 for the study of the CO vs OA class. Likewise, the values of $\beta$ were 0.01 and 0.00065 for the CO vs RA and CO vs OA studies respectively.

For training using the LSK algorithm, the output points were labeled as $\pm 1$, depending on whether they belonged to the CO or patient class, i.e., for the training points $\{(x_i, z_i), i = 1, 2, \ldots N\}$, $z_i = 1$ if $x_i$ belongs to CO class and $z_i = -1$ if $x_i$ belongs to RA or OA class. For testing, $f(x) = 0$ was selected as the threshold, i.e., a point $x$ was estimated to be in the CO class if $f(x) \geq 0$, else it was estimated to be a patient.

For SOM and LVQ, the networks used in this investigation had 4 nodes arranged linearly. The parameters used were $\eta_i = 1.0$, $\eta_f = 0.03$, $\sigma_i = 10$ and $\sigma_f = 0.1$. These parameters were chosen by using cross validation to give an optimal performance of the network.

The parameters for the MLP network were the following: the number of hidden layer units was 100 and the number of output nodes was 2. The parameters used for the network were the following: learning rate = 0.1, momentum = 0.9, fahlman offset = 0.1 and bias value = -1. These parameters were chosen by using cross validation to give an optimal performance of the network.

## III. Experimental Results

In this section we report the results of our EMG analysis using the LDA, kernel and neural network methods. The results are given in the form of the mean $\pm$ std.deviation. The result section is organized in the following manner. In section III-A we compare the classification performance of the different methods. In section III-B we report on the convergence rates of the different algorithms. In section III-C we provide classification results obtained by using k-fold cross validation for the data sampling. Finally in section III-D, we use LSK to demonstrate which muscle groups are critical in distinguishing patients from controls.

### *A. Classification Performance*

*1) Accuracy:* The accuracy measure gives the overall performance of the algorithms. Fig. 2 gives the accuracy rate of the CGF, LDA and neural network algorithms on CO vs RA data. All the LSK algorithms classified the data with an accuracy rate of around 91% (CGF: $91.48\%\pm$ 7.57%, CGPI: 90.95% $\pm$7.4%, CGPII: 91.41% $\pm$7.52%, CGPIII: 91.48% $\pm$7.57%). On the other hand, all the neural network methods failed to classify the data. The LDA algorithm with a mean performance of 72% $\pm$ 20% performed better than the best neural net performance of 57% $\pm$18% ($p < 0.05$, ANOVA, Tukey HSD *posthoc*).

In the case of CO vs OA data also, LSK showed an excellent performance in terms of the accuracy measure. Fig. 2 gives the accuracy rate of the CGF, LDA and neural network algorithms on CO vs OA data. The accuracy rates of all the four LSK algorithms were around 97% (CGF: 96.67% $\pm$3.77%, CGPI: 97.04% $\pm$ 2.43%, CGPII: 96.7% $\pm$3.86%, CGPIII: 96.71% $\pm$3.79%). Of the four neural network methods, LVQ produced

the best accuracy rate ($89.4\% \pm 11.8\%$), as seen in Fig. 3. In this case, we did not find a significant difference between the performance of LDA and LVQ ($p > 0.05$, ANOVA, Tukey HSD *posthoc*).

*2) Sensitivity and Specificity:* Sensitivity determines the capacity of the algorithms for identifying the positive data (patients with arthritis) while the specificity rate measures their capacity for identifying the negative data (normal subjects). Table I displays the sensitivity and specificity rates of the classification by each algorithm in the case of the CO vs RA class. The LSK algorithms succeeded in identifying both the RA and CO data, as their sensitivities and specificities were around 90%. All the other algorithms failed to predict the RA data, since their mean sensitivities were less than 60%. The abilities of the SOM and LVQ methods for identifying the CO data were much better than for the RA data, as their specificities were greater than 80%. As in the case of the above neural net algorithms, the LDA technique was better at identifying the CO data than the RA data.

All the four LSK methods succeeded in identifying the OA subjects as well as CO subjects as can be seen in Table II. The SOM showed a 100% specificity rate, while it failed to identify the OA data. The LVQ and LDA algorithms succeeded well in detecting the CO class. However they showed a poorer capacity in identifying the OA data. The sensitivity of LVQ was 76.88% $\pm$ 27.95% while that of LDA was 79% $\pm$ 11%. The MLP neural net failed to identify both the OA and CO data.

We compared the performance of the LSK methods using ROC curves also. See figures 4 and 5. The ROC area was approximately equal to one in both the classification tasks. This means that they showed an excellent classification performance.

From the above discussion it is clear that in terms of the three performance measures we used viz, accuracy, sensitivity and specificity, the LSK methods showed a superior performance over SOM, LVQ, MLP and LDA.

### B. Convergence Analysis

The performance of the LSK algorithms and the neural networks were also compared in terms of the number of epochs required for training. The convergence rate of the LSK method depends on the entire eigenspectrum of the kernel matrix $K$ and they converge in at most $r$ steps, where $r$ is the number of distinct eigenvalues of $K$ . In the case of the CO vs RA experiment, the number of distinct eigenvalues of the kernel matrix $K$ was $131 \pm 11$ whereas for the CO vs OA experiment, it was $197 \pm 12$. All the LSK methods took less than 19 epochs to converge in the case of the CO vs RA experiment ( CGF: 9 epochs, CGPI: 11 epochs, CGPll: 18 epochs and CGPlll: 10 epochs) and less than 23 epochs for the CO vs OA experiment (CGF: 15 epochs, CGPI: 13 epochs, CGPll: 22 epochs and CGPlll: 18 epochs). The SOM and LVQ algorithms on the other hand required 1000 epochs for convergence while MLP took 200.

### C. Model evaluation using k-fold cross validation

To ensure that the successful performance of the LSK method was not due to the sampling methods used in the tests above, we also carried out tests using the k-fold cross validation technique [42]. We chose k in such a way that each fold contained atmost 2 subjects. Hence, k was 8 for RA vs CO and 9 for OA vs CO. The reason for not selecting 1 subject per fold (leave-one-out) is due to the high variability associated with it [44]. With 8 fold cross validation, the CGF algorithm classified the RA and CO data with a success of 91.07% $\pm$ 9.7%. The mean sensitivity in this case was 81%$\pm$34% while the mean specificity was 82% $\pm$ 36%. Nine fold cross validation in order to distinguish the CO and OA data using the CGF method also yielded a similar success rate of 93.42% $\pm$ 8.52%. The mean sensitivity in this case was 91% $\pm$ 20% while the mean specificity was 84% $\pm$ 35%.

### D. Identification of important muscles by deletion

Using CGF we identified some of the important muscular differences between patients and controls, as described in Section II-H. Table III shows the classification capacity of the algorithm after deleting each muscle at a time from the CO vs OA class. The deletion of information from the gluteus medialis dropped the classification rate to 74.57%$\pm$14.76%. On the other hand, the classification capacities of the algorithm following the elimination of a muscle other than the gluteus medialis was greater than $91\%$ (see Table III). Any decrease in performance with the elimination of any muscle other than the gluteus medialis was not found to be significant ($p > 0.05$, ANOVA, Tukey HSD *posthoc*). The elimination of the gluteus medialis effected the capacity for the identification of both OA patients and controls as shown by a significant decrease of both the sensitivity and specificity.

The classification results obtained by the deletion of each muscle of in the CO vs RA studies is given in Table IV. The algorithm's performance deteriorated significantly only when the soleus or the biceps femoris were deleted ($p < 0.05$ ANOVA, Tukey HSD *posthoc*). Other than a difference in accuracy following the deletion of these two muscles, there was a difference in the type of errors in the two cases. The elimination of the soleus muscle effected mainly the correct identification of RA subjects. This can be seen by a statistically significant decrease in the sensitivity ($p < 0.05$, ANOVA, Tukey HSD *posthoc*) but not the specificity of the categorization in comparison with the complete input vector. The elimination of information from the biceps femoris on the other hand led to a statistically significant decrease in specificity ($p < 0.05$, ANOVA, Tukey HSD *posthoc*) but not sensitivity.

## IV. Discussion

The purpose of this research was to investigate the use of machine learning techniques for the analysis of EMG data recorded during gait. The success of several of these techniques in classifying patient and non-patient data in this study shows us that we can exploit these techniques in order to understand the neuromuscular aspects of gait disorders. The

classification task was used as a means to identify some of the muscular differences between patients and control subjects. This knowledge is important for undertaking the correct rehabilitative measures for such patients. This could involve increasing muscular strength either through physical exercise or electro muscle stimulation. Such measures are currently undertaken without a clear knowledge of the differences in muscular activity involved. At best, a gait analysis is used to obtain information on differences in kinematics [12] and [13]. Different types of muscular activity however can give rise to the same kinematics. Knowledge on muscular differences can therefore be used to better undertake rehabilitative measures. The altered muscles can also be the target for monitoring the evolution of a patient in response to some treatment.

Our study is based on the results from 7 CO subjects, 8 RA subjects and 10 OA subjects. The small number of subjects in the study is the result of strict inclusion and exclusion criteria that were utilised (see Methods). All the exclusion criteria applied to the arthritic patients were also applied to the age matched control subjects. They were also required in addition, to be free of any arthritic symptoms. Despite the small number of subjects, the high success rate of the kernel method in the testing phase (91.48% $\pm$ 7.57% for the RA patients and 96.67% $\pm$3.77% for the OA subjects using the CGF kernel algorithm) indicates that the training was based on generalizable aspects of the EMG signals. As we will be continuing our work on these types of patients, these identified muscles will be the first group of muscles checked in newly recruited patients and controls.

The most successful method for the classification, was the kernel LSK method. The algorithms were compared using accuracy rate, sensitivity and specificity. The LSK algorithms showed an excellent performance in analyzing the data compared with the neural network or LDA algorithms that were employed. This was especially demonstrated in the case of the RA subjects. During the data gathering phase of these studies, the gait of these subjects appeared very similar to those of normal subjects. A comparison of the standard parameters from 3D gait analysis had in fact confirmed that there were few differences in the gait of the two groups [26]. The LSK method however had a mean success higher than 90% in identifying the two groups while the success of all the neural network techniques were close to chance. This is probably due to the higher capacity of LSK algorithms for learning noisy data with the use of the Tikhonov regularization method. For the RA data, the accuracy of the LDA algorithm at 72% $\pm$ 20% was better than that of the neural nets. It was still however outperformed by the LSK algorithms, all of which had mean success rates of around 90% or slightly higher.

In our investigation, the speed of convergence of the SOM, LVQ and MLP methods lagged far behind those of the LSK algorithms. The faster convergence of the LSK algorithms is due to their optimization technique, viz, the CG algorithm. The convergence rate of LSK algorithms is independent of the dimensionality of the space and is determined by the entire eigenspectrum. For both the classication experiments, the number of epochs taken for convergence by the four LSK algorithms was less than 15% of the total number of distinct eigenvalues of the kernel matrix $K$.

In terms of implementation overhead as well, LSK is a better choice. Kernel algorithms are nonparametric methods for which the machine architecture is defined by the data. On the other hand, neural network algorithms are parametric methods. For this reason the LSK algorithms have only two pre-defined parameters, viz, the regularization parameter and the kernel width. The SOM and LVQ algorithms have five parameters while MLP has seven.

To date, the LSK algorithms have been applied only to simulated data [14] and [15]. This is the first time they have been tested on real biological data. The EMG data had several of the characteristic problems that plague biological data such as noise and high dimensionality. The success of our experiments introduced four new algorithms (CGF, CGPI, CGPII and CGPIII) to the biological domain. A comparison of machine learning techniques in the study of gait in children with cerebral palsy has been carried out by Kamruzzaman and Begg [23]. Unlike our study, these authors did not use EMG recordings but several basic gait parameters such as stride length and cadence. Even though these authors also found that the kernel method outperformed the neural network method and LDA, they did not observe differences as big as we had between the capacities of the neural networks and kernel methods for the RA data. This is very likely due to the fact that a disorder such as cerebral palsy gives rise to much more severe problems in gait than arthritis. As we have already mentioned, in the case of the RA patients especially, it was difficult to detect any anomalies with the naked eye. We observe already in the case of OA patients with more gait abnormalities, a closing of the gap between the capacities of the kernel and other methods.

Several researchers have productively used recurrent neural networks in the study of locomotion. Cottrell et al [45] used kinematic variables at a previous time step to predict the kinematic angles at a defined later time step. Cheron et al [22] used EMG signals in order to predict lower limb kinematics. A recurrent network is primarily useful in situations where it is desirable not to present at once, all the information from an entire locomotion cycle in the input layer. It is used to predict the future values of a signal from values that were produced from an earlier time step. This type of network would therefore be indispensable in the control of prostheses [46]. In our case however, we did not seek to produce information in a sequential manner. Within each locomotor cycle temporal information for each muscle as well as between muscles should have been captured by the way in which the input sequence was constructed i.e. by the concatenation of the EMG data of all the studied muscles for a full locomotion cycle. The success of the kernel method shows that sufficient information was present in such a vector for a fairly successful classification.

Following the classification, we identified the muscles that were critical to the classification success. In the case of the RA patients, this was the soleus and the biceps femoris, while for the OA patients, it was the gluteus medialis. The values from this test are provided in tables III and IV. The elimination of information from these muscles from the input

vector led to significant decreases in the classification capacity of the kernel algorithm. In neither case did the elimination of muscles other than the critical muscles, lead to statistically significant changes in the classification capacity of LSK. The results from these tests indicate that these muscles in patients, display a different dynamic during gait than those of control subjects. By observing the phases during which these muscles are active, we can also deduce the points in the locomotor cycle which are likely to be altered. The soleus muscle starts to come into action during the middle of the loading response and continues till the early parts of pre-swing. It reaches the peak of its activity level in the middle of the terminal stance phase. The biceps femoris on the other hand is mostly active during terminal swing and continues some activity into the early loading phase [7]. With alterations in the activities of both these muscles in RA patients, we can expect anomalies in gait starting from terminal swing through to the end of terminal stance. For the OA patients, we should expect to see alterations in the loading and mid stance phases where the gluteus medialis is most active [7].

A great benefit of using EMG data as opposed to kinetic or kinematic data, is that it provides information which is more directly related to the physiological differences between groups. This information can then be used for rehabilitative measures that could improve the walking capacities of the patients. Future work will now involve identifying the exact difference between the activities of the muscles identified as crucial in the classification. Some possibilities are a change in amplitude or phase shifts. We will also have to carry out future experiments to ascertain if the muscular differences observed are a cause or a compensation for the inflammation observed in arthritis.

We have demonstrated in this paper that the LSK kernel method is successful at classification and hence the identification of the muscles that are the most altered in RA and OA patients. A full study of the pathology would however require for establishing the relationship between the altered EMG and the altered patient kinematics. Several neural networks have been used to map the nonlinear relationship between EMG data and kinematics [17] and [22]. In our case a comparison again of neural nets, kernel methods and more classical methods of regression analysis to map this nonlinear relationship would be the subject of a future study.

While in this paper we discussed the EMG recordings collected during locomotion, the techniques described here can be applied to almost any study involving EMG data. Studies of both upper and lower body movements can sometimes involve recordings from as many as 20 or more muscles. Multivariate methods that can rapidly classify and identify the differences between muscular activities are therefore important in all areas of EMG analysis.

## V. Conclusions

We studied the EMG data collected from the CO, RA and OA subjects by applying kernel, neural network and linear discriminant algorithms (LDA). The kernel algorithms showed a superior performance over the neural networks and LDA in terms of accuracy, sensitivity and specificity. The kernel method was also better than the neural networks in terms of computational efficiency. By means of a classification task, we were able to identify the subset of muscles that most differentiated these subjects. They were the soleus and the biceps femoris muscles in the case of the RA patients and the gluteus medialis in the case of the OA subjects. This indicates that the activities of these muscles are altered in arthritis patients. Current rehabilitative measures to increase muscular strength in such patients can be better undertaken with a clearer understanding of the muscular differences during gait of these patients. These muscles can also be the targets used to follow the evolution of a patient following any therapeutic measures.

## Appendix
## CGPI, CGPII and CGPIII

To find the regularized solution of (3) the following cost functions can be used:

$$J_{reg}(c) = ||Kc - z||^2_{\mathbb{R}^N} + \mu||c||^2_{\mathbb{R}^N} \tag{11}$$

$$J_{reg}(c) = ||Kc - z||^2_{\mathbb{R}^N} + \mu||L^*c||^2_{\mathbb{R}^N} \tag{12}$$

$$J_{reg}(c) = \langle Kc, c\rangle - \langle c, z\rangle + \mu||c||^2_{\mathbb{R}^N} \tag{13}$$

where $c \in \mathbb{R}^N$.

CGPI is the CG algorithm derived for solving the normal equation corresponding to (11), i.e. to solve

$$(K^2 + \mu I)c = Kz. \tag{14}$$

CGPII is the CG algorithm to solve the normal equation corresponding to (12), which is

$$K(K + \mu I)c = Kz. \tag{15}$$

CGPIII is the CG algorithm to solve

$$(K + \mu I)c = z \tag{16}$$

which is the normal equations corresponding to (13) [14] and [15].

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## References

[1] C. G. Helmick, D. T. Felson, R. C. Lawrence, S. Gabriel, C. K. K. R. Hirsch, M. H. Liang, H. M. Kremers, M. D. Mayes, P. A. Merkel, S. R. Pillemer, J. D. Reveille, and J. H. Stone, "Arthritis and rheumatism," *National Arthritis Data Workgroup*, vol. 58, pp. 15–25, 2007.

[2] R. Grasso, L. Bianchi, and F. Lacquaniti, "Motor patterns for human gait: Backward versus forward locomotion," *The Journal of Neurophysiology*, vol. 80, pp. 1868–1885, 1998.

[3] R. Grasso, Y. Ivanenko, M. Zago, M. Molinari, G. Scivoletto, V. Castellano, V. Macellari, and F. Lacquaniti, "Distributed plasticity of locomotor pattern generators in spinal cord injured patients," *Brain*, vol. 127, pp. 1019–1034, 2004.

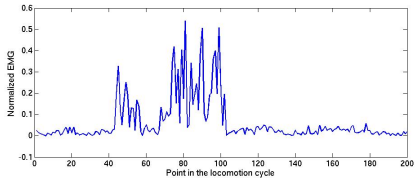


Fig. 1. The EMG signal from the right soleus of an RA patient. The EMG signal recorded at 2000 Hz, was filtered, rectified, normalized and finally time interpolated over individual gait cycles to fit a normalized 200-point time base.


[4] Y. P. Ivanenko, R. Grasso, V. Macellari, , and F. Lacquaniti, "Control of foot trajectory in human locomotion: Role of ground contact forces in simulated reduced gravity," *The Journal of Neurophysiology*, vol. 87, no. 6, pp. 3070–3089, 2002.

[5] D. A. Winter, *Biomechanics and Motor Control of Human Gait: Normal, Elderly and Pathological*. Waterloo, Ontario: Waterloo Biomachanics Press, 1991.

[6] Y. P. Ivanenko, R. E. Poppele, and F. Lacquaniti, "Five basic muscle activation patterns account for muscle activity during human locomotion," *The Journal of Physiology*, vol. 556, pp. 267–282, 2004.

[7] J. Perry, *Gait Analysis: Normal and Pathological Function*. SLACK Incorporated, New Jersey, 1992.

[8] R. R. Pate, M. Pratt, S. N. Blair, W. L. Haskell, C. A. Macera, and C. B. et al, "Physical activity and public health: a recommendation from the centers for disease control and prevention and the american college of sports medicine," *JAMA*, vol. 273, pp. 402–7, 1995.

[9] A. H. Taylor, N. T. Cable, G. Faulkner, M. Hillsdon, M. Narici, and A. K. V. D. Bij, "Physical activity and older adults: a review of health benefits and effectiveness of interventions," *Journal of Sports Science*, vol. 22, pp. 703–25, 2004.

[10] E. B. Kahn, L. T. Ramsey, R. C. Brownson, G. W. Heath, E. H. Howze, and K. E. P. et al, "The effectiveness of interventions to increase physical activity: a systematic review," *American Journal of Preventive Medicine*, vol. 22, pp. 73–107, 2002.

[11] A. D. A, S. J. Rose, J. M. McKowen, R. C. L. RC, J. A. T. JA, and R. A. Shively, "Electrical stimulation versus voluntary exercise in strengthening thigh musculature after anterior cruciate ligament surgery," *Phys Ther*, vol. 68, pp. 660–663, 1988.

[12] D. C. Kerrigan, A. Xenopoulos-Oddson, M. J. Sullivan, J. J. Lelas, and P. O. Riley, "Effect of a hip flexor-stretching program on gait in the elderly," *Archives of Physical Medicine and Rehabilitation*, vol. 84, pp. 1–6, 2003.

[13] M. DiBenedetto, K. E. Innes, A. G. Taylor, P. F. Rodheaver, J. A. Bower, H. J. Wright, and D. C. Kerrigan, "Effect of a gentle Iyengar program on gait in the elderly: an exploratory study," *Archives of Physical Medicine and Rehabilitation*, vol. 86, pp. 1830–7, 2005.

[14] T. J. Dodd, S. Nair, and R. F. Harrison, "Gradient based methods: Functional vs parametric forms," in *Proceedings of the 16th IFAC World Congress, Prague*, 2005.

[15] S. Nair, "Function estimation using kernel methods for large data sets," Ph.D. dissertation, The University of Sheffield, 2007.

[16] T. Evgeniou, M. Pontil, and T. Poggio, "Regularization networks and support vector machines," *Advances in Computational Mathematics*, vol. 13, pp. 1–50, January 1999.

[17] T. Chau, "A review of analytical techniques for gait data. part 1 : fuzzy, statistical and fractal methods," *Gait and Posture*, vol. 13, no. 1, pp. 49–66, 2001.

[18] ——, "A review of analytical techniques for gait data. part 1 : neural network and wavelet methods," *Gait and Posture*, vol. 13, pp. 102–120, 2001.

[19] H. Savelberg and W. Herzog, "Prediction of dynamic tendon forces from electromyographic signals: an articial neural network approach," *Neuroscience Methods*, vol. 78, pp. 65–74, 1997.

[20] M. Liu, W. Herzog, and H. Savelberg, "Dynamic muscle force predictions from emg: an articial neural network approach," *Electromyography and Kinesiology*, vol. 39, pp. 391–400, 1999.

[21] C. A. Tucker and P. Smagt, "Neurocomputational approaches to pattern recognition and time-series analysis of electromyographic data obtained during treadmill walking," in *International Society of Biomechanics. XVIIth Congress*, 1999.

[22] G. Cheron, F. Leurs, A. Bengoetxea, J. P. Draye, M. Destree, and B. Dan, "A dynamic recurrent neural network for multiple muscles electromyographic mapping to elevation angles of the lower limb in human locomotion," *Journal of Neuroscience Methods*, vol. 129, p. 95104, 2003.

[23] J. Kamruzzaman and R. Begg, "Support vector machines and other pattern recognition approaches to the diagnosis of cerebral palsy gait," *IEEE Transactions on Biomedical Engineering*, vol. 53, pp. 828– 838, 2006.

[24] R. Begg and J. Kamruzzaman, "A machine learning approach for automated recognition of movement patterns using basic, kinetic and kinematic gait data," *Journal of Biomechanics*, vol. 38, pp. 401–408, 2005.

[25] R. K. Begg, M. Palaniswami, and B. Owen, "Support vector machines for automated gait classification," *IEEE Transactions on Biomedical Engineering*, vol. 52, pp. 828 – 838, 2005.

[26] D. Laroche, P. Ornetti, E. Thomas, Y. Ballay, J. F. Maillefert, and T. Pozzo, "Kinematic adaptation of locomotor pattern in rheumatoid arthritis patients with forefoot impairment," *Exp Brain Res*, vol. 13, no. 1, pp. 185–97, 2007.

[27] N. Aronszajn, "Theory of reproducing kernels," *Transactions of the American Mathematical Society*, vol. 63, pp. 337–404, May 1950.

[28] A. N. Tikhonov and V. Y. Arsenin, *Solutions of Ill-Posed Problems*. New York: Wiley, 1977.

[29] T. J. Dodd and R. F. Harrison, "Gradient descent approach to approximation in reproducing kernel Hilbert spaces," The University of Sheffield, U.K, Tech. Rep. 821, 2002.

[30] W. J. Kammerer and M. Z. Nashed, "On the convergence of the conjugate gradient method for singular linear operator equations," *SIAM Journal on Numerical Analysis*, vol. 9, pp. 165–181, March 1972.

[31] C. W. Groetsch, *Generalized Inverses of Linear Operators*. New York: Marcel Dekker, 1977.

[32] A. M. Martïnez and A. C. Kak, "PCA versus LDA ," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 23, pp. 228–233, 2001.

[33] J. Hertz, A. Krogh, and R. G. Palmer, *Introduction to the theory of Neural Computation*. Addison-Wesley, 1991.

[34] F. Laurene, *Fundamentals of neural networks*. Prentice-Hall, 1994.

[35] J. L. McClelland, D. E. Rumelhart, and the PDP research group, *Parallel distributed processing: Explorations in the microstructure of cognition*. MIT Press, 1986, vol. 2.

[36] S. E. Fahlman, "Faster-learning variations on back-propagation: An empirical study," in *1988 Connectionist Models Summer School*, 1989, pp. 38–51.

[37] T. Schneider, "Analysis of incomplete climate data: Estimation of mean values and covariance matrices and imputation of missing values," *Journal of Climate*, vol. 14, pp. 853–871, 2001.

[38] R. J. A. Little and D. B. Rubin, *Statistical Analysis with Missing Data*. John Wiley & Sons, Inc, 1986.

[39] E. Thomas, M. V. Hulle, and R. Vogels, "Encoding of catgories by noncategory-specic neurons in the inferior temporal cortex," *Cognitive Neuroscience*, vol. 13, pp. 190–200, 2001.

[40] R. M. French, "Semi-distributed representations and catastrophic forgetting in connectionist networks," *Connection Science*, vol. 4, pp. 365–377, 1992.

[41] ——, "Catastrophic forgetting in connectionist networks," in *Encyclopedia of Cognitive Science*, L. Nadel, Ed. London: Nature Publishing group, 2003, pp. 431–435.

[42] G. Wahba, *Spline Models for Observational Data*. Philadelphia: SIAM, 1990.

[43] M. H. Zweig and G. Campbell, "Receiver-operating characteristic (roc) plots: a fundamental evaluation tool in clinical medicine," *Clinical Chemistry*, vol. 39, pp. 561–577, 1993.

[44] W. J. Fu, R. J. Carroll, and S. Wang, "Estimating misclassication error with small samples via bootstrap cross-validation," *Bioinformatics*, vol. 21, pp. 1979–1986, 2005.

[45] G. W. Cottrell, M. Nguyen, and F. Tsung, "Tau net: the way to do is to be," in *Proceedings of the 15th Annual Conference of the Cognitive Science Society*, 1993, pp. 365–370.

[46] G. Cheron, J. P. Draye, M. Bourgeios, and G. Libert, "A dynamic neural network identification of electromyography and arm trajectory relationship during complex movements," *IEEE Transactions on Biomedical Engineering*, vol. 43, pp. 552–558, 1996.

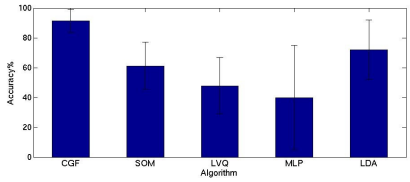


Fig. 2. Accuracy rate: CO vs RA class.

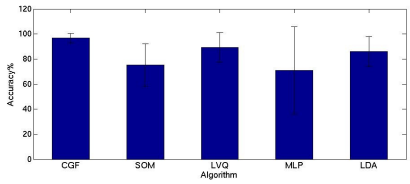


Fig. 3. Accuracy rate: CO vs OA class.

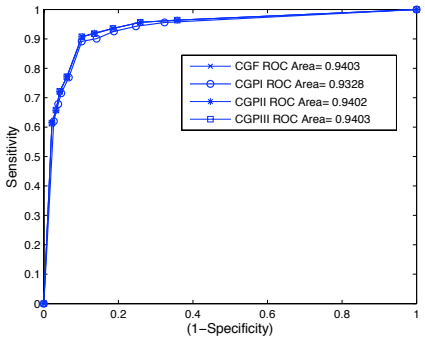


Fig. 4. ROC curve and ROC area of LSK: CO vs RA class.

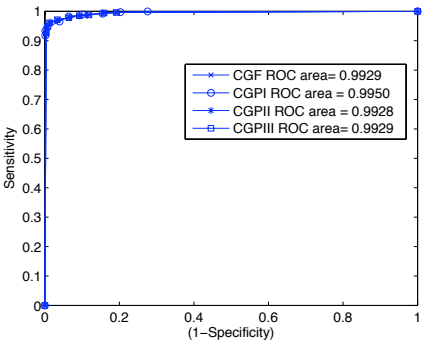


Fig. 5. ROC curve and ROC area of LSK: CO vs OA class.

TABLE I
SENSITIVITY AND SPECIFICITY: CO VS RA CLASS.

| Method | Algorithm | Sensitivity(%) | Specificity(%) |
|---|---|---|---|
| Kernel | CGF | 90.72±18.4 | 89.8±10.08 |
| | CGPI | 89.14±19.62 | 89.82 ±10.6 |
| | CGPII | 90.72±18.4 | 89.7±10.02 |
| | CGPIII | 90.72±18.4 | 89.8±10.08 |
| | LDA | 54 ± 25 | 88±14 |
| Neural Nets | SOM | 37.81±35.99 | 86.99±30.93 |
| | LVQ | 43.15±41.77 | 83.26±30.49 |
| | MLP | 58.33±30.01 | 19.2±26.79 |

TABLE II
SENSITIVITY AND SPECIFICITY: CO VS OA CLASS.

| Method | Algorithm | Sensitivity (%) | Specificity(%) |
|---|---|---|---|
| Kernel | CGF | 97.81±4.71 | 93.41±10.61 |
| | CGPI | 98.23±3.25 | 93.6 ±10.14 |
| | CGPII | 98±4.67 | 93.32±10.86 |
| | CGPIII | 97.81±4.71 | 93.56±10.61 |
| | LDA | 79±11 | 91±10 |
| Neural Nets | SOM | 58.88±29.59 | 100 |
| | LVQ | 76.88 ±27.95 | 96.23±18.33 |
| | MLP | 75.56±24.66 | 67.5±32.26 |

TABLE III
DELETION OF MUSCLE: CO VS OA CLASS.

| Muscle | Accuracy | Sensitivity (%) | Specificity(%) |
|---|---|---|---|
| Soleus | 94.92±7.44 | 95.59 ±10.84 | 92.89±12.07 |
| Gactrocnemius | 96.18±4.18 | 97.63±4.93 | 92.30±11.55 |
| Gluteus | 74.57±14.76 | 87.71±21.58 | 50.41±28.81 |
| Tibialis | 97.30± 3.14 | 97.92± 4.49 | 94.83±9.87 |
| Biceps | 95.26±5 | 98.51±3.28 | 88.81±12.88 |
| Vastus | 91.89±9.55 | 94± 10.01 | 89.85±16.50 |

TABLE IV
DELETION OF MUSCLE: CO VS RA CLASS.

| Muscle | Accuracy | Sensitivity (%) | Specificity(%) |
|---|---|---|---|
| Soleus | 79.82±12.81 | 75.37±22.65 | 88.49±13.80 |
| Gactrocnemius | 92.89±5.0198 | 93.59 ± 9.18 | 90.91±8.31 |
| Peroneus | 86.79± 8.62 | 89.91±13.33 | 82± 14.71 |
| Tibialis | 91.9963±6.40 | 94.03±10.29 | 87.92±10.15 |
| Vastus | 93.47± 5.41 | 92.91± 10.26 | 93.08 ±7.67 |
| Biceps | 82.46± 11.93 | 84.49 ± 17.46 | 80.28±13.92 |