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Fuzzy logic based anaesthesia monitoring systems for the detection of absolute hypovolaemia

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A B S T R A C T

Anaesthesia monitoring involves critical diagnostic tasks carried out amongst lots of distractions. Computers are capable of handling large amounts of data at high speed and therefore decision support systems and expert systems are now capable of processing many signals simultaneously in real time. We have developed two fuzzy logic based anaesthesia monitoring systems; a real time smart anaesthesia alarm system (RT-SAAM) and fuzzy logic monitoring system-2 (FLMS-2), an updated version of FLMS for the detection of absolute hypovolaemia. This paper presents the design aspects of these two systems which employ fuzzy logic techniques to detect absolute hypovolaemia, and compares their performances in terms of usability and acceptability. The interpretation of these two systems of absolute hypovolaemia was compared with clinicians' assessments using Kappa analysis, RT-SAAM $K=0.62$, FLMS-2 $K=0.75$; an improvement in performance by FLMS-2.

1. Introduction

In the operating room (OR) the anesthesiologist is required to manage various responsibilities simultaneously: the patient's physiological monitors and audio alarms, their fluid needs and drug administration, as well as teaching/training of junior doctors. Although the anesthesiologists carefully prioritise these tasks, the cumulative need may still exceed the limit of even highly trained, focused clinicians [1]. Technology, in the form of an expert system, can convey more precise information about a patient and potentially improve vigilance, standardise clinical protocols, enhance situational awareness, and reduce errors in anaesthetic practice [2]. Computers have the capacity to monitor large volumes of diverse data rapidly, while humans are only able to monitor a maximum of seven different parameters at any given time [3].

Hospital intensive care units/operating theatres generate enormous amounts of real-time and off-line data related to the status of acutely ill patients: multi-parameter real-time physiological signals, ventilator data, laboratory tests, imaging studies, medications, clinical observations, etc. [4]. Human errors contribute to a large portion of the anaesthesia-related mishaps; these could be reduced by providing decision support to the anesthesiologists [5,6]. Patient monitoring during anaesthesia in operating theatres involve meticulous scrutiny of various physiological parameters including blood pressure (BP), plethysmography/pulse volume (PV), end tidal carbon dioxide ($EtCO_2$), inspired carbon dioxide ($FiCO_2$) and pulse oximetry SpO_2. The purpose of this study was to assess two related diagnostic systems that may enhance the diagnosis of hypovolaemia during surgery.

1.1. Need for expert systems in anaesthesia monitoring

Human errors in anaesthesia account for more than 80% of the preventable mishaps [5]. Van den Eijkel et al. suggested that by using a knowledge-based anaesthesia monitor (an expert system) some of the difficulties may be reduced [6]. In addition, providing information to the anaesthetist with an integrative, ergonomic user interface may also reduce the response time of the anaesthetist in detecting pathological events [7].

1.2. Decision support systems in anaesthesia monitoring (DSS)

Decision Support System (DSS) is an emerging and potentially beneficial technology that shows great promise in reducing medical errors and delivering improvements in the quality, safety, and efficiency of health care. The DSSs can be integrated into a patient monitoring information system by using a computerised medical knowledge base, electronic medical records, health information systems and an inference engine to generate case-specific and situation-specific advice [8,9]. These systems should also help

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anesthesiologists make decisions in complex situations where continuous monitoring of highly critical physiological parameters require an immediate response [10]. Following are brief reviews in this area of monitoring using a DSS. Dunsmuir et al. [11] developed software for use as a knowledge authoring tool for physiological monitoring in anaesthesia. This application enables clinicians to create knowledge rules without the need for a skilled computer engineer or programmer. The rules are designed to provide clinical diagnoses, explanations, and treatment advice to the clinician in real time for optimal patient care. The knowledge base consists of a set of rules, and each rule is designed as an IF-THEN statement that represents expert knowledge. Each rule consists of a list of patterns and an outcome. Each pattern is a statement about a data parameter; each will be true or false, depending on the value of the data parameter. The outcome is a descriptor of the patient's status that exists given that all the rule's patterns are true. By intelligently combining data from physiological monitors and demographic data sources, the expert system can use these rules to assist in monitoring the patient. The Post-Study System Usability Questionnaire (PSSUQ) was used to record feedback on usability of the DSS; the result showed strong agreement of about 80%.

1.3. *Fuzzy systems—fuzzy logic based systems in anaesthesia monitoring*

Computer programs employing fuzzy logic are intended to imitate human thought processes in complex circumstances, but at greater speed [12]. Fuzzy logic-based expert systems have been developed in many areas of anaesthesia monitoring. The work towards the control of anesthetic gases and blood pressure by Sieber et al. [13] reported accurate control of the mean alveolar concentration (MAC) of isoflurane by a system that altered the gas flow rates. Postoperative pain control resulting in the patient's target analgesia level was achieved 77% of the time, as reported by Carregal et al. [14], and there are many more such examples.

Lowe [15] developed a system called SENTINEL; this computer software was designed for fault detection and diagnosis (FDD) during anesthesia. The advantage of this system over others is that it provided a measure of objectivity. It uses a fuzzy time-domain pattern matching technique, termed *fuzzy trend templates*, to detect vaguely specified patterns in multiple physiological data streams. These patterns are representative of symptoms associated with undesirable patient states. The system achieved a sensitivity and specificity of 90%.

Lowe and Harrison [16] developed a fuzzy logic based algorithm for detecting malignant hyperpyrexia (MH). In this study, rule-based algorithms are followed to detect the changes in the patterns of physiological variables. In an offline validation of the algorithm (using the complete time series data of one patient) the system detected MH nine minutes before the anaesthetist diagnosed it. This work shows how expert systems can be implemented to facilitate and enhance anesthesiologists' performance in the clinical environment, thus improving patient safety.

Mahfouf et al. [17] developed a model in a Mamdani type of fuzzy model using anesthesiologists' knowledge described by fuzzy IF-THEN rules. Clinical data are used to construct the patient model. The effect of the actual concentrations of anaesthetic and analgesic drugs was used to model the pharmacodynamic interactions of the two drugs on the cardiovascular parameters, and on the auditory evoked potentials. An Adaptive Network-based Fuzzy Inference System (ANFIS) was then used to train fuzzy Takagi–Sugeno–Kang (TSK) models so as to describe the different signals. A stimulus model was used to establish the effects of the surgical stimulus on Heart Rate (HR) and systolic arterial pressure (SAP) according to the level of analgesia used to model the different signals.

The majority of expert systems have been developed for offline/retrospective analysis of clinical data and hence have not been tested in real-time [16,18–20]. Some recent works in the field have given way to new online monitoring techniques like fuzzy logic based diagnosis [21–26], artificial neural network based diagnosis [26–29], logistic regression based trend detection [30,31] and statistical/probability based techniques [32–35].

An expert diagnostic system mimics an expert's behaviour by executing a series of smart/intelligent algorithms which scan the available data for information. The expert knowledge implemented by anesthesiologists for making the diagnosis exists in the form of linguistic rules. These linguistic rules are required to be converted into programmable sets of rules for the development of smart computer algorithms. Fuzzy logic based algorithms and probabilistic alarm algorithms discussed in the following sections have the potential for implementing these linguistic rules into logical algorithms.

By using a fuzzy logic based algorithm, expert diagnostic systems can be developed to match or exceed the performance of the anesthesiologists as discussed by Grant and Naesh [12]. The authors have also pointed out some applications for control of depth of anaesthesia where decision making algorithms have outperformed the anaesthetist. It was also suggested that the expert diagnostic systems are more reliable than manual interventions.

Section 2 describes the data collection and pre-processing of digital signals, Section 3 explores the design and modelling of real-time smart anaesthesia alarm system (RTSAAM) and fuzzy logic monitoring system (FLMS-2) and Section 4 presents results, validation and comparisons. Section 5 discusses the improvements in the monitoring systems and the paper concludes by discussing future challenges in the domain.

2. Data collection and pre-processing of digital signals

After obtaining ethical approval and patient consent, data were collected from anaesthesia monitors in operating theatres at Auckland City Hospital. The physiological data was collected from the RS232 port of the Datex Ohmeda S/5 anesthesia monitor (Fig. 1). The signals of interest were the invasive arterial pressure waveform (P1), the plethysmograph (SpO_2-ir) (a surrogate for the pulse volume (PV) and the exhaled CO_2 waveform. The waveforms were collected at 100 Hz. Data collection was enabled using

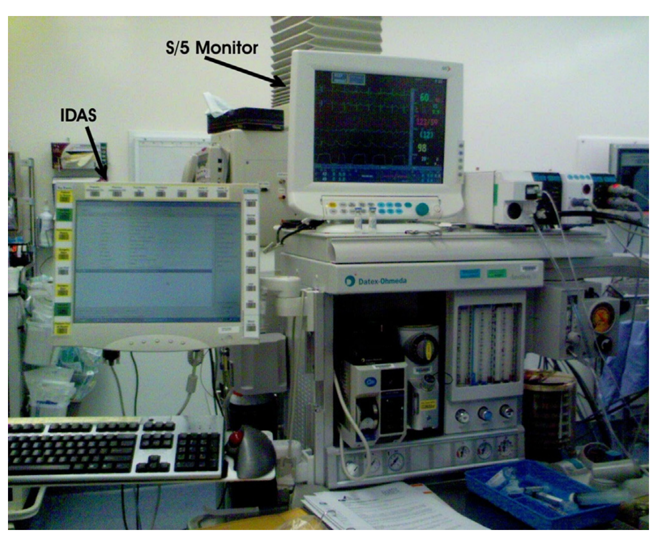

Fig. 1. Operating room setup with Datex S/5 monitor and IDAS system. IDAS is the hospital's automated data recording system (SaferSleep).