Detection and Classification of Hypovolaemia during Anaesthesia

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Abstract—In recent years, there has been a rapid growth in patient monitoring and medical data analysis using decision support systems, smart alarm monitoring, expert systems and many other computer aided protocols. The main goal of this study was to enhance the developed diagnostic alarm system for detecting critical events during anaesthesia. The proposed diagnostic alarm system is called Fuzzy logic monitoring system-2 (FLMS-2). The performance of the system was validated through a series of off-line tests. When detecting hypovolaemia a substantial level of agreement was observed between FLMS-2 and the human expert and it is shown that system has a better performance with sensitivity of 94%, specificity of 90% and predictability of 72%.

I. INTRODUCTION

Computers have the capability to monitor large volumes of diverse data rapidly, whereas humans are only able to monitor a maximum of seven different parameters at any one time [1]. Human errors in anaesthesia account for more than 80%of the preventable mishaps [2]. However, monitoring systems are not designed to replace clinicians, but rather to assist the anaesthetist in rapidly processing the vast amount of information available from monitoring equipment, and to convey this information in a meaningful manner so that rapid intervention can occur. Computer programs employing fuzzy logic are intended to imitate human thought processes in complex circumstances, but to function at greater speed [3-4].

The prototype diagnostic system, fuzzy logic monitoring system-2 (FLMS-2), was developed using three physiological features; heart rate (HR), blood pressure (BP) and pulse volume (PV). The system detects hypovolaemia and classifies it into mild, moderate and severe. Hypovolaemia refers to a decrease in volume of blood plasma. The heuristic relationship of hypovolaemia is identified by the transformation in observable physiological variables like BP, HR and PV [5]. The patients' data were

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collected from the existing S/5 Datex-Ohmeda anaesthesia monitor in the operating theatre with ethical approval from the local ethics committees. The collected data were converted into a readable format using DOMonitor.net [6]. The accuracy of the diagnostic results from the proposed system was analyzed using Kappa analysis. Kappa [7] gives a statistical measure for evaluating inter-observer variability, that is, how often two or more observers agree/disagree in their interpretation. In this research project, the expert (anaesthetist) and FLMS-2 are the two observers interpreting the diagnoses for the pathological events using the physiological data.

II. BACKGROUND

Many expert decision support systems have been proposed in the past to enhance the anaesthetist's performance thus aiding the anaesthetist and, in some cases, even outperforming the anaesthetist. Our previous work for detecting hypovolaemia [3] showed a substantial level of agreement between FLMS and the anaesthetist during surgical procedures. An expert system called "SENTINEL" [5] diagnosed the onset of malignant hyperpyrexia about ten minutes before the anaesthetist. Bhupendra et al. [8] developed the diagnostic system, Real Time – Smart Alarms for Anaesthesia Monitoring (RT-SAAM); results showed RT-SAAM was capable of diagnosing the pathological events. Numerous intelligent techniques have been proposed in the past and some have been employed for developing diagnostic alarm systems. The recent work in this area shows rapid growth in patient monitoring using fuzzy logic [9], wireless, mobile and internet technologies [10]. It was found that pre-processing of raw patient data is required for the development of such monitoring systems.

III. PRE-PROCESSING

A. Preparing Data for Analysis

The collected data from the Datex-Ohmeda S/5 monitor was in a digital format (dof). We employed the DOMonitor.net application to convert the (dof) format data to readable text files (.txt).

- Removing/deleting missing values (values with zero or negative) in order to have a unique data set throughout the processing.
- Sampling data: The collected raw data contains sampling period of 10sec to 30sec, the sampling period was set at 30sec.
- Checking and removing outliers in the data plot;

there are some points which appear to dramatically differ from the rest of data, such points are outliers.

- Calculating descriptive statistics: minimum, maximum, mean, median, mode, standard deviation and range.
- Smoothing/filtering data using a combination of variance based filtering, low pass filtering and threshold based noise rejection techniques to remove unwanted noise and disturbance.

B. Data Analysis

Data analysis was carried out by using a time series technique in Matlab; this stored data and time values as well as the metadata information that included units, events, data quality and interpolation methods. Data analysis consisted of:

- Creating time series objects, which allow the monitoring system to work in real time.
- Time plots – morphological features can be extracted from the plotted data versus time. Some of these features can be used for the development of monitoring system such as managing outliers in the data set, discontinuity in data, and trends in the data set can be de-trended at any time interval containing the data of interest.
- Plotting time series in real time – different types of plots in the time series tools are; time plot, histogram, spectral plot, correlation plot and XY plot.

IV. SYSTEM DEVELOPMENT

A. FLMS-2 Structure

Figure 1 shows a hierarchical block diagram for FLMS-2, each major component works as follows:

1. Signal processing – Multirate data processing (using an interpolation technique to increase the sampling period from 10 sec to 30 sec), smoothing, filtering and calculating descriptive statistics.
2. Data analysis – using a time series tool for multiple plots in real time.
3. *Adaptive neuro fuzzy inference system (ANFIS)* – training the model with 10 patients' data and testing with 20 patients' data selected randomly (Mamdani type model) [11].
4. *Fuzzy inference system (FIS)* – is used to train the fuzzy model (Sugeno type model) [12].
5. *Membership functions (MFs)* –The MFs for each input are set as mild, moderate, and severe. The selection of the MF's limits is set after analysing the data statistics, time series analysis and ANFIS outputs.
6. *Rules* – These are set using all MFs and all possible levels of hypovolaemia which were detected throughout the training sessions.
7. *Sugeno Model* – This model is used for ANFIS training and testing.
8. *Mamdani Model* – This model is used for testing.

B. FLMS-2 Configuration

The test conditions for the detection of hypovolaemia were classified as: mild, moderate, and severe. The following three principles were set before the generation of alarms in the system:

1) Principle 1- Sampling period: The system checks the sampling period of the input data which should be 30sec.

2) Principle 2- Three Inputs: The system is set to accept only three inputs which are HR, BP, and PV. Therefore, if any input data set is missing, the system will return the present alarm status as false, and wait for the next 15 minutes of the data set.

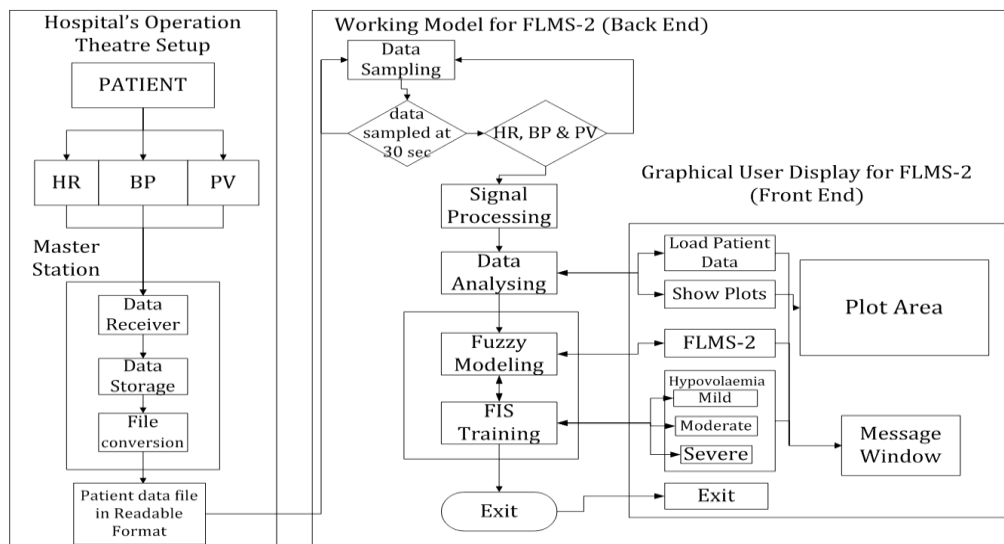*3) Principle 3- Membership Functions:* The limits of the

Fig. 1. A hierarchical block diagram for FLMS-2.

membership functions were set after considering the following points:

- The limits are set so that the FLMS-2 can detect the changes in the parameters, rather than the crisp numerical values and filtered data were divided into five-minute intervals.
- The relative value of each parameter (such as HR) is found by removing its average and dividing the result by its standard deviation (SD) for each five-minute interval.
- The SDs were calculated for the whole parameter values which include both hypovolaemic data as well as data that was normal.
- Considering the limits of SD in the whole data set as indicated in Table I.

TABLE I
CONDITION 2 TESTING SD VALUES AND LIMITS FOR FLMS-2

Hypovolaemia	Mild	Moderate	Severe
Heart Rate (SD)	1.75-3	3-5	5 & >
Blood Pressure (SD)	2.75-5	5-6	6 & >
Pulse Volume (SD)	4-6	6-8	8 & >

4) Principle 4- Ten Rules: The rules are set for testing of the patients' data with their MFs.

i. If (HR is mild) and (BP is mild) and (PV is mild) then (Hypovolaemia is mild)
ii. If (HR is moderate) and (BP is moderate) and (PV is moderate) then (Hypovolaemia is moderate)
iii. If (HR is severe) and (BP is severe) and (PV is severe) then (Hypovolaemia is severe)
iv. If (HR is mild) and (BP is moderate) and (PV is moderate) then (Hypovolaemia is moderate)
v. If (HR is severe) and (BP is severe) and (PV is moderate) then (Hypovolaemia is severe)
vi. If (HR is moderate) and (BP is mild) and (PV is mild)
then (Hypovolaemia is mild)
vii. If (HR is mild) and (BP is moderate) and (PV is severe) then (Hypovolaemia is moderate)
viii. If (HR is mild) and (BP is mild) and (PV is severe) then (Hypovolaemia is moderate)
ix. If (HR is severe) and (BP is mild) and (PV is mild) then (Hypovolaemia is moderate)
x. If (HR is mild) and (BP is moderate) and (PV is mild) then (Hypovolaemia is mild)

According to these principles, the system checks whether each parameter is true with the input values (principle 1 & 2) and each parameter exceeds the SD limit (principle-3). If both conditions are true, then principle-4 with ten rules will be checked. The system generates alarm/warning in one of the three hypovolaemia levels of; mild, moderate, or severe.

C. Graphical User Interface

Figure 2 shows the snap shot of major components of the FLMS-2, GUI display with pushbuttons;

1. *Load Patient Data* – This will load the original patient data and a message window will appear with 'Patient data loaded successfully'
2. *Show Plots* – This will plot the complete waveform of BP, HR and PV.
3. *FLMS-2* – By clicking this, the 'FLMS2' system will test the loaded data and check for Hypovolaemia, and display the message 'FUZZY LOGIC MONITORING SYSTEM has detected hypovolaemia'
4. *Hypovolaemia (mild, moderate and severe)* – These buttons will check for the level of hypovolaemia detected by the monitoring system and displays the message with its real time.

V. VALIDATION AND TESTING

A. Testing

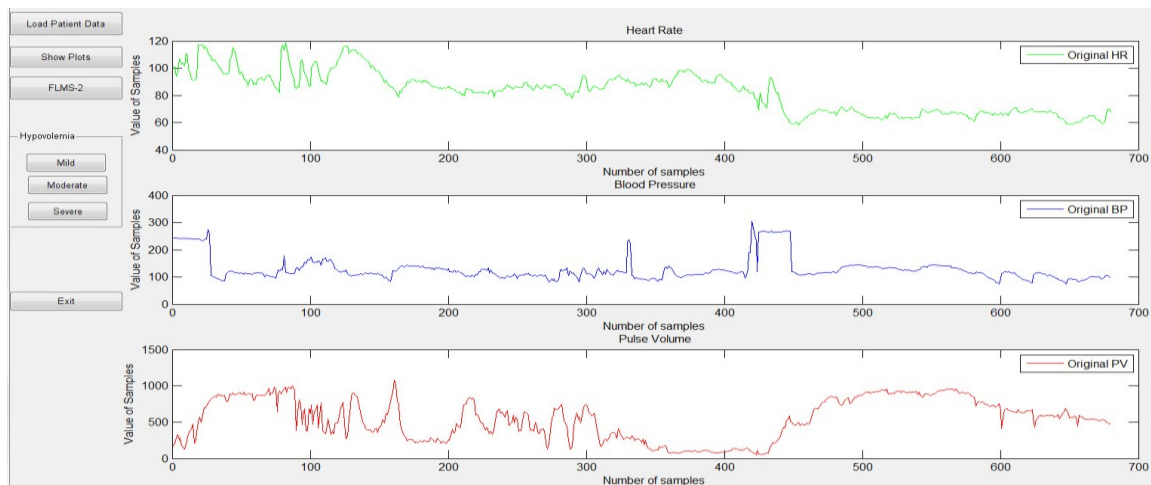Evaluating FLMS-2's diagnostic performance was done by

Fig. 2. FLMS-2 graphical user interface window.

measuring the level of agreement between FLMS-2 and the anaesthetists; using Kappa analysis [7]. The value of the computed Kappa in the following section indicates the level of agreement/disagreement between the two. The diagnostic performance of the FLMS-2 was verified through a series of offline (retrospective) tests in a simulation environment. In off-line analysis the FLMS-2 was tested with data from 20 patients. Figure 3 shows the testing and validation structure.
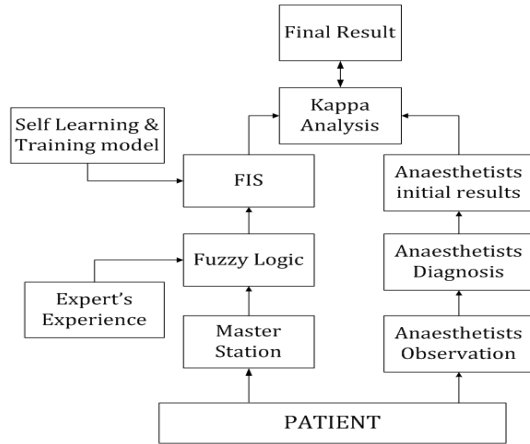

Fig. 3. FLMS-2 testing and validation structure.

B. Results and Discussion

The FLMS was tested with offline data using 20 patients data divided into sub-intervals of five minutes for each record. In compare with the anaesthetists who normally check the hypovolaemia every 15 minutes, the allocated five-minute delay in triggering the FLMS alarm was found acceptable. The expert has access to all the 30 patient data and other clinical information made offline diagnostic report for the hypovolaemia. Expert's diagnostic results are compared with the FLMS-2 results in Kappa analysis. Table II summarizes the kappa analysis results for performance validation of FLMS-2. P_o, P_{pos}, and P_{neg} are overall, positive, and negative agreements respectively. SE represents the standard error, $CI_{95\%}$ is 95% Confidence Intervals for kappa and K is the kappa value.

TABLE II
RESULTS FROM FLMS-2 VALIDATION TESTS

Monitoring System	Po	Ppos	Pneg	Pe	SE	CI95%	K
FLMS-2	0.91	0.82	0.94	0.64	0.03	0.82-0.67	0.75

It shows the system has sensitivity of 94%, specificity of 90% and predictability of 72%. The developed diagnostic system is capable of diagnosing the pathological events with a substantial level of agreement between FLMS-2 and the anaesthetist. The level of disagreement needs further analysis and a more definitive study is required.

VI. RESULT COMPARISON

Table III shows the results of comparing FLMS-2 with similar monitoring systems available today.

TABLE III
FLMS-2 RESULT COMPARISON WITH OTHER MONITORING SYSTEMS

Monitoring Systems	Po	Ppos	Pneg	Pe	SE	CI95%	K
RT-SAAM [8]	0.81	0.83	0.79	0.50	0.06	0.73-0.51	0.62
SMS [4]	0.87	0.79	0.91	0.57	0.06	0.82-0.58	0.70
FLMS [3]	0.89	0.80	0.92	0.59	0.06	0.85-0.61	0.73
FLMS-2	**0.91**	**0.82**	**0.94**	**0.64**	**0.03**	**0.82-0.67**	**0.75**

VII. CONCLUSION

The developed diagnostic alarm system has shown that evidence-based expert diagnostic systems can accurately diagnose a hypovolaemia and could be useful in providing decision support to anaesthetists. It is shown that the proposed FLMS-2 performs better in comparison with similar systems available today (Table III). The complete validation of the system, as a clinically useful diagnostic alarm system, can only be verified after real-time testing. This system is ready to be tested in the real-time environment, although it may need further refinement and enhancement with additional features for routine clinical use.

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