MODELLING FUZZY SOURCES OF INTRANATAL MONITORING BY OXYGEN SATURATION MEASUREMENTS

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Abstract. The study discusses the nature of fuzziness in oxygen saturation (SaO_2) values taken by spectrophotometry measurements during intranatal fetal monitoring. The SaO_2 were taken from umbilical artery (UA) and umbilical vein (UV) with corresponding gestational week. Then, we employ a set of fuzzy rules relates SaO_2 values to output pH values in a neurofuzzy system. The output of the neurofuzzy system generates values for intranatal monitoring.

Mothers with singleton, livebirths were included in the study (N=1537). The afterbirth measurements were also included. But it is assumed that they have indicated SaO_2 values just before birth. Fuzzy rules extracted to model uncertainty at the input. It is verified that the local oxygen saturation information approximates the pH values for the continuous intranatal monitoring. The significance and reliability of the method were discussed.

1. Introduction

During intranatal monitoring, continuous and reliable information of the conditions of fetus is required. Various methods are used individually or combined to obtain indication of intranatal fetal conditions. One of noninvasive methods, spectrophotometry measurements [2-7] is used and it discusses the effect of measurements of oxygen saturation in various cases. Although there is not a clear conclusion of these studies that shows the effect of umbilical artery (UA) and umbilical vein (UV) oxygen saturation on the acidosis clues, it is shown that there is a particular relationship. But this relationship still needs a better discussion. On the other hand, there are some empirical studies of preductal oxygen saturation that indicates oxygen values of intranatal fetus [3-4]. Also, it is obvious that there is a need for this area to be introduced a better discussion and conclusion of methods. Overall, the most important issues of the intranatal monitoring become the speed and reliability.

Our study employs a neurofuzzy approach [8-14] that extracts fuzzy information from inputs which are the oxygen saturation (SaO_2) measurements. The approach then relates the input variables to the output pH values. The pH values correspond to normal/ risk of hypoxia cases. The study also models fuzzy sources of input data.

The principal goal of this study is to indicate two fuzzy sources caused by spectrophotometry measurements: first is the spectrophotometry method itself and the second is commonly-used prediction equation of oxygen saturation. Also, we assume that the data values do not change during a very short time difference. This is interpreted as oxygen saturation values regarded unchanged during and after delivery. Previous studies [2-3] express conventional prediction of hypoxic cases through the spectrophotometry measurements of oxygen saturation. Here, our fuzzy model reflects the effects of these sources.

The sections are organized as follows: the second section discusses material and method. Here, we describe potential predictive factors. In the third section, fuzzy rules of oxygen prediction are presented. Then, fuzzy conditions that occur in the intranatal monitoring are discussed and *ANFIS* simulator is described. In the fifth section, experimental results are given and discussed. Finally, in the last section, conclusions are made.

2. Materials and Methods

The study analyzes umbilical cord blood samples of 1537 live-born singleton neonates. The measurements were taken from deliveries performed by practicing obstetricians affiliated with a hospital [2-3]. Oxygen saturation, pH and base excess were available. The aim is to use fuzzy predictive value of oxygen saturation for the risk assessment of hypoxemia and acidosis by PO_2 during intranatal fetus monitoring. For this purpose, we only employ the measurements of umbilical artery (UA) and umbilical vein (UV) oxygen saturation levels (Figure 1). As an important indicator, afterbirth pH levels and base excess are used: acidosis was defined as below the value of 7.09 for UA pH or 10.50 mmol/L for base excess.

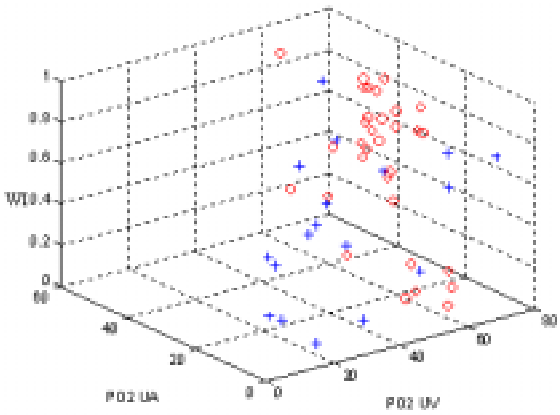

Figure 1: A group of 1537 cases with measurements: SaO_2 UA, SaO_2 UV and week index (WI) value.

The region of oxygen saturation for a typical case of asidosis is raised as an important issue. Various studies of preductal oxygen saturation are available [4]. In these studies, an empirical equation was used to compute the value with vein and artery oxygen saturation values:

$$\textit{Preductal } SaO_2 = (0.8 \times UA\ SaO_2) + (0.2 \times UV\ SaO_2) \quad (1)$$

In our study, we use a fuzzy model that generates fuzzy rules to predict the pH values from oxygen saturation values. This models the two sources of vagueness on measuring SaO_2 values at the input. As the second task, we examine the ability to continuously distinguish the birth modes through the measurements: normal case or a case of acidosis risk based on the rules defined on fuzzy-input level of neurofuzzy system. Here, we assume that the pH values under and over 7.09 are indicated as major risk cases.

The proposed neurofuzzy system is trained with fuzzy input-output (SaO_2, pH) pairs. In the fuzzy-input level, fuzzy rules are defined, then, weighted fuzzy rules are combined at the output level. The testing was performed with (SaO_2, unknown) values. The neurofuzzy structure has been modified for various input organiza tions. With the proposed approach, we combine the following sources of fuzziness: empirical prediction of SaO_2 values of UA and UV, and the blood oxygen saturation (SaO_2) and spectrophotometry measurements relationship. Various fuzzy membership functions are used such as triangle, gaussian, etc. The gaussian functions were then used. The output of the fuzzy-input level is then applied to layers 2-5 and trained with known pH values. At the training phase, the weights of the 5th hidden unit are computed for the given output function of pH values. During the test phase, unknown output values are approximated to the discrete pH function values.

The measurements are taken during the delivery operation and the pH value estimates are obtained instantly. The afterbirth tests, base excess and pH values were made available to check the findings of the study.

3. Fuzzy rules for oxygen saturation

In literature [2-6], empirical estimation for the oxygen level of fetus during intrapartum has been studied. An estimated value was introduced and used in the experiments.

The proposed neurofuzzy method has two levels: fuzzy-input level and neural hidden unit level. The fuzzy-input level defines the fuzzy rules based on given input SaO_2 values. The gaussian membership functions are used to obtain a number of rules up to 9. Rules of fuzzy-input are then used to train to weights of hidden units in the neural structure.

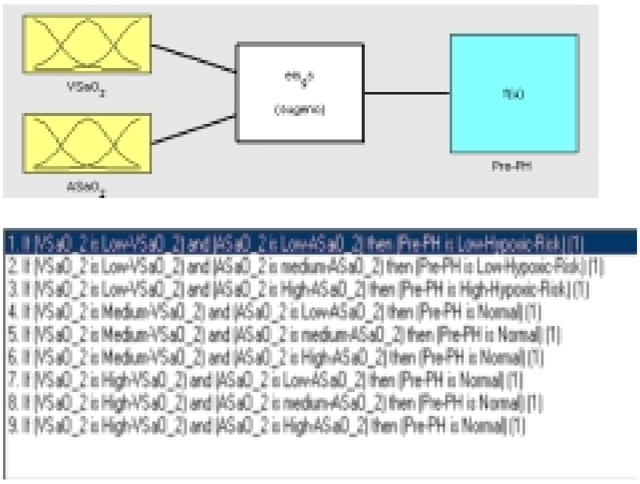

Figure 2: Neurofuzzy structure (*ANFIS*) for fuzzy sources and risk regions

The fuzzy sources of intranatal monitoring are:

- The correlation between spectrophotometry measurements and blood oxygen saturation. The accuracy of readings is also affected by factors such as the placement of electrode, noise interference.
- Emprical preductal oxygen saturation method.

In example case, fuzzy rules are inducted from the given data (Figure 2). Data values at the output of the system can be categorized in three regions of hypoxic risk:

- Normal region
- Low-hypoxic-risk region
- High-hypoxic-risk region

4. Fuzzy conditions that occur in spectrophotometry measurements and *ANFIS* simulator

The main cause of fuzziness comes from spectrophotometry measurements that were suggested for intranatal monitoring [2-3]. The previous results have proven that there is no clear conclusion. The oxygen saturation measurements suggest a vague correlation between the values and the risk conditions of fetus. Also, measurements are affected by electrode noise, etc. This source becomes a main cause of uncertainty.

The second cause of uncertainty comes from the fact that there is no exact formulation to find the oxygen saturation of fetus from the measurements. UA and UV values are combined with a preductal equation to come up with a single value. This is an empirical estimation that is related to previous animal experiments.

Both sources of fuzziness are combined in the decision procedure with fuzzy computations. We employ *ANFIS* system for our computations (Figure 3). *ANFIS* is a neurofuzzy system simulator that receives input values and applies to the user-defined system model. Various parameters are set and system simulator is trained with these data. Then, test set or unseen data are applied to model to obtain results.

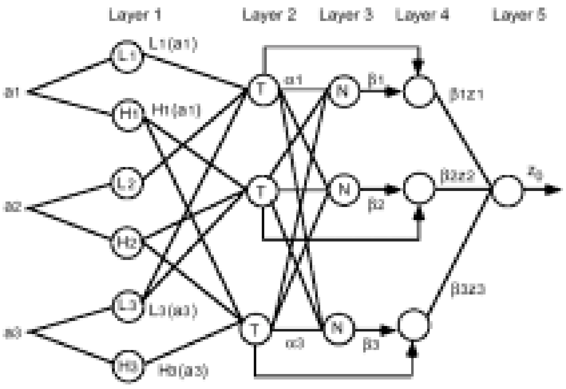

Figure 3: The neurofuzzy system (*ANFIS*) [14].

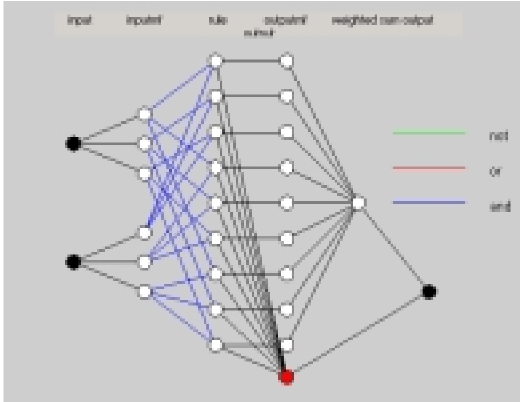

Figure 4: The proposed neurofuzzy structure

Layer 1: the output of the node is the degree to which the given input satisfies the linguistic label associated to this node**.** Thus we describe our first-fuzzy level for entrance to the ANN structure.

Layer 2: each node computes the firing strength of the associated rule.
The output of top neuron is

$$\alpha_1 = L_1(a_1) \wedge L_2 (a_2 \wedge L_3 (a_3),$$

the output of the middle neuron is

$$\alpha_2 = H_1(a_1) \wedge H_2 (a_2) \wedge L_3(a_3), \tag{2}$$

and the output of the bottom neuron is

$$\alpha_3 = H_1 (a_1) \wedge H_2 (a_2) \wedge H_3 (a_3).$$

All nodes in this layer are labelled by T, because we can choose other t-norms for modeling the logical “and” operator. The nodes of this layer are called “rule” nodes.

Layer 3: every node in this layer is labeled by N to indicate the normalization of the firing levels. The output of the top, middle and bottom neuron is the normalized firing level of the corresponding rule

$$\begin{aligned} \beta_1 &= \alpha_1/(\alpha_1 + \alpha_2 + \alpha_3), \\ \beta_2 &= \alpha_2/(\alpha_1 + \alpha_2 + \alpha_3), \\ \beta_3 &= \alpha_3/(\alpha_1 + \alpha_2 + \alpha_3), \end{aligned} \tag{3}$$

Layer 4: the output of the top, middle and bottom neuron is the product of the normalized firing level and the individual rule output of the corresponding rule

$$\begin{aligned} \beta_1 z_1 &= \beta_1 VB^{-1}(\alpha_1), \\ \beta_2 z_2 &= \beta_2 B^{-1}(\alpha_2), \\ \beta_3 z_3 &= \beta_3 S^{-1}(\alpha_3), \end{aligned} \tag{4}$$

Layer 5: the single node in this layer computes the overall system output as the sum of all in-coming signals, i.e.

$$z_0 = \beta_1 z_1 + \beta_2 z_2 + \beta_3 z_3 \tag{5}$$

Suppose we have the following crisp training set

$$\{(x_1, y_1),..., (x_k, y_k)\}$$

where x_k is the vector of the actual exchange rates and y_k is the real value of our portfolio at time k.
We define the measure of error for the k th training pattern as usually

$$E_k = \frac{1}{2}(y_k - o_k)^2 \tag{6}$$

where o_k is the computed output from the neurofuzzy system corresponding to the input pattern x_k, and y_k is the real output, k =1,...,K.

The steepest descent method is used to learn the parameters of the conditional and the consequence parts of the fuzzy rules. We show now how to tune the shape parameters b_4, c_4 and c_5 of the portfolio value. Learning rule for the slope, b_4, of the portfolio values

$$b_4(t+1) = b_4(t) - \eta\frac{\partial E_k}{\partial b_4} = b_4(t) - \frac{\eta}{b_4^2}\delta_k\frac{\alpha_1+\alpha_2-\alpha_3}{\alpha_1+\alpha_2+\alpha_3} \tag{7}$$

In a similar manner we can derive the learning rules for the center c_4

$$c_4(t+1) = c_4(t) - \eta\frac{\partial E_k}{\partial c_4} = c_4(t) + \eta\delta_k\frac{\alpha_1+\alpha_2+\alpha_3}{\alpha_1+\alpha_2+\alpha_3} = c_4(t) + \eta\delta_k \tag{8}$$

and for the shifting value c_5

$$c_5(t+1) = c_5(t) - \eta\frac{\partial E_k}{\partial c_5} = c_5(t) + \eta\delta_k\frac{\alpha_1}{\alpha_1+\alpha_2+\alpha_3} \tag{9}$$

where δ_k =(y_k -o_k)denotes the error, η>0 is the learning rate and t indexes the number of the adjustments [14].

5. Experimental results

Experiments are conducted with a neurofuzzy system (Figure 4) built in *ANFIS* simulator. The neurofuzzy structure is trained with oxygen saturation values. At the first fuzzy-level rules were constructed from given two inputs: oxygen saturation values from UA and UV. Even though gestational week value is tried as additional input, it was not improving average error. At the further levels (layers 2-5) firing levels are obtained and normalized. Layer 2 is used for logical AND operation of three units for each UA SaO_2 and UV SaO_2 (a total of 6 units). Layer 3 is used for normalized firing level of the outputs. It has a total of 9 units. Layer 4 is employed for the product of the normalized firing level and the individual rule output of the corresponding rule. Layer 4 includes 9 units and an extra normalization unit (a total of 10 units). Then, at the last level weighted firings are transferred to output for approximating to pH values. But they indicate the effect of fuzzy input rules derived from input SaO_2 values.

Experimental data were divided into three portions: training, validation and test portions. Each portion has 466 samples. Time complexities for training data were taken a few minutes. Testing results were taken a moment. This requirement of fast, continuous monitoring is thus satisfied. As it is known, the obstetrician takes spectrophotometry measurements and continuously operates on the case during delivery. The values are counted as significant if they are on time and contribute to doctor's decision.

The rules obtained from the first-fuzzy level was shown in the Figure 2. Each rule makes a contribution to the firing level of the next level. Extracted rules are thus conveyed to the output of neurofuzzy system. The value at the output is a pH values that correspond to normal, risky or hypoxic region.

The results (Figure 5) confirm the importance of fuzzy information derivation from the input level. This information is conveyed to the output by means of logical-based and weight-based transition. The mapping between SaO2 and pH is constructed by fuzzy rules and firings of logical and weighted connections. Fuzzy-input layer models the vagueness of the measurements and transfers them to output. Instead of a preductal equation which is commonly used in the literature [4], here, we include this empirical formula included in the fuzzy input. Table 1 shows average error values for the estimation of pH values. It has a total error value of 7%. It generates warnings for cases that are in hypoxia suspicion.

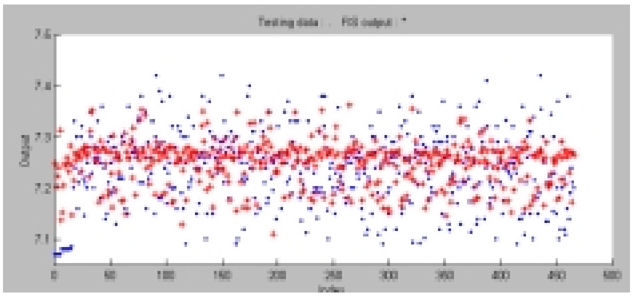

Figure 5: The pH output of neurofuzzy intranatal system (* : system output, ₒ : real data)

Data Set	Average Error
Training Data	%7.33
Checking Data	%7.60
Testing Data	%7.20

Table 1 Error of the estimation of pH values

1537 live-born singleton neonates becomes a reasonable size to study. In this database, the ages of women and the sizes of babies are obtained as the other quantities. The mapping between oxygen saturation values and pH values generated a conclusion for each individual case. The total number of training samples is chosen from 1537 cases: mostly normal cases (1489) were available and 48 cases were observed as in hypoxia risk. After the delivery, the most of the cases were normal in the database.
The results also support our claim of reliability of diagnosis decision for the 1537 cases. The speed issue does not introduce any important problem in this vital application since this neurofuzzy system denotes the conditions immediately after the entrance of inputs to it. In case of oxygen saturation based mapping (during delivery), the pH values have an average of 7% error

rate for testing data. Especially, as a non-invasive method, the spectrophotometry becomes reliable in a limited degree. This result would certainly affect the reliability of the measurements. The performance results support that the intranatal monitoring technique based on spectrophotometry with neurofuzzy system is applicable for given data.

6. Conclusions and Discussion

Accuracy and reliability the information related to oxygen saturation of hemoglobin for intrapartum fetal evaluation is still a discussable issue. As an intelligent data processing approach, hypoxic values of pH are monitored instantly as an indicator. Fuzzy sources of intranatal monitoring by oxygen saturation are modeled by Gaussian fuzzy membership functions. The outcome of neurofuzzy system is defined as the approximated value of pH. It was an assumption that SaO_2 values did not change just before and just after the birth. We may also conclude that when we have more information about important monitoring parameters, we obtain a better accuracy and reliability. But the delivery process is always under the control of obstetrician.

A literature survey was conducted using Medline and other sources to identify articles describing various methods for predicting oxygen saturation. Our method stands as a unique, efficient method for various intranatal cases.

This method becomes a fruitful line of enquiry to obtain a fast, reliable system for intranatal diagnosis applications. The experiments should be continued to validate the method with the other cases and the new inputs.

Acknowledgements

This study is supported by Yildiz Technical University Research Fund 23-7-03-01 and Boğazici University Research Fund 03A103 project. We express our sincere thanks for their support.

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