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An Efficient IKSVM Based Multi-parameter Patient Monitoring System

Dhanya Mohan
Machine Intelligence Research Lab,
Amrita Vishwa Vidyapeetham,
Coimbatore, India-641112.
E-mail: mailme2dhanya@gmail.com

C. Santhosh Kumar
Machine Intelligence Research Lab,
Amrita Vishwa Vidyapeetham,
Coimbatore, India-641112.
E-mail: cs_kumar@cb.amrita.edu

Abstract

Multi-parameter patient monitors (MPMs) are extensively used for enhancing the quality of healthcare in both intensive care units (ICU) and in-patient wards. MPMs make use of the vital signs, respiration rate, heart rate, blood pressure and oxygen saturation (SpO_2), for predicting the condition of patients. Support vector machine (SVM) is one of the most popularly used classification algorithms for developing MPMs. The kernel function, used in an SVM is a measure of similarity between any two examples, either belonging to same class or different classes. The selection of the kernel is an important aspect for the optimization of the system using SVM. If two patients have heart rates of 60 bpm and 80 bpm, intuition suggests that their heart rate similarity is 60 bpm. Extending this to n features, we may say that the total similarity is a summation of the individual similarities over n features, suggesting that intersection kernel is an ideal choice for MPM.

In this paper, we explore the effectiveness of using intersection kernel SVM (IKSVM) for improving the performance of MPMs. We also compare the performance improvement of the MPM using IKSVM with the popularly used linear, polynomial and radial basis function (RBF) kernel MPMs. The results suggest that the use of intersection kernel can help enhance the performance of the MPMs significantly. Using IKSVM system, we obtained an improvement of 2.74 % absolute for overall accuracy, 1.86 % absolute for sensitivity and 3.00% absolute for specificity over the best baseline MPM using RBF kernel.

AMS subject classification:
Keywords: Multi-parameter Patient Monitoring system; Intersection kernel; Support Vector Machine; MIMIC-II Database.

Multiparameter patient monitors (MPM) make use of the human vital signs, respiration rate (RR), heart rate (HR), blood pressure (BP) and oxygen saturation (SpO_2) for monitoring the conditions of patients in intensive care units and in-patient wards [4]. The use of MPMs in intensive care units (ICU) can help identify the deteriorations in the patients' health condition and initiate timely interventions to save life [2]. For the reliable performance of MPMs, the probability of missing alarms as well as false alarms should be minimum. This means that the alarm accuracy or sensitivity and no alarm accuracy or sepcificity of the system should be as high as possible.

The invention of early warning score (EWS) system marked the begining of MPMs in healthcare field [10]. Here the system assigns different scores, individually to the vital signs based on the variation from the clinically assumed normal range and the patient will be prompted for clinical review, if the score of any vital sign data or the sum of scores exceeds a predefined threshold [11]. But, this method has many disadvantages such as high error rate, fixed threshold based decision making leading to increased false alarm rate, etc. The developments in the field of machine learning had a significant impact in the healthcare domain. Machine learning techniques were widely used for the detection of physiological deterioration in patients' health. Support vector machine [3] (SVM) is an efficient classifier method which has been used for classification purposes. The SVM is well known for its generalization ability and efficiency of classification even with higher dimensional data. The efficiency of the system performance highly depends on the type of kernel being used in the SVM. This indicates that for obtaining better accuracy, we can either use an appropriate kernel, matching the feature vectors or the feature vectors can be mapped to match a kernel description. When dealing with linearly non seperable data, nonlinear kernels give better performance at the cost of increased computational complexity and memory requirement.

In the case of MPMs, the analysis of the vital parameters shows that they are not linearly seperable. This relationship is measured in SVMs by using kernel functions, that measures the similarity between any two examples. If the two examples belongs to same class the similarity should be maximum and if they belong to different classes, the similarity should be minimum. Thus, the efficiency of the SVM classifier significantly depends on the selection of an appropriate kernel function. Each of these kernel functions are evaluated by finding the similarity between data points. In the case of linear kernels, the dot product between the two selected data points is the measure of similarity whereas in RBF (radial basis function) kernel, the inverse exponential of the Euclidian distance between the two is the measure of similarity.

Considering two persons with heart rate x and z, intuition suggests that the similarity between the two persons can be obtained as the minimum of the two heart rates and the kernel function representing this similarity may be expressed as:

$$k(x, z) = min(x, z) \tag{1}$$

Extending the kernel to four vital parameters, we may rewrite equation (1) as:

$$k(x, z) = \sum_{i=1}^{4} min(x_i, z_i) \tag{2}$$

where $x = \{x_1, x_2, x_3, x_4\}$ and $z = \{z_1, z_2, z_3, z_4\}$ are the two examples. Equation (2) represents the intersection kernel. IKSVM is popularly used in the image classification applications and are popularly known as histogram intersection kernels [5]. In the case of image classification using 'bag-of-words' as input features, it was found that the performance improved significantly when IKSVM was used [7].

In our work, we study the effectiveness of using IKSVM for the development of an MPM and compare the results with the popularly used kernel implementations such as, linear, RBF and polynomial kernel SVMs. The results show that the MPMs using IKSVM outperforms the MPM implementations using other populary used kernel SVMs.

The rest of the paper is organized as follows: section 1 describes SVM as a classifier and the intersection kernel used in our system. The details of the experiments and results are presented in section 2 and finally, section 3 concludes our work.

1. System Description

1.1. Support Vector Machines

Support Vector Machines (SVMs) have emerged as a popular approach to machine learning, for classification and regression, demonstrating state-of-art performance in various applications and offering an attractive alternative to artificial neural network and expert-based approaches. Following the proposal of statistical learning theory by Vapnik [3], SVMs gained popularity as an efficient classification algorithm. It is a discriminative method where the posterior probabilities are directly estimated without modeling the underlying probability distribution.

The entire classification process using SVM has two phases: training or learning phase and testing or classification phase. During the training phase, the system is trained with a sample dataset containing the input features and the corresponding label, where the features indicate the four vital sign values (heart rate, respiration rate, blood pressure and oxygen saturation) and the label indicates the corresponding class of the patient (alarm/no alarm). The training is an optimization process, where the classifier finds out an optimum seperating hyper plane which gives maximum margin between the two classes of data. Based on the training data and the obtained seperating hyper plane, the SVM constructs a 'model' which has information regarding the list of support vectors (x_{sv}), the corresponding weights, the bias (b) etc. These support vectors are the data points from the training dataset, which are close to the seperating hyper plane and defines the maximum allowable margin.

During the testing phase, the input data sample will be classified as either alarm or no alarm based on the decision function. The decision function of the SVM system is defined as:

$$f\,(x) = sign\left(\sum_{j=1}^{N_{sv}} \alpha_j y_j \sum_{i=1}^{4} k(x_i, x_{sv,i}(j)) + b\right) \tag{3}$$

where α_j is the Lagrangian coefficient, y_j is the class label, $x = \{x_1, x_2, x_3, x_4\}$ is the input data, $x_{sv} = \{x_{sv,1}, x_{sv,2}, x_{sv,3}, x_{sv,4}\}$ is the support vector, $k(x, x_{sv})$ is the kernel function, b is the bias, i is the feature index and j is the support vector index.

1.2. IKSVM

In an IKSVM, the kernel function, the measure of similarity, is given as a 'min' function and since it is positive definite [7] for the non negative vital signs, it can be used for an MPM with discriminative classification using SVM, ensuring convergence. The intersection kernel is based on the idea similar to intersection in 'sets relations and functions'. In sets, the shared portion between two sets are considered as the similarity wheras in the case of IKSVM, the minimum value among the two is considered as the similarity. In MPM system, the decision whether the patient is normal or abnormal is made based on the decision function. Using the intersection kernel, the classification decision may be expressed as:

$$f\,(x) = sign\left(\sum_{j=1}^{N_{sv}} \alpha_j y_j \sum_{i=1}^{4} min\left(x_i, x_{sv,i}\,(j)\right)\right) \tag{4}$$

where we implicity refer to the four vital parameters namely, heart rate, respiration rate, blood pressure and oxygen saturation.

In an MPM using IKSVM, we take a direct measure of similarity. When a test data is to be classified, each vital sign value in the input is compared with the corresponding vital sign of each of the support vectors using the intersection kernel and are summed across all the support vectors. The IKSVM predicts the class of the input data based on the decision function in equation (4). The results show that the performance of the MPM with IKSVM outperforms the MPMs using linear, polynomial and RBF kernels.

2. Experiments and Results

The experiments were carried out using MIMIC-II [1] dataset. The database consists of the labeled vital sign data of 421 patients collected during the time of their admission in a hospital [6]. The data from 20 patients were found to be inappropriate and the remaining data from 401 patients were split into train and test datasets. Training set consisted of data from 300 patients and test set consisted of data from 101 patients. From the training dataset,we created seven subsets of data, each consisting of 50,000 randomly selected samples of data for seven different trials. Similarly from the test dataset, we created seven subsets of data, each consisting of 20,000 randomly selected samples of data for seven different trials.The size of the training and testing subsets were restricted to 50,000 and 20,000 for reducing computational complexities. We used $LIBSVM$ [9] for all the experiments presented in this work.

The performance of the classifier was analyzed and compared using the analysis techniques like overall classification accuracy, alarm accuracy (sensitivity) and no-alarm accuracy (specificity) where, sensitivity is the alarm recognition accuracy and specificity is the no alarm recognition rate. The overall classification accuracy gives the percentage of total correct predictions. In our work, based on the vital sign vaues, the data is classified as either abnormal (alarm case) or normal data (no alarm case).

Table 1 shows the overall classification accuracy, sensitivity and specificity performance of the MPM as an average across all the seven clusters of data. We report the performance of three baseline systems, linear, polynomial and RBF along with the IKSVM MPMs. The vital sign data, being non linearly seperable, gives a low alarm accuracy performance of 9.38% when implemented using linear kernel MPMs. The overall classification accuracy of the linear kernel MPM is the lowest among the baseline systems with a value of 78.08%. Using the polynomal kernel, the overall classification accuracy and sensitivity of the system were enhanced to 86.88% and 60.24% whereas the specificity got reduced to 95.19%. The RBF kernel MPM is the best among the baseline systems with an overall classification accuracy of 96.88%, 96.53% for sensitivity and 96.98% for specificity. Finally, it may be noted that the intersection kernel MPM achieved an overall classification accuracy of 99.62%, 98.39% for sensitivity and 99.99% for specificity which is an iprovement of 2.74% absolute for overall classification accuracy, 1.86% absolute for sensitivity and 3.00% absolute for specificity over the RBF baseline system.

The system performance was also analyzed using detection error trade-off (DET) [8] curve. The DET has been widely used in the field of speaker recognition and language identification and is effective in evaluating a system under varying operating conditions. With the help of DET, it is possible to fine tune the system for diverse requirements. When the MPM is to be used in an ICU, it is desirable not to miss any alarms. This emphasizes that the alarm accuracy of the MPMs implemented in an ICU should be high. On the other hand, in general wards, since the risk rate is low, the false alarms should be as minimum as possible indicating that the specificity of the system should be as high as possible.

The detection error trade-off graph plots the miss alarm probability against the false alarm probability. Fig. 1 compares the error tradeoff performance of the improved MPMs using IKSVM with that of RBF MPMs. The DET plot in Fig. 1 clearly shows that the detection error trade off plot of IKSVM MPM is closer to origin than that of RBF MPM, indicting that IKSVM is far more better than the RBF MPMs in all operating conditions. It is possible to calculate an optimum point with minimum detection cost function (min

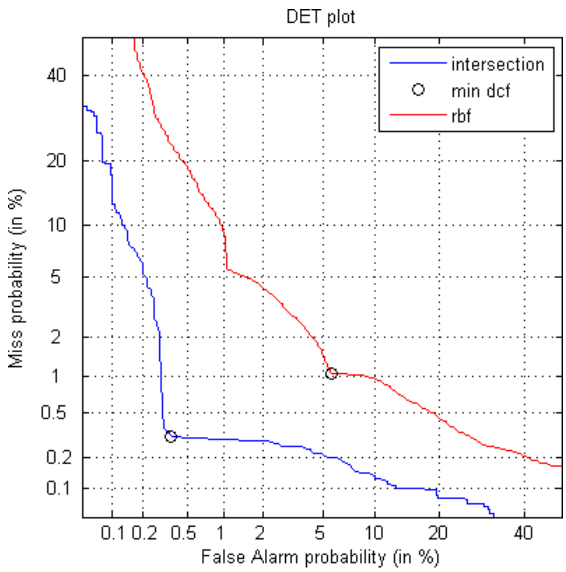

Figure 1: DET plot

dcf) for any particular appication.The optimum operating point is calculated as:

$$opt\_th = \frac{c\_fa * (1 - p(tar))}{c\_miss * p(tar)} \quad (5)$$

where, c_fa represents the cost of false alarm, c_miss represents the cost of missing an alarm and $p(tar)$ represents the probabiity of target,which is the alarm probability. The 'min dcf point' in the figure indicates the optimum operating point for the system provided, missing an alarm has higher penality (cost of miss=10) than a false alarm (cost of false alarm=1), a condition suitable for ICU MPMs. From the analysis, we obtained an optimum threshold as 0.33 to be used in ICUs.

Table 1: Performance comparison of 4-feature SVM Kernel

Kernel	Overall accuracy	Sensitivity	Specificity
Linear	78.08	9.38	98.87
Polynomial	86.88	60.24	95.19
RBF	96.88	96.53	96.98
Intersection	99.62	98.39	99.99

3. Conclusion

In this paper, we explored the use of intersection kernel for enhancing the performance of multiparameter patient monitors (MPMs) using support vector machines (SVMs). The

MPMs using intersection kernel SVMs (IKSVMs) gives the best performance with a significant improvement in overall accuracy, specificity and sensitivity compared to the best baseline radial basis function (RBF) kernel MPMs. IKSVM gives a performance improvement of 2.74% absolute for overall classification accuracy, 1.86% absolute for sensitivity and 3.00% absolute for specificity.

The results from the experiments suggest that IKSVM is very appropriate for the implementation of high accuracy MPMs. IKSVM MPMs does not require the complex feature mapping as required by the RBF kernel, making it suitable for hardware implementations. The hardware implementation of the MPM using IKSVM is being carried out for the development of a low cost MPM and the results in this direction will be reported in due course of time. It is also worth exploring how the performance could be further improved by removing the redundant feature informations from patients' data.

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