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Fuzzy Logic System for Fetal Heart Rate Determination

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Abstract-This paper focuses on the Fuzzy Logic System for fetal heart rate determination. The clinical interpretation of fetal heart rate trace is a difficult task and this has led to the development of computerised systems. These systems are limited by their inability to represent uncertainty. This paper describes the development of a fuzzy expert system for fetal heart rate. The fuzzy logic system improved on the crisp system and has achieved the highest overall performance. With the results obtained, it is evident that the fuzzy logic system can be used to improve the efficiency of the clinician position for making accurate diagnosis.

Keywords: Fuzzy logic system, uncertainty, fetal heart rate, efficiency.

I. Introduction

The Cardiotocography (CTG) is regularly monitored in the clinical routine antepartum and during the labour in order to prevent a possible fetal sufferance status. It consists of the simultaneous recording and printout of two signals; the heartbeat frequency of the feotus and the toco signal relative to the uterine contractions.

The outcome of labour is usually good for the feotus, however problems may occur that can result in permanent fetal brain damage or even death. Cardiotocogram interpretation is a difficult task requiring clinical experience and significant expertise. Studies have shown that this is often lacking in the clinical setting, with CTG misinterpretation implicated in a large number of preventable fetal deaths and unnecessary interventions [1].

As a result, many computerized systems have been developed to encapsulate expert interpretation of the Cardiotocogram. These range from simple feature extraction and classification systems to intelligent expert systems that assess the CTG along with clinical information to provide management advice [2]. One of the main problems that have impeded progress is the inherent uncertainty in clinical knowledge relating to Cardiotocogram interpretation. This uncertainty has not been effectively represented in any automated Cardiotocogram system.

The normal fetal heart rate (FHR) pattern is characterized by a baseline frequency between 110 and 159 beats per minute, presence of periodic accelerations, a normal heart rate variability with a bandwidth between 5 and 25 beats per minute and the absence of decelerations. The FHR pattern is abnormal when the following features are observed. These are the baseline frequency below 110 or above 160 beats per minute, absence of accelerations for more than 45 minutes, absence of FHR variability and late decelerations. A baseline frequency between 100 and 110 can be considered as normal when the duration of pregnancy has exceeded 41 weeks [3].

II. Materials and Methods

Fuzzy logic system is the process of formulating the mapping from a given input set to an output set using fuzzy logic. This mapping process provides the basis from which the inference or conclusion can be made. A fuzzy inference process consists of the following five steps:

- Fuzzification of input variables
- Application of fuzzy operator (AND, OR, NOT) in the IF (antecedent) part of the rule
- Implication from the antecedent to the consequent (THEN part of the rule)
- Aggregation of the consequents across the rules and Defuzzification.

At the top left of the fuzzy inference system, the names of the defined input fuzzy variables are given and at the right of the system, the output variable is shown. The membership functions are located in the boxes and the system name and the Mamdani inference method used are also indicated. The Mamdani-type fuzzy inference, which formulates a mapping from a given input to an output using fuzzy logic, is used as the inference engine [4]. The mapping provides a basis which decisions can be made or patterns recognized.

The inference process includes block building, structuring, firing, implication and aggregation of rules [5]. The number of rules is determined by the complexity of the associated fuzzy system. At the lower left of the system, the various steps of the inference process are shown and at the lower right, the name of the input or output variables, its associated MF type, and its range are shown. Figure 1 shows the fuzzy inference system.

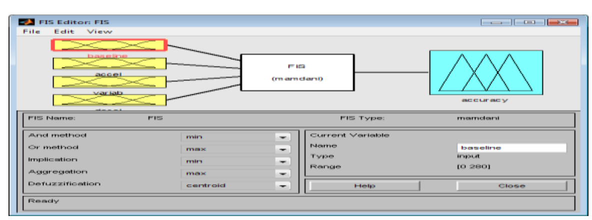

Fig 1: Fuzzy Inference System

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The rule Editor for the Fuzzy Inference System is shown in figure 2.

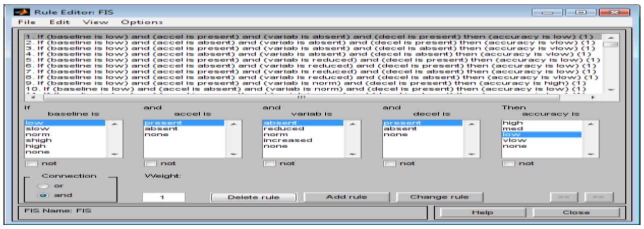

Fig 2: Screenshot of rules defined in MATLAB

Once the rule matrix is designed and the fuzzy variables are defined in the fuzzy inference system editor, construction of the actual rules by the rule editor is easy. The logical connectives of rules, AND, OR, and NOT can be selected by buttons. The rules can be changed, deleted or added as desired

The membership functions of the Fuzzy Inference System for the input variable are given in figures 4, and 5.

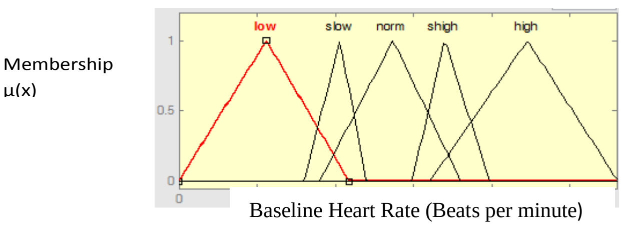

Fig. 4: Fuzzy membership sets for baseline heart rate

The fuzzy classification of accelerations is found by considering the total duration of identified accelerations as a proportion of the segment length. The acceleration classification set is:

Accelerations = {Absent, Present}

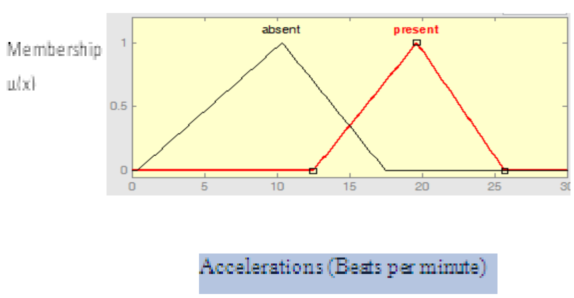

Fig.5: Fuzzy membership sets for accelerations.

A. Determination of the optimization

To verify the optimal condition necessary for high quality Cardiotocogram, we plotted the graphs of accuracy against baseline, accuracy against variability, accuracy against acceleration and accuracy against deceleration as shown in figures 6, 7, 8, and 9, respectively.

In figure 6, the optimal solutions are possible between 120-140 bpm values, figure 7 shows that the optimal solutions are possible within 6 bpm, and between 22-40 bpm and figures 8 and 9 the optimal solutions are possible between 19-25 bpm. These values are different from the theoretical guidelines used by the clinicians as contained in Table 1.

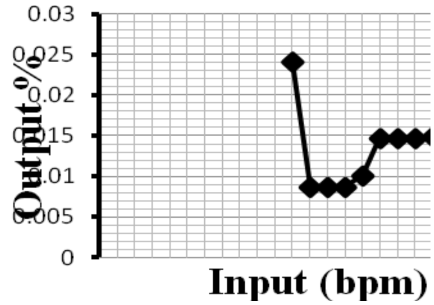

Fig 6: Accuracy versus Baseline

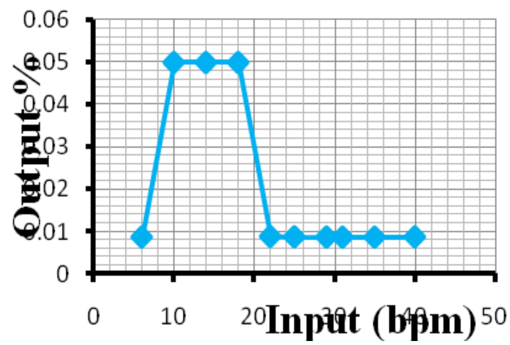

Fig 7: Accuracy versus Variability

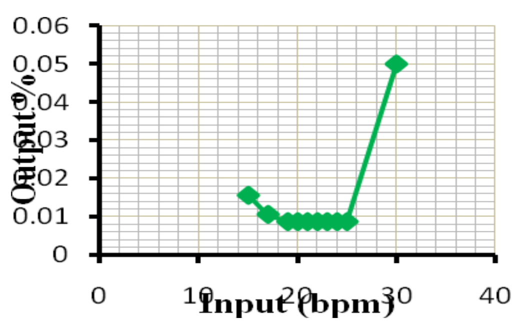

Fig 8: Accuracy versus Acceleration

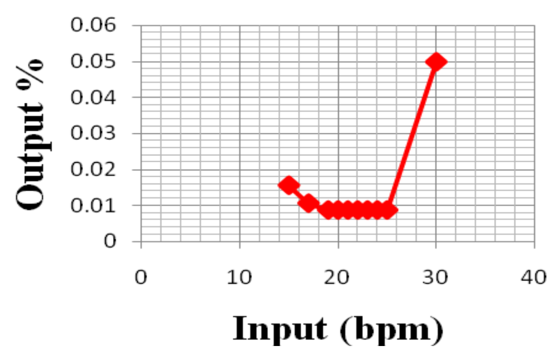

Fig 9: Accuracy versus Deceleration

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Table 1: Linguistic terms describing the linguistic variables and their target input range

In Cardiotocogram (CTG) system analysis, each feature is identified and classified using rules derived from some guidelines based on empirical observations [6].

Linguistic variable (heart rate features)	Linguistic term	Target input range (beats per minute)
Baseline rate	{Low, Slightly low, Normal, Slightly high, High}	{<90, 90-109, 110-159, 160-179, >180}
Acceleration	{Absent, Present}	{<15, ≥ 15}
Baseline variability	{Absent, Reduced, Normal, Increased}	{<2, 2-5, 6-25, >25}
Deceleration	{Absent, Present}	{<15, ≥ 15}

III. THE RESULTS

To validate the feasibility of the Fuzzy Logic Based model [7], the researchers simulated the theoretical range for each CTG features. The inputs and outputs of the respective ranges for baseline {110-200}, variability {6-40}, acceleration {15-30}, and deceleration {15-30} are shown in Table 2

Table 2: Simulation of the inputs and outputs of theoretical CTG features

Baseline		Variability		Acceleration		Deceleration	
Input	Output	Input	Output	Input	Output	Input	Output
110	0.0241	6	0.00869	15	0.0156	15	0.0156
120	0.0087	10	0.05	17	0.0106	17	0.0106
130	0.0087	14	0.05	19	0.0087	19	0.0087
140	0.0087	18	0.05	20	0.0087	20	0.0087
150	0.0101	22	0.00884	21	0.0087	21	0.0087
160	0.0147	25	0.00874	22	0.0087	22	0.0087
170	0.0147	29	0.00868	23	0.0087	23	0.0087
180	0.0147	31	0.00866	24	0.0087	24	0.0087
190	0.0149	35	0.00866	25	0.0087	25	0.0087
200	0.0147	40	0.00873	30	0.05	30	0.05

The results obtained from the Fuzzy Inference System shows that seventy –nine rules were developed for the Fuzzy Inference System (FIS) model. For defuzzification, [8] the value of all the highest values of the aggregate rules output is used to map the fuzzy rules output to a crisp (single) point to the accuracy as illustrated in figure 10.

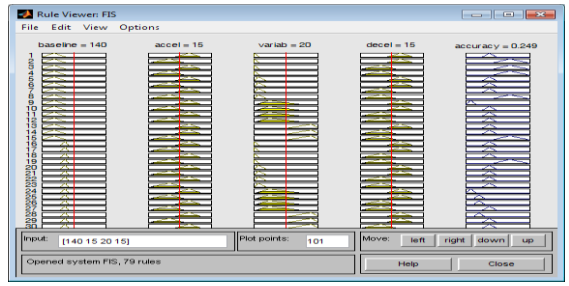

Fig 10: Rule view for defuzzification of the aggregate rules output

The resulted fuzzy surface forms the IF- THEN rules showing the relation between the inputs and output is shown in figure 11.

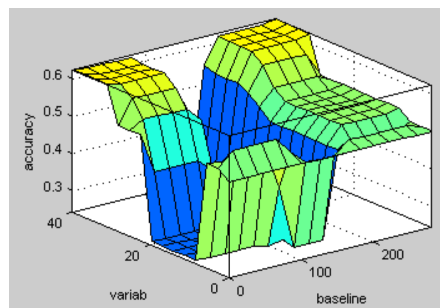

Figure 11: Fuzzy surfaces showing the relation between the inputs and output

IV. ANALYSIS OF RESULTS AND DISCUSSIONS

The degree of uncertainty in the Cardiotocogram (CTG) measured values has a strong positive correlation of 0.9723 while the fuzzy inference system has a weak correlation of 0.017.
These results were compared to the results in the literature; it found that the fuzzy inference system correlation of 0.017 was lower than the rank correlation of 0.0623. The CTG correlation of 0.9723 was higher than reviewers' crisp correlation of 0.505.
The accuracy obtained from the fuzzy inference system has lower accuracies than the one from the Cardiotocogram measured values.

V. CONCLUSION

Presently, automated methods possess limited clinical applications in Cardiotocography. A greater percentage of this unsatisfactory performance rests on the weakness of methods employed for classifying fetal condition that generates risk alarms during pregnancy. More so, even if the heart rate readings became an integral part in fetal evaluation, the lack of standardization compounds the comparison of these readings [9].

The researchers have developed a fuzzy logic inference system, and have derived rules directly from practical observations, which gave greater flexibility to the classification criteria, and widened knowledge acquisition through training. The simulation of the theoretical guidelines was also carried out to further determine the optimality conditions of the fuzzy system. The researchers observed that the measured readings produced higher classification errors compared to the fuzzy system.

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