Using Fuzzy Logic for Decision Support in Vital Signs Monitoring

Shohas Dutta, Anthony Maeder, Jim Basilakis
School of Computing, Engineering & Mathematics, Telehealth Research & Innovation Laboratory
University of Western Sydney
Private Bag 1797, Penrith 2751, NSW

shohas6@gmail.com, a.maeder@uws.edu.au, j.basilakis@uws.edu.au

Abstract

This research investigated whether a fuzzy logic rule-based decision support system could be used to detect potentially abnormal health conditions, by processing physiological data collected from vital signs monitoring devices. An application of the system to predict postural status of a person was demonstrated using real data, to mimic the effects of body position changes while doing certain normal daily activities. The results gathered in this experiment achieved accuracies of >85%. Applying this type of fuzzy logic approach, a decision system could be constructed to inform necessary actions by caregivers or for a person themself to make simple care decisions to manage their health situation.

Keywords: fuzzy logic, patient monitoring, decision support, assistive technologies, care management.

1 Introduction

Current trends in health within our society include the move towards an ageing population profile, and increased needs for complex care management for people with chronic diseases and multiple co-morbidities. These are fast growing segments of the population; and so is the need for covering their broad ranging and diverse care requirements. External support to manage high-risk (or unsafe) health situations is often needed for them to continue their everyday living routines. This support is typically given by both professional and informal caregivers.

Due to technological advances in wireless data communication systems in the last decade, the application of wireless-based vital sign monitoring devices for patient monitoring has gained increasing attention in the clinical arena. Patient health status can be determined based on the acquisition of basic physiological vital signs, suggesting that a system providing wireless monitoring of vital signs has potential benefits for clinical care management of independently living patients as well as their carers. A patient's physiological state, which includes heart rate, blood pressure, body temperature etc., can be monitored continuously using wearable medical body sensor devices. The remaining challenge is to gain sufficient understanding of this data to assist in health care needs.

The overall aim of this research was to utilise information gathered from personal vital signs monitoring in a laboratory-based smart home environment, and to assist with clinical care decisions using a fuzzy logic rule-based clinical decision support system. Fuzzy logic has benefits over other algorithmic approaches, as it has the potential to incorporate values from ordinal, nominal and continuous datasets within its rules, and can capture the knowledge associated with these rules in ways that are more intuitive to humans.

2 Vital Signs Monitoring Concepts

There are numerous examples in literature describing how monitoring of basic vital signs (i.e. heart rate, blood pressure, temperature and respiration rate) can play a key role in health care, e.g. Norris (2006) [39]. This approach requires software to discover patterns and irregularities as well as to make predictions. By collecting and analysing vital signs continuously it can be shown how well the vital organs of the body are working, e.g. heart and lungs (Harries et al. 2009) [40].

Lockwood et al. (2004) [30] provided a review of the clinical usage of vital signs, including monitoring purpose, limitations, frequency and importance of vital signs measurements. They suggested that vital signs monitoring should become a routine procedure in chronic disease patients' care. Bentzen (2009) [43] defined chronic diseases as:

"diseases which are long in duration, having long term clinical course with no definite cure, gradually change over time, and having asynchronous evolution and heterogeneity in population susceptibility."

Living with a chronic disease, which increases in severity with age, has a significant impact on a person's quality of life and on their family. Chronic disease patients would be able to play a more active role in managing their own health by taking vital signs measurements daily and participating in meaningful electronic information exchanges with clinicians.

A number of authors have suggested that using smart homes for health monitoring is a promising area for health care. Chan et al. (2009) [2] in their review paper described the smart home as a promising and cost-effective way to improve home care for elderly people and people suffering with different chronic diseases.

Vincent et al. (2002) [19] identified three research areas, which combined to produce the concept of "health smart home". These three areas are *medicine*, *information systems*, and home based automatic and remote *control* *devices*. A smart home contributes to monitoring of the patient's health status continuously, taking into consideration the patient's personal needs and wishes in addition to their specific medical requirements. The information gathered through health status monitoring systems can feed into an access controlled electronic patient records system for further medical interpretation.

LoPresti et al. (2008) [21] identified different assistive technologies which can be used in smart homes to reduce the effect of disabilities and improve quality of life. Wearable and portable devices are used which help to monitor the vital signs or physiological behaviour of a person living in a smart home. Those devices are worn by the user or embedded in the smart home. They are wired or wirelessly connected to a monitoring centre. Recently, robotic technology has been developed to support basic activities and mobility for elderly people too.

3 Fuzzy Logic Concepts

Fuzzy logic (Zadeh 1990) [68] is a well established computational method for implementing rules in imprecise settings, where some adaptability for prescribing the rules is necessary. A fuzzy system can be used to match any set of input-output combinations. Fuzzy logic can provide us with a simple way to draw definite results from vague, ambiguous or imprecise information. The rule inference system of the fuzzy model (Jang 1993) [67] consists of a number of conditional IF-THEN rules. For the designer who understands the system, these rules are easy to write, and as many rules as are necessary can be supplied to describe the system adequately.

To improve clinician performance, fuzzy logic-based expert systems have shown potential for imitating human thought processes in the complex circumstances of clinical decision support (Pandey 2009) [75]. A key advantage of using fuzzy logic in such situations is that the fuzzy rules can be programmed easily, and as a result they are easily understood by clinicians. It is different from neural networks and other regression approaches, where the system behaves more like a black box to clinicians. Schuh (2008) [73] found that fuzzy logic holds great promise for increasing efficiency and reliability in health care delivery situations requiring decisions based on vital signs information. This has also been observed in specialised situations such as intensive care (Cicilia et al 2011) [81].

Fuzzy control is the core computational component of a fuzzy logic system. It includes the processing of the measured input values based on the fuzzy rules, and their conversion into decisions with the help of fuzzy combination logic. A full description of fuzzy control principles is beyond the scope of this paper and can be found in numerous fuzzy logic texts. The functional elements of fuzzy control can be represented in a block diagram in Figure 1, based on fuzzy membership functions of variables of interest, as shown in Figure 2 for the example of body temperature represented by the variable T.

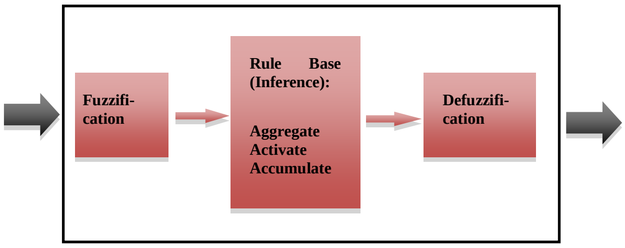

Figure 1. Elements and structure of fuzzy control.

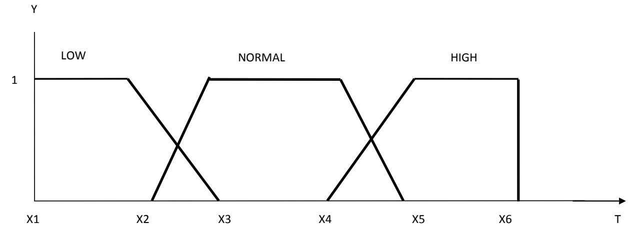

Figure 2. Fuzzy membership functions of variable T.

4 Experimental Methodology

This section will discuss the design of a laboratory experiment to undertake validation of the approach, using a longitudinal data set of physiological signals which have been gathered from an experiment involving monitoring of blood pressure and heart rate signals. It is well known that changes to these vital signs will occur if the body position is changed from vertical to horizontal. The nature and rapidity of these changes mimics the changes in vital signs that may occur with onset of some exacerbated or acute health status in patients.

The laboratory setup used a tilt table to generate changes in heart rate and blood pressure measurements that were correlated with the angle of the tilt table (Figure 3). These physiological changes would be similar to changes one would expect in circumstances such as changing health status or other physiological stressors such as an infection or blood loss. The result of the fuzzy logic analysis of such data can be used to detect a change in physiological state occurring when the vital signs measures are either increasing or decreasing, compared to a steady state where there are no longitudinal changes in the vital sign measures. This output can be compared against the angle of the tilt table, that will serve as a gold standard for determining whether the system is in a steady state or not.

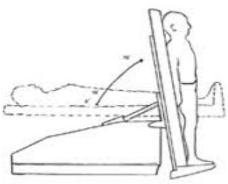

Figure 3. Movement range of tilt table.

The tilt table used was a motorized table with a metal footboard. The subject's feet were rested on the footboard. Soft Velcro straps were placed across the body for safety reasons, to secure the person when the table was tilted during the test. When using the tilt table, it was always tilted upright so that the head of the subject was above his feet. Small, sticky patches containing electrodes were placed on the subject's chest. These electrodes were connected to an electrocardiograph monitor (ECG) to record the electrical activity of the person heart to be shown as an ECG graph. The ECG showed the heart rate and rhythm during the test, at a raw sampling rate of 100Hz and an accuracy of 3%. A blood pressure measuring device was also attached on the subject's finger. This was connected to monitors so that the blood pressure could be observed during the test as well as being recorded.

At the very beginning of the test, the subject was laid flat on his back on the tilt table. At that time his initial blood pressure, ECG, and his position angle data were recorded. After resting for few minutes, the test was started. The blood pressure and ECG was constantly monitored throughout the test and instantaneous readings of the data stream were recorded every second for subsequent analysis. The following protocol was applied for changing the positioning of the tilt table:

1. Lying flat at rest for ~60 sec (to gain statistics of resting state)
2. Fast tilt upwards over ~10 sec
3. Very slow tilt downwards over ~30 sec
4. Lying flat resting state ~30 sec
5. Medium tilt upwards over ~20 sec
6. Upright resting state ~30 sec
7. Fast tilt downwards over ~10 sec
8. Lying flat resting state ~30 sec
9. Fast tilt upwards over ~10 sec
10. Upright resting state ~30 sec
11. Medium tilt downwards over ~20 sec
12. Lying flat resting state ~30 sec

A sample data set collected recorded using the above protocol is shown in the graphs in Figure 4. Data sets from three repetitions of the protocol were captured using one of the investigators as the subject, as a pre-ethics proof-of-concept exercise needed to justify a full human research ethics application for extending the work for recruited subjects in the future. Little variability was observed in the three data sets, so it was considered unnecessary to collect further test data.

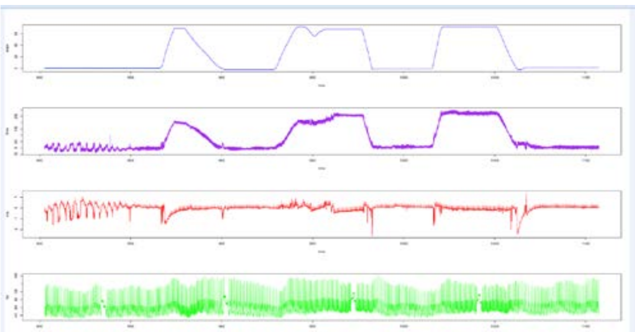

Figure 4. Data captured from the experiment: (top to bottom): angle, footplate force, ECG, blood pressure.

5 Experimental Results

The fuzzy logic rules were derived using the blood pressure and heart rate signals from the first of the three cycles. These signals were pre-processed to find a smoothed curve of the recorded raw signals. In this smoothing process, the averages of the values of heart rate and blood pressure were calculated for every five timestamps using non-overlapping windows. Then these average values were used to plot a smooth curve of the systolic blood pressure and peak-to-peak heart rate to establish the trends. Figure 5 shows the training dataset.

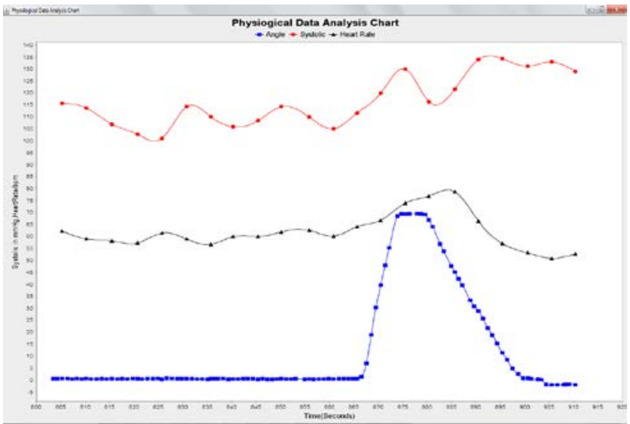

Figure 5. Training dataset (top to bottom): blood pressure, heart rate, tilt angle.

The fuzzy logic solution has two input variables and one output variable. Using the mean and standard deviation as a tolerance band for the input variables, three states (Low, Normal, High) are defined. The two input variables are combined by the AND (i.e. MAX) operator and valid states inferred from the values for the tilt angle, as represented in the decision matrix shown in Table 1.

Table 1. The decision matrix for the training data.

		Input Variable 1: Systolic Blood Pressure		
Input Variable 2: Heart Rate		**Low**	**Normal**	**High**
	Low			Static
	Normal	Static	Static	Lowering
	High		Lowering	Raising

The following rules based on this table were derived:

RULE 1: IF systolic IS low AND heart_rate IS low THEN physiological_status IS Unclassified;

RULE 2: IF systolic IS low AND heart_rate IS normal THEN physiological_status IS Static;

RULE 3: IF systolic IS low AND heart_rate IS high THEN physiological_status IS Unclassified;

RULE 4: IF systolic IS normal AND heart_rate IS low THEN physiological_status IS Unclassified;

RULE 5: IF systolic IS normal AND heart_rate IS normal THEN physiological_status IS Static;

RULE 6: IF systolic IS normal AND heart_rate IS high THEN physiological_status IS Lowering;

RULE 7: IF systolic IS high AND heart_rate IS low THEN physiological_status IS Static;

RULE 8: IF systolic IS high AND heart_rate IS normal THEN physiological_status IS Lowering;

RULE 9: IF systolic IS high AND heart_rate IS high THEN physiological_status IS Raising;

The derived fuzzy rules were applied to the smoothed data of the test set for the second and third cycles, to determine the physiological status. By applying fuzzy logic to these two cycles of testing data, different regions in the data were classified into predicted statuses of Static, Raising and Lowering. Figure 6 shows the results with yellow indicating static status, grey indicating lowering status and green indicating raising status.

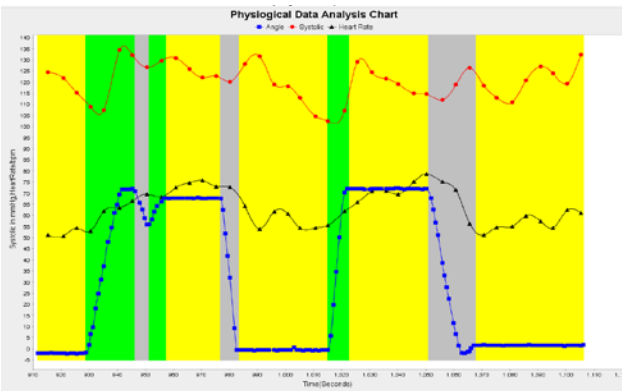

Figure 6. Classifying status using the trained rules.

In order to compare the fuzzy logic output to the gold standard, statuses needed to be inferred from the angle of the tilt table. The following protocol was established to determine three different states categorised as: Static, Raising and Lowering. Only changes of one or more smoothing period timesteps (i.ee >4 sec) were considered. The protocol used was as follows:

1. If the change of angle is < 5° and timestamp interval >4 sec, then the tilting table is in static state.
2. If the change of angle (upward) is: 25°< angle<90° and timestamp interval >4 sec, then the tilting table is in abnormal state and in the raising state.
3. If the change of angle (downward) is: 25°< angle<90° and timestamp interval >4 sec, then the tilting table is in the lowering state.

The results using these steps are summarised in Table 2, and the overall rate of positive and negative outcomes is shown in Table 3. These outcomes were used to analyse classifier performance using the following indicators:

Sensitivity = TP/(TP+FN) = Prob(+ve test)

Specificity = TN/(TN+FP) = Prob(-ve test)

Accuracy = (TP+TN)/total obs = Prob(correct)

Error = (FP+FN)/total obs = Prob(wrong)

Table 2. Matching actual states and predicted states.

		Predicted State (Computed)			
Actual State (Gold standard)		Static	Raising	Lowering	Total
	Static	24	1	2	27
	Raising	2	2	2	6
	Lowering	1	0	5	6
	Total	27	3	9	39

Table 3. Classifier positive and negative outcomes.

	Test Outcome (Static case)	
Gold Standard Set (Static case)	True Positive (24)	False Positive (3)
	False Negative (3)	True Negative (9)
	Test Outcome (Raising case)	
Gold Standard Set (Raising case)	True Positive (2)	False Positive (4)
	False Negative (1)	True Negative (32)
	Test Outcome (Lowering case)	
Gold Standard Set (Lowering case)	True Positive (5)	False Positive (1)
	False Negative (4)	True Negative (29)

The resulting indicator values were calculated as follows:

Sensitivity (Static) = 24 / (24+3) = 24 / 27 = 0.89

Specificity (Static) = 9 / (9+3) = 9 / 12 = 0.75

Sensitivity (Raising) = 2 / (2+1) = 2 / 3 = 0.67

Specificity (Raising) = 32 / (32+4) = 32 / 36 = 0.89

Sensitivity (Lowering) = 5 / (5+4) = 5 / 9 = 0.56

Specificity (Lowering) = 29 / (29+1) = 29 / 30 = 0.97

Accuracy (Static) = (24+9) / 39 = 33 / 39 = 0.85

Error (Static) = (3+3) / 39 = 6 / 39 = 0.15

Accuracy (Raising) = (2+32) / 39 = 34 / 39 = 0.87

Error (Raising) = (4+1) / 39 = 5 / 39 = 0.13

Accuracy (Lowering) = (5+29) / 39 = 34 / 39 = 0.87

Error (Lowering) = (1+4) / 39 = 5 / 39 = 0.13

Across the three states, Sensitivity values ranged from 0.56 to 0.89, and Specificity values ranged from 0.75 to 0.97. The low Sensitivity values are related to the smaller sample sizes for the Raising and Lowering states. Accuracy rates ranged from 0.85 to 0.87, and Error rates ranged from 0.13 to 0.15, indicating good performance.

In considering the performance of this approach, several drawbacks affected the achievable accuracy negatively. The first issue was the time lag in the dropping of the vital sign values when changing the angle of the tilting table. While the tilting table was moved rapidly, it took several seconds for the physiological status of the human body to adapt accordingly. As a result, this problem has affected accuracy in determining the physiological status of a person in FastUp or in FastDown status.

Another problem was related to the error rate associated with using the vital signs measurement equipment. When the position of the tilt table was changed, small movements of the body affected accurate measuring of the physiological data by the monitoring devices. For example, the blood pressure measuring device was attached with the finger and due to the movement of the body and fingers it sometimes gave erroneous readings. The smoothing function that was applied was intended to damp out such errors but there is some residual effect.

6 Conclusion and Future Work

We have described an efficient computational approach to the problem of personal monitoring of vital signs, to provide alerts under well defined abnormal health status conditions which are caused by a known or anticipated health situation. The purpose of such alerts is to provide decision support inputs to carers, to prompt closer observations or direct interventions to be performed to help the subjects of care. This could be useful over a wide range of situations such as elderly or disabled living alone, or patients with chronic diseases or multiple co-morbidities.

Fuzzy logic was chosen as an appropriate computational approach due to its simplicity and ease of tuning to suit relatively smoothly changing vital signs values. Then the approach was implemented in software, providing a multistage process for classifying the condition of a subject using fuzzy functions for each of several observed vital signs, and then combining these using rules to determine the overall health status.

Using this approach, a fuzzy logic rule-based decision support system could, for example, be used to monitor daily activities of living and detection of falls for smart home residents, in combination with other technologies that have more sensitivity in detecting sudden change of body posture such as tri-axial accelerometers. Further research is required to find out the usefulness of such a fuzzy logic rule-based decision support system when a combination of vital signs and acceleration data is used to detect sudden changes in body posture.

On the basis of this foundation work, fuzzy logic has been shown to provide a plausible approach to the general problem of classifying health status in situations of abnormalities in vital signs patterns. It is anticipated that a more extensive system could be built by including further parameters and more complex rules, using the same fundamental algorithm. The implementation methodology using an SQL database and fixed form parameter labelling functions for the fuzzy assignments, provides a robust implementation environment and a sufficiently simple rule specification mechanism to allow users who are not IT experts to reconfigure the system to suit a given vital signs classification problem.

A worthwhile extension of this work would be to improve the level of sophistication and automation of the threshold values for the fuzzy logic classification process. Instead of a simple statistical approach using a set of "normal" observations, actual patterns could be captured and stored which could be tested with greater severity than smooth fuzzy functions. The work offers scope to increase the amount of ambient intelligence which could be provided in the "smart home" of the future, to help sustain occupants' health circumstances.

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