Classification of RR-Interval and Blood Pressure Signals Using Support Vector Machine for different Postures

Indu Saini, Arun Khosla, and Dilbag Singh

***Abstract*— In this paper, the classification of RR-interval and blood pressure series for two different physical activities postures has been performed using support vector machine (SVM). Without understanding the changes in these features from lying to standing posture in the same subject it is not possible to decipher the hidden dynamics of cardiovascular control. Thus classification of the subjects based on their RR-interval and blood pressure series, prior to spectral analysis, is essential. Therefore support vector machine, a classifier motivated from statistical learning theory, is used here for classifying the subjects based on lying and standing postures. The efficiency of SVM lies in the choice of the kernel for a given problem. Here in this paper a comparative study has been performed between Linear, Polynomial and Radial Basis kernel functions, and based on highest classification accuracy linear kernel function is proposed for SVM classifier for deciphering the postural related changes in RR-interval and blood pressure signals.**

***Index Terms*— Classifier, Support Vector Machine, Kernel functions, Postures**.

I. Introduction

Heart Rate Variability (HRV) analysis is based on measuring the variability of heart rate signals, and more specifically, variations per unit of time of the number of heartbeats (also referred to as the RR interval, since it is the time interval between consecutive R points of the QRS complex of the electrocardiogram). A large value of this index reveals complicated systems that can response better to a wide variety of conditions. Thus, a healthy person usually presents large values of HRV, while a decreased value may indicate pathological cases. HRV analysis has gained significant clinical attention as can be seen from the large number of research efforts of the past two decades [1]-[4]. In addition, the HRV, for most part, is the reflection of underlying Blood Pressure Variability (BPV) operating by the way of baroreflex. If the causal BP variations are not taken into considerations, conclusion based on HRV alone may be spurious. Therefore the BPV and its interaction with HRV have also been taken into account for understanding cardiovascular modulation [5], [6]. Further, although the analysis of variability in HR and BP was proven to be useful in understanding the cardiovascular regulation, of the subjects rested in lying position, in a range of conditions including heart failure, hypertension, diabetes etc. But the interpretation of their power spectra when any subject is under some physical activity is still not totally resolved [7]-[9].

Manuscript received March 10, 2012; revised May 3, 2012.

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Various studies have been done using different classification tools like neural networks, wavelet transform etc. In this paper, we use Support Vector Machine (SVM) for classification. SVM has been successfully used as a high performance classifier in many applications including bioinformatics, pattern recognition and data mining. Two innovations of SVM are responsible for the success of this method namely the ability to find a hyper plane with widest margin that divides the sample into two classes and to optimize the classification using kernel functions [10]. The proposed approach is more efficient and gives higher accuracy.

This paper presents an application of SVM for classifying RR-interval and blood pressure variation of the same subject under lying and standing postures. The rest of the paper is organized as follows: Section II presents the overview of linear-SVM classifier and Kernel based SVM classifier, the classification method used in the experiments. Section III explains the methodology adopted for classification. Section IV presents the results and Section V draws the conclusion.

II. Overview of SVM

A. Linear SVM Classifier

SVM is an algorithm of machine learning introduced by Vapnik based on the structural risk minimization principle from statistical learning [11].SVM is a method for finding a hyperplane in high dimensional space that separates training samples of each class which maximizing the minimum distance between that hyperplane and the training samples. SVM identifies those samples that are closest to hyperplane and thus play a greater role in classifying a test sample. However classification rate is not very high when samples are close to hyperplane. The training data samples along the hyperplanes near the class boundary are called support vectors and the margin is the distance between the support vectors and the class boundary hyperplanes. The SVM are based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between sets of objects having different class memberships. SVM is a useful technique for data classification. A classification task usually involves with training and testing data which consists of some data instances. Each instance in the training set contains one target value (class label) and several attributes (features) [12].

Consider a set of training examples $(x_1, y_1),.....,(x_i, y_i)$ where input $x_i \in R^N$ and class labels $y_i \in \{-1,+1\}$.

$$\{x_i, y_i\}, i = 1.....,l, y_i \in \{-1,1\}, x_i \in R^d \tag{1}$$

where y_i represents the class to which input x_i belongs. Each input x_i is a d-dimensional real vector. We want to find a separating plane (hyperplane) that divides the data into two classes represented by $y_i = +1$ or $y_i = -1$, with maximum margin. The points **x** which lie on the hyperplane satisfy

$$w.x - b = 0 \tag{2}$$

where $(w.x)$ denotes inner product of w and x, w is weight vector and b is bias. We want to choose the w and b to maximize the distance between the parallel hyperplanes that are as far as possible while separating the data. These hyperplanes can be described by equations:

$$w.x - b \geq 1 \text{ for } \quad y_i = +1 \tag{3}$$

and

$$w.x - b \leq -1 \text{ for } \quad y_i = -1 \tag{4}$$

These can be combined into one set of inequalities

$$y_i(w.x - b) - 1 \geq 0 \tag{5}$$

In many practical situations a separating hyperplane does not exist without non-linearly separable data. To allow for possibilities of violating (5), slack variables, ξ_i are introduced like

$$\xi_i \geq 0 \qquad i = 1.....,l \tag{6}$$

to get

$$y_i(w.x_i) + b \geq 1 - \xi \qquad i = 1.....,l \tag{7}$$

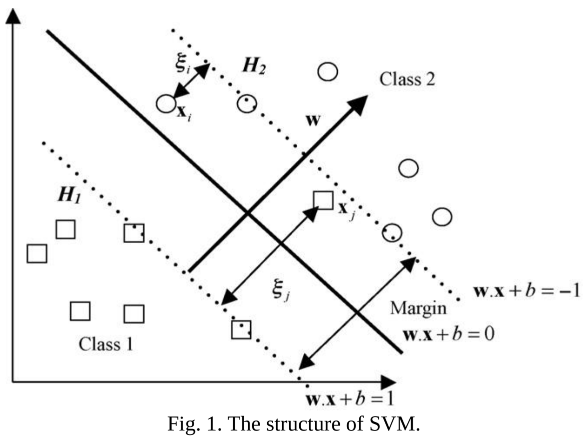

Fig. 1. The structure of SVM.

As shown in Fig. 1, SVM is constructed to classify the data set which contains two separable classes. The point x_j as shown in Fig. 1 is misclassified thus introducing error, ξ_i. Also, the error is introduced even if the classification is correct but with the margin smaller than the target margin. The training points lying on one of the hyperplanes H1, H2 and whose removal would change the solution found are called support vectors. To reduce the support vectors, we have to minimize the following equation [10], [13], [14]

$$\phi(w, \xi) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{1}\xi_i \tag{8}$$

subject to constraints (6) and (7) where C is a given value determining the tradeoff between minimizing training errors and minimizing the model complexity term $\|w\|^2$ [13]. The above minimization problem can be posed as a constrained quadratic programming (QP) problem. The solution gives rise to the decision function of the form

$$f(x) = \text{sgn}\left[\sum_{i=1}^{l} y_i \alpha_i (x.x_i) + b\right] \tag{9}$$

where α_i are lagrange multipliers.

B. Kernel-based SVM Classifier

The accuracy of an SVM model is largely dependent on the selection of the kernel method applied. By replacing the inner product $(x.x_i)$ with kernel function $K(x.x_i)$ the input data are mapped to a higher dimensional space that a separating hyperplane is constructed to maximize the margin. $K(x.x_i) = \phi(x)\phi(x_i)$ is called kernel function. There are number of kernel functions results in different kinds of SVMs with different performance levels. These include linear, polynomial, radial basis functions [12].

$\phi = \{x * x_i\}$	*Linear kernel*
$(\gamma x x_i + coeff)^d$	*Polynomial*
$Exp(-\gamma\|x - x_i\|^2)$	*RBF*

The original SVM is a linear classifier. For SVMs, using the kernel trick makes the maximum margin hyper plane fit in a feature space. The feature space is a non linear map from the original input space, usually of much higher dimensionality than the original input space. In this way, non linear SVMs can be created. Support vector machines are an innovative approach to constructing learning machines that minimize the generalization error. They are constructed by locating a set of planes that separate two or more classes of data. By construction of these planes, the SVM discovers the boundaries between the input classes and the elements of the input data that define these boundaries are called support vectors.

III. Methodology

The study was performed on ten sets of lying and ten sets of standing postures of RR-interval and BP obtained from standard Eurobavar database available on internet (http://www.cbidongnocchi.it/glossary/eurobavar.html). The data obtained is a matrix where each row corresponds to an observation and each column corresponds to a feature or variable. Here the features used are RR interval and blood pressure. Two experiments have been done for evaluating correct classification accuracy for the given data.

This experiment is done by applying SVM classifier to the feature vectors of the 20 files of lying and standing datasets. In this framework, by using svmtrain and the training data, a classification model was created. In this model, the data corresponding to lying was marked as ones and data corresponding to standing was marked as zeros. This model forms a hyperplane between the two types of data and then it was used to classify the testing data into standing and lying. The classification can be made more optimized by use of different kernel functions.

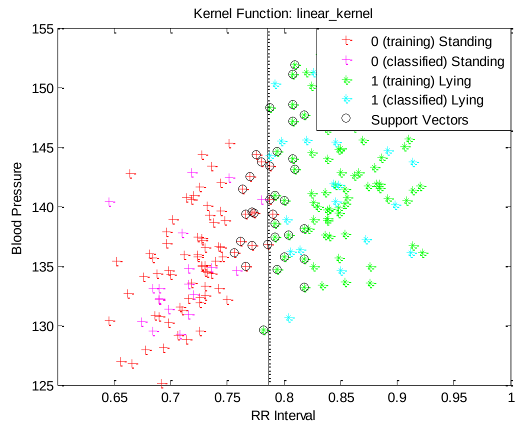

Fig. 2. SVM structure using linear_kernel.

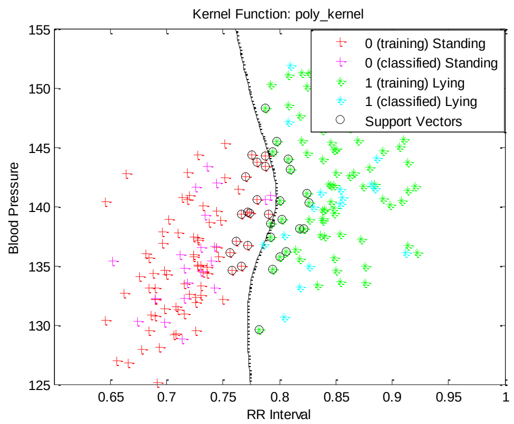

Fig. 3. SVM structure using polynomial_kernel.

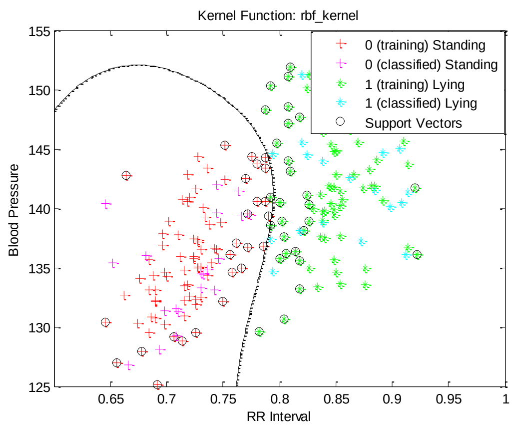

Fig. 4. SVM structure using RBF_kernel.

SVM structures created by this algorithm, for three different kernel functions are as shown in Fig. 2, 3 and 4 respectively. Two features used in this paper i.e RR-interval and blood pressure are plotted along X-axis and Y-axis. In these graphs red (+) used for training data and pink (+) for test data for the standing postures whereas green (*) and blue (*) represents training data and testing data for lying posture and circle shows support vectors. Fig. 2 shows the SVM structure with linear kernel function; here a straight line divides the two datasets in two parts, (+) for standing and (*) for lying datasets. Fig. 3 and 4 represents SVM structure using polynomial and RBF kernel functions. In these graphs different types of hyperplanes are created as these kernel functions makes feature space as non linear map from the original input space. The classification accuracy has been calculated for all three kernel functions and discussed in next section.

IV. Results

The aim of the study which we performed here is two folds: firstly to visualize the effect of varying postures on heart rate and blood pressure series using a SVM classifier and secondly to propose the optimal kernel function for achieving the highest possible classification accuracy. In this paper a comparative analysis has been performed between different kernel functions using SVM algorithm by selecting (i) RR-interval (ii) blood pressure records of 14 subjects under lying and standing positions as features. Here we first trained the SVM classifier by presenting 10 lying and 10 standing files. After training is over, in the classification phase firstly 4 files of the subjects from I to IV under lying and standing postures, different from the training phase, were given to the SVM classifier in a random manner and the results in terms of classification accuracy for different kernel functions respectively were obtained, for lying and standing postures are shown in Table I and II respectively. After verifying the results shown in Table I for lying posture it is found that averaged classification accuracy using linear kernel function is 98.79% in comparison to polynomial (91.83%) and RBF (92.49%) kernel functions. Similarly the averaged classification rate as shown in Table II for standing postures is 99.52% for linear and 95.14% , 98.52% for polynomial and RBF respectively. Thus it is clear from above results that linear kernel function gives the maximum classification accuracy as compared to other two kernel functions.

Hence it is found that when SVM algorithm is implemented for three kernel functions the highest classification accuracy is obtained with linear kernel function in comparison to polynomial and radial basis function.

V. Conclusion

A definite correlation has been observed between the changes in heart-rate associated with variations in the elevation of the head, and body. These changes are observed in RR-interval and blood pressure. Subjects have been successfully classified using the support vector machine classifier for classification on the basis of correlation between the known parameters and it is proposed that linear kernel give the best classification accuracy with both the algorithms. In future this approach can be used to classify the data of a healthy and unhealthy person.

TABLE I: CLASSIFICATION ACCURACY OBTAINED USING LINEAR, POLYNOMIAL AND RBF KERNEL FUNCTIONS FOR THE SUBJECTS UNDER LYING POSTURE.

Subject No.	Linear Kernel	Polynomial Kernel	RBF Kernel
I	98.85	85.43	89.43
II	99.82	99.10	96.76
III	96.52	95.83	93.56
IV	100	86.98	90.23
Average	98.79	91.83	92.49

TABLE II: CLASSIFICATION ACCURACY OBTAINED USING LINEAR, POLYNOMIAL AND RBF KERNEL FUNCTIONS FOR THE SUBJECTS UNDER STANDING POSTURE.

Subject No.	Linear Kernel	Polynomial Kernel	RBF Kernel
I	100	100	100
II	99.01	89.40	95.58
III	99.09	92.15	98.52
IV	100	99.01	100
Average	99.52	95.14	98.52

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