Investigating Adaptation in Type-2 Fuzzy Logic Systems Applied to Umbilical Acid-Base Assessment

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ABSTRACT: In this paper, we describe the development of a type-2 Fuzzy Logic System (FLS) based expert system for Umbilical Acid-Base (UAB) assessment. The aim of this work is to develop an expert system which can adapt to an individual expert's decision making mechanism by determining the parameters that define the uncertainties of the terms used. Umbilical acid-base assessment of a newborn infant can provide vital information on the infant's health and guide requirements for neonatal care. However, there are problems with the technique. Blood samples used for UAB assessment frequently contain errors in one or more of the important parameters, preventing accurate interpretation and many clinical staff lack the expert knowledge required to interpret error-free results. A type-1 FLS-based expert system was previously developed and implemented to overcome these difficulties [1]. However, it was observed that the type-1 fuzzy expert system was not capable of fully capturing the linguistic uncertainties in the terms used and the inconsistency of the experts' decision making. Type-2 FLSs offer better capabilities to handle linguistic uncertainties by modelling the uncertainties using type-2 membership functions and provide diagnosticians with decision-making flexibilities. The development of a type-2 FLS for UAB assessment will provide the capability to handle linguistic uncertainties better and will lead to the creation of mechanisms to allow the system to adapt to individual experts decision-making. Such a system would truely be a *smart adaptive fuzzy expert system*.

KEYWORDS: Type-2 fuzzy logic systems; Umbilical acid-base assessment

INTRODUCTION

Uncertainty pervades all decision-making and appears in a number of different forms. The general framework of fuzzy reasoning allows handling of much of this uncertainty. Fuzzy systems usually employ type-1 fuzzy sets, which represent uncertainty by numbers in the range [0,1]. Type-2 fuzzy sets are an extension of this approach in which uncertainty is represented by the addition of an extra dimension. This extra dimension gives more degrees of freedom for better representation of uncertainty compared to type-1 fuzzy sets. FLSs using type-2 sets provide the capability of handling a higher level of uncertainty and provide a number of missing components that have held back successful deployment of fuzzy systems in human decision making. Diagnostic medicine, in which the systematic handling of perceptual uncertainties is crucial to success, is an important application domain for type-2 FLSs. The work presented in this paper aims to develop a type-2 FLS-based expert system for UAB assessment and to investigate mechanisms for allowing the system to adapt to an individual expert's decision making by determining the parameters that define the uncertainties of the terms used.

Oxygen deprivation during labour can lead to fetal distress, permanent brain damage and, in the extreme, fetal death. Once an infant has been delivered the attending clinicians must make an immediate assessment of the need for neonatal resuscitation. An assessment of neonatal outcome may be obtained from UAB assessment of an infant immediately after delivery. The umbilical cord vein carries blood from the placenta to the fetus and the two smaller cord arteries return blood from the fetus. A sample of blood is taken from each of the blood vessels in the clamped umbilical cord and a blood gas analysis machine measures the acidity (pH), partial pressure of oxygen (pO_2) and partial pressure of carbon dioxide (pCO_2). The blood from the placenta has a relatively high pO_2 and low pCO_2. Oxygen in the blood fuels *aerobic* cell metabolism, with carbon dioxide produced as waste. Thus the blood returning from the fetus has relatively low oxygen and high carbon dioxide content. Some carbon dioxide dissociates to form carbonic acid in the blood, which increases the acidity (lowers the pH). If oxygen supplies are too low, *anaerobic* (without oxygen) metabolism can supplement aerobic metabolism to maintain essential cell function, but this produces lactic acid as waste. This further acidifies the blood, and can indicate serious problems for the fetus. A parameter termed *base deficit of extracellular fluid* (BDecf) can be derived from the pH and pCO_2 parameters [2]. This can distinguish the cause of a low pH between the distinct physiological conditions of *respiratory acidosis*, due to a short-term accumulation of CO_2, and a *metabolic acidosis*, due to lactic acid from a longer-term oxygen deficiency. An interpretation is then made based on the pH and BDecf parameters from both arterial and venous blood.

There are, however, a number of difficulties with the procedure. The cord arteries are very small in comparison to the vein, which can lead to difficulties in obtaining an arterial sample of adequate volume. Due to the narrow diameter of the artery, it is also possible to stick the needle right through the arterial wall and accidentally sample the vein. Two samples, supposedly from each of the artery and vein, can thus actually be from the same vessel. Once the samples are taken it is possible for the pO2 and pCO2 values to alter through exposure to air. Blood gas analysis machines require regular internal calibration and external quality control checks to ensure continuing accuracy and precision to the manufacturer's specifications, and failure to perform this routine maintenance can lead to erroneous results.

To overcome these difficulties an expert system was previously developed for the UAB assessment, encapsulating the knowledge of leading obstetricians, neonatologists and physiologists gained over years of acid-base interpretation [1]. The expert system combines knowledge of the errors likely to occur in acid-base measurement, physiological knowledge of plausible results and statistical knowledge of a large database of results. The expert system was developed in three main incremental stages. Initially, a crisp expert system was developed incorporating conventional forward-chaining logic. Next, the existing crisp system was extended by deriving a preliminary type-1 FLS in which the crisp rules for interpretation of error-free results were converted directly into a rule set whose terms were associated to type-1 fuzzy sets. This preliminary model was automatically tuned to match expert opinion using an algorithm based on simulated annealing [3]. Finally, the limitations of the preliminary fuzzy expert system were overcome through the creation of an integrated fuzzy expert system in which fresh knowledge elicitation resulted in new rule sets for the tasks of identification of vessel origin and interpretation of results [4]. The performance of both aspects of this integrated system was validated in a further comparison with expert opinion [5].

This paper describes the development of a type-2 FLS for UAB assessment. The terms of the rule set in a type-2 FLS are associated with type-2 fuzzy sets which provide additional degrees of freedom to capture more information about the uncertainty of the terms they represent. Moreover a type-2 FLS provides more information as a result of knowledge inference. A type-1 FLS inference produces a type-1 fuzzy set and the result of defuzzification of the type-1 fuzzy set, a crisp number, whereas a type-2 FLS inference produces a type-2 fuzzy set, its type-reduced fuzzy set which is a type-1 fuzzy set and the defuzzification of the type-1 fuzzy set. The type-reduced fuzzy set output gives decision-making flexibilities to the diagnosticians. The remainder of this paper is organised as follows. In the next section, we provide more insight into type-2 fuzzy sets. Then we present the notation, terminology and operations used by type-2 FLSs. In the final section, we present the outline of the work in progress, results of which will be presented at the conference.

TYPE-2 FUZZY SETS AND FLSs

All fuzzy sets are characterised by membership functions. Type-1 fuzzy sets are characterised by two-dimensional membership functions in which each element of the type-1 fuzzy set has a membership grade that is a crisp number in [0, 1]. Type-2 fuzzy sets are characterized by *fuzzy membership functions* that are three-dimensional. The membership grade for each element of a type-2 fuzzy set is a fuzzy set in [0, 1]. The additional third dimension provides additional degrees of freedom to capture more information about the represented term. Type-2 fuzzy sets are useful in circumstances where it is difficult to determine the exact membership function for a fuzzy set, which is useful for incorporating uncertainties. Type-1 fuzzy sets handle uncertainties by using precise membership functions that the user believes capture the uncertainties. Once the type-1 membership functions have been chosen, all the uncertainty disappears, because type-1 membership functions are totally precise. However, type-2 fuzzy sets handle uncertainties about the meaning of the words that they represent by modelling the uncertainties using type-2 membership functions.

Fuzzy logic systems (FLSs) which are used for representing and inferring with knowledge that is imprecise, uncertain, or unreliable consists of four main interconnected components: *rules, fuzzifier, inference engine, and output processor*. Once the rules have been established, a FLS can be viewed as a mapping from inputs to outputs. The rules are the heart of a FLS and can be expressed as a collection of IF-THEN statements. The IF-part of a rule is its *antecedent*, and the THEN-part of a rule is its *consequent*. Fuzzy sets are associated with terms that appear in the antecedents or consequents of rules, and with the inputs to and the output of FLS. Type-1 FLSs use type-1 fuzzy sets and a FLS which uses at least one type-2 fuzzy set is called a type-2 FLS. Type-2 fuzzy sets let us model the effects of uncertainties in rule-based fuzzy logic systems (FLSs).

There are (at least) four sources of uncertainties in type-1 FLSs [6]:

- The meanings of the words that are used in the antecedents and consequents of rules can be uncertain (words mean different things to different people)
- Consequents may have a histogram of values associated with them, especially when knowledge is extracted from a group of experts who do not all agree
- Measurements that activate a type-1 FLS may be noisy and therefore uncertain
- The data that are used to tune the parameters of a type-1 FLS may also be noisy

All of these uncertainties translate into uncertainties about fuzzy set membership functions. Type-1 fuzzy sets are not able to directly model such uncertainties because their membership functions are totally crisp. On the other hand, type-2 fuzzy sets are able to model such uncertainties because their membership functions are themselves fuzzy.

Type-2 FLSs are applicable when [6]:

- The data-generating system is known to be time-varying but the mathematical description of the time-variability is unknown (e.g., as in mobile communications)
- Measurement noise is nonstationary and the mathematical description of the nonstationarity is unknown (e.g., as in a time-varying SNR)
- Features in a pattern recognition application have statistical attributes that are nonstationary and the mathematical descriptions of the nonstationarities are unknown
- Knowledge is mined from a group of experts using questionnaires that involve uncertain words
- Linguistic terms are used that have a nonmeasurable domain

Rule-based type-2 FLSs can be applied to every area where type-1 rule-based FLSs have been applied in which some uncertainty is present. Type-2 fuzzy sets can also be applied to non-rule-based applications of fuzzy sets, again if uncertainty is present. One of the specific areas in which there is no doubt lots of uncertainties present is diagnostic medicine. Fuzzy logic methods are already used in medicine, a field that abounds in uncertainties. Rule-based FLSs that account for all kinds of uncertainties would provide diagnosticians with decision-making flexibilities. Diagnostic medicine is an application where both linguistic and numerical rules will need to be developed.

The concept of a type-2 fuzzy set was introduced by Zadeh [7] as an extension of the concept of an ordinary fuzzy set i.e., a type-1 fuzzy set. Mizumoto and Tanaka studied the set theoretic operations of type-2 fuzzy sets and properties of membership grades of such sets [8]; and examined type-2 fuzzy sets under the operations of algebraic product and algebraic sum [9]. Karnik and Mendel extended the works of Mizumoto and Tanaka and obtained algorithms for performing union, intersection, and complement for type-2 fuzzy sets, and developed the concept of the centroid of a type-2 fuzzy set and provided a practical algorithm for computing it [10].

Dubois and Prade discussed fuzzy valued logic and gave a formula for the composition of type-2 relations as an extension of the type-1 sup-star composition for the minimum t-norm [11]. Karnik et al. presented a general formula for the extended sup-star composition of type-2 relations [12]. Hisdal studied rules and interval sets for higher-than-type-1 FL [13]. Liang and Mendel developed the theory for interval type-2 FLSs for different kinds of fuzzifiers, and showed how the free parameters within such FLSs can be tuned using training data [14]. [15], [16], [17], [18], [19], [20], [21], and [22] present additional discussions on the use of interval sets in fuzzy logic. Lee and Lee introduced a ranking method for type-2 fuzzy values and used this result in solving the shortest path problem in a type-2 weighted graph [23], [24]. Some other examples of application of type-2 FLSs are: [25], [26], [27], [28], and [29].

NOTATION AND TERMINOLOGY

In the rest of this paper, we use A to represent a type-1 fuzzy set, and the membership grade of $x \in X$ in A is $\mu_A(x)$, which is a crisp number in [0,1]. If X is a continuum, A can be represent as

$$\int_{x \in X} \frac{\mu_A(x)}{x} \qquad (1)$$

where the integral denotes logical union. If X is discrete, the integral in (1) is replaced by a summation.

A type-2 fuzzy set in X is $\tilde{A}$, and the membership grade of $x \in X$ in $\tilde{A}$ is $\mu_{\tilde{A}}(x)$, which is a type-1 fuzzy-set whose domain in [0,1]. The elements of the domain of $\mu_{\tilde{A}}(x)$ are called *primary memberships* of x in $\tilde{A}$ and the memberships in $\mu_{\tilde{A}}(x)$ are called *secondary memberships* of x in $\tilde{A}$. Secondary membership defines the possibilities for the primary membership. The membership grade of any $x \in X$ in $\tilde{A}$ can be represented as

$$\int_{u\in[0,1]} \frac{f_x(u)}{u} \qquad (2)$$

When the secondary membership functions are type-1 interval sets, the type-2 set is called an *interval type-2 set*. Interval type-2 sets are the simplest kind of type-2 sets, and [10] presents fast algorithms to compute the output of a type-2 FLS which uses interval type-2 sets.

The shaded region in Fig 1 is called *footprints of uncertainty*, and each represents the collective domain of the respective type-2 fuzzy set. Footprint of uncertainty enables us to graphically depict type-2 fuzzy sets in two-dimensions.

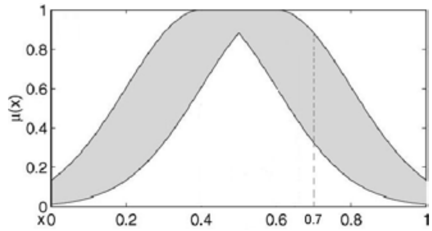

Figure 1: An interval type-2 membership function

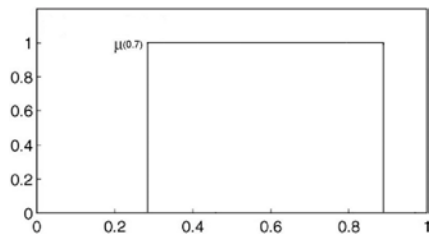

Figure 2: Secondary membership function corresponding to a vertical slice of the primary membership function

Figure 1 is an example of an *interval type-2 fuzzy set* whose primary membership is a Gaussian membership function and corresponding *secondary grade* is 1 for all points as shown for x=0.7 in Figure 2.

OPERATIONS ON TYPE-2 FUZZY SETS

The membership grades of type-2 sets are type-1 sets; therefore, in order to perform operations like union and intersection on type-2 sets, we need to be able to perform t-conorm and t-norm operations between type-1 sets. This is done using Zadeh's Extension Principle [7] and also proven in [6] using a representation method without having to use the Extension Principle. A binary operation $*$ between two crisp numbers can be extended to two type-1 sets $F= \int_v f(v)/v$ and $G= \int_w g(w)/w$ as

$$F * G = \int_v \int_w \frac{[f(v) \bullet g(w)]}{(v * w)} \qquad (3)$$

where $\bullet$ denotes the chosen t-norm (generally product or minimum t-norm is used). For example, the extension of the t-conorm (generally the maximum t-conorm is used) operation to type-1 sets is:

$$\mathrm{F} \sqcup \mathrm{G} = \int_v \int_w \frac{[f(v) \bullet g(w)]}{(v \vee w)} \qquad (4)$$

This is called the *join* operation [9]. Similarly, the extension of the t-norm operation to type-1 sets, which is also known as the *meet* operation, is:

$$F \sqcap G = \int_v \int_w \frac{[f(v) \bullet g(w)]}{(v \wedge w)} \qquad (5)$$

The complement of a type-2 set which is called as the *negation* operation is defined as:

$$\neg F = \int_v \frac{f(v)}{1 - v} \qquad (6)$$

An n-ary operation $f(\theta_1, \ldots, \theta_n)$ on crisp numbers can be extended to n type-1 fuzzy sets $F_1, \ldots, F_n$ as [10]

$$f(F_1, \ldots, F_n) = \int_{\theta_1} \ldots \int_{\theta_n} \frac{[\mu_A(\theta_1) \bullet \ldots \bullet \mu_A(\theta_n)]}{f(\theta_1, \ldots, \theta_n)} \qquad (7)$$

where all integrals denote to logical union, and $\theta_n \in F_i$ for i=1,…,n.

The concept of the *centroid* of a type-2 set can be defined using (7). This concept is required in a type-2 FLS. The centroid of a type-1 set A, whose domain is discretized into N points is given as

$$C_A = \frac{\sum_{i=1}^{N} x_i \mu_A(x_i)}{\sum_{i=1}^{N} \mu_A(x_i)} \qquad (8)$$

Similarly, the centroid of a type-2 set Ã, whose domain is discretized into N points, can be defined using (8) as follows. If we let $D_i = \mu_{\tilde{A}}(x_i)$, then

$$C_A = \int_{\theta_1} \ldots \int_{\theta_n} \frac{[\mu_{D_1}(\theta_1) \bullet \ldots \bullet \mu_{D_n}(\theta_n)]}{\frac{\sum_{i=1}^{N} x_i \theta_i}{\sum_{i=1}^{N} \theta_i}} \qquad (9)$$

where $\theta_i \in D_i$, and all the integrals denote logical union.

METHODOLOGY

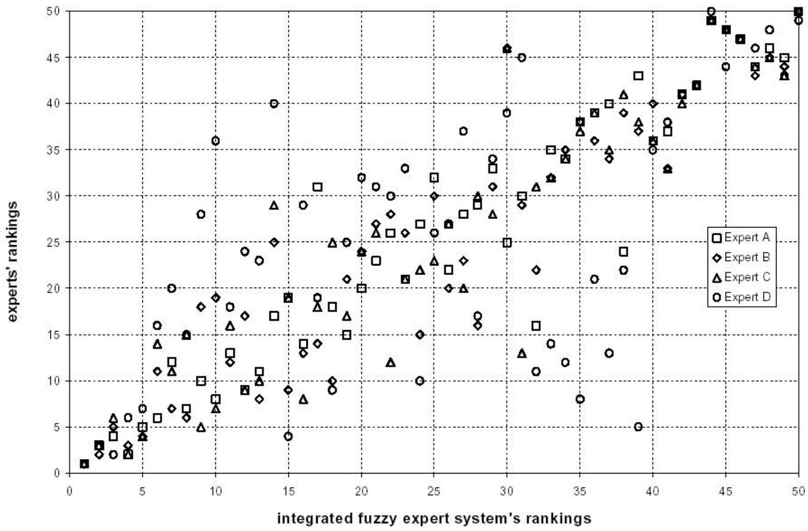

Figure 3: Graph of four experts ranking against the integrated fuzzy expert system

Figure 3 shows the rankings of 50 UAB assesments by four experts against the type-1 FLS-based expert system. A perfect agreement, which would be a straight line from (0,0) to (50,50), is the ideal desired result. However, as can be seen from Figure 3, there is neither perfect agreement with the expert system nor among the experts. The rules of the type-1 FLS-based expert system use fixed type-1 membership functions to represent linguistic terms. However experts have diverse opinions about meanings of linguistic labels and they often provide different consequents for the same antecedents of a rule. In the type-1 FLS-based experts system a typical rule is like:

`IF arterial pH is` ***high*** `and venous pH is` ***high*** `THEN Acidemia is` ***alkalotic***

Using a type-2 FLS can effectively provide a natural mechanism to present the vagueness inherent in the italicized linguistic labels. The initial phase of our work is to extend the type-1 FLS-based expert system by deriving a preliminary type-2 FLS converting the rule set directly by using interval type-2 fuzzy sets with Gaussian primary membership functions. We will compare the rankings of this system with the experts' rankings and assess its capability to adapt its behaviour to best match the opinions of individual experts. Then, this preliminary model will be tuned to see if any improvements can be achieved. For tuning the type-1 FLS-based expert system, a simulated annealing method was used. A similar method can be developed to set the parameters of the type-2 FLS-based expert system. Some alternative methods for tuning the parameters of interval type-2 FLSs using training data are presented in [10].

The main purpose of this work is to capture the inconsistency in the decision making of the experts and to investigate mechanisms of adaptation through which a fuzzy expert system may self adapt according to individual expertise. We will present the results of this work at the conference.

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