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Multisensor Data Fusion Based Early Warning System For Wireless Healthcare Monitoring

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ABSTRACT
Recent advancements in biosensor design, wireless embedded technology and machine-learning systems bring together the evolution of intelligence in healthcare monitoring. In the past, various applications have been designed in the filed of wireless data collection and analysis to enable early warning systems in healthcare. One major shortcoming in designing effective intelligent algorithms for healthcare system is immunity over the restricted bandwidth to accommodate larger sensor data. This constrain possibly restricts the healthcare system to accommodate sufficient cognitive performance, analysis and interpretations over the observed healthcare data. In this paper we propose a cognitive intelligent early warning system using multisensor data fusion technique for effective data analysis and interpretation. This system issues a distress-warning signal whenever the vital signs deviate from its specified limits and also indicates the status of patients' health condition. MATLAB is used to develop the cognitive modules using hybrid fusion as it provides an accommodative software platform to perform data acquisition, signal processing, fuzzy inferences and data analysis. The system helps the medical personnel to overcome alarm fatigue as well as information overloading. This proposed system will be a major contribution for clinicians in intensive care units.
KEYWORDS: Cognitive systems, early warning system, healthcare monitoring, machine learning, multisensor data fusion, fuzzy inference.

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I. INTRODUCTION

Wireless healthcare monitoring with cognitive abilities has been a research area of high interest during past years [1] [2] [3] as it provides unobtrusive monitoring of patients physiological conditions and enables early detection of abnormalities. Multi-sensor integration focuses on system architecture and control level, whereas data fusion focuses more on distinct combination of multisensor information acquired through sensors. Some of the common prevailing multisensor data fusion (MSDF) techniques include Kalman filter, Bayesian estimate, Fuzzy inferences and Dempster-Shafer methods.

Effectiveness of cognition is a major concern in any multi-sensor data fusion modeling. The reasons for using fuzzy inferences in automated vital sign monitoring are (1) It increases the perceptive nature of Early Warning System (EWS) to analyze the abnormalities of patients at an earlier stage (2) it allows clinicians to attend others tasks, hence to have an intact control on emergency situations (3) it drastically reduces false alarm rates and thus eradicating alarm fatigues for clinicians (4) effectively monitors complex multi-patient scenario with optimized resources and finally (5) It resembles and emulates human reasoning and decision making in complex situations. Ajay Mahajan et.al [4] developed a multi-sensor integration and fusion model using fuzzy inference system for structural health monitoring. A unique fuzzy inference based data fusion strategy limited to three sensors with different resolution has been presented only to analyze the confidence in sensor behaviors and performance. According to Luo and Key [5], multisensor fusion and integration is performed using three basic methods based on how sensor data is being treated for a chosen application. Low-level estimation methods deal directly with raw sensor data acquired from sensors, classification method classifies the extracted sensor data features and inference method employs decision-making based on various sensor data combinations. Multisensor fusion and integration approaches have been proposed for various applications [6][7][8] other than medical healthcare. The difficulty in applying them to healthcare is that, it involves vast amount of data with accuracy and precision requirements.

Recent development in wireless, biosensors and networking has provided incentives for researchers to use them in health care systems. The application of this technology has attracted a lot of attention due to its potential improvement in quality of life and reduction in cost of healthcare.
The importance of multisensor data fusion in healthcare monitoring aids physicians to provide accurate and adequate diagnosis on health condition based on effective estimation, classification and inferential data from medical sensors [9][10][11][12]. Because MSDF techniques can incorporate cognitive abilities through classifiers, they can be well utilized for patient vital sign monitoring (VSM) systems. The background of this paper is our previous work in which a simple bio-sign approach has been devised to perform an alarm indication on abnormal condition of patients' vital signs.
Figure 1 illustrates a generic wireless approach where various vital biosensors are connected individually over set of patients to monitor the real time vital sign and notify the clinical person through graphical display and alarm. In this prevailing approach, possibilities of unwarranted alerts are high which might lead to alarm fatigue and information overload for clinicians.

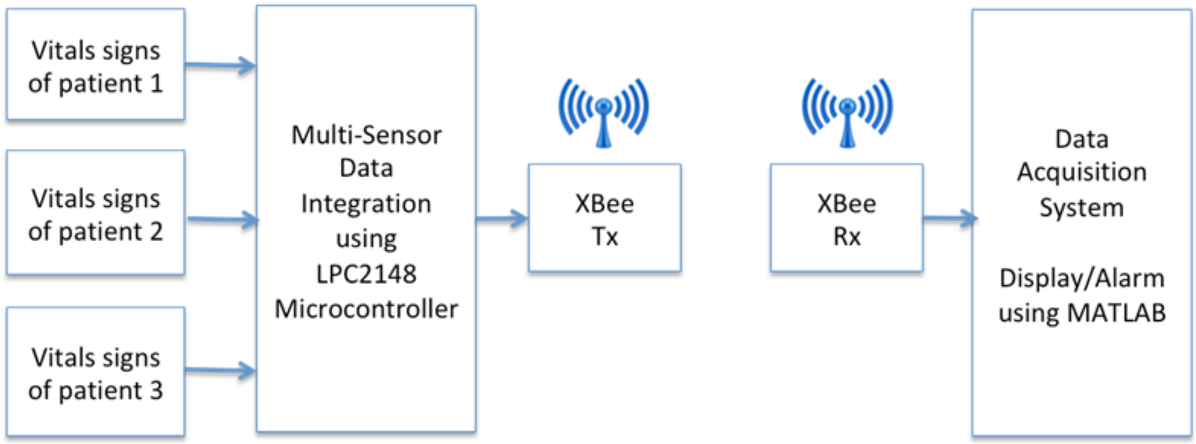

Fig 1. Wireless VSM system without sensor fusion

A solution to this problem could be a VSM system adopting data fusion approach followed by decision-making classifiers to incorporate effective cognition in monitoring abnormalities accurately. In this paper, an enhanced approach using multisensor data fusion algorithm has been designed to achieve high precision alerts that will help clinicians to overcome alarm fatigue as well as information overloading. This system as shown in Figure 2 has an effective EWS console, displaying more information on vital sign conditions and corresponding abnormalities.

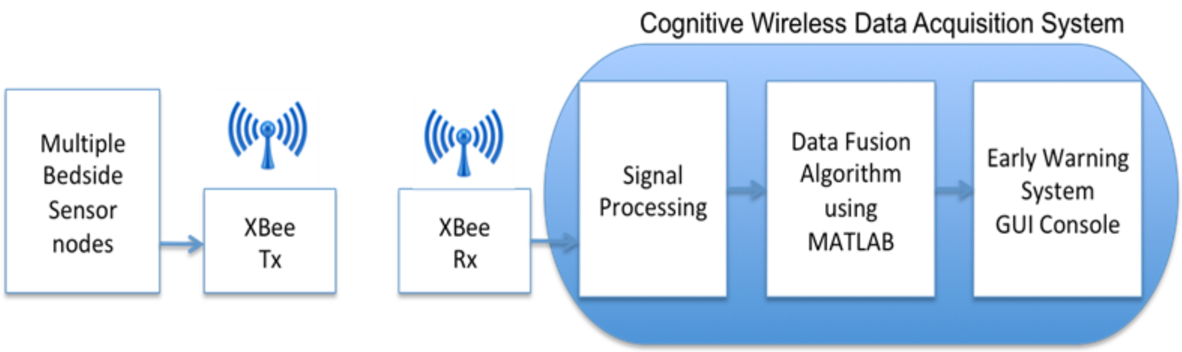

Fig 2. Wireless VSM system with multi-sensor data fusion

Various important aspects in designing a cognitive based wireless healthcare monitoring systems are considered in this approach. Firstly, the number of vital sensors associated with each patient and the number of patients being accommodated in the network is consistent. Second aspect is the choice of wireless medium to afford an intact indoor wireless communication, which substantially improves scalability in the network. The last important aspect is the design of an intelligent data fusion algorithm to enable a real-time, continuous, automated and self-adaptable emergency healthcare monitoring service. In this paper, we focus more on devising an MSDF algorithm involving feature extraction from the signals acquired through multiple sensors, fuse these extracted data and apply a fuzzy classifier for an effective decision making.

II. METHODOLOGY

In general multisensor data fusion refers to synergetic fusion of sensor data from multiple sensors to obtain reliable and accurate information [13]. The strategy of fusion can be implemented at three different levels. Signal fusion is low-level fusion and directly fuses raw sensor data using statistical and estimation methods. Feature level fusion deals with concatenating the feature points obtained from multiple sensors utilizing the concepts of normalization, reduction and matching techniques in extracting and fusing the data. This middle level fusion has a better outcome with higher discriminations. Finally, the symbol fusion termed as high-level fusion treats the sensor data as a symbolic representation of process parameters much like human descriptions. Inference techniques such as Bayesian, Dempster-Shafer and fuzzy methods are used to perform symbolic fusion. In our design a hybrid fusion model combining both feature and symbol fusion is being implemented to perform feature extraction and decision making analysis. The block diagram of the implemented spectral based data fusion algorithm is shown in figure 3.

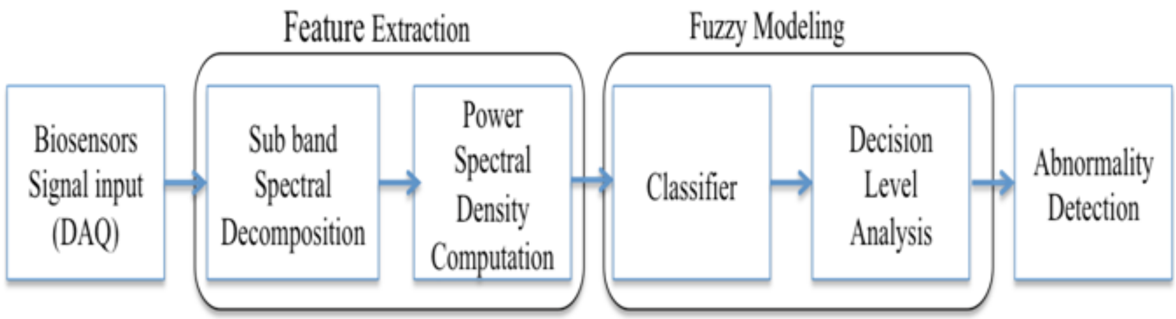

Fig 3. Block diagram of Implemented Data Fusion Algorithm

For the processing of measured vital sign component, signal-processing tools of MATLAB are used. The discrete and fast Fourier signal transform techniques are mostly used in continuous monitoring until a new concept of multi-spectral coding approach has been proposed. The concept of multi spectral coding provides a finer level of signal processing using successive decomposition of signal into multiple sub bands. The advantage of such coding is the extraction of finer frequency details, which reveals the features more accurately than the FFT approach.

2.1. Feature extraction

Spectral decomposition (SD) and wavelet coding are the basic steps involved in feature extraction. In the process of SD, successive wavelet based filtration is been used to perform dilations and translations resulting in decomposition of signal into a finer frequency band. Based on trial and error, we chose 4 levels of decomposition to extract only the features having high dense vital information for further processing. It has been observed that sub-bands (SBSs) 1 and 3 exhibit higher coefficients variation than the other bands hence more vital parameter information is present in these two functions. To select the required SBSs for feature extraction, a power spectral density computation is done to obtain the energy density for each band as shown in figure 4. This technique improves the selection of feature relevancy, in terms of selectivity since features are selected based on variation density rather than magnitudes. Taking each SBS 'I_i' as reference, power spectral density (PSD) for each SBS, 'PI_i' is computed. The PSD features for the obtained four SBSs are then defined by, PI_i = PSD (I_i), for i = 1 to 4. The SBS PSD's are derived as,$PB_i = \lim_{T\to\infty} \frac{1}{2T}\int_{-T}^{T} B_{hi}(t)^2\ dt$.From these obtained energy values, SBSs are selected based on a defined selection criterion, defined by, MPI_i = max (PI_i). For these selected SBSs, features are then computed by the approach of peak picking, as carried out in spectral coding approach. For each selected SBS a maximum value is computed and all the coordinates above 60% of this maximum value are taken as shape features 'sf_i'. All the peaks above this threshold have been recorded as the feature magnitude with its corresponding coordinates, recording the dominant vital parameter peaks. With this approach the finer frequency contents are chosen for feature extraction.

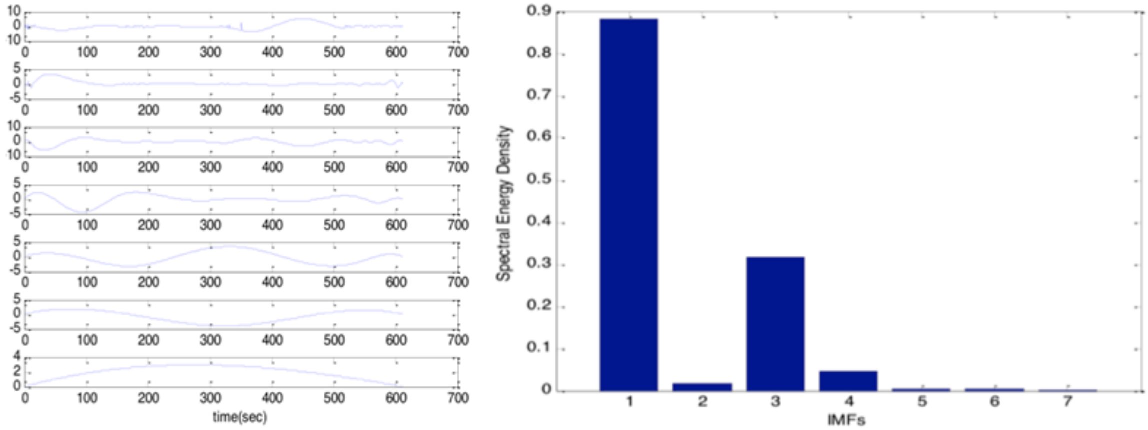

Fig 4. Linearized sub bands and spectral energy densities of decomposed sub bands

2.2. Fuzzy modeling

In the context of patient monitoring, data fusion corresponds to the combination of data from multiple channels to provide an aggregate patient status index. Data fusion for alarm generation can be split into knowledge based and machine learning systems. Knowledge-based systems combine the expert knowledge from clinical experts to define set of rules or criteria according to which an alarm system is designed.

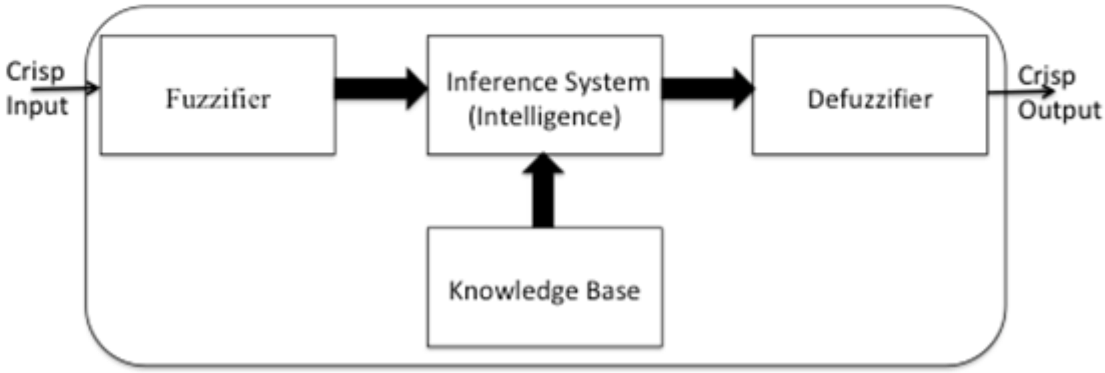

Figure 5. Structure of fuzzy logic system

Machine learning systems, on the other hand avoids this dependency on rules. In our design, fuzzy classifier is trained through a set of data using knowledge based learning in order to alert the abnormalities. In general fuzzy models are developed using rule-based systems, which are formulated using collection of linguistic variables. This also provides a non-linear mapping between input stimuli and output responses in decision-making. MATLAB has been deployed in designing fuzzy system with necessary membership functions and user interface utilities. The basic fuzzy logic system is as shown in Figure 5.

The fuzzifier uses membership functions (MF) to describe the situations graphically. The major vital signs that are considered in this application are Blood Pressure (BP), Blood Oxygen Saturation (SpO_2), Pulse Rate (PR), Respiratory Rate (RR) and the Body Temperature (BT). These vital signs acquired through data acquisition system have the signal variation between maximum and minimum at a specified time interval from each patient. The MFs are formulated using different levels of linguistic variables namely normal, low and high as shown in table 1.

Table 1. Linguistic variables and associated membership functions

Vital Signs	Normal	Low	High
Systolic(mmHg)	120	90	140
Diastolic(mmHg)	80	60	90
Pulse Rate(pm^{-1})	75	60	100
SpO_2 (%)	99	98	100
Respiratory Rate(bm^{-1})	12-18	10	20
Body Temperature(°C)	99	97	102

The values of vital signs across linguistic variables (LV) are chosen based on various theoretical studies and literature surveys. Fuzzification is applied using an intuition-based approach to assign the membership values for the given input of crisp physiological parameters. A triangular MF approach has been used to compute the membership sets of vital sign inputs as shown in figure 6.The term 'x' is the observed input crisp vital sign value, 'a' and 'b' are the maximum and minimum limits, the value 'm' varies between the 'a' and 'b' values and the term $\mu_A(x)$ is the membership function of the given fuzzy set.

$$\mu_A(x) = \begin{cases} 0, & x \leq a \\ \dfrac{x-a}{m-a}, & a < x \leq m \\ \dfrac{b-x}{b-m}, & m < x < b \\ 0, & x \geq b \end{cases}$$

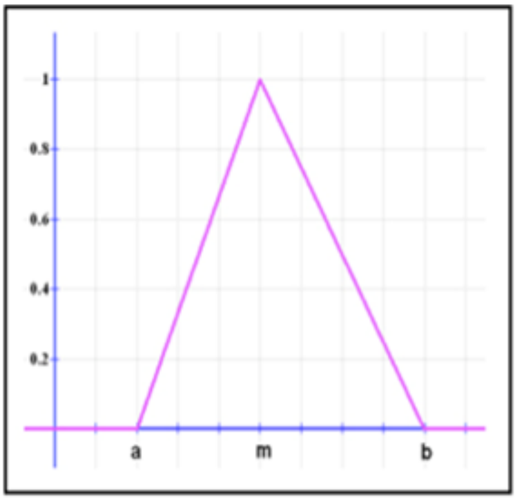

Figure 6. Triangular membership function

The intelligence level of any fuzzy system directly relies upon the knowledge base (KB), which can be categorized as rule base or database. Fuzzy rules are basically collection of linguistic statements, which characterize the fuzzy inference system on deciding the input classification or controlling the output. Fuzzy inference systems (FIS) apply the fuzzy rules in decision-making using IF-THEN structure over the formulated fuzzy rules. It utilizes the knowledge base inputs to simulate human reasoning. The intelligence level of the fuzzy system depends upon effective formulation of FIS. Inference engine of FIS combines the KB rules and compares it with MAX MIN values using AND/OR operators to evaluate the conditions and hence results in a final decisive action. Mamadani FIS method is intuitive in nature and well suited for human inputs. Therefore it is being given preference of usage in this design. In this method MF having an interval between MAX and MIN is estimated for mean and is given as input for inference engine. In turn FIS uses IF-THEN-ELSE structure along with AND/OR logical operators to fuse all the MFs to identify an event and categorize it into controlled outputs. In this approach three major controlled outputs Normal, Critical and Attention Needed have been chosen to identify the condition of patient's health condition and accordingly initiate the EWS system with an alert. Table 2 shows the basic formulation of KB rules using only two vital sign inputs systolic blood pressure (SYS_VS1) and the pulse rate (PR_VS2) and table 3 shows the respective expert knowledge base using Mamadani for few combinations of MFs. Likewise various sets of rules have been formulated using maximum possible permutation and combinations of all vital signs into consideration.

Table 2. Knowledge base rules

SYS_VS1 / **PR_VS2**	Low	Normal	High
Low	Critical	Attention Needed	Critical
Normal	Attention Needed	Normal	Attention Needed
High	Critical	Attention Needed	Critical

Table 3. Membership functions

IF										THEN
SYS	**DIA**	**Logic**	**SpO_2**	**Logic**	**PR**	**Logic**	**RR**	**Logic**	**BT**	**Status**
Low	Low	AND	Low	AND	Low	AND	Low	AND	High	Critical
High	High	AND	Norm	AND	High	AND	High	AND	Norm	Attention Needed
Norm	Norm	AND	Norm	AND	Norm	AND	Norm	AND	Norm	Normal
Norm	Norm	AND	Low	AND	Norm	AND	Low	AND	High	Attention Needed
High	High	AND	Low	AND	High	AND	Low	AND	Low	Critical

On the other hand, defuzzifier converts the actual output of FIS into understandable numeric crisp outputs. Among several methods available for defuzzification, Mean of Maximum (MoM) technique has been used here to obtain the crisp values. MoM calculates the mean of maxima from the FIS output distribution and correlates it to a single crisp output and its associated controlled output. Table 3 shows the chosen numeric MoM crisp value that relates to the controlled output, which is an alarm here.

Table 3. Defuzzifier output

Status	MoM Crisp Output	Controlled Output-Alarm
Normal	0	0 - OFF
Attention Needed	0.5	1 - ON
Critical	1	1 - ON

Thus the abstraction of this fuzzy based cognitive model involves defining the linguistic variables, constructing the membership functions, formulating a series of knowledge bases using FIS, implementing the MF to fuzzify the crisp data and finally defuzzifying to obtain numeric crisp values. EWS message is displayed in the monitoring window as shown in figure 7. This EWS window continues to beep with an alarm until the clinician as an acknowledgement of the abnormal condition clicks the ‘ok’ button.

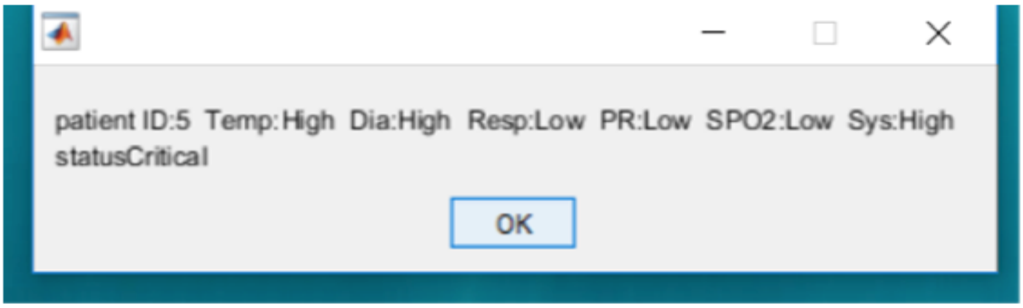

Figure 7. Early warning message box of observed vital sign parameters

III. SYSTEM ANALYSIS AND DISCUSSION

For the evaluation of the design approach, the developed system has been validated for accuracy levels of the alarm rates. The k-fold test is used to measure its robustness for a random selection of k-feature patterns. For a k value of 2 and 3 are performed for the trained data set, where for each of the test iteration 3 set of training and 2 set of testing feature are grouped to perform retrieval operation. The suggested approach is validated over vital data set on the observations. To extract the feature a multi instance wavelet feature is computed, which is defined as a correlative feature value of recurrent bands values processed in a group. The test result for k=2, 3 is presented below. The validation is carried out by the cross validation of the original sample into randomly equal portioned dataset and tested. The observations are presented in table 4and for the disease case. The conventional case without data fusion is compared with the spectral correlate method. The developed system is validated for different abnormal vital signs data for a cardiac disease case based on National Institute of health (NIH) article [14]. Each of this case is trained with their corresponding wavelet features, and the test features are randomly been selected to 2, 3 test sets to perform a k-fold test analysis. The parameters accuracy and precision are used to evaluate the performance of the developed approach. $\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}$, where, TP =True Positive (correctly identified), FP= False Positive (incorrectly identified), TN=True Negative (correctly rejected), FN=False negative (incorrectly rejected)

Table 4. Accuracy and Precision for the developed approaches using k-fold test

Abnormal vital sign Case	Accuracy (%)				
	Direct Correlate	Linear map	MSDF	Fuzzy MSDF	Spectral Correlate
Case1	63.16	69.47	71.53	78.10	**85.33**
Case2	57.33	60.18	65.75	70.27	**79.16**
Case3	61.56	69.43	71.21	79.22	**84.52**
Case4	66.87	70.22	73.88	78.45	**82.55**

Abnormal vital sign Case	Precision				
	Direct Correlate	Linear map	MSDF	Fuzzy MSDF	Spectral Correlate
Case1	0.42	0.53	0.56	0.73	**0.83**
Case2	0.41	0.51	0.60	0.70	**0.81**
Case3	0.46	0.55	0.61	0.75	**0.89**
Case4	0.44	0.59	0.59	0.69	**0.88**

For the given simulation case of abnormal vital sign, totally four classes each class having five subjects were processed to train. In testing a query sample with case1, abnormal vital sign is selected and given for support vector machine (SVM) classifier. The SVM classifier compares the given query sample features with database features. Along with accuracy, to show the enhancement of design approach, precision is also evaluated as,$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}}$.

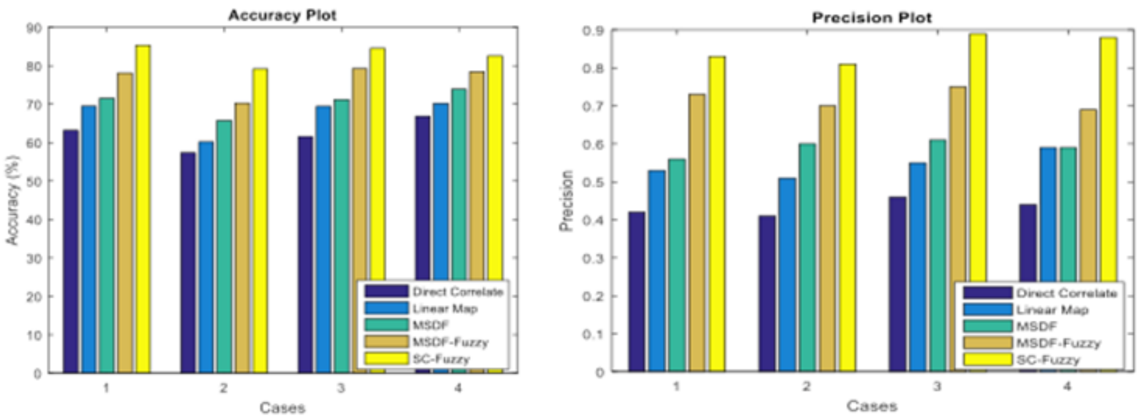

Figure 8. Comparison of different data fusion approaches

The performances of the alarm system for four abnormal cases using the developed data fusion approaches are illustrated in figure 8. Compared with direct correlation without data fusion, it is observed that for the combination of Fuzzy with data fusion and spectral correlate approaches having more accuracy and precision levels in monitoring the health diseases.

IV. CONCLUSION AND FUTURE SCOPE

A data fusion-based decision support architecture that aggregates data stream from multiple devices is designed. A health care monitoring system with the capabilities of wireless networking of vital sign sensors, risk analysis, control measures and a graphical user interface (GUI) software for users to interact with the system is presented. This approach aims to reduce false alarm rates in monitoring vital sign abnormalities. A new spectral correlate approach of feature selection and fuzzy based decision making analysis is developed using MATLAB. The main purpose of this cognitive early warning system is to facilitate the clinicians in effectively monitoring the vital sign of multiple patients simultaneously with lesser burden by over coming alarm fatigues and information overloading.

This work can be extended with additional enhancements in design with respect to additional sensors, data analysis and graphical user interface. Additional biosensors such as ECG, EMG, accelerometers can be integrated or replaced to suit other health monitoring applications such as patient movement detection, elderly health care and stress level detection. Secondly, the vast amount of vital sign data acquired from different patients can be facilitated with cloud computing for prediction and pattern analysis. This facility helps us to stir towards patient data analytics using Internet of Things (IoT) platform. Finally the visualization of the graphical interface can be improvised to show individual patient's vital sign with multiple windows over a single screen and different colors to indicate the intensity of emergency situations.

REFERENCES

[1]. U. Anliker, J. A. Ward, P. Lukowicz, G. Troster, F. Dolveck, M. Baer, F. Keita, E. B. Schenker, F. Catarsi, L. Coluccini, A. Belardinelli, D.Shklarski, M. Alon, E. Hirt, R. Scmid, M. Vuskovic,. AMON: A Wearable Multiparameter Medical Monitoring and Alert System. IEEE Trans. on Information Technology in Biomedicine, Vol. 8,4, Dec. 2004.

[2]. Milenkovic, C. Otto, E. Jovanov. Wireless sensor networks for personal health monitoring: Issues and an implementation, Computer Communications. pp.2521-2533, 2006.

[3]. David L. Hall, Senior Member, Ieee, And James Llinas. An Introduction to Multisensor Data Fusion. Proceedings Of The IEEE, Vol. 85, No. 1, January 1997.

[4]. Ajay Mahajan, Kaihong Wang, and Probir Kumar Ray. Multisensor Integration and Fusion Model that Uses a Fuzzy Inference System. IEEE/ASME Transactions On Mechatronics. Vol. 6, No. 2, June 2001.

[5]. Ren C. Luo, Fellow, IEEE, Chih Chia Chang, and Chun Chi Lai. Multisensor Fusion and Integration: Theories, Applications, and its Perspectives. IEEE Sensors Journal, Vol. 11, No. 12, December 2011.

[6]. Maes, S., Tuyls, K. Vanschoenwinkel, B., and Manderick, B. Credit Card Fraud Detection using Bayesian and Neural Networks. 1st International NAISO Congress on Neuro Fuzzy Technologies. 2002.

[7]. Phua, C., Lee, V., Smith, K., and Gayler, R. A Comprehensive Survey of Data Mining-based Fraud Detection Research. Arxiv preprint arXiv: 1009.6119), pp 1-14, 2010.

[8]. Kumar, V. and Rathee, N. Knowledge discovery from database Using an integration of clustering and classification. International Journal of Advanced Computer Science and Applications (2:3), pp29-33, 2011.

[9]. Borowski, M., Siebig, S., Wrede, C. and Imhoff, M. Reducing False Alarms of Intensive Care Online-Monitoring Systems: An Evaluation of Two Signal Extraction Algorithms. Computational and Mathematical Methods in Medicine (2011), p 11, 2011.

[10]. Gorges, M. Markewitz, B. A, and Westenskow, D. R. Improving alarm performance in the medical intensive care unit using delays and clinical context, Anesthesia & Analgesia (108:5). pp 1546-1552, 2009.

[11]. Imhoff, M., Kuhls, S., and Gather, U. Smart alarms from medical devices in the OR and ICU. Best Practice & Research Clinical Anesthesiology (23), pp 39-50, 2009.

[12]. Jazzar, M., and Jantan, A. B. Using fuzzy cognitive maps to reduce false alerts in SOM based intrusion detection sensors. Second Asia International Conference on Modeling& Simulation: Kuala Lumpur. pp. 1054-1060.2008.

[13]. Shrestha et al. Data Fusion-based Decision Support Architecture for Intensive Care Units. Twentieth Americas Conference on Information Systems. Savannah.2014.

[14]. Andersen et al. The Prevalence and Significance of Abnormal Vital Signs Prior to In-Hospital Cardiac Arrest.HHS Public Access. 2016 January ; 98: 112–117.

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