MONITORING SYSTEMS IN INTENSIVE CARE UNITS USING INCREMENTAL SUPPORT VECTOR MACHINES

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ABSTRACT

In this paper, we adapt the incremental Support Vector Machines, denoted by I-SVM to the medical field in order to solve the issue of monitoring system in Intensive Care Unit (ICU). In fact, we have already proved the effectiveness of the SVM to reduce false alarms in batch mode in ICU. In this work, our purpose is to prove that the SVM can provide spectacular results not only in batch modes but also in online mode in training phase. In fact, the main problem in ICU consists of the increasing of the rate of false alarms what presents a real threat for the patient life. Our work aims to decrease this rate and to monitor the different states of patients by using the I-SVM. This technique will allow us to incorporate new measurements relative to patients through its ability to handle the large amount of data streams in ICU. Besides, it will provide more correct description for the patient states. As a result, the I-SVM will generate more accurate alarms than the current system. Experiments using real-medical databases have shown its efficiency to reduce the rate of false alarms and to reproduce true ones compared to both the current monitoring system and the system using SVM on batch mode.

KEYWORDS

Intensive Care Units, Monitoring System, Support Vector Machines, Incremental SVM, Classification.

1 INTRODUCTION

Monitoring system presents one of the most important tasks in Intensive Care Unit (ICU). Actually, in ICU the patient is supervised by an online monitoring system. This latter measures medical parameters in order to detect any unstable patient state. As a result, the system produces a high number of alarms. The medical staff qualified the most frequently alarms as irrelevant (false alarms) since, they result of the exceeding of specified alarms thresholds. These alarms are considered as ineffective and have not clinical significance. Besides, they are not helpful for the medical staff and they even make the monitoring task in ICU harder by disturbing both of patients and physicians.

Such monitoring system can affect the working conditions of the medical staff instead of detecting relevant abnormal changes in the patients' conditions.
Reducing such alarms can be of a great interest for both patients and medical staff. It can improve the working condition by helping intensivists to quickly detect any unstable state of patient and to provide the adequate treatment.

Thus, online monitoring system needs an improvement in order to keep its performance and sensitivity (detecting true alarms) and overcome its limits. Numerous works have been proposed to solve this issue, we can mention the digital signal processing [1], the trend extraction methodology [2] and the intelligent monitoring [3], etc. Moreover, the problem of high number of false alarms has been reported in several studies [4], [5] as attempt to emphasize on its importance and to overcome it.

In this paper, we propose to use the Incremental Support Vector Machines technique (I-SVM) [6], [7], in order to reduce the rate of false alarms in ICU. This approach generates, first, an optimal model relative to a particular patient then, it updates this model by adding new measurements corresponding to the new state of this patient in training phase.
The choice of the SVM is based on its efficiency on mode batch proved in our previous works [8] and [9]. In addition to that, the incremental SVM

is considered as faster than the standard SVM [6], [10] when building the classification model. Besides, it has shown its interesting results in different applications [11], [12] and can improve the monitoring system in ICU. In fact, the I-SVM is able to easily improve its model by taking into account new instances, in our case, new measurements relative to the patient in the ICU. As a result, the I-SVM guarantees the continuous monitoring of patients and provides a precise description of his state in order to generate only true alarms. Hence, the I-SVM allows the incorporation of additional training instances without re-training from scratch as opposite to batch algorithm (i.e. the SVM). This latter, in which all data points are available at the same time from the beginning, will fail due to the existence of ambiguous information that varies over time.

This paper is structured as follows: Section 2 and Section 3 give respectively an overview of the monitoring system in ICU and the incremental SVM technique. Section 4 describes how we adapt the I-SVM to the medical field. Section 5 detail experiments. Section 6 concludes the paper.

2 MONITORING SYSTEM IN INTENSIVE CARE UNITS

ICU, also called critical care or intensive therapy department, is a special ward (department or section) in the hospital that provides a continuously treatment and intensive care for patients whose conditions are life-threatening. Patients in ICU suffer from dangerous illness or have critically and unstable conditions. Intensivists who are specialized physicians look after them in order to keep their normal body functions going.

Monitoring system in ICU measures medical parameters (physiological signals). We can mention the cardiac monitoring measuring the Heart Rate (HR), the hemodynamic monitoring for the Arterial Blood Pressure (ABP), the respiratory monitoring relative to the Saturated Percentage of Oxygen in the blood (SPO_2), etc. This monitoring aims to ensure a quick detection of abnormal variation in the patients' states. Each parameter has a specific threshold, set by physicians, that indicates if the state of a patient is normal or critical. In fact, when the measured value relative to a particular parameter does not exceed its threshold, the patient is in stable state otherwise, an alarm is generated from the monitoring device expressing an abnormal condition.

Actually, alarms in ICU can consist of one or more sensors, display devices, communication links that records the results via a monitoring network. Their generation can be due to a critical condition (e.g. very high blood pressure) or just a technical problem (e.g. problem in the monitoring device).

Unfortunately, monitoring systems in ICU use devices that can generate false alarms i.e. alarms without useful meaning for the medical staff. Generating continuously false alarms have bad effect on both patients and medical staff and causes permanent stress for them. This fact can make the patient recovery more difficult. Additionally, generating false alarms and missing the true ones lead to endangerment of patients and threat the patient safety. Besides, these alarms can disturb nurses and physicians and delay taking the appropriate measures at the right time since, staff will have constant doubt about the generated alarms.

Although the high number of alarms generated in the ICU, some critical situations, in which the patient life has been in real danger, have not been detected by the monitor devices.

In order to avoid false alarms, the medical staff can modify the threshold of the parameters and, in some cases, they even turn off the monitoring devices.

As attempt to decrease the high number of false alarms, many researchers have focused on this issue [4], [12]. In 2007, Reslan [13] showed in US study that the response time of alarm can be up to 40 min. Besides, in other study [4] the authors explained that only 10% of alarms are attended by the medical staff. Furthermore, the study in [14] has reported that 50% of all relevant and true alarms were not detected by physicians.

Despite of the different works that have been already proposed, the problem of monitoring system has not been resolved yet. So, we propose to use a classification technique in order to detect relevant alarms and to reduce the rate of false alarms. We aim also to perform an online monitoring system using I-SVM by adding new measurements relative to the patient state over the time.

We detail as follows the I-SVM classification technique by presenting its main procedures.

3 INCREMENTAL SVM

3.1 The SVM

Support Vector Machines (SVM) has been defined by Cortes and Vapnik in [15] and improved by several researchers in [16], [17].
It has been used as a classification tool and it is suitable to various applications [11], [17]. Besides, the SVM technique has been successfully applied in classification problems and has produced promising results.

The main aim of the SVM is to determine the optimal hyper-plane using a subset of training instances known as support vectors and guarantee the maximization of the margin.
The minimization problem relative to the cases of the linearly and nonlinearly separable data is described in the following.

a. In the case of linearly separable data

If the training data is linearly separable then, a pair (w, b) exists such that:

$$\begin{aligned} w^T.x_i + b \geq 1, for\ all\ x_i \in P. \\ w^T.x_i + b \leq -1, for\ all\ x_i \in N. \end{aligned} \quad (1)$$

with the decision rule given by:

$$f_{w,b}(x) = sign(w^T.x_i + b). \quad (2)$$

where w is termed the weight vector, b the bias (or $-b$ is termed the threshold), x_i is an observation and P and N present respectively positive and negative data. When it is possible to linearly separate two classes, an optimum separating hyper-plane can be found by minimizing the squared norm of the separating hyper-plane. The minimization can be set up as a convex quadratic programming (QP) problem:

$$\begin{cases} min\frac{1}{2}\|w\|^2, w \in\ R^d, b \in R, \\ \quad subject\ to \\ y_i(w.x_i + b) \geq 1, \\ \quad for\ i = 1, \dots, m. \end{cases} \quad (3)$$

with y_i the class of the observation x_i, m the number of observations and R^d the dimension number.

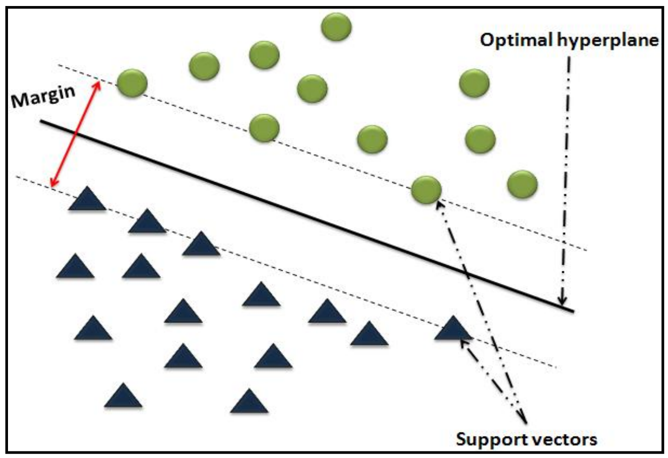

Figure 1. The optimal hyper-plane for linearly separable data

Figure 1 details as follows the optimal hyper-plane given by the SVM technique in the case of linearly separable data.

b. In the case of nonlinearly separable data

In this case, instances cannot be separated by a hyper-plane. Thus, we have to project this data into a feature space.

Figure 2 shows how the SVM maps data points, into a transformed feature space in order to obtain a linear separation between positive and negative instances of the training set.

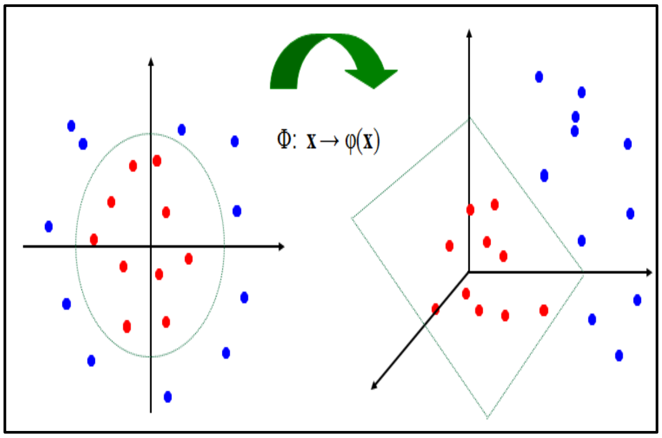

Figure 2. The mapping data for nonlinearly separable data

The data mapping is defined through the function φdefined by$R^d \rightarrow R^D, (D \gg d)$. with $R^d$is HILBERT space.

To determinate the hyper-plane, we have to solve the following optimization problem.

$$\begin{cases} min\frac{1}{2}\|w\|^2 + c\sum_{i=1}^{m} \xi_i \\ \quad subject\ to \\ y_i(w.x_i + b) \geq 1 - \xi_i \\ \xi_i \geq 0, for\ i = 1, \dots, m \end{cases} \quad (4)$$

The SVM has been considered as a technique with a high learning performance and more important generalization ability than the existent learning approaches. Besides, this technique has been known by its interesting theoretical foundation and its ability to handle high-dimensional data. Generally, it is trained using batch mode where all training instances are given a priori in the same time. However, if there is a new training instance that we want to add latter, we have to re-train the SVM technique from the beginning. Thus, the standard SVM technique does not support the incremental learning task.

Incremental learning algorithms are widely applied and produced interesting results in data mining area, medicine, knowledge discovery, Visual Sensor Networks, etc.

In this work, we aim to adapt and apply a well-known incremental learning algorithm, based on the SVM technique, called the I-SVM in the medical field in order to classify the new patients' states in the intensive care unit and reduce the rate of false alarms.

We present the I-SVM technique as follows.

3.2 The Incremental SVM: I-SVM

The term incremental has been used widely with learning tasks to mean that training instances are not available a priori but are gradually added over time. Incremental SVM (I-SVM) has essentially two main advantages. It can be trained with huge training data sets. Besides, data is not necessarily known a priori but it can be available at periodic intervals.

The incremental and decremental SVM is a well-known online algorithm [6], based on the SVM, that has proved its efficiency in several works [18], [19].

Incremental SVM learning algorithm describes how to exploit the new data over time, in our case we received a new sample at periodic time, by ignoring all previous data except their support vectors. As follows, the pseudo code of the incremental SVM detailed in [6].

1- Train the initial SVM on the initial training set.
2- Classify the new sample using the initial model in step 1.
3- Check if this new sample is a support vector or an error vector, if it is a support vector updates the initial model of SVM.
4- Go to step 2.

The main idea of the I-SVM is to find whether the inputted data is in question and to submit these instances to the user to determine its right class. In the questing process, the machine quests the interrogative instance by the distance between the point and hyper-plane.

The distance can be defined as:

$$DIS(x,w) = \left|\sum_{\in SV} \alpha_i y_i \big(\varphi(x).\varphi(x_i)\big) + b\right|, x_i \quad (5)$$

with w the weight vector, b the bias, x_i is an observation, SV the set of support vectors, and φ the mapping function.

4 MONITORING SYSTEM USING INCREMENTAL SVM

The current monitoring system used in ICU does not always describe the real state of the patient since, it produces, in some cases, false alarms with no clinical significance and missed true alarms. In order to avoid this issue, we propose to use an intelligent and online system that uses the incremental support vector machines (I-SVM). This latter will be adapted to the monitoring system and will build a model that classifies new patients' states over time.

The structure of the new incremental system is described in Figure 3.

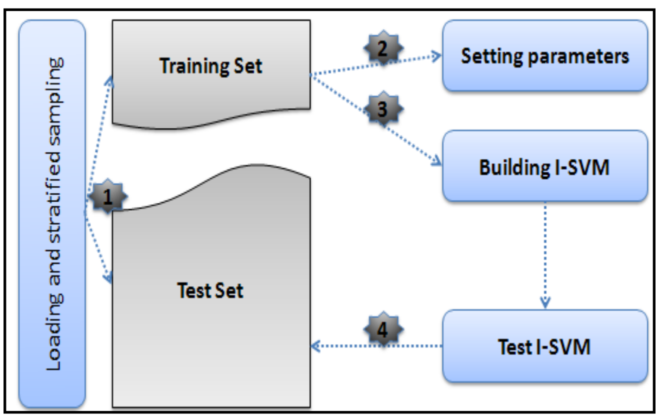

Figure 3. Structure of the system

The following steps are followed to build the incremental support vector machines as showed in Figure 3.

Step 1: We divide the used data set on two main sets, they consist of training and test sets. The stratified sampling is used and it affects 70% of the data points to the training set and 30% of data points to the test set.

Step 2: We set the appropriate parameters for the I-SVM using the grid search technique proposed by Chen and Lin in [20] and based on the cross-validation. A good setting of parameters guarantees a high level of accuracy.

Step 3: We build the new incremental system i.e. the I-SVM from training data. We adapted the algorithm proposed by Christopher P. Diehl and G. Cauwenberghs [6].

Step 4: We use the test set for the evaluation and the test of the I-SVM. Several tests are performed in order to prove the performance of the new system.

5 EXPERIMENTS

5.1 The Framework

This section describes the details of experiments on fourteen datasets.
There 14 datasets are chosen from MIMICII (Multiparameter Intelligent Monitoring for Intensive Care) database taken from Physiobank [3].
This database contains data from hemo-dynamically unstable patients hospitalized in 1996 in ICU of the cardiology division in the Teaching Hospital of Havard Medical School. It includes 100 patients' records of continuous data recorded each second. Each recording is accompanied with detailed annotations or labels made by an expert in order to precise if the current state of the patient is critical or not. For each patient, several variables are measured such as Heart Rate (*HR*), Oxygen Saturation (*SpO*$_2$), Non-Invasive Blood Pressure (*NBP*), Respiratory rate (*Resp*), Artery Blood Pressure (*ABP*), Pulmonary Artery Pressure (*PAP*) [10].

Table 1 gives more detail for the used databases with #Attributes and #Instances present respectively the total number of measured parameters and the total number of instances in a particular data set.

Table 1. Description of the used data sets

Databases	#Attributes	#Instances
Patient 01	6	4101
patient 02	8	42188
patient 03	8	42188
patient 04	7	42188
patient 05	9	42188
patient 06	9	5350
patient 07	7	11300
patient 08	7	10600
patient 09	12	5700
patient 10	5	42188
patient 11	7	42188
patient 12	7	42188
patient 13	9	42188
patient 14	7	42188

5.2 Evaluation Criteria

Our aim is to evaluate the new monitoring system and to compare its performance to the current one and to the results obtained in [9] on mode batch. The used evaluation criteria are described as follows:

1. The false alarm reduction rate FARR defined by [1]:

$$FARR = \frac{Suppressed\ false\ alarms}{Total\ number\ of\ false\ alarms} \quad (6)$$

2. The rate of false alarms expressed by the error rate (ER) as follows:

$$ER = \frac{FP + FN}{TP + TN + FP + FN} \quad (7)$$

   with FP, FN, TP and TN present respectively False Positive, False Negative, True Positive and True Negative alarms.

3. The sensitivity (S) of the system presents the ratio of TP divided by all significant alarms which are declared by experts as critical and they are correctly identified by the system. The S is defined by this formula:

$$S = \frac{TP}{TP + FN} \quad (8)$$

5.3 Experimental Results

In this section, we focus on the different evaluation criteria relative to the different systems (i.e. the current system which presents the current used system in ICU, the SVM system and the I-SVM system) namely the FARR (Equation 6), the ER (Equation 7), and the S (Equation 8).

Figure 4 shows a plot of the FARR.

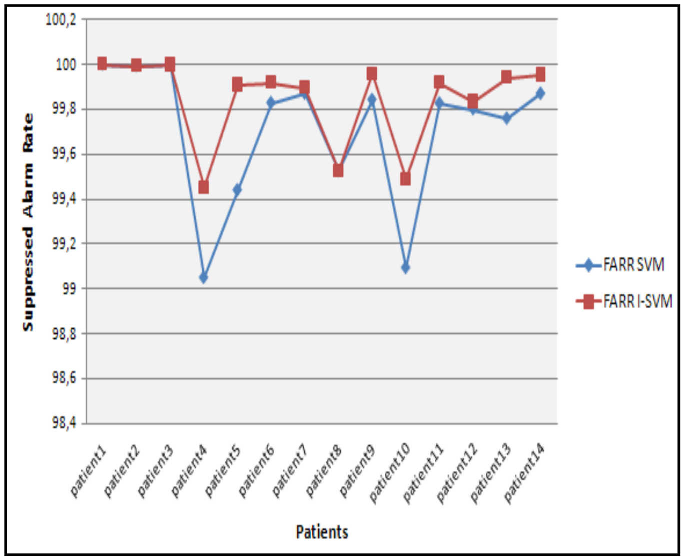

Figure 4. Suppressed false alarm for the different patients

As shown in Figure 4, the new system based on the I-SVM is able to avoid the false alarms more than the system based on the SVM. This fact can be explained by the ability of the I-SVM to improve the first model by learning from new instances added over time. In contrast to the SVM system which builds the model using training instances that should be available a priori.
For example, for the three first patients we remark that both of the SVM and I-SVM have suppressed all false alarms. However, for the fourth patient the I-SVM reduces the number of false alarms more than the standard SVM.

Figure 5 illustrates the results of the I-SVM versus the SVM and the current system based on the error rate.

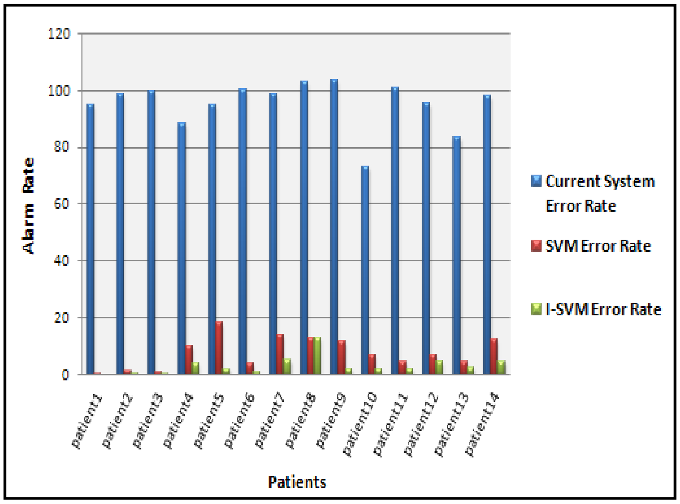

Figure 5. Error rate of the I-SVMvs the SVM and the current system

It is clear from Figure 5 that both the SVM and the I-SVM have improved the monitoring system by reducing the error rate. This improvement is obvious especially for the two first patients (patient 1 and patient 2) where the error rate is very low (near to zero). However, the error rate generated by the current system is very high (near to 100%).

Figure 6 details how sensitive is the I-SVM compared to the SVM and the current system.

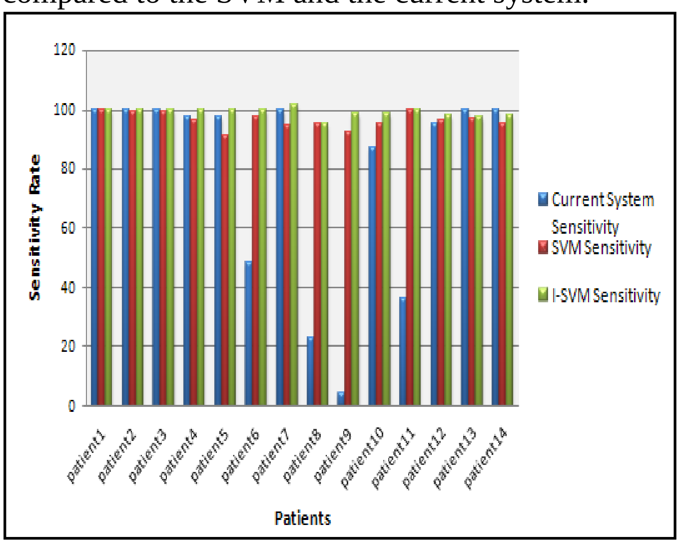

Figure 6. Sensitivity of the I-SVM vs the SVM and the current system

Based on Figure 6, we can notice that the current system loses its sensitivity to detect alarms especially for the ninth patient. This low sensitivity can be explained by the setting of bad thresholds relative to the measured variables. In fact, the staff has changed the thresholds of the variable *ABP* and *Resp* respectively from [80; 140] to [80; 220] and from [5; 25] to [8; 35] which has decreased the number of triggered alarms. However, the I-SVM has a stable and an important sensitivity in contrast to the SVM which has a variable sensitivity.

Table 2 compares the number of true positive alarms of the three systems vs the expert, where CSTA, SVM-TA and I-SVM-TA denote the number of true alarms relative respectively to the current system, the SVM and the I-SVM.

Table 2.TP alarms of the systems vs the expert

Database	CS-TA	SVM-TA	I-SVM-TA	Expert
Patient 01	309	308	309	309
patient 02	1076	1066	1074	1076
patient 03	740	734	738	740
patient 04	4533	4476	4622	4636
patient 05	1942	1823	1987	1995
patient 06	883	1783	1819	1826
patient 07	54	51	55	54
patient 08	24	98	98	103
patient 09	27	543	580	587
patient 10	2002	2189	2273	2301
patient 11	378	1042	1042	1042
patient 12	1232	1245	1264	1290
patient 13	6909	6685	6750	6909
patient 14	697	663	683	697

Looking at Table 2, we remark the ability of the I-SVM to detect true alarms for all databases (i.e. for the different patients). However, the SVM system based on the batch mode does not produce interesting results when it deals with small databases.

Generally, we can conclude that the results provided by the I-SVM are closed to the expert opinion which proves the ability of this new system to simulate the expert approach.

6 CONCLUSION

In this paper, we have applied an incremental SVM (I-SVM) on the monitoring system in ICU in order to improve this medical system.

Our system based on I-SVM is able to give results very close to the expert opinion. This is due to the ability of the I-SVM to learn from new instances and to improve the hyper-plane for each new observation.

For the evaluation of the new system, we have performed tests and the I-SVM has been compared to both the original SVM and the current system. All obtained results have proved the efficiency of the new system i.e. I-SVM in reducing the rate of false alarms and maintaining the high level of sensitivity.

As future work, we aim to improve the model by applying the notion of incremental in the test phase.

7 REFERENCES

1. Borowski, M., Siebig, S., Wrede, C. Imhoff, M.: Reducing false alarms of intensive care online monitoring systems: An evaluation of two signal extraction algorithms. In Computational and Mathematical Methods in Medicine, vol. 2011 (2011).
2. Charbonnie, S., Gentil, S.: A trend-based alarm system to improve patient monitoring in intensive care units. In Control Engineering Practice 15, pp. 1039--1050 (2007).
3. Nouira, K., Trabelsi, A. : Intelligent monitoring system for intensive care units. In Journal of Medical Systems, vol. 36, pp. 2309--2318 (2011).
4. Chambrin, M. C.: Alarms in the intensive care unit: how can the number of false alarms be reduced. In Journal of Critical Care, vol. 5, pp. 184--188 (2001).
5. Tsien, C.: Reducing False Alarms in the Intensive Care Unit: A Systematic Comparison of Four Algorithms. In Proc. Proceedings of the AMIA Annual Fall Symposium, American Medical Informatics Association (1997).
6. Cauwenberghs, G., Poggio, T.: Incremental and Decremental Support Vector Machine Learning. In: Proc. Advances in Neural Information Processing Systems NIPS, pp. 409--415 (2000).
7. Diehl, C. P., Cauwenberghs, G.: SVM Incremental Learning, Adaptation and Optimization. In Proc. of the International Joint Conference on Neural Networks, pp. 2685--2690 (2003).
8. Ben Rejab, F., Nouira, K.: Reducing False Alarms in Intensive Care Units Monitoring System Using Support Vector Machines. In: Proc. CCCM 2010, MA, vol. IV, pp. 106--109 (2010).
9. Ben Rejab, F., Nouira, K., Trabelsi, A.: Support Vector Machines versus Multi-layer Perceptrons for Reducing False Alarms in Intensive Care Units. In International Journal of Computer Applications, Foundation of Computer Science, New York, USA, vol. 49, pp. 41--47 (2012).
10. Bordes, A., Bottou. L.: The Huller: a simple and efficient online svm. In Proc. European Conference on Machine Learning: ECML 2005, Lecture Notes in Artificial Intelligence, LNAI 3720, pp. 505--512. Springer Verlag (2005).
11. Ivanciuc, O.: Applications of Support Vector Machines in Chemistry, Rev. Comput. Chem., vol. 23, pp. 291--400 (2007).
12. El Sayed, A.,Wahed, I., Al Emam, A. B.: Feature Selection for Cancer Classification: An SVM based Approach. In International Journal of Computer Applications IJCA, vol.46, pp. 20--26 (2012).
13. Reslan, Z. A.: Clinical alarm management and noise reduction in hospitals. Storrs, CT: University of Connecticut (2007).
14. Cropp, A., Woods, L., Raney, D., Bredle, D.: Name that tone. The proliferation of alarms in the intensive care unit. In Chest, vol. 105, pp. 1217--1220 (1994).
15. Cortes, C., Vapnik, V.: Support vector networks. In Machine Learning, vol. 20, pp. 273--297 (1995).
16. Ming, H. T., Vojislav, K.: Gene extraction for cancer diagnosis by support vector machines an improvement. In Artificial Intelligence in Medicine, vol. 35, pp. 185--194 (2005).
17. Zhang, S. W., Pan, Q., Zhang, H. C., Zhang, Y. L., Wang, H. Y.: Classification of protein quaternary structure with support vector machine. In Bioinformatics, vol. 19, 2390--2396 (2003).
18. Tong, T., Koller, D.: Support Vector Machine Active Learning with Applications to Text Classification. In Journal of Machine Learning Research, pp. 45--66 (2001).
19. Luo, J., Pronobis, A., Caputo, B., Jensfelt, P.: Incremental learning for place recognition in dynamic environments. In Proc. IROS07 (2007).
20. Chen, Y. W., Lin, C. J.: Combining SVMs with various feature selection strategies, http://www.csie.ntu.edu.tw/cjlin/papers/features.pdf