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A Fuzzy Inference Model-based Non-reassuring Fatal Status Monitoring System

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Abstract

Clinical fatal examination requires thorough and continuous monitoring. Obstetricians are required to check fatal monitoring signals for anomalies. Manual processing of ultrasonic data is time-consuming and labor-intensive. To overcome this problem, a fatal status monitoring system was designed to help obstetricians detect non-reassuring fatal status. In the proposed system, the weighted average is employed to estimate the fatal heartbeat baseline and uterine contraction baseline. These baseline values allow five patterns to be recognized including heartbeat acceleration, heartbeat deceleration, uterine contraction, heartbeat noise pattern, and uterine noise pattern. Moreover, the monitoring system considers four non-reassuring fatal status types. Fuzzy logic is used to analyze the signals for each non-reassuring status type. A total of 23 fuzzy rules are used to recognize non-reassuring fatal status that triggers an alarm mechanism. Non-reassuring conditions are detected and alarm signals are sent to obstetricians for immediate treatment of the patient. The fuzzy sets can be modified and adopted to fit the requirements of individual patients. A signal simulator is used to verify the applicability of the system.

Keywords: Non-reassuring fatal status, fuzzy inference method, fatal heart rate, uterine pressure.

1. Introduction

In order to ensure that pregnant women will give birth to healthy babies, complete and reliable antenatal examination is required. By investigating the fatal monitoring system records, obstetricians decide the optimal time for treatment and determine the probable premonition of congenital diseases of the fetus.

Traditional fatal monitoring systems are mainly used for monitoring fatal heart rate (FHR) and maternal uterine pressure (UP). Doppler ultrasound can be used on the mother's abdomen to detect simultaneous trends of beat-to-beat FHR. In addition, UP can be recorded by a tocotransducer strapped to the abdomen in the area of the uterine fundus. The data recorded by the transducers is subsequently plotted on the built-in dual channel strip chart recorder of a fatal monitoring machine. Also the FHR and UP are displayed continuously on the front-panel LCD display.

In clinical practice, fatal monitoring systems have been used for more than ten years. Although the traditional fatal monitoring systems can measure FHR and UP accurately, there are still two problems that remain to be solved. First, it takes time and effort for obstetricians to manually inspect the ultrasound cardiotocography records and find any possible anomalies. Sometimes, obstetricians should stay with the mother while monitoring to avoid the emergent risks of mother and fatal. Second, obstetricians usually analyze these graphical records visually. It may result in human error and false recognitions. To overcome these problems, plenty of research has been conducted with the purpose to improve the manual recognition procedure. Suzuki [1] and Linh et al. [2] used neural network to analyze electrocardiograms (ECG's). In addition to the digital wave filter technique that is generally used to analyze FHR signals [3-6], Cazares et al. [7] studied the relationship between FHR and UP and by calculating the peak-to-trough interval, they identified some abnormal states leading to non-reassuring fatal status. Skinner et al. [8] proposed a fuzzy inference method that could recognize FHR states, although the non-reassuring fatal status problem was not addressed explicitly. This study proposes a more practical approach than reported in previous studies, where a new fuzzy inference-based monitoring system that is capable of auto-diagnosing non-reassuring fatal status based on FHR and UP signals is proposed.

This paper comprises five parts. In the second section, four cases of medical non-reassuring fatal status are briefly defined and the proposed recognizing method is outlined. Section 3 describes the implementation of the framework. Next, experimental results are provided in section 4. Finally, the last section summarizes the present study and indicates future work.

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2. Recognizing Non-reassuring Fatal Status

During the process of pregnancy and labor, obstetricians, nurses, and other specialized medical personnel should carefully monitor the fatal states to ensure the fetus can be born healthily. We will introduce four types of non-reassuring fatal status and measures of recognizing fatal state.

(1) Type-1: Steady fatal heart rate

Generally speaking, normal fatal heart rate should be within the range of 120 bpm to 160 bpm irrespective of the pattern such as acceleration or deceleration. With the exception of situations where the mother has fever, values outside these bounds can be dealt with as non-reassuring fatal status.

(2) Type-2: Variation of fatal heart rate

A normal fatal heart rate should have a slight variation. If the FHR does not vary over a span of a defined threshold, it is regarded as fetus sleep or probably a shortage of oxygen. The system should under such circumstances trigger an alarm.

(3) Type-3: No unusual FHR variance and uterine contraction

Usually, uterine contraction does not cause FHR violent reaction. Sometimes, FHR acceleration is allowed. Sometimes uterine contraction happens simultaneously with FHR deceleration. This indicates that the uterine contraction results in an insufficient oxygen supply for the fetus.

(4) Type-4: Normal FHR deceleration

A FHR deceleration might occur during monitoring. A normal deceleration should quickly return to FHR baseline within a given time. An alarm should be raised when decelerations are sustained over time and the FHR does not return to its baseline.

2.1 Baseline calculation

The baseline is fundamental to the detection of non-reassuring fatal status. Once the baseline is calculated, the five wave patterns can be recognized. First, all the FHR and UP signals are sorted in descending order and the weighted average of the top 5 occurring frequencies of FHR and UP signals are used as the baseline as follows:

$$BL_{FHR.UP} = \frac{\sum_{k=1}^{5} V_k \times N_k}{\sum_{k=1}^{5} N_k}. \tag{1}$$

Where $BL_{FHR.UP}$ is the average of the top 5 signals, V_k is the kth highest value of signals, N_k is the repeated times of V_k. The above expression is used to calculate the average of the top 5 signals and these results are used as the FHR and UP baseline. The first calculation is performed 5 minutes after starting the system and it is recalculated every 2 minutes thereafter.

2.2 Recognizing non-reassuring fatal status using fuzzy inference

(1) Type-1 non-reassuring fatal status:

For better recognition, a FHR variable that has three labels, “Low”, “Medium” and “High,” is defined, as shown in Fig. 1. When the FHR signal is received, the model activates the fuzzy rule base given in Table 1 to decide the degree of alarm (DA). If the degree is greater than the predefined threshold (1.85 pre-assigned), it is treated as a non-reassuring fatal status. In addition, the system incorporates the temperature of the mother. In order to adapt to individual variations, the degree of fever is manually decided by the obstetricians. Clinical data shows that FHR increases 10 bpm with every degree of increase in fewer temperature of the mother [9]. We adjust these boundaries, 120 and 160, as the reference values. Then, the degree of alarm is calculated as the center of gravity defuzzification as follows:

$$DA = \frac{F_l \mathrm{C}_\mathrm{a} + F_\mathrm{m} \mathrm{C}_\mathrm{n} + F_\mathrm{h} \mathrm{C}_\mathrm{a}}{F_l + F_\mathrm{m} + F_\mathrm{h}}. \tag{2}$$

Where F_l, F_m and F_h are the membership values from fuzzy labels, Low, Medium and High, respectively. C_a and C_n are the singleton outputs for Alarm and Not-alarm, respectively. Note that the singleton outputs, Alarm, Attention, and Not-Alarm are represented using 2, 1, and 0, respectively.

(2) Type-2 non-reassuring fatal status:

Two parameters for this non-reassuring fatal status type are defined. The first is FHR variation (VAR) shown in Fig. 2. The second is duration (DUR) shown in Fig. 3. At first, the system uses the maximum variation to calculate the degree of variability. If the variation reads “High”, the system resets the low variation duration. If the variation is not “High” enough, the low variation duration will remain counted. Next, the system uses the fuzzy rule base to calculate the degree of alarm (DA). The rule base for VAR and DUR that is used to determine whether an alarm should be activated is summarized in Table 2. There are nine rules in Table 2 since each variable of VAR and DUR has three labels. The degree of alarm is also calculated using center of gravity defuzzification.

(3) Type-3 non-reassuring fatal status:

According to medical documents [9], a FHR deceleration that occurs behind an UP peak value point and continues for 30 seconds, is regarded a non-reassuring status. To be on the safe side, a threshold of only 25 seconds is used. The system first checks the start time of the deceleration. When the start time is in-between the UP peak point and two times of duration of UP peak point to the end point, the membership functions of uterine contraction (UP) and FHR deceleration (DEC) shown in Fig. 4 and Fig. 5, respectively, are used for fuzzification. When the UP signals remain higher than the UP baseline for 8 seconds, the system will start estimating the degree of uterine contraction. Next, the system employs the fuzzy rules in Table 3 to calculate the defuzzification value of the condition occurrence degree. If the degree is greater than the threshold, the system will fuzzify the duration of FHR deceleration (DECP) by using the membership functions shown in Fig. 6. Finally, the defuzzification value is used together with the fuzzy rules in Table 4 as the basis of alarm.

(4) Type-4 non-reassuring fatal status:

Fig. 7 depicts three fuzzy sets for the duration of the FHR deceleration (DDUR). When the FHR signals remain lower than FHR baseline for 8 seconds, the system starts estimating the degree of deceleration. If the system detects the occurrence of deceleration, then the deceleration duration counter starts recording the duration time until the FHR signal crosses the baseline. At the same time, the system calculates the membership values of the DDUR. Then, the system employs the fuzzy rule base shown in Table 5 to calculate the degree of alarm and infer whether to activate the alarm or not.

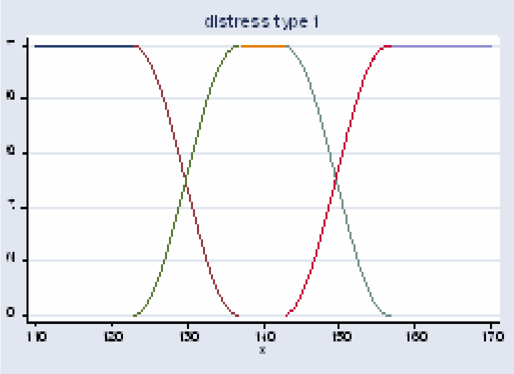


Figure 1. Three fuzzy sets for the FHR.

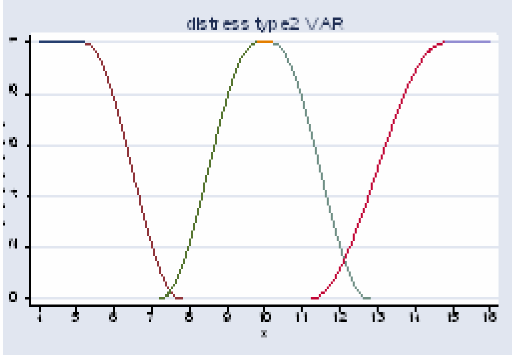


Figure 2. Three fuzzy sets for the VAR.

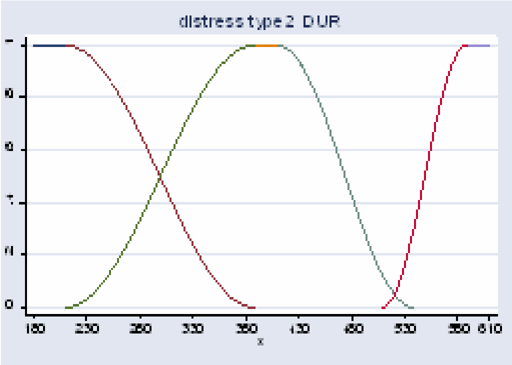


Figure 3. Three fuzzy sets for the DUR

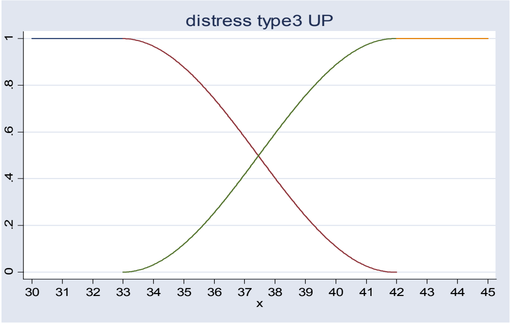


Figure 4. Two fuzzy sets for the UP.

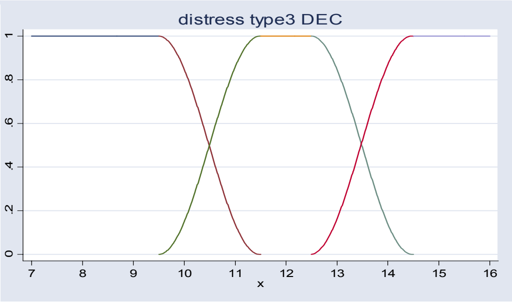


Figure 5. Three fuzzy sets for the DEC.

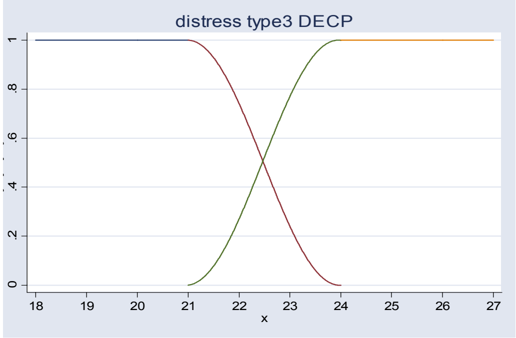


Figure 6. Two fuzzy sets for the DECP.

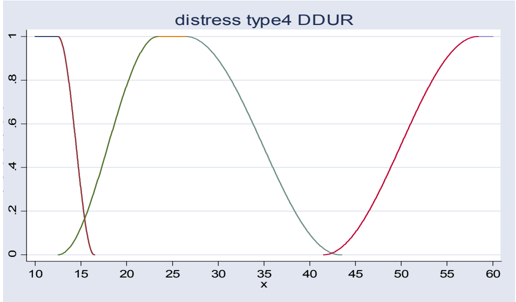


Figure 7. Three fuzzy sets for the DDUR.

Table 1. Fuzzy rule base for FHR.

	Low	Medium	High
FHR	Alarm	Not alarm	Alarm

Table 2. Fuzzy rule base for VAR and DUR.

DUR VAR	Low	Medium	High
Low	Not alarm	Attention	Alarm
Medium	Not alarm	Attention	Alarm
High	Not alarm	Error	Error

Table 3. Fuzzy rule base for DEC and UP.

UP DEC	Not Occur	Similar	Occur
Not occur	Not occur	Not occur	Not occur
occur	Not occur	occur	occur

Table 4. Fuzzy rule base for DECP.

DECP UP-DEC	Similar	Occur
Occur	Attention	Alarm

Table 5. Fuzzy rule base for DDUR.

	Short	Normal	Abnormal
DDUR	Not alarm	Not alarm	Alarm

3. Implementation and Experiment Setup

The goals of the proposed system are to automatically analyze the fatal monitoring signal and detect non-reassuring fatal status. Due to hospital regulations, we were unable to obtain the signal directly from a fatal monitoring system in a hospital; therefore, a fatal heartbeat and uterine pressure signal simulator was designed to synthesize a test signal. To ensure that the signal produced is realistic, obstetricians were invited to assess it. The system therefore comprises a fatal heartbeat simulator and a fatal monitoring system. The architecture of the proposed system is shown in Fig. 8.

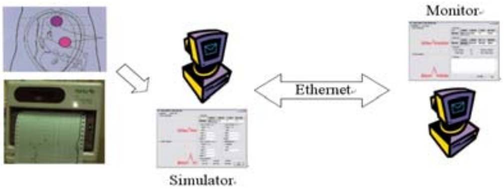


Figure 8. The block diagram of the fatal monitoring system.

(1) The simulator

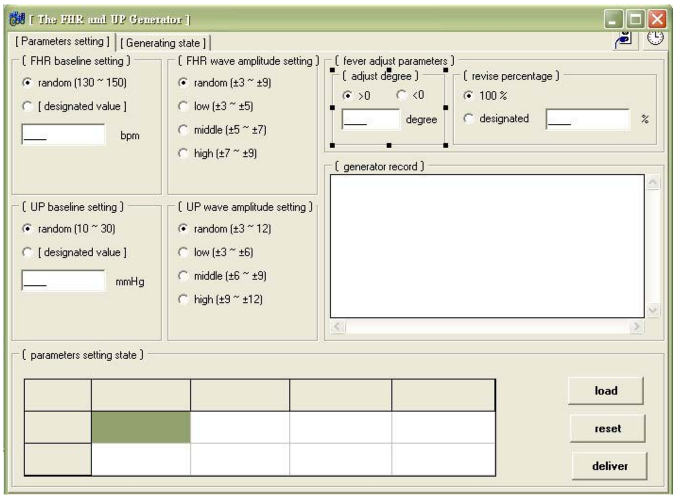
The simulation operates in seven steps. Step 1: users provide five basic parameters that define the nature of the signal before starting the simulator. Step 2: If there is any wave pattern running, the system calculates the shift in baseline. If there is no wave pattern, the baseline shift is set to the default value of 0. Step 3: The variation in the FHR and UP signals are added. Step 4: The output signals are computed by adding the baselines, the shift values and the variations. Step 5: If there are noises that must be generated, the related output signal is set to –1. Step 6: The signal is transmitted to the monitoring system. Step 7: Go to step 2 until the simulator is stopped. A new signal reading is output every second.

Fig. 9 and 10 show the five basic feature-setting panels and a wave pattern log of the generated waveform. At the bottom of Fig. 9, the five user settings are shown including the FHR baseline, the UP baseline, the FHR wave pattern, the UP wave pattern, and the fever adjustment parameter. The left side of Fig. 10 shows two graphic real-time simulator signal displays, one for fatal heartbeat rate and the other for uterine pressure. Users can therefore easily observe the variation of the simulator signals. The top-right part of Fig. 10 shows a real-time signal panel which is used to display the real-time value of the FHR, the FHR baseline, the UP and the UP baseline. An interface for defining five additional wave patterns is shown in the bottom-right part of Fig. 10. The five wave patterns include an accelerative heartbeat wave pattern, declarative heartbeat wave pattern, uterine contract, heartbeat noise pattern and uterine noise pattern. Four wave patterns can be generated simultaneously (alternative acceleration or deceleration of heartbeat).

(2) The non-reassuring fatal status monitoring system

The monitoring process comprises six steps. Step 1: The monitoring system is in a "listening state" when it is first switched on and it continuously listens for the monitoring signal. After receiving the first signal, the system goes into a "monitoring state" and signal readings are temporarily stored in a signal buffer (queue). Step 2: A signal reading is fetched from the signal buffer. If the signal buffer is empty, a "signal loss" alarm is raised by the system. Step 3: the system checks the timestamp of the signal reading. If it is time to perform a baseline calculation, then the system sorts the received signals and computes the mean of the top 5 readings. These results are used as the new FHR and UP baselines. Step 4: If new baselines have been calculated, the system checks if signals crosses the baseline. Signals that do not cross the datum line for 8 seconds are identified as pattern occurrences and the duration before the signal crosses the baseline is measured. Step 5: Fuzzy logic is employed to analyze the monitoring signals and recognize the non-reassuring fatal status. First, the fuzzy set of FHR is used to analyze the fatal heart rate. If the result is greater than the defined threshold, the situation is identified as a non-reassuring fatal status. Second, the fuzzy sets of VAR and DUR are used to analyze the variability of fatal heart rate. If the variation halts in a low state for a long time interval, the situation is identified as a non-reassuring fatal status. Third, the DEC fuzzy set is used to determine the degree of heartbeat deceleration, the DECP fuzzy set to examine the degree of heartbeat deceleration caused by uterine contraction, and the DDUR fuzzy set to analyze the time interval between heartbeat deceleration occurrence and back to FHR baseline. If a deceleration occurs, but the heart rate stays in the low speed rate and does not return to the baseline, it usually signals that the fetus lacks oxygen. Finally, the UP fuzzy set is used to recognize the uterine contraction by analyzing the degree of uterine pressure. Generally, the uterine contraction sometimes responds to heart rate acceleration. Therefore, if the uterine contraction coincides with a heartbeat deceleration, it is the indication of abnormal fetus. Any abnormal state recognized during these test are triggered as alarms and are recorded. Step 6: Go to step 2 unless the monitoring system is stopped.

The left side of Fig. 11 shows parameters specific to the mother and parameters that are used by the obstetricians to fine-tune the system. The third block contains parameters controlling the characteristics of the behavior of the fuzzy sets. These parameters are adjusted semi-automatically after each monitoring session, and the adjustments are recorded for subsequent sessions. Users can choose to use these adjustments or not in subsequent monitoring sessions. Moreover, the fuzzy model block allows obstetricians to regulate and fine-tune each fuzzy inference model based on the patient's individual needs. Users can easily select rules and change slope parameters. As shown in the Fig. 12, users can choose any of the functions provided on the bottom-right. When users start the monitoring system the real-time signals of FHR and UP received from the simulator are shown in the image block. And the real-time FHR and UP states are shown in the left side panels. The three panels shown in Fig. 11 show the individual top 5 frequencies of the FHR and UP used for generating the baselines. During monitoring, users can adjust the two baselines on the parameters setting page and the "stop buzz" can stop the alarm sound at any time. If the system detects that the fetus is in a non-reassuring fatal status state, an alarm message log that contains the information of the non-reassuring fatal status will be recorded. After monitoring, users can click "start training" to regulate function parameters using in fuzzy rules. A list containing all non-reassuring status messages that occurred during monitoring is provided. Obstetricians or other professionals can click those messages for revises. Based on the transmitted revision, the system automatically recalculates the associated fuzzy set's curve in proportion. That allows the system to be used by different obstetricians. Summed up, the monitoring system provides a semiautomatic reconfiguration mechanism allowing it to be adapted to different mothers and different obstetricians.



[FHR baseline setting]
● random (130 ~ 150)
○ [designated value]
___ bpm

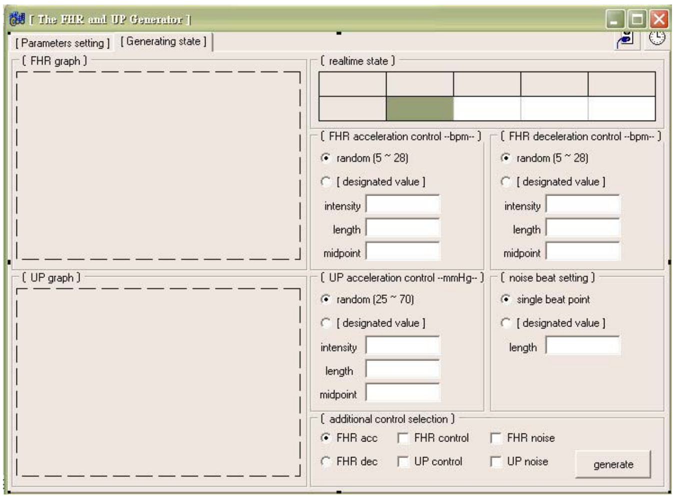
[FHR wave amplitude setting]
● random (±3 ~ ±9)
○ low (±3 ~ ±5)
○ middle (±5 ~ ±7)
○ high (±7 ~ ±9)

[fever adjust parameters]
[adjust degree]
● >0 ○ <0
___ degree
[revise percentage]
● 100 %
○ designated ___ %

[UP baseline setting]
● random (10 ~ 30)
○ [designated value]
___ mmHg

[UP wave amplitude setting]
● random (±3 ~ 12)
○ low (±3 ~ ±6)
○ middle (±6 ~ ±9)
○ high (±9 ~ ±12)

Figure 9. The simulator parameter setting view.



[FHR acceleration control --bpm--]
● random (5 ~ 28)
○ [designated value]
intensity
length
midpoint

[FHR deceleration control --bpm--]
● random (5 ~ 28)
○ [designated value]
intensity
length
midpoint

[UP acceleration control --mmHg--]
● random (25 ~ 70)
○ [designated value]
intensity
length
midpoint

[noise beat setting]
● single beat point
○ [designated value]
length

[additional control selection]
● FHR acc ☐ FHR control ☐ FHR noise
○ FHR dec ☐ UP control ☐ UP noise

Figure 10. The simulator displaying view.

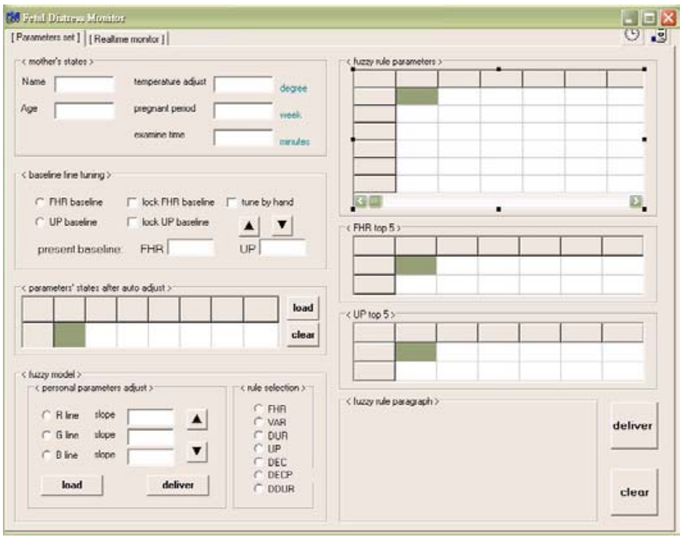


Figure 11. The monitor parameter setting view.

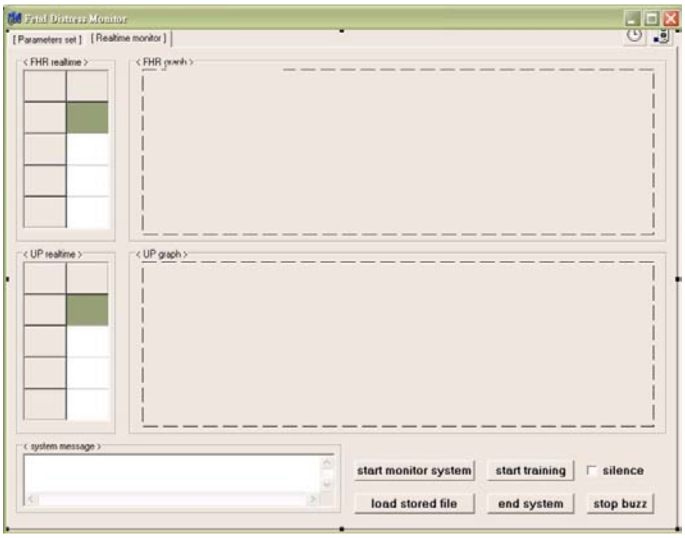


Figure 12. The monitor displaying view.

4. Experimental Results and Discussion

In our experiments, the heartbeat signals and uterine pressure signals of 25 patients for 30 minutes each were simulated. The FHR and UP variability were assigned randomly. The acceleration, deceleration, uterine contraction, and noise patterns were also assigned randomly. During the simulations, 4 non-reassuring fatal status types were randomly created and the alarms were observed to evaluate the accuracy of our system. Moreover, we put different number of fuzzy sets into the same 25 patients' signals to check the toughness of our purposed system.

In order to verify that the proposed method of baseline calculation is suitable for a diverse range of patient with different levels of variations, 9 kinds of patients were tested, including low, medium, and high variations in FHR and UP. Table 6 lists the number of cases simulated for each combination of FHR and UP. Totally, there are 25 different patient signals.

(1) Baseline calculation

As Table 7 shows, among the 25 testing samples, there are 23 samples with 1 bpm, one sample with 2 bpm and one sample with over 2 bpm deviations from the real baselines. The accuracy exceeds 90%. As Table 8 shows, the maximum deviation of the UP baseline calculation is larger than the FHR baseline calculation. In general, the amplitude of the UP signal is higher than the FHR signal. Normally, only uterine acceleration patterns without inverse wave pattern would happen. These factors may result in higher maximum deviations in the UP baseline calculation.

(2) Recognition of type-1 non-reassuring fatal status

Among the 25 test samples, we used the designed heartbeat simulator to generate 47 wave patterns that have stronger amplitudes to form the type-1 non-reassuring fatal status. Besides, noise is also added to the 47 wave patterns. Table 9 and 10 list the recognition results for type-1 non-reassuring fatal status with different fuzzy sets. Among the 47 patterns, we apply different fever settings during the analysis. The results show that if the FHR variation is caused by stable fever adjustments, the identified probability will be higher.

(3) The recognition of type-2 non-reassuring fatal status

Among the 25 testing samples, 11 type-2 non-reassuring fatal status were generated. Noise was also added. The experimental results show that the noise did not affect the recognition of type-2 non-reassuring fatal status. Table 11 lists 100% recognition rate for type-2 non-reassuring fatal status.

(4) Recognition of type-3 non-reassuring fatal status

A total of 16 type-3 non-reassuring fatal statuses were generated. The type-3 non-reassuring fatal status combined a uterine contraction and a heartbeat deceleration. Table 11 shows almost 100% recognition of type-3 non-reassuring fatal status for all the test cases.

(5) Recognition of type-4 non-reassuring fatal status

We generated seven abnormal deceleration patterns to form type-4 non-reassuring fatal status. As Table 13 shows, our system recognized almost all of the seven type-4 non-reassuring fatal statuses.

In summary, we can prove our system permits any number of fuzzy sets. The system still triggered some false non-reassuring fatal status alarms caused by noise signal. These errors may be produced by manual examination. The strengthening of the system for dealing with noise patterns is an important future improvement.

Table 6. The number of cases simulated for each combination of FHR and UP.

	Low	Medium	High
Low	2	2	3
Medium	2	4	3
High	3	3	3

Table 7. The result of FHR baseline calculation.

Max deviation of FHR	Amount	%
±1	23	92
±2	1	4
Over ±2	1	4

Table 8. The result of UP baseline calculation.

Max deviation of FHR	Amount	%
±1	5	20
±2	6	24
±3	8	32
Over ±4	6	24

Table 9. Recognition result of type-1 non-reassuring fatal status with 3 fuzzy sets.

fuzzy model with 3 sets	Amount (fever 100%)	%	Amount (fever others)	%
Recognized	46	97.87	44	93.62
Missed	1	2.13	3	6.38

Table 10. Recognition result of type-1 non-reassuring fatal status with 5 fuzzy sets.

fuzzy model with 5 sets	Amount (100%)	%	Amount (others)	%
Recognized	46	97.87	43	91.49
Missed	1	2.13	4	8.51

Table 11. Recognition result of type-2 non-reassuring fatal status.

		Amount	%
Fuzzy model with 3 sets	Recognized	11	100
	Missed	0	0
Fuzzy model with more sets	Recognized	11	100
	Missed	0	0

Table 12. Recognition result of type-3 non-reassuring fatal status.

		Amount	%
Fuzzy model with 3 sets	Recognized	16	100
	Missed	0	0
Fuzzy model with more sets	Recognized	15	93.75
	Missed	1	6.25

Table 13. Recognition result of type-4 non-reassuring fatal status.

		Amount	%
Fuzzy model with 3 sets	Recognized	7	100
	Missed	0	0
Fuzzy model with more sets	Recognized	7	87.5
	Missed	1	12.5

5. Conclusion and Future Work

In this paper, a monitoring system that can automatically detect non-reassuring fatal status to reduce the manual effort traditionally needed in fatal monitoring was proposed. By employing the fuzzy inference technique to infer the non-reassuring fatal status our system can automatically emit an alarm signal while the non-reassuring fatal status has been recognized.

Although the system can detect almost all the non-reassuring fatal statuses, there are still some problems that need to be addressed. According to the experimental results, our system may misjudge noise patterns. In order to realize personalized monitoring, some manual adjustment is needed. How to reach a good balance between efficiency and convenience is one of the hardest tasks in design of a medical device.

In order to validate the accuracy of the proposed system, clinical experiments will be conducted in the future. Finally, we hope our proposed monitoring system can be implemented as a product and make the fatal monitoring process more convenient and safe. Expanding our system to a multi-client system will be one of our focuses in the future. The central non-reassuring fatal status monitoring system can collect signals from different patients.

Acknowledgments

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