Applied Soft Computing 14 (2014) 489–497

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Interval type-2 fuzzy logic based antenatal care system using phonocardiography

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ARTICLE INFO

Article history:
Received 28 March 2012
Received in revised form 22 July 2013
Accepted 20 August 2013
Available online 12 October 2013

Keywords:
Antenatal care
Type-2 fuzzy logic
Phonocardiography
Fetal heart rate

ABSTRACT

The assessment of fetal wellbeing depends heavily on variations in fetal heart rate (FHR) patterns. The variations in FHR patterns are very complex in nature thus its reliable interpretation is very difficult and often leads to erroneous diagnosis. We propose a new method for evaluation of fetal health status based on interval type-2 fuzzy logic through fetal phonocardiography (fPCG). Type-2 fuzzy logic is a powerful tool in handling uncertainties due to extraneous variations in FHR patterns through its increased fuzziness of relations. Four FHR parameters are extracted from each fPCG signal for diagnostic decision making. The membership functions of these four inputs and one output are chosen as a range of values so as to represent the level of uncertainty. The fuzzy rules are constructed based on standard clinical guidelines on FHR parameters. Experimental clinical tests have shown very good performance of the developed system in comparison with the FHR trace simultaneously recorded through standard fetal monitor. Statistical evaluation of the developed system shows 92% accuracy. With the proposed method we hope that, long-term and continuous antenatal care will become easy, cost effective, reliable and efficient.

1. Introduction

Prenatal anomalies do not occur suddenly but are initiated and regulated by complex integrated reflexes of fetal central nervous system which is very sensitive to hypoxic changes in fetus [1]. One of the important goals of antepartum antenatal care is to prevent hypoxia related neurological damage and still-births [2]. Fetal heart rate is one of the most important diagnostic parameters for evaluation of fetal health [3]. It has been used in routine continuous monitoring, long-term surveillance and early prediction of prenatal anomalies [4]. Analysis of the FHR trace provides a reproducible and objective interpretation of FHR pattern and also quantifies the parameters that are difficult to assess by visual inspection. Reactive patterns provide indirect evidence about the adequacy of oxygen supply and functioning of the central nervous system of the fetus [5]. The FHR trace, if observed for longer time intervals, show highly irregular patterns. Even episodes of fetal distress are preceded by alterations of interbeat intervals before detection of any appreciable change in the FHR [6].

Medical experts can extract only a small piece of information by visual inspection whereas the main part remains hidden in the FHR trace. Accurate interpretation of FHR trace based on visual inspection is usually the resultant of experience and expertise of the clinician involved. Because of these facts, the interpretation of whether an FHR trace is reassuring, non-reassuring or ominous, remains inconsistent. Hence, the computer-aided analysis along with diagnostic expert system will improve the results of interpretation of objectivity and repeatability of the FHR patterns [6]. This will definitely help the medical experts to assess the health status of the fetus.

Earlier studies have provided strong evidence of a correlation between erratic changes in FHR pattern progressing to certain abnormal conditions of the fetus [7]. Several studies and guidelines on EFM based on analysis of FHR trace have been published during the last two decades [8–12]. The goal of these guidelines is the assessment of analytical parameters for evidence-based surveillance of the fetus during its intra-uterine life and at the time of delivery.

Doppler ultrasound based fetal cardiotocography (fCTG) technique is currently being used for recording and analysis of the FHR. This technique cannot be used for long-term monitoring of the fetus due to several reasons [13] such as the cost and complexity

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http://dx.doi.org/10.1016/j.asoc.2013.08.016

of the monitoring instrument, ultrasound radiation exposure and gel application. Moreover, this instrument might not be easily obtained or accessed, which reduces its practicability in daily preventive actions. Fetal phonocardiography (fPCG), the recording of fetal heart sound from the maternal abdominal surface, gives one physiological signal reflecting mechanical heart events [14]. The periodic patterns of fetal heart sound enable the accurate measurement of FHR. The fPCG signals can be acquired using a small and economical acoustic sensor. This technique provides a permanent and lasting record of FHR trace through which an automated diagnostic system for monitoring of fetal health can be developed [15]. The major advantage of the system based on this technique will be to minimize the possible human error that may occur in subjective diagnosis.

There have been significant initiatives to develop expert systems for assessment of variations in FHR patterns using type-1 fuzzy logic and artificial neural network (ANN). Skinner et al. [16] investigated the improvements in CTG analysis using fuzzy logic over the crisp expert system. Ifeachor et al. [17] presented a method for handling imprecision and uncertainty in computer-based analysis of fetal heart rate patterns obtained through ECG. A computational intelligence model based on fuzzy logic techniques was proposed. Czabanski et al. [18] described an application of the ANN based on logical interpretation of fuzzy if-then rules for classification of the fetal state as normal or abnormal. Liszka-Hackzell [19] used digitized data from CTG measurements for categorization of typical heart rate patterns before and during delivery. Warrick et al. [20] used the combined tools of signal processing and neural networks to detect the FHR patterns of baseline, acceleration and deceleration. Noguchi et al. [21] composed neural network software of three layers with the back propagation. Krupa et al. [22] proposed a new approach for FHR feature extraction based on empirical mode decomposition (EMD), which was used along with support vector machine (SVM) for the classification of FHR recordings as ‘normal’ or ‘at risk’ [22].

Although some approaches discussed above have shown good results, none has been yet widely accepted and implemented for assessment of fetal wellbeing. The main reason behind this is, the type-1 fuzzy and ANN based methods are unable to detect the uncertain variations in the FHR trace. Additionally, these research efforts have shown that it is still worth to further investigate completely reliable method to analyze the FHR patterns for assessment of fetal wellbeing with minimal intervention from medical experts. In this work, interval type-2 fuzzy logic is used for assessment of fetal health status. The fPCG signals are recorded through developed wireless signal acquisition system. The recorded signals are denoised and processed for extraction of FHR and FHR trace. Important diagnostic parameters, based on standard clinical guidelines, are extracted from the FHR trace. These parameters are served as input to the type-2 fuzzy logic based intelligent diagnostic system. The output of the proposed system will be a classified diagnosis of the fetal health. Experimental tests are performed with the real fPCG signals and the results are compared with the existing fCTG based fetal monitor.

The rest of the paper is organized as follows. In Section 2, a brief introduction on the interval type-2 fuzzy logic is provided. Section 3 presents methods for fPCG signal acquisition and processing, parameters extraction and diagnostic decision-making. Section 4 presents experimental results. Section 5 concludes the paper.

2. Interval type-2 fuzzy logic

The type-1 fuzzy sets were introduced by Zadeh in 1965 to process/manipulate data and information affected by uncertainty/imprecision [23,24]. These were designed to mathematically represent the vagueness and uncertainty of linguistic problems. Fuzzy logic based expert systems are fundamental tools for modeling complex systems. Type-2 fuzzy sets, introduced again by Zadeh in the year 1975, are used for modeling uncertainty and imprecision in a better way. These type-2 fuzzy sets were essentially ‘fuzzy fuzzy’ sets where the fuzzy degree of membership is a type-1 fuzzy set [25]. Later in the year 2001, Mandel introduced a new concept in which type-2 fuzzy sets can be characterized with an upper membership function and a lower membership function [26]. These two functions can be represented each one by a type-1 fuzzy set membership function. The interval between these two functions represents the footprint of uncertainty (FOU), which is used to characterize a type-2 fuzzy set. The FOU is used to verbalize the shape of type-2 fuzzy sets it implies that there is a distribution that sits on top of that shaded area. The FOU provide additional degrees of freedom that can make it possible to directly model and handle the uncertainties. Therefore type-2 fuzzy sets have the potential to handle higher uncertainty levels than their type-1 fuzzy sets.

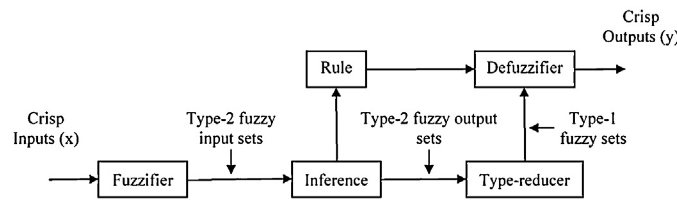

Fig. 1. Structure of singleton interval type-2 fuzzy logic system.

Similar to a type-1 FLS, a type-2 fuzzy logic system (FLS) includes fuzzifier, rule base, fuzzy inference engine, and output processor as shown in Fig. 1. The output processor includes type-reducer and defuzzifier; it generates a type-1 fuzzy set output (from the type-reducer) or a crisp number (from the defuzzifier) [27]. A type-2 FLS is also characterized by IF-THEN rules, but its antecedent or consequent sets are type-2.

A type-2 fuzzy set $\bar{A}$ is defined by a type-2 membership function $\mu_{\bar{A}}(x, u)$, where $x \in X$ and $u \in J_x \subseteq [0,1]$, i.e.

$$\bar{A} = \{((x, u), \mu_{\bar{A}}(x, u)) | \forall_x \in X, \forall_u \in J_x \subseteq [0, 1]\} \tag{1}$$

in which $0 \leq \mu_{\bar{A}}(x, u) \leq 1$. $\bar{A}$ can also be expressed in the usual notation of fuzzy sets as:

$$\bar{A} = \int_{x \in X} \int_{u \in J_x} \frac{\mu_{\bar{A}}(x, u)}{(x, u)}, \quad J_x \subseteq [0, 1] \tag{2}$$

x and u are the primary and secondary variables and J_x is the primary membership of x. All secondary grades of fuzzy set $\bar{A}$ are equal to 1. The FOU of a type-2 fuzzy set which is described by its upper and lower membership function is given by:

$$\mathrm{FOU}(\bar{A}) = \bigcup_{\forall_x \in X} (\underline{\mu}_{\bar{A}}(x), \overline{\mu}_{\bar{A}}(x)) \tag{3}$$

The concepts of FOU and the lower and upper membership function are depicted in Fig. 2. Two type-1 fuzzy membership functions (the upper, $\overline{\mu}_{\bar{A}}(x)$, and the lower $\underline{\mu}_{\bar{A}}(x)$, boundary of the FOU) are used to describe each type-2 fuzzy set.

In order to obtain an output value, the resulting output type-2 fuzzy set $\overline{B}$ is first type-reduced and then defuzzified. The interval centroid of the type-2 fuzzy set $\overline{B}$ is defined as:

$$C_{\overline{B}} = \int_{\theta_1 \in J_{x_1}} \cdots \int_{\theta_N \in J_{x_N}} \frac{1}{\sum_{i=1}^{N} x_i\theta_i / \sum_{i=1}^{N} \theta_i} \tag{4}$$

In this work, the Nie–Tan (N–T) type reduction method is used due to its computational inexpensiveness [28]. The N–T method first computes the centroid of each vertical slice in each primary