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Data Fusion in the O.R.: Improved Clinical Measurements and Intelligent Patient Monitoring

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Abstract

Data fusion is concerned with combining information from knowledge sources such as sensors to provide a greater understanding of a given situation. Two major classes of fusion techniques in robotics and machine intelligence are (1) those based on probabilistic (such as Bayesian reasoning and the theory of evidence) models and (2) those based on least squares techniques (such as extended Kalman filtering). In other domains, such as medicine, the use of artificial neural networks (ANN) and fuzzy logic have also become important in this context. This contribution aims to give an overview of the data fusion techniques that are prevalent in the operating room (OR). In particular the use of data fusion methodologies to provide (a) improved patient measurements and (b) intelligent patient monitoring are considered.

Keywords: Operating Room, Data fusion, Intelligent monitoring, Smart sensors.

1 Introduction

Data fusion is concerned with combining information from knowledge sources such as sensors to provide a greater understanding of a given situation. The area of data fusion has generated great interest among researchers in many science and engineering disciplines. Abidi and Gonzalez [1] have identified two major classes of fusion techniques in robotics and machine intelligence as (1) those that are based on probabilistic (such as Bayesian reasoning and the theory of evidence) models and (2) those based on least squares techniques (such as extended Kalman filtering). In other domains, such as medicine, the use of artificial neural networks (ANN) and fuzzy logic have also become important in this context. This contribution aims to give an overview of the data fusion techniques that are prevalent in the operating room (OR). In particular the uses of data fusion methodologies to provide (a) improved patient measurements and (b) intelligent patient monitoring are considered.

2 Measurement Systems

In the area of improved patient measurements in the OR the work of Feldman et al [2,3] has been most explicit in its promotion of a data fusion approach. The work was motivated by general concerns about the quality of sensor derived clinical data in the OR with data corruption and periods of missing information being fairly common occurrences. The particular objective was to provide a more robust estimate of the continuous heart rate by fusing independent measures of the heart rate available from a variety of different sensors. Data from the electrocardiogram, pulse oximeter and intra-arterial catheter are fused using a Kalman filter-based estimator, to produce the continuous heart rate estimate.

In addition to improving the quality of patient measurements, such as the robust heart rate estimator indicated in the initial application above data fusion is also used in “smart sensors”. These usually provide an estimate of, previously unobtainable, patient related values using powerful signal processing and pattern recognition algorithms. Artificial neural networks (ANN) are by far the most popular tool though wavelet transformation and spectral analysis are also widely used as an initial data processing stage wherein the output might be fed into, for example, an ANN for feature extraction.

Intubation of the trachea in mechanically ventilated patients continues to be a necessary procedure. Inadvertent esophageal intubation of the patient remains a serious risk and accounts for a significant number of major anaesthesia related accidents. Given the severity of the consequences there has been much work on developing methods to try and help the clinician differentiate between tracheal and esophageal intubation. Researchers, for example [4], have shown that waveforms obtained from the trachea and from the esophagus are different and also that the CO_2, volume, and temperature waveforms obtained from the esophagus change substantially from one breath to the next. Leon et al [5] investigated using features such as these to design an ANN-based system to detect the mechanical differences between lung and esophagogastric ventilation in pigs. This study raises many issues for the future development of a smart sensor that can possibly detect esophageal intubation in humans. If using the breathing waveform is indeed the best approach to use then the necessity of acquiring clinical data to train the ANN must be addressed. A system that just detects when tracheal intubation is not taking place, using the readily available data from successful patient intubations, would be by far the most practical approach at this time.

There is related work on developing a technique to monitor obstructions of the respiratory tract [6] which could possibly be used to indicate esophageal intubation. The approach used has developed a dynamic acoustic model of the respiratory tract that takes into consideration such factors as turbulent sound sources and varying glottal aperture. Measured sound power variations over the 300-600 Hz frequency band are used to indicate changes in the glottal aperture area.

By far the most OR-related 'smart sensor' research has been into providing an indicator for the depth of anaesthesia (DOA) in the patient. In the OR drugs are mainly used to render patients unconscious as well as relaxing the muscles. Anaesthetists are generally most concerned about the possibility that the patient might be aware during a surgical procedure Traditionally a number of indicators, such as blood pressure, heart rate, lacrimation, facial grimacing and movement, are used to judge if the DOA is too low but the introduction of neuromuscular blocking agents, which diminish some of these effects, has created the need for a more reliable technique.

Initial control-orientated studies used pharmacokinetic compartmental models [7] while other researchers turned to using single haemodynamic variables, such as systolic arterial pressure (SAP) [8], and MAP [9] to infer DOA. The use of ANN-based data fusion that uses haemodynamic and other variables as inputs has also proved popular, for example respiration rate, heart rate and SAP, as well as sex, age and weight, have been used to train a DOA indicator [10]. With recent advances in signal processing techniques research now mainly concentrates on using features extracted from the processed EEG (electroencephalogram) to infer the DOA. Currently the most popular approach uses the evoked potentials, the mid-latency auditory evoked potentials (MLAEP's) are the most popular, of the EEG as the input to the pattern recognition approach – this has been found to provide greater correlation and better reliability than using the EEG alone [11]. The use of an ANN approach to provide the pattern recognition from the EEG evoked potentials is also becoming the accepted approach. Robert et al, in their survey on monitoring DOA [12], state "the potential and efficiency of the combination does indeed stand out". Other researchers have tried hybrid approaches whereby the EEG-evoked potential approach is combined with additional inputs like haemodynamic parameters (such as heart rate, systolic and mean arterial blood pressure) [13] and anaesthetic concentration [14] in an attempt to improve the accuracy of DOA estimation. In fact one of the most recent hybrid studies combines many elements of previous approaches in both DOA estimation and control. In their study Huang et al. [14] use the MLAEP's of the EEG signal to which they then apply wavelet transformation and finally use the most discriminating wavelets (between the sleep and awake states) as inputs to an ANN to generate an indication of the DOA. The controller uses this value as well as a fuzzy logic component, where MAP and heart rate measurements are used as inputs.

In addition to the auditory evoked response of the EEG many researchers continue to analysis the EEG directly and extract features from it. Yet again the use of ANN's to carry out the feature extraction is very popular. EEG derived parameters such as the bospectal index (BIS) [15], spectral edge frequency, and median frequency have been used. The BIS is the most popular indicator with commercial instruments based on the BIS being available for a number of years.

Cardiac output (CO) is used clinically to evaluate cardiac function because it is a direct measure of blood flow to the systemic circulation. Most presently used techniques are invasive being based on either the Fick method or the thermodilution method [16]. However these are for the most part, impractical or risky for most patients undergoing general anaesthesia in the OR. Much research has therefore been directed at developing non-invasive approaches to CO estimation. The most popular non-invasive approach has involved trying to estimate CO from the patient's measured arterial pressure waveform in conjunction with an aorta model. Min et al [17] used, two simultaneous non-invasive arterial pressure measurements and an ultrasonic measurement of aortic diameter to provide a CO estimate. Welkowitz et al [18] extended this approach by using adaptive aorta models in conjunction with two simultaneous femoral and cartoid pressure measurements to calculate the aortic flow. A more recent qualitative approach, that only provides an indication of when there is a decrease in the patients CO, uses a theory of evidence approach to fuse the MAP, end-tidal carbon dioxide, expired anaesthetic agent, and pulse volume measurements [19]. This approach is introduced in more detail in the intelligent monitoring section.

In addition to continuous CO estimation recent work on real-time estimation of respiratory parameters has taken a leap forward. Monitoring respiratory mechanics is of paramount importance in mechanically ventilated patients with chronic obstructive pulmonary disease. Also it has long been recognised that respiratory parameters can be estimated from flow-pressure-volume measurements to help in assessing a patients' pulmonary condition and therefore help in optimising ventilator settings. A recent approach to estimating the expiratory time constant involves the use of fuzzy clustering [20]. By partitioning the entire respiratory cycle into 4 phases fuzzy clustering is able to produce a linear relationship for each phase and these are used in determining the expiratory time constant.

3 Intelligent Monitoring

In an environment such as the OR there is a huge amount of patient information available, which can place excessive demands on the cognitive skills of the clinician. AI techniques, have been introduced into the OR for decision support purposes to (a) relieve some of the common information management problems, (b) to better reflect the possibility that a patient problem exists and, (c) to try to identify the cause of the problem [21].

Most of the intelligent monitoring systems developed for the OR can be viewed within five distinct functional levels: data acquisition, signal validation, feature extraction, trend analysis and inference. The most important levels from a data fusion perspective are feature extraction and inference. Feature extraction involves the transformation from numerical features that characterise the signals, to a symbolic presentation. The inference level consists of the reasoning elements to arrive at diagnoses.

The majority of the research into intelligent patient monitors has been directed at the intensive care unit (ICU), for example see [22], but these monitoring techniques are not wholly transferable to the OR. Typically, patients remain in the ICU for days not hours and are generally critically ill. Patients undergoing operations are usually in reasonable health. Consequently the critically ill patient is attached many more sensors which provide a lot more data for detection and diagnosis purposes than would be available in the OR.

Initial work on patient monitoring during anaesthesia concentrated solely on the diagnosis of faults in the breathing circuit [23]. Even now there are only a few OR designed intelligent monitoring systems that are suitable for general day-to-day surgery. This is due to:

- The available information and measurements not being consistent between operations.
- Patient variability being extremely high.
- Fault detection and diagnostic knowledge is largely linguistic, using concepts that are both vague, and difficult to represent mathematically.

Because expert knowledge is largely linguistic - clinicians identify faults by recognising clinically significant changes in a number of patient signals – OR intelligent monitoring systems are usually "shallow knowledge" or qualitative approaches. The knowledge is usually represented in terms of "**IF** (antecedent expression) **THEN** (action)" form with this approach being the most transparent, for clinician understanding, because it mimics the actual decision making process of the expert. 'Black-box' approaches, such as ANN-based systems, generally hide their decision making process and are therefore perhaps not acceptable in this context [24].

Temporal pattern recognition systems have used many techniques to identify characteristics in time-series data. Approaches have included using parameter estimation, heuristic signal processing and template-based classification. Various researchers have pointed out the advantages and limitations of such systems [25, 26]. Once again 'black-box' approaches are usually inappropriate due to their need for large amounts of data for training and/verification [27].

Possibly the most appropriate approach for real-time intelligent monitoring in the OR, if we ignore the special case of ECG analysis, is that of template-based temporal pattern recognition. Recent work in this area [28, 29] has concentrated on introducing a consistent mechanism for accounting for vagueness and uncertainty in temporal templates using fuzzy set and measure theory.

Intelligent patient monitoring systems based on fuzzy logic have met with varying degrees of success [11, 30, 31] with almost all of the fuzzy rules being derived linguistically and structured around the present values of measured variables, for example, 'high blood pressure'. The most successful applications are in critical, well-controlled, data-rich environments such as cardio-anaesthesia. In the OR the fluctuations in a patient's physiological parameters are much greater and the static classification techniques normally used in fuzzy logic become far less useful.

Three deficiencies have been identified in fuzzy logic when it is used in certain fault detection and diagnosis applications. These are related to the

- Uncertainty as to which symptoms should be used.
- Inability to convey (reliability) information (that indicates the uncertainty of the diagnosis). [32]
- Specification of fuzzy operators. [33]

The first two points may be partially addressed by using a relational fuzzy model in which alternative rules map to the same diagnosis. In this way different combinations of symptoms can be used to form diagnoses. The weights in the relation matrix can then be used to limit the conclusion to less than some measure of reliability. The CADIAG-2 system [34] uses multiple fuzzy relations to hold information related to the certainty and reliability of diagnoses. These relations may be found by equating weights with linguistic terms such as *always* and *often.* The system copes with unspecified relations by assigning a nominal weight of 0.5.

The choice of symptoms on which to base diagnoses is a question of the amount of information they provide. Reliability is related to the characteristics of the sources of the information. Likewise, combination operators should be determined by the relationships between the sources of information. By turning to a theory of evidence framework [35], these problems can be resolved whilst still preserving a fuzzy relational model structure. Belief and plausibility methods for fault detection and diagnosis in engineering circles have almost always been rejected in favour of fuzzy logic techniques because these are much easier to apply. A closely related use of belief measures is given by Smets [36] who acknowledges that information necessary for diagnoses may be unavailable. However, Smets uses an adaptation of Bayes' rule for determining the degree of belief in a diagnosis, precluding any analogy with linguistic or relational fuzzy models. Kuncheva [37] addresses the idea of having supporting and contradicting evidence as determinants of belief but proposes a neural network based approach for reasoning. SENTINEL [38] is a prototype intelligent monitor that uses temporal pattern recognition on relevant clinical measurements to provide the bodies of evidence that a particular medical condition has occurred. Limiting rules of combination, applied to the bodies of evidence, are used to provide the diagnostic output. Currently this system is able to identify seven different patient conditions and is also the basis of the qualitative approach to identifying a decrease in a patient's CO introduced earlier [19].

Bayesian networks are also very popular in medical reasoning though limited in their application in the OR because for many diagnoses, prior probabilities are not known, conditional probabilities are dependent on too many different factors and physiologic models are inaccurate or unavailable. The ICU being a more controlled, and data rich, environment with the emphasis specifically on cardiovascular-related or ventilation problems is more fertile ground for their use [32]. A recent study though has investigated using a Bayesian network to try and model the effect of remifentanil and propofol drug interaction on patient wake-up time after closed-loop controlled anaesthesia in the OR [39].

As previously indicated ANN approaches for decision support in the OR, are rare because of doubts over transparency and training data. Orr and Westenskow [23] have developed an ANN-based anaesthesia alarm system, which can really be interpreted as a smart sensor, which IS used to detect circuit faults. This has been tested using simulators, animal studies and in the OR.

4 Discussion

The main motivation in using data-fusion methodologies in the OR is to improve clinical outcome, whether it is through a reduction in error rates or the optimisation of treatment delivery. Intelligent patient monitoring and smart sensing has a good chance of making a significant and positive contribution to healthcare in the OR. The relevant advantages of different components of each developed intelligent monitoring system have begun to be recognised and the direction of future work will concentrate on developing 'hydrid' approaches to produce the most effective approach for a given situation. Challenges do still exist though in the definition of the clinical role that the AI-based monitoring systems should fulfil and the way in which they will be used by clinicians. Long [40] stresses that the biggest challenge is how to integrate decision tools in the normal practice of medicine in a seamless fashion.

The continuing development of different types of smart sensors, and the patient measurements they produce, for example "depth of anaesthesia" (DOA), does provide the possibility of automatic control. There are a number of reasons why it is desirable to develop automatic control systems for drug infusion. The most important is that automatic control systems would relieve the clinician of the time consuming and tedious manual drug infusion duties and allow them to concentrate on monitoring the patients for any adverse conditions that are not easily measured. In addition, the difference in sensitivity to drug infusion for different patients can be extreme which can make it difficult for the clinician to provide good manual control. A well-designed automatic drug infusion system has the potential to provide better control.

The Biomedical control research groups at the University of Sheffield, led by Linkens, and at the Rensselaer Polytechnic Institute, led by Roy, have examined the drug infusion control of mear arterial blood pressure (MAP), CO, DOA and muscle relaxants over the last 25 years. Though there are excellent contributions from other researchers the concerted research efforts of the group leaders and their collaborators during this period has provided the greatest insight into the methods that might be most appropriate for automatic control of drug infusion in the OR (and ICU). Linkens and Mahfouf [41] commented on the evolution of their biomedical control research stating, "initially this used quantitative approaches but increasingly this has moved towards qualitative techniques, in particular that of fuzzy logic". The same sort of trend can also be seen in the work of Roy and his group – the initial work on adaptive control with recursive parameter estimation followed by Multi-Model Adaptive Control, with fixed models, in conjunction with predictive control and then more recently the utilisation of fuzzy control [14].

5 Conclusions

At the heart of the challenges to data fusion and artificial intelligence in medicine is their ability to identify, and satisfy fundamental clinical needs. Because the main motivation is to improve clinical outcome, whether it be through a reduction in error rates or the optimisation of treatment delivery, intelligent monitoring, sensing and control has a good chance of making a significant and positive contribution to healthcare in both the ICU and OR.

Challenges do still exist in the definition of the clinical role that such systems should fulfil and the way in which they will be used by clinicians. Diagnosis has been traditionally seen as a key task with which clinicians require assistance. Evidence now suggests that the primary effort for decision-makers is not at the moment of choice, but rather in situation assessment. If it is the case that situation assessment of monitored data may be of more utility than systems that attempt to manufacture a diagnosis.

In many ways, work to date in the design of patient monitoring systems has been fragmented. There has been a steady effort concentrated on the technical aspects of intelligent diagnosis, monitoring and automatic control of drug infusion. There is also a large, if diverse, amount of research on human factors in the clinical environment, suggesting areas in which decision support might be appropriate. A large variety of approaches will probably be needed to make decision support systems more useful and effective, because despite nearly four decades of research they have yet to become indispensable tools within the clinical setting. The relevant advantages of different components of each developed intelligent monitoring system have begun to be recognised and the direction of future work will concentrate on developing hybrid approaches to produce the most effective approach for a given situation.

While much work has been directed towards supporting clinicians in patient diagnosis rather less has been said about supporting their control tasks. Considering the time and effort the clinician spends in the OR administering drugs this relative lack of emphasis is surprising. So far the focus has been on the development of automatic controllers, which take clinicians out of the control loop. Research has developed to the point where systems for controlled drug infusion of MAP and DOA are possible though their introduction is being hampered by medico-legal and ethical considerations.

6 References

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