THESIS TITLE

Automating ICU Emergency Signaling

Rashida Bengali 09210011

Nabila Yeazdani 09210008

Naima Zaman   09210025

Department of Electrical and Electronic Engineering (EEE)

Program – Electronics and Communication Engineering (ECE)

August 2013

BRAC University

Dhaka, Bangladesh

DECLARATION

We hereby declare that the work and the research conducted for the thesis is our original work. We have not copied from any other students' work or from any other sources except where due reference or acknowledgement are made explicitly in the text, nor has any part been written for us by another person.

Rashida Bengali

Nabila Yeazdani

Naima Zaman

Signature of Advisor   Signature of Students

DEDICATION

This Thesis is dedicated to our parents and faculties who have supported and motivated us through out our Under Graduate Life in BRAC University. We also dedicate this work to each other for being there in the whole process. We appreciate each other's effort in making this work happen.

ACKNOWLEGEMENTS

ABSTRACT

In this thesis, a recursive algorithm based on kernel mapping is applied to develop an automated, ICU Signaling. The method is portable and adaptive, and has lower complexity. Streams of different medical parameters are used to identify normal and abnormal conditions of individual patients in ICU. Using a system as such, the slightest of anomaly deviated from the norm, can be detected and alarmed, so that the medical team can take immediate and emergency action.

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I. INTRODUCTION

A. Problem Statement

An Intensive Care Unit (ICU) is powerful in evaluating critically ill patients. But for ages, ICUs have appointed a medical person, a nurse, for every patient in the ICU. The job of the nurse is similar to being a human monitor to a patient, to see if anything goes wrong and to summon emergency medical help. Technology has been cutting a lot of salary cost these days and here also we have planned and evolved ideas to remove this hectic human operations. Disadvantages are crucial as the human operator might get exhausted and miss a critical condition of the patient to report. So here is the remedy. Our Kernel-based Online Anomaly Detection (KOAD) algorithm helps to automate the ICU and it is the algorithm that will call for medical emergency if required. KOAD takes over the whole human monitoring system as it directly monitors any change in the measuring parameters in real time, computes it, compares it to the normality space and detects what ranges of values are normal for a particular patient. It saves the normal ranges in a dictionary and raises an orange alarm if values spans beyond the normality space. It resolves the orange alarm to green if it computes that the value is normal and to a red alarm if it crosses the normality span. When a red alarm is raised, a literal alarm rings, thus calling the medical team for help. This is a very effective method of automation with high detection rate and with the added advantage of being an adaptive and online algorithm with bounded complexity.

B. Our Contributions

Most prior work in network anomaly detection has used block-based methods, which are only suitable for offline applications, requiring waits of up to hours before alerts occur. Thus our algorithm takes the alternative approach of learning the behavior of online anomaly, and autonomously adapting to shifts in the structure of normality itself. Initially, we worked with a hypothetical data on the basic and important medical parameters of an ICU patient. Having successfully achieving our goals in making the algorithm run, we gathered the real data and applied it on the algorithm and achieved expected results. In this paper we develop a sequential, real-time anomaly detection algorithm that incrementally constructs and maintains a stream of medical parameters which defines the region of normal behavior. The parameters adapts over time to address changes in the structure of normal range values of parameters, with new elements being added obsolete members deleted as the normality region expands or migrates. We provide a comparative study on real data of our proposed Kernel-based Online Anomaly Detection (KOAD) algorithm. The results indicate that the detection performances are approximately equivalent, with the KOAD algorithm offering lower computational complexity and faster time-to-detection.

C. Outline of Thesis

This paper is organized as follows. Section II gives an overview of different applications used in ICU emergency signaling and also states details about the other networks that use Kernel based algorithm. Section III presents the KOAD algorithm, analyses computational complexity, and discusses the choice of the algorithm parameters. It mainly monitors whether or not our algorithm will run effectively on ICU patients. This section discusses in detail the applications and the code used to achieve our means. Section IV compares the performance of our algorithm on data recorded on the network. Initially, the use of hypothetical data gave us desired results. Later the collection of real data and its application on KOAD showed results of an ICU patient in both its normal form and caused alarm when an anomaly was detected. Section V provides concluding remarks and describes avenues for future research.

II. RELATED WORK

A. Apart from our work which mainly focuses on the recursive Kernel based Online Anomaly Detection; there have been a series of works used in ICU Emergency Signaling.

- Lakhina et al. demonstrate the intrinsic low-dimensionality of network flows, and the high spatial and temporal covariance structure between the flows. Lakhina et al. used the technique of Principal Component Analysis (PCA) to separate the space occupied by a set of traffic metrics into two disjoint subspaces, corresponding to normal and anomalous behavior, respectively. They signal an anomaly when the magnitude of the projection onto the residual, anomalous subspace exceeds an associated PCA Qstatistic threshold. The PCA subspace method was shownto be more effective than EWMA and Fourier approaches in automatic diagnosis of anomalies. Lakhina et al. also suggested an online formulation of the PCA-based algorithm in. This involved using a sliding window implementation to identify the normal and anomalous subspaces based on a previous block of time. The variation in the structure of multivariate network traffic statistics over time is, however, non-negligible. Further, the PCA-based detection algorithm is extremely sensitive to the proper determination of the associated Q-statistic threshold. We implemented the proposed online version of PCA and observed that although the anomalous and normal subspaces remained relevant over time, using stale measurements to calculate the Q-statistic threshold resulted in an unacceptable number of false positives. This indicates that straightforward extensions to the PCA-based method are not robust and motivates alternative approaches for an online application.

- Brutlag uses as an extension of the Holt-Winters forecasting algorithm, which supports incremental model updating via exponential smoothing. His algorithm defines a "violation" as an observation that falls outside an interval (a confidence band), and identifies a "failure" (an anomaly) when the number of violations within an observation window exceeds a threshold. Hajji uses a Gaussian mixture model, and develops an algorithm based on a stochastic approximation of the Expectation-Maximization (EM) algorithm to obtain estimates of the model parameters.

- Recently there has been an upsurge of interest in strategies for detecting at-risk patients in order to trigger the timely intervention of a Medical Emergency Team (MET), also known as a Rapid Response Team (RRT). We review a real-time automated system, BioSign, which tracks patient status by combining information from vital signs monitored non-invasively on the general ward. BioSign fuses the vital signs in order to produce a single-parameter representation of patient status, the Patient Status Index. The data fusion method adopted in BioSign is a probabilistic model of normality in five dimensions, previously learnt from the vital sign data acquired from a representative sample of patients. BioSign alerts occur either when a single vital sign deviates by close to ±3 standard deviations from its normal value or when two or more vital signs depart from normality, but by a smaller amount. In a trial with high-risk elective/emergency surgery or medical patients, BioSign alerts were generated, on average, every 8 hours; 95% of these were classified as 'True' by

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clinical experts. Retrospective analysis has also shown that the data fusion algorithm in BioSign is capable of detecting critical events in advance of single-channel alerts.

- A prospective observational study was done comparing invasive monitoring and noninvasive monitoring in 60 critically ill or injured patients who required hemodynamic monitoring shortly after entering the ED of a university-affiliated county hospital. Cardiac output (CO) values measured by the standard then no dilution pulmonary artery catheter technique were compared with simultaneously obtained measurements using a noninvasive bio-impedance method. Concurrent measurements were made of pulse oximetry to screen pulmonary function and transcutaneous oximetry to assess tissue perfusion. Noninvasive monitoring can provide hemodynamic and perfusion information previously available only by invasive thermo-dilution catheters. Such noninvasive monitoring can display continuous on-line real-time data, allowing immediate recognition of circulatory abnormalities and providing a means to titrate therapy to appropriate therapeutic goals.

- MicroEEG is a portable, battery-operated, wireless EEG device, developed by Bio-Signal Group to overcome the obstacles to routine use of EEG in emergency departments (EDs). The standard system was used to obtain EEGs from healthy volunteers in the EEG laboratory, and studies recorded from patients in the ED or ICU were also used for comparison. In one experiment, a signal splitter was used to record simultaneous microEEG and standard EEG from the

same electrodes. EEG signal analysis techniques indicated good agreement between microEEG and the standard system in 66 EEGs recorded in the EEG laboratory and the ED. In the simultaneous recording the microEEG and standard system signals differed only in a smaller amount of 60 Hz noise in the microEEG signal. The results suggest that the technical qualities of microEEG are non-inferior to a standard commercially available EEG recording device. EEG in the ED is an unmet medical need due to space and time constraints, high levels of ambient electrical noise, and the cost of 24/7 EEG technologist availability. This study suggests that using microEEG with an electrode cap that can be applied easily and quickly can surmount these obstacles without compromising technical quality.

B. The proposed algorithm is based on the kernel version of the recursive least squares algorithm. It assumes no model for network traffic or anomalies, and constructs and adapts a dictionary of features that approximately spans the subspace of normal behavior. There are many other systems that use the Kernel Recursive Algorithm.

- An extensive network of surveillance and security network is prevalent in many places in today's world. They range from analogue closed-circuit television (CCTV) systems to sophisticated networks of infra-red and motion sensors in sensitive areas such as banks and museums. A recursive algorithm based on kernel mappings to propose an automated, real-time intruder detection mechanism for surveillance networks. Our proposed method is portable and adaptive, and does not require any expensive or sophisticated components.

- The formation of disulphide bridges between cysteines plays an important role in protein folding, structure, function, and evolution. Here, we develop new methods for predicting disulphide bridges in proteins. We first build a large curated data set of proteins containing disulphide bridges to extract relevant statistics. We then use kernel methods to predict whether a given protein chain contains intrachain disulphide bridges or not, and recursive neural networks to predict the

bonding probabilities of each pair of cysteines in the chain. These probabilities in turn lead to an accurate estimation of the total number of disulphide bridges and to a weighted graph matching problem that can be addressed efficiently to infer the global disulphide bridge connectivity pattern. It can classify individual cysteine residues as bonded or nonbonded with 87% specificity and 89% sensitivity. The estimate for the total number of bridges in each chain is correct 71% of the times, and within one from the true value over 94% of the times. The prediction of the overall disulphide connectivity pattern is exact in about 51% of the chains. In addition to using profiles in the input to leverage evolutionary information, including true (but not predicted) secondary structure and solvent accessibility information yields small but noticeable improvements. Finally, once the system is trained, predictions can be computed rapidly on a proteomic or protein-engineering scale.

- The Cerebellar Model Articulation Controller (CMAC) neural network is an associative memory that is biologically inspired by the cerebellum, which is found in the brains of animals. The standard CMAC uses the least mean squares algorithm to train the weights. Recently, the recursive least squares algorithm was proposed as a superior algorithm for training the CMAC online as it can converge in one epoch, and does not require tuning of a learning rate. Recently also, the use of kernel methods in the CMAC was proposed to reduce memory usage and improve modeling capabilities. In this paper the Kernel Recursive Least Squares (KRLS) algorithm is applied to the CMAC. Due to the kernel method, the computational complexity of

the CMAC becomes dependant on the number of unique training data, which can be significantly less than the weights required by non-kernel CMACs. Additionally, online sparsification techniques are applied to further improve computational speed.

- A real-time network anomaly detection method that is not based on an *a priori* model is the time based inductive learning machine (TIM) of Teng et al. Their machine constructs a set of rules based upon usage patterns. The detection algorithm detects a deviation when the premise of a rule occurs but the conclusion does not follow. Applying machine learning approaches to network anomaly detection is a recent phenomenon. Examples include the use of statistical learning techniques to detect email worms and viruses by Martin et al., and an algorithm based on Kernel PCA proposed by Heafield.

III. THEORETICAL FRAMEWORK

A. Monitoring Architecture

Tentatively one monitoring architectures can be proposed, similar to the KOAD application in BRAC University surveillance system. A distributed approach where the algorithm is run locally for each and every ICU patients and after each timestep, each node makes a decision whether any anomaly has been detected or not and then communicates a binary result in Central Monitoring Unit (CMU). If anomaly has been detected, an alarm would ring to draw the attention of the operator, and the operator checks which patient condition is showing critical and send immediate medical team for assistance. The alarm room should be quite far from the ICU room as any alarm might as well make other patients' situation critical.

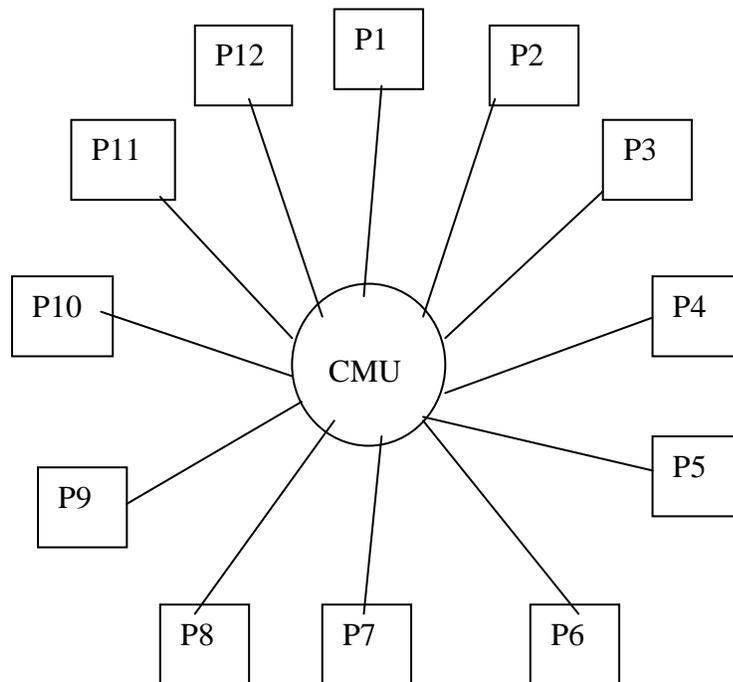A proposed architecture is given below -

Fig1: Monitoring Architecture

The topology shown is a star topology. The CMU, central monitoring Unit, monitors all incoming traffic from ICU of individual patients. From P1 to P12 are ICU patients connected to the algorithm monitoring them 24/7. The idea is to monitor all patients simultaneously, through the CMU which is included in the hospital surveillance system. The patients online data is transmitted through a dedicated transmission line could be optical fiber or E1 connections. Optical fibers are expensive but delay is a factor for critical patients. KOAD itself saves a lot of hardware implementation and thus a high speed transmission fiber is the key to effective automation.

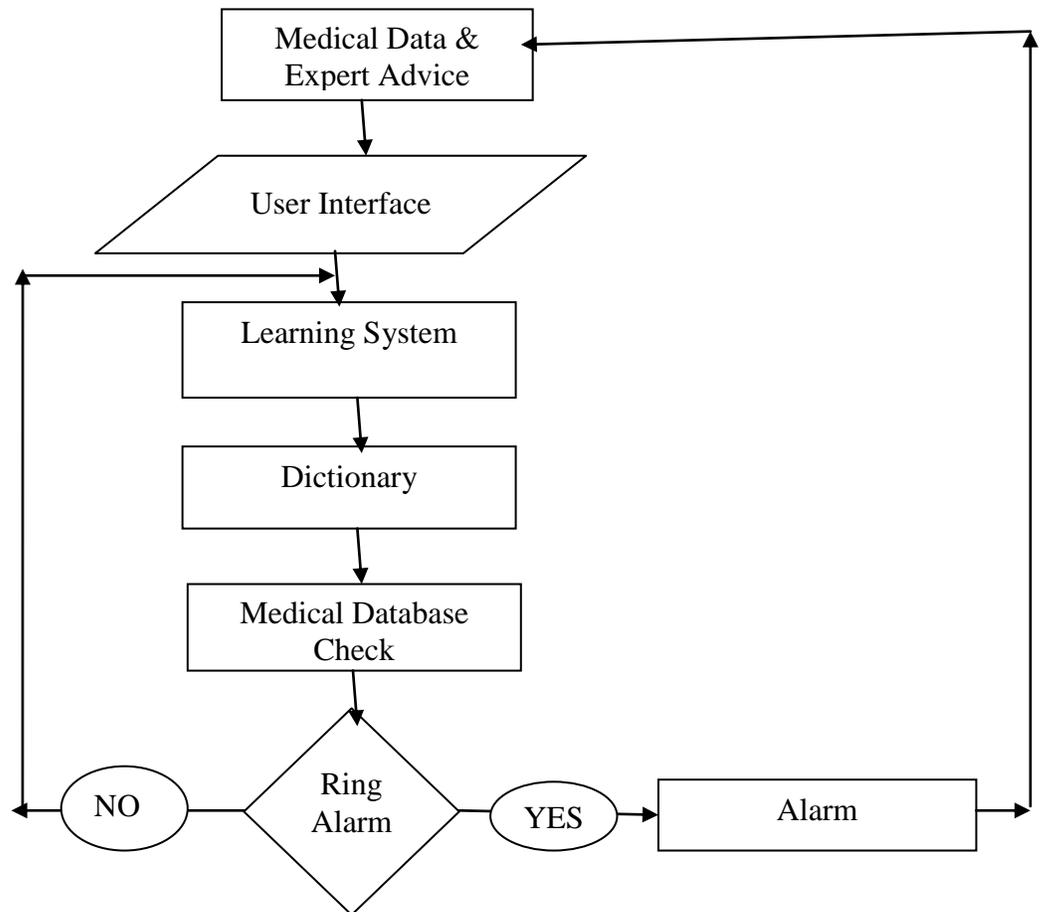The flowchart of monitoring architecture is shown below -

Fig2:- Flowchart of monitoring architecture

B. Kernel Online Anomaly Detection (KOAD)

Algorithms based on the so-called "kernel trick" involve using a kernel function that maps the data into a feature space of much higher dimension, with the expectation that points depicting similar behavior would cluster in the higher dimensional feature space. The idea is that a suitable kernel function, when applied to a pair of input vectors, may be interpreted as an inner product in the feature space. This subsequently allows inner products in the feature space (inner products of the *feature vectors*) to be computed without explicit knowledge of the feature vectors themselves, by simply evaluating the kernel function:

$$k(\mathbf{x}i, \mathbf{x}j) = (\varphi(\mathbf{x}i), \varphi(\mathbf{x}j)) \qquad (1)$$

where $\mathbf{x}i$, $\mathbf{x}j$ denote the input vectors and φ represents the mapping onto the feature space.

Consider a set of multivariate measurements $\{\mathbf{x}t\}^{T}_{t=1}$. In an appropriately chosen feature space F with an associated mapping φ, the feature vectors corresponding to the points in $\{\mathbf{x}t\}^{T}_{t=1}$ that depict normal behaviour, $\{\varphi(\mathbf{x}t)\}^{T}_{t=1}$, are expected to cluster. Then, it should be possible to explain the region of normality (in the feature space) using a relatively small *dictionary* of *approximately* linearly independent elements $\{\varphi(\tilde{\mathbf{x}}j)\}mj =1$. Here $\{\tilde{\mathbf{x}}j\}mj =1$ represent those $\{\mathbf{x}t\}T t=1$ that are entered into the dictionary. The size of the dictionary, m, is expected to be much less than T, thereby leading to computational and storage savings. Feature vector $\varphi(\mathbf{x}t)$ is said to be *approximately* linearly dependent on $\{\varphi(\tilde{\mathbf{x}}j)\}mj=1$ with approximation threshold v, if the projection error δt satisfies the equation of:-

$$\delta_t = \min_a \left\| \sum\nolimits^{m}_{j=1} \mathbf{a}_j \phi(\mathbf{x}_j) - \phi(\mathbf{x}_t) \right\|^2 \qquad (2)$$

The kernel-based Online anomaly detection algorithm operates at each timesteps t on a measurement vector $\mathbf{x}t$. It begins by evaluating the error δt in projecting the arriving $\mathbf{x}t$ onto the current dictionary (in the feature domain). Observe that (2) involves an L2 norm, which may be simplified exclusively in terms of the inner products of $\varphi(\tilde{\mathbf{x}}j)$ and $\varphi(\mathbf{x}t)$, and thus evaluated using the kernel function without explicit knowledge of the feature vectors themselves. This error measure δt is then compared with two thresholds $v1$ and $v2$, where $v1 < v2$. If $\delta t < v1$, KOAD infers that $\mathbf{x}t$ is sufficiently linearly dependent on the dictionary, and represents normal behaviour. If $\delta t > v2$, it concludes that $\mathbf{x}t$ is far away from the realm of normality and immediately raise

a "Red1" alarm to immediately signal an anomaly. If $v1 < \delta t < v2$, KOAD infers that $\mathbf{x}t$ is sufficiently linearly independent from the dictionary to be considered an unusual event. It may indeed be an anomaly, or it may represent an expansion or migration of the space of normality itself. In this case, KOAD does the following: it raises an "Orange" alarm, keeps track of the contribution of the relevant input vector $\mathbf{x}t$ in explaining subsequent arrivals for l timesteps, and then

takes a firm decision on it. At timestep $t + l$, KOAD re-evaluates the error δ in projecting $\mathbf{x}t$ onto dictionary $Dt+l$ corresponding to timestep

$t + l$. Note that the dictionary may have changed between timesteps t and $t + l$, and the value of δ at this re-evaluation may consequently be different from the δt at timestep t. If the value of δ after the re-evaluation is found to be less than $v1$, KOAD lowers the orange alarm and keeps the dictionary unchanged.

If the value of δ is found instead to be greater than $v1$ after the re-evaluation at timestep $t + l$, KOAD performs a secondary "usefulness" test to resolve

the orange alarm. The usefulness of **x**t is assessed by observing the kernel values of **x**t with *{**x**i}t+_i=t+1*. If a kernel value is high (greater than a threshold *d*), then $\varphi(\mathbf{x}t)$ is deemed close enough to $\varphi(\mathbf{x}i)$. If a significant *number* of the kernel values are high, then **x**t cannot be considered anomalous; normal traffic has just migrated into a new portion of the feature space, and **x**t should be entered into the dictionary. Contrarily if almost all kernel values are low, then **x**t may be concluded to be a reasonably isolated event, and should be heralded as an anomaly. We evaluate:

$$[\textstyle\sum^{t+1}_{i=t+1} \prod (k(\mathbf{x}_t , \mathbf{x}_i)>d)] > \varepsilon l \qquad\qquad (3)$$

where *I* is the indicator function and $\varepsilon \in (0, 1)$ is a selected constant. In this manner, by employing this secondary "usefulness test", KOAD is able to distinguish between an arrival that is an anomaly, from one that is a result of a change in the region of normality. If (3) evaluates true, then KOAD lowers the relevant orange alarm to green (no anomaly) and adds **x**t to the dictionary. If (3) evaluates false, it elevates the relevant orange alarm to a "Red2" alarm.

KOAD also deletes obsolete elements from the dictionary as the region of normality expands or migrates, thereby maintaining a sparse and *current* dictionary. In addition, it incorporates exponential forgetting so that the impact of past observations is gradually reduced.

IV. EXPERIMENTS

A. Hypothetical Data

The concept of hypothesis came by, when we were to see whether KOAD works for ICU parameters. The search began from where we will be able to collect parameters. After considering all probable options, National Heart Foundation and Research Centre (NHFRC) seemed quite eligible as they have a research unit involved and therefore they were even apt to provide us with any help that we would require in our proposed research. The first step was to have an insight of what parameters does an NHFRC ICU measures and to know their normal and abnormal ranges. Dr. Fazle Elahi Chowdhury, a pioneer in implementing a research unit in Heart foundation, provided us with the parameters through our advisor Mr.Tarem Ahmed.

The lab work began next. We tabled all the parameters accordingly in a spreadsheet and input data over hundred intervals hypothetically but based on the legitimate range each parameter can support. After we have a complete spreadsheet with parameters and data for 100 intervals, we input the hypothesis in the KOAD. As KOAD is written in Matlab, we were lucky to have a spreadsheet reading option and got a matrix of parameter values against time intervals. The algorithm was modified accordingly then to have some expected results in terms of graphs and alarms, incubated within the algorithm. The hypothetical table was designed as such, so that every single parameter has some anomaly compared to the normal range value, which is so not typical of the real life phenomenon; i.e., even a critical ICU patient will not show abnormality in all the available parameters. This was done on purpose, just to check that the algorithm works even in the utmost worst case scenario. The accomplishment of this hyper hypothesis, led us to pursue for

some real patients' data to feed in our algorithm and check the validity of our research.

B. Results

As mentioned above in the hypothetical data part, we were successful into getting results after running the unrealistic table of parameters. The results included complexity analysis and graphs of sensitivity and detection vs. false alarms.

- Sensitivity graph shows how much lower or higher values the algorithm can detect. The detection is set with various thresholds of *nu1* and *nu2*, which is again parameter dependent. When all the parameters have errors no particular thresholds can be set, because again it is unrealistic for all the parameters to be anomalous all at the same time. The only valid conclusion that all parameter anomalies give us is that the algorithm is even capable of detecting all at the same time. When one or few related parameters like mean blood pressure and heart rate or diastolic blood pressure and blood vessel pressure is combined, a sensible set of thresholds was figured out. This particular threshold differs from patient to patient, which again is responsible for various height, weight and age of the individual. Through the sensitivity check, we concluded that the first goal of automation is served.

- The detection versus false alarm graph provided insight about how keenly the threshold should be set to be alarmed with the critical condition of the patient. Sensitivity tells us how much the algorithm is efficient and this makes us use it as an advantage. The scenario is such: an alarm is always ringing if situation goes beyond normal.

For any time period it is better if there rings an alarm for 100% of the given interval and only 5% being the false alarm rate. Thus the graph shows how much effectively an automated system alarms the medical team even if it is not needed, but at the same time, serving to intensive monitoring of the patient under observation. Also the lesser the time it takes to make 100% detection, the better, which is also served by our hypothetical data. However, when all parameters were shown to have anomaly, the curve shows inefficiency. The reason is quite reasonable. If thought in literal terms, the alarm would not stop ringing and medication is impossible. The detection versus false alarm graph for the unrealistic data made us realize that, all parameters cannot go wrong all at the same time or the patient would need to be declared medically dead. When one or related parameters are shown to have anomaly, the detection rate is high and false alarms are also in track with the thresholds set. Each parameter has a different threshold for a particular patient; i.e., the threshold for ph is way different from the threshold of base excess.

- Complexity analysis is a key to ICU application. In terms of storage requirements, the maximum dimensions of the variables that KOAD stores are $m \times m$, where m is the dictionary size. KOAD also retains the input vectors that raise orange alarms for l timesteps, and an additional $L \times m$ binary matrix. The computational complexity is O $(m2)$ for every standard timestep, and O $(m3)$ on the rare occasions when an element removal occurs. KOAD complexity is thus independent of time, making it naturally suited for ICU application, where anomaly occurrence doesn't have any time specification. Our experiments have shown that high sparsity levels are achieved in

practice, and the dictionary size does not grow indefinitely. Note that the data streams are fixed in the hypothesis and are fed in the algorithm at regular continuous intervals.

C. Real Data Collection

Successful implementation of the hypothetical data led us to go for some real patients' data which would reflect real issues. Data collection has never been an easy job for any research and this time it had not been an exception either. After being verified about the algorithm running in extreme conditions we asked for real data through our advisor Mr.Tarem Ahmed from Dr. Fazle Elahi Chowdhury.

We first sent the hypothetical data table to the doctor, acknowledging him about our research success. He looked through all of it and emailed us with few of his ICU patients' data spreadsheet. The items were raw and far stretched from our laboratory data. We analyzed the data and figured out that a lot of formulae are associated closely with few parameters and this is the association that made the parameters related. To exemplify, cardiac index was related to cardiac output and body surface area which in turn is related to height and weight of the individual concerned. So the constraint we faced while tabulating the hypothesis about the related parameters is solved here. Also, along with real patient's data the doctor attached some normal extends of parameter range which has unusually been reported as normal. Also we are notified that, being a heart specialized hospital, National Heart Foundation and Research Centre has constraint of not measuring or dealing with any non-heart related parameters. But as far as our algorithm is concerned, we knew that if real Cardiac ICU parameters can work, any ICU parameter is going to run successfully in our proposed KOAD algorithm.

The first step of our report, which is the real data accumulation, concludes here.

D. Application and Results

The idea of applying the real data parameters to our algorithm was simply substituting the hypothetical ones. But it didn't turn out to be that simple. Every individual patient showed a familiar trend of anomaly. For example, the one whose data showed considerable fluctuations in partial pressure of CO_2 also showed variations in partial pressure of O_2 as well. Another's showed very random values on the concentration of magnesium ions. It was daunting to us about its not following any range, but, later as we figured out its value is assessed seldom and can take any value.

After all the data have been fed into the spreadsheet and the algorithm ran, a completely different structure was observed from the hypothetical data. The sensitivity curve shows pretty much the same results but the detection versus false alarm curve shows significant change. With the hypothetical data, even if only few related parameters were changed, the rate of alarms in the hypothetical data was less than the real ones. In other words, spikes showed off more in the real data than in the hypothetical ones. The reason was, we hypothesized anomalies to occur at a given time only once in any given interval. Whereas, in real times, anomalies occurred quite often for a critical patient - the reason the patient is admitted in ICU. We checked the thresholds and figured out no matter how much we try to concise the nu1 and nu2 range, it will alarm the team as many times as needed, or else the algorithm gets inefficient. For example, if thresholds are set with a higher

value, medical unit will not be alarmed even when the patient has reached critical point.

The conclusion that we have drawn from the real data implementation is that, the version of KOAD is perfectly capable of taking ICU data and provide significant outcome. It can give different outcomes with different patients, as it learns automatically the condition of the newly admitted patient and allows medical team to set thresholds accordingly.
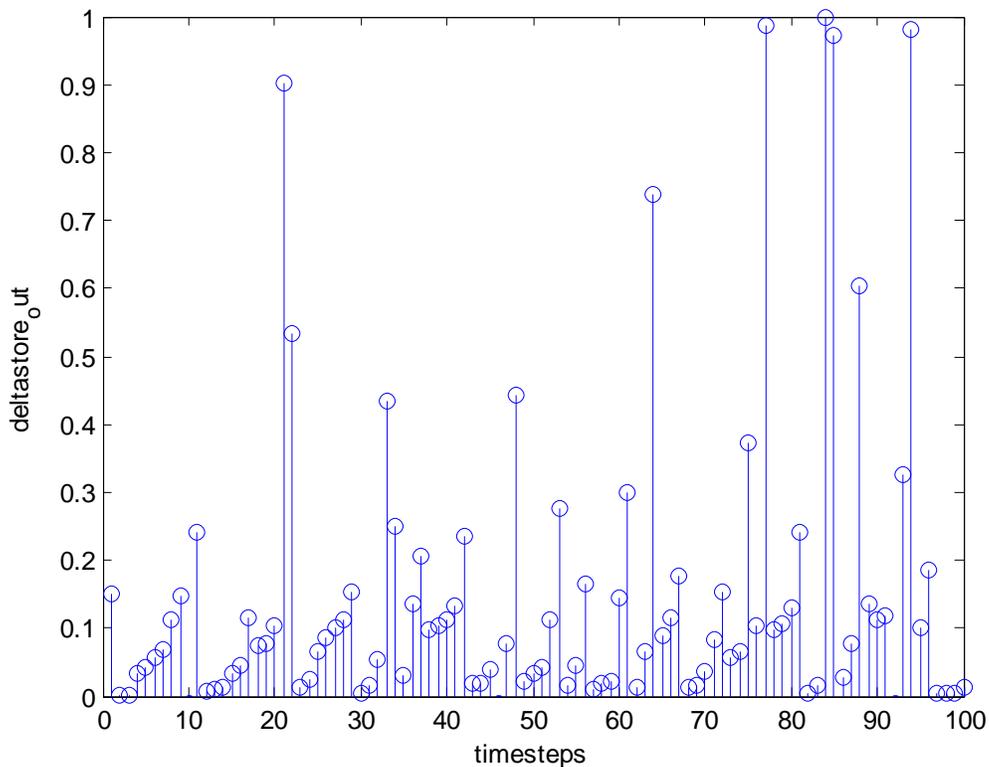

Fig3: Abnormal output

The above figure shows the output of all-anomaly parameters, which is considered as unrealistic. As a figure shows, it is impossible to set a threshold as there is no pattern. The purpose of this was to check to what extent the algorithm can detect changes and anomalies effectively. This is

the hypothetical data, designed to analyse the complexity and detection rate of the algorithm.
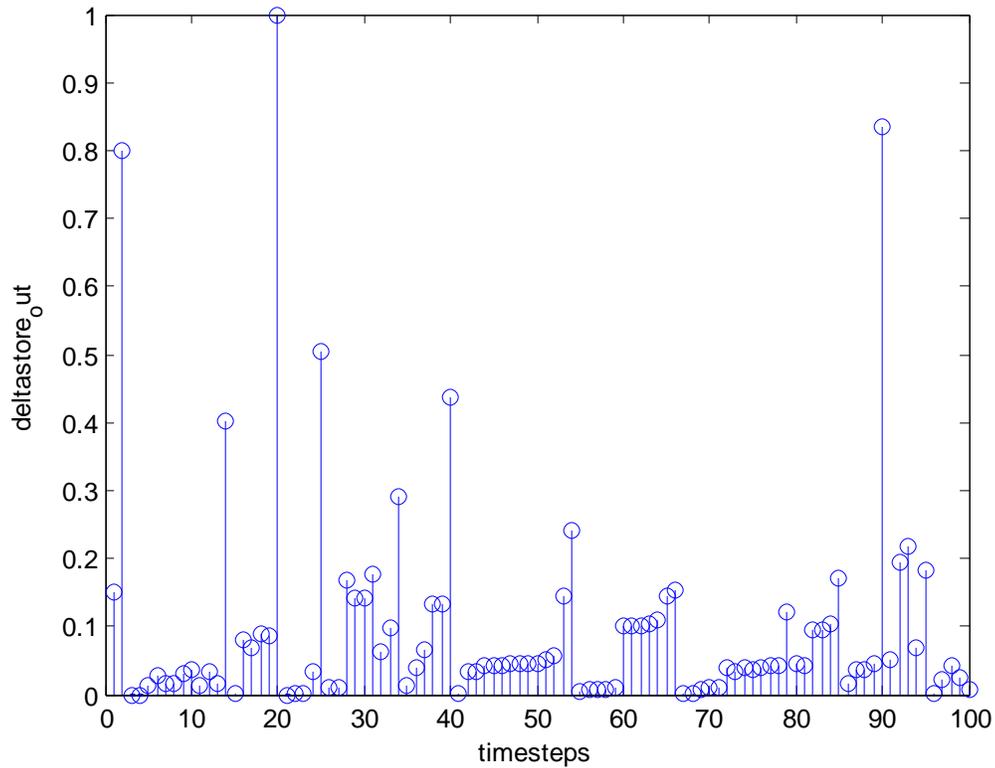
Fig4: Normal Patient (SVRI)

The above figure shows Systemic vascular Resistance index anomaly only. As seen in the figure it is easy to detect and set thresholds. Most of the points lie below 0.25 of deltastore. Therefore a medical expert will set the threshold greater than 0.25 for an anomaly to be alarmed.
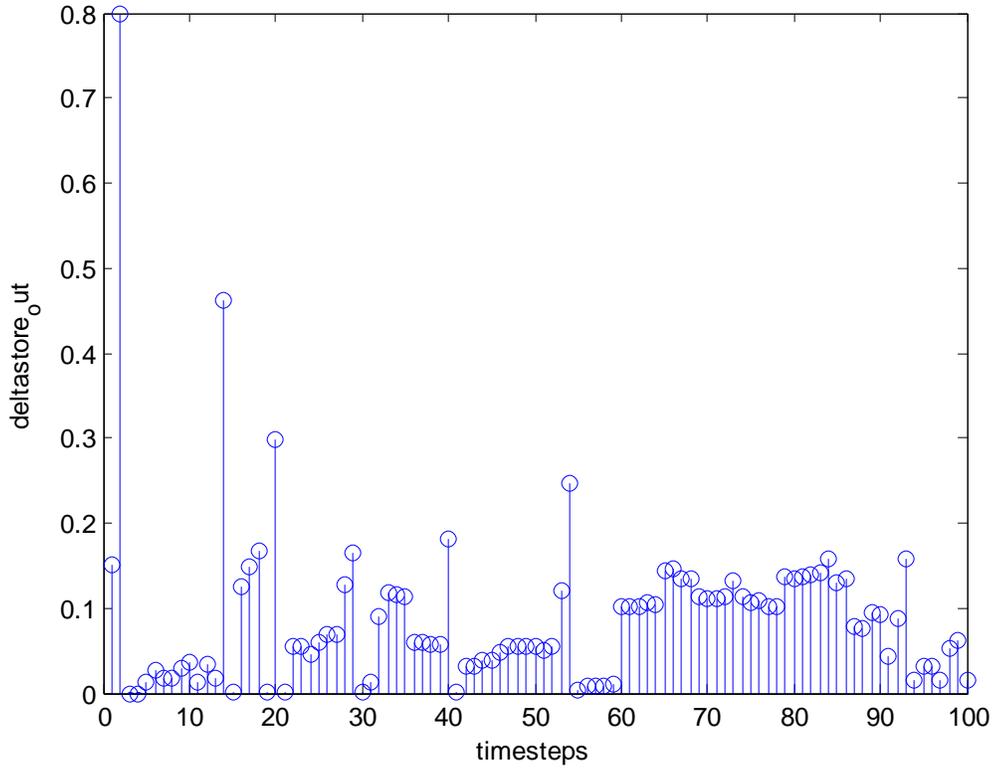
Fig5: Normal Patient (ETCO2)

The above figure shows End tidal Carbon-dioxide tension. Again it's easy to set thresholds. Clearly most of the values are below 0.2 and thus a medical expert would set the threshold as 0.2 and above for anomaly to be detected and ring the alarm.

V. CONCLUSION AND FUTURE WORKS

We have described a kernel-based online anomaly detection algorithm that is able to detect anomalous events in real time. We have demonstrated that the proposed algorithm achieves similar detection performance to the most effective block-based approaches, but has a faster time-to-detection and lower computational complexity. Hypothetical analyses have shown the algorithm to work almost perfectly. But implementation of such a system in real time requires planning. The algorithm runs on hardwares that must be compatible to run such files. As mentioned in the section of monitoring architecture, the medical service location must have a team to be able to implement such technology. A topology, servers, transmission mechanism, monitoring experts, system analysts, and IT support are additional keys and costs to run this system.

Our work is restricted only to the algorithm – to see whether KOAD is able to analyze medical parameters. All the modification has been done to make it available for all future works related to enhance medical services. May it be network enhancement or overall medical surveillance, further improvement is possible from this point of work where finally the system (servers, database, workstations, and application software) will run smoothly and the goal of automating critical care units will be accomplished. Some components of success would be high availability of system architecture, medical device integration, usability, clinical surveillance, global data repository, deployment scope and 24/7 turnkey support. Architectural future work might include:-

- Interpretation technique for patho-physiological data collected at the ICU to support parameter specification.

- Interfaces and representations for effectively integrating and interpreting knowledge from multiple sources.
- Techniques to organize different levels of generality.

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