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Refining the diagnostic quality of the abdominal fetal electrocardiogram using the techniques of artificial intelligence

***Abstract**. This article deals with utilization of the combination of the fuzzy system and artificial intelligence techniques, called the Adaptive Neuro Fuzzy Inference System ANFIS, with the aim to refine the diagnostic quality of the abdominal fetal electrocardiogram FECG. Within the scope of the experiments carried out and based on the ANFIS structure the authors created a complex system for removing the undesirable mother's MECG degrading the abdominal FECG. Current research shows that the application of the conventional systems for enhancing the diagnostic quality of the abdominal FECG faces a series of problems (e.g. non-linear character of the task to solve, computational complexity of RLS algorithms, etc.). The need for a higher diagnostic quality of the abdominal FECG is reflected in the authors' intention to utilize the designed system for the latest intrapartum monitoring method, called ST analysis. In terms of this advanced method, the aspect subjected to a diagnostic analysis is the ST segment of the FECG curve. The results indicate that the system utilizing ANFIS shows better experimental results than the conventional systems based on the LMS or RLS adaptive algorithms. The proposed adaptive system aims to clear any doubts in evaluation of the results of ST analysis while using a non-invasive method of external monitoring.*

***Streszczenie.** W artykule przedstawiono wykorzystanie fuzji metod: zbiorów rozmytych i sztucznej inteligencji ANFIS do poprawy jakości diagnostyki elektrokardiografii płodu. Głównym problemem jest usunięcie sygnału pochodzącego od matki który znacznie przewyższa sygnał płodu. (**Poprawa jakości sygnału elektrokardiogramu płodu przy wykorzystaniu narzędzi sztucznej inteligencji**)*

Keywords: ANFIS, FECG, MECG, ST analysis.
Słowa kluczowe: ANFIS, elektrokardiogram

Introduction

Modern medical diagnostic apparatuses [7], [8], [23], which are used for external (abdominal) monitoring of FECG [1], encounter a number of problems relating to the quality of the records. Physicians have raised a demand for refining of the diagnostic quality of FECG. This demand corresponds to the introduction of new medical diagnostic methods [14], [15], [6]. It is therefore necessary to develop new systems directed towards an increase in the diagnostic quality of FECG, resulting in elimination of doubts in evaluation of the monitoring results.

The authors of this article deal with the issue of the intrapartum fetal monitoring [23]. In the course of labour, one of the greatest fights for life takes place. This is due to the fact that during labour an endless number of complications may occur [12]. One of them is oxygen deficiency in the fetal organism, the so-called hypoxia [14]. In the event of hypoxia the fetus is exposed to a very high risk which may result in permanent pathophysiological changes [14], or even death.

Nowadays there are modern measurement and prediction technologies available [7], [8], [23], which open the door to other possibilities of fetal monitoring. This article concentrates on the fetal electrocardiogram [1], or more specifically on the ST analysis (STAN) [7], [18]. At present this progressive approach is only applied in the medical diagnostic technology in terms of internal monitoring systems [1].

This article is based on the results of the authors' own study published in [1]; it draws on this study and extends it. Latest research implies that the future of the intrapartum fetal monitoring lies in the diagnostic technology combining two simultaneously applied methods in a single apparatus (cardiotocography CTG [23] and ST analysis). According to the published studies, such as [14], [9], [10], the doubts in evaluation of the results (identification of hypoxia) should now be eliminated to a great extent thanks to this approach. At present, however, such diagnostic equipment is only available in the version for internal monitoring (e.g. STAN S31 [7]). In this article the authors are presenting a system with the help of which it will be possible to utilize the gentler, non-invasive external monitoring in everyday practice. In real conditions, the non-invasive analysis of the heart activity of the fetus using external monitoring is degraded by a series of undesirable elements, as clearly shown in Fig. 1 [12].

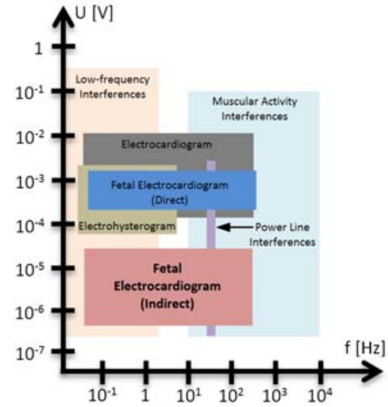

Fig.1. The amplitude range and frequency band of particular components of the signal recorded noninvasively from the maternal abdominal wall

The authors covered the issue of elimination of these disturbing elements using the linear adaptive filtration in their previous study [1]. The linear adaptive filters play an important role in the signal statistical processing [2]. However, the system implementation in practice has revealed that we are facing disturbances of a non-linear character [3], [4] [1], which cannot be completely suppressed by a linear filter [1], [2]. Another problem revealed by the performed experiments is a high computational complexity of the RLS adaptive algorithms [2]. For these reasons the authors focus in this article on the utilization of the neuro-fuzzy system [21], [22].

The neuro-fuzzy system is designed in such a way that it interprets the fuzzy system [21] while maintaining the advantage of the neural network [3], namely its ability to learn from examples and after learning from them to identify the hidden, non-linear relations. It is a combination of the fuzzy system and the neural network. On the outside it looks like a fuzzy system, which is internally structured by a neural network. Its ability to learn is identical with neural networks and at the same time the knowledge representation of the fuzzy system is maintained. The linguistic variables are set during the learning process going on in the neural network in contrast with the fuzzy approximation, where this activity depends exclusively on an expert. One of the neuro-fuzzy systems is ANFIS, the Adaptive Neuro-Fuzzy Inference System [4].

The issue of refining the diagnostic quality of the abdominal fetal electrocardiogram is currently being studied by a number of academic institutions all over the world. So far a whole series of methods has been developed, applying different approaches towards improvement of the informative value of FECG. The overview of these methods is available in [1], [23]. Nevertheless, none of these methods seems to have reached satisfactory results [1].

The adaptive neuro-fuzzy inference system

ANFIS (Adaptive Neuro-Fuzzy Inference System) [23] represents a forward, adaptive neural network that is functionally equivalent to the fuzzy inference system of the Sugeno type (Takagi-Sugeno) [22].

A Two Rule Sugeno ANFIS has rules of the form [3]:

(1) $$\begin{aligned}&\text{If } x \text{ is } A_1 \text{ and } y \text{ is } B_1\\ &\text{THEN } f_1 = p_1 x + q_1 y + r_1\end{aligned}$$

(2) $$\begin{aligned}&\text{If } x \text{ is } A_2 \text{ and } y \text{ is } B_2\\ &\text{THEN } f_2 = p_2 x + q_2 y + r_2\end{aligned}$$

where *x* and *y* are the inputs, A_i and B_i are the fuzzy sets, f_i, i =1,2 are the output of fuzzy system, and p_i, q_i and r_i are the design parameters which are determined during the training process [4].

The ANFIS architecture to implement these two rules is shown in Fig. 2 [21], in which a circle indicates a fixed node whereas a square indicates an adaptive node. As figure illustrates, ANFIS architecture consists of five layers [3].

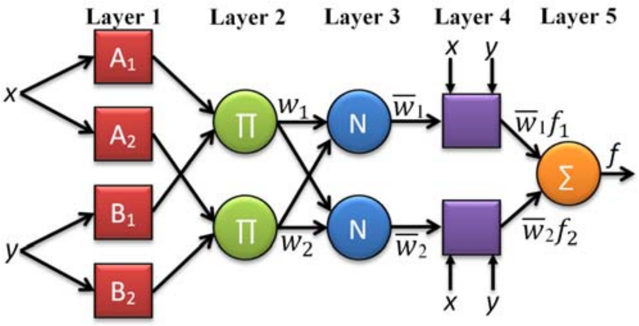

Fig.2. The architecture of ANFIS

The functioning of the ANFIS (Fig. 2) is described as (for more detail see [22]):

Layer 1

The output of each node is [3]:

(3) $$O_{1,i} = \mu_{A_i}(x) \qquad \text{for } i = 1,2$$

(4) $$O_{1,i} = \mu_{B_{i-2}}(y) \qquad \text{for } i = 3,4$$

where *x* and *y* are the inputs to node *i* , *A* is a linguistic label and $\mu_{A_i}(x)$ and $\mu_{B_{i-2}}(y)$ can adopt any fuzzy membership function. So, the $O_{1,i}(x)$ is essentially the membership grade for *x* and *y*. The membership functions could be anything but for illustration purposes we will use the bell shaped function given by [22]:

(5) $$\mu_{Ai}(x) = \frac{1}{1 + \left|\dfrac{x - c_i}{a_i}\right|^{2b_i}}$$

where {a_i, b_i, c_i} is the parameter set which changes the shapes of the MF degree with maximum value equal to 1 and minimum equal to 0.

Layer 2

Every node in this layer is a fixed node labelled Π, whose output is the product of all incoming signals [21]:

(6) $$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \qquad i = 1,2$$

Layer 3

The *i*-th node of this layer, labelled N, calculates the normalized firing strength as [21]:

(7) $$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}), \qquad i = 1,2$$

Layer 4

Every node *i* in this layer is an adaptive node with a node function [21]:

(8) $$O_{4,i} = \overline{w_i}\, f_i = \overline{w_i}(p_i x + q_i y + r_i),$$

where $\overline{w_i}$ is the output of layer 3. The parameters in this layer (p_i, q_i, r_i) are to be determined and are referred to as the consequent parameters.

Layer 5

The single node in this layer is a fixed node labelled Σ, which computes the overall output as the summation of all incoming signals [21]:

(9) $$Overall\_output = O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

Electrocardiography of the fetus (ST analysis, STAN)

This represents the latest approach in the analysis of fetal hypoxia during labour. The system is abbreviated as STAN (ST segment analysis) of the fetal ECG. Its ability to predict hypoxia was confirmed by a number of studies, e.g. [14], together with the evaluation of the fetal cardiotocography (CTG).

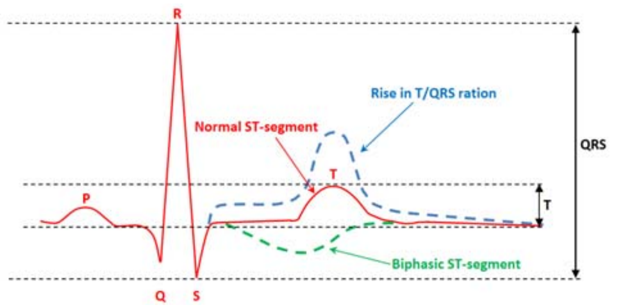

Fig.3. Changes of the fetal ECG during hypoxia: elevation of ST segment – reaction of the myocardium to hypoxia, depression of ST segment – the fetus has run out of its reserves, it is not able to cope with deepening hypoxia

ST analysis enables not only tracing but also direct diagnosing of the foeti endangered by hypoxia during labour. Thus a physician can compare the cardiotocographic records simultaneously (screening) and if finding them suspicious or pathological, the physician may decide, based on the ECG curve analysis, namely its ST segment, whether the identified changes are positively caused by hypoxia (diagnostics) or not. This is due to the fact that the occurrence of a relatively high rate of false positivity of CTG has been known for a long time. In terms of the ST analysis we evaluate:

- T-wave elevation
- ST segment

A more detailed description of the diagnostics using the ST analysis was discussed by the authors in the publication [1]. For a more detailed description of ST analysis see also [18], [14] and [7]. The changes in ST segment that endanger the health of the fetus are shown in Fig. 3 [14].

Implementation of ANFIS within the FECG monitoring system

Fig. 7 shows the basic diagram of the designed system in which the experiments were carried out. The designed system contains two inputs - MECG(n) and FECG(n).

The first input is the signal detected on the skin of a mother's thorax MECG(n), see the green curve in Fig. 4.

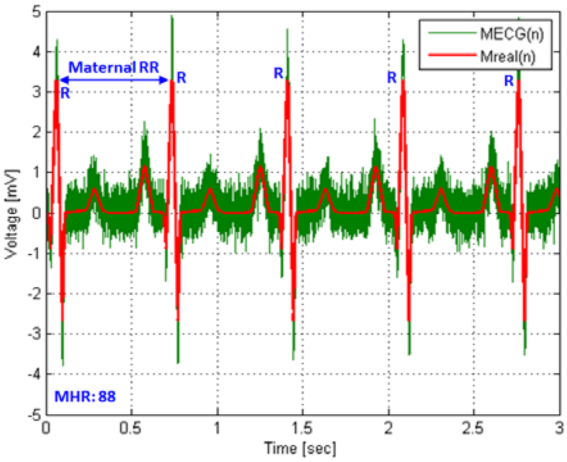

Fig.4. Green colour: Basic, non-processed MECG, Red colour: conventionally processed MECG (input for experiments)

The mother's ECG signal reflects the electrical activity of the mother's heart HR_1. From the point of view of the performed experiments, MECG(n) signal is considered as an undesirable noise contaminating the FECG(n) under examination. It is supposed that this undesirable signal represents almost perfect mother's ECG. This is due to application of the conventional processing methods [2] to MECG(n):

- Narow-band filter (the so-called Notch filter [20]) at the frequency of 50 Hz [20]
- FIR filter of the upper limiting type with the threshold oscillation frequency from 30 to 35 Hz in order to eliminate muscle interferences [20]
- Filter of the lower limiting type with the threshold oscillation frequency of 0.5 Hz in order to compensate for drifts [20]

In this way we acquire the $M_{real}(n)$ signal, see the red curve in Fig 4. This signal will serve us as an input to the ANFIS filter and further for the diagnostics of MECG, especially for identification of MHR (Maternal Heart Rate [13]).

The second input to the experimental system is the signal detected on the mother's abdomen FECG(n). The fetal ECG reflects the electrical activity of the heart of the fetus HR_2. The ideal shape of FECG (or the desired shape from the experimental point of view) is shown in Fig. 5.

In case of the non-invasive acquisition of FECG using abdominal electrodes a range of problems occurs relating to the quality of the records; see [1]. The authors of this study presuppose that the main source of disturbance to the FECG signal is the MECG signal. Therefore the application of the conventional processing methods to FECG(n) is presumed, similarly as in case of the previous MECG(n). In this way the basic sources of interference by which FECG is contaminated (EMG [20], power line interference [20], random electrical interferences [24], etc.) are eliminated. The problems of elimination of the interferences mentioned above are analysed in numerous publications, e.g. [24], [20].

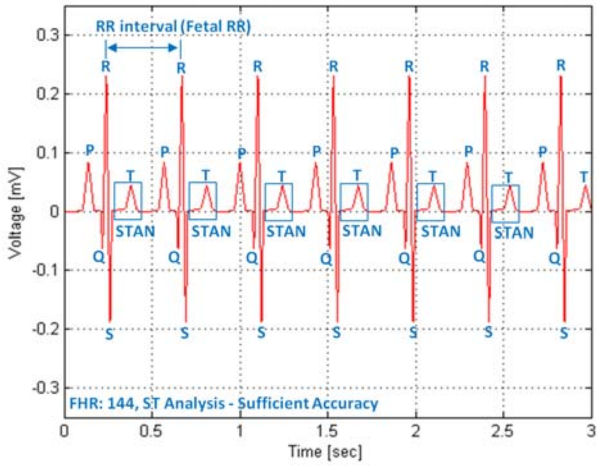

Fig.5. The ideal shape of FECG

In terms of the performed experiments, the first input is $M_{real}(n)$ with the amplitude level reaching 50 μV - 5 mV; see the red curve in Fig 4. The second input, $F_{real}(n)$, reaches the amplitude level of 10 – 300 μV, where the required FECG is degraded by much stronger MECG; see Fig. 6. Thus we can state that there are two hearts; see Fig. 7:

- HR1 mother's heart – disturbing signal
- HR2 heart of the fetus – useful signal

These two hearts are electrically separated and work independently. Within the conducted experiments, the ECG signal sample frequency of 500 Hz was selected. The time period for sampling was set to 30sec (15000 samples) but the graphic outputs show only 3 seconds to enable better readability. The conventional processing methods were used for acquisition of the ECG signals [24].

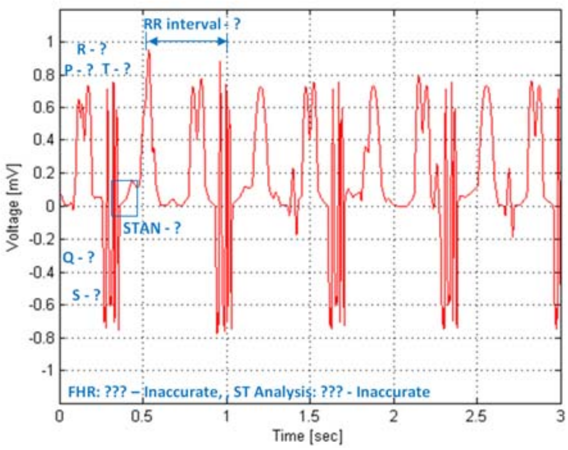

Fig.6. The actual (measured) shape of FECG (contaminated by MECG)

Reducing the undesirable MECG

According to the schematic representation in Fig. 7, the simplest way to suppress the undesirable MECG from FECG would be a direct subtraction of $M_{real}(n)$ from $F_{real}(n)$. However, this approach does not work if the MECG detected by the thorax electrodes is not identical with the MECG detected by the abdominal electrodes. The result of the direct subtraction of $M_{real}(n)$ from $F_{real}(n)$ is shown in

Figure 9. The unknown human body system gets involved in here (signal deformation owing to the surrounding environment - interference [3], delay, etc.).

As shown in Fig. 7, $M_{real}(n)$ represents mere MECG. $F_{real}(n)$ represents the FECG(n) and the noise n(n) after passing through the unknown system of human body. The auxiliary signal d(n) is then expressed by the equation:

$$d(n) = FECG(n) + n_1(n) \tag{10}$$

Another possible way is application of the linear filtration (frequency selective filters) [2]. However, these conventional filtration techniques [17] cannot be used for our purposes due to the time variability of the spectra of both the disturbing and the useful signals.

Supposing we regarded the unknown system as linear, we could apply an adaptive algorithm that would teach the FIR filter how to distinguish the channel characteristic. And if we later applied this filter to the FECG signal containing the undesirable MECG signal, we could successfully subtract the interference (mother's ECG). But many studies [1], [4], [5], point to the fact that the environment of human body is of non-linear character. In such case the techniques of non-linear adaptive filtration do not bring satisfactory results (especially the LMS algorithms [2]). The authors focused on the study of the LMS and RLS linear adaptive filters [2] in the publication [1] on which this article is based.

The interference signal $n_1(n)$ that appears in the measured signal is assumed to be generated via an unknown nonlinear equation:

$$n_1(n) = \frac{2\cos(n(n))n(n-1)}{(1 + n(n-1)^2)} \tag{11}$$

This nonlinear characteristic is shown as a surface in the window. Fig. 8 shows the unknown channel characteristics that generate interference.

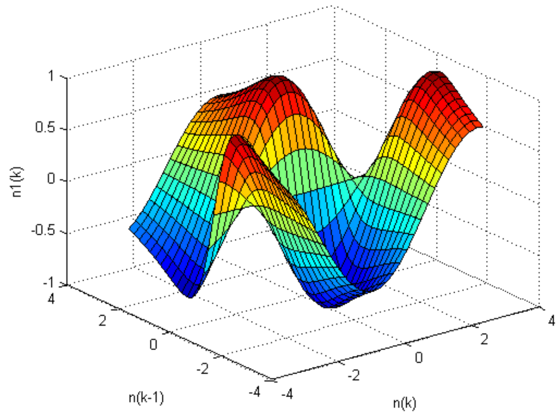

Fig.8. Unknown channel characteristics that generate interference

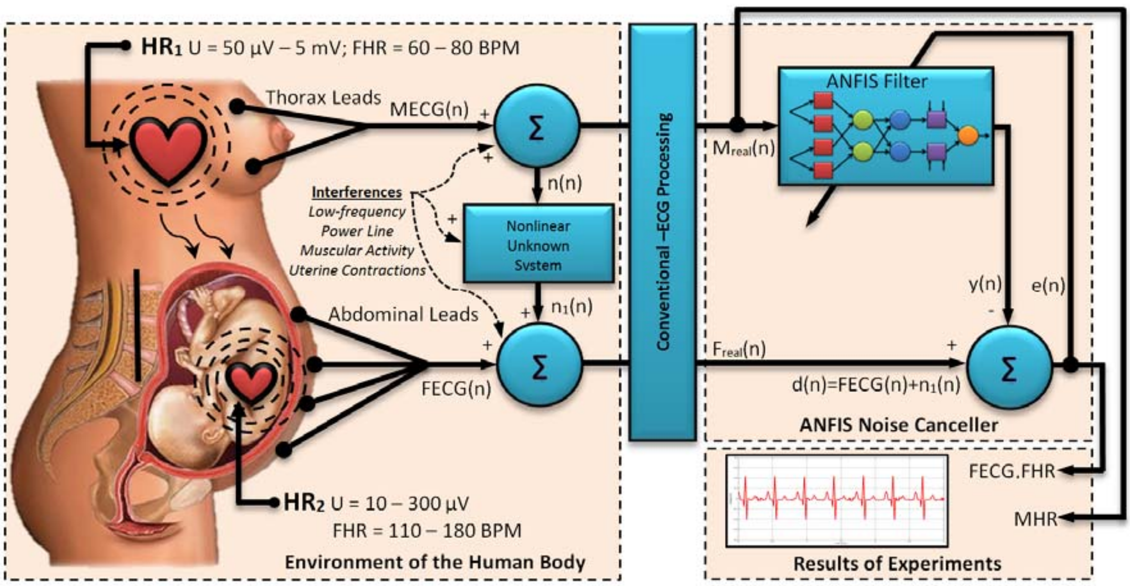

Fig.7. The experimental system designed for FECG monitoring using ANFIS

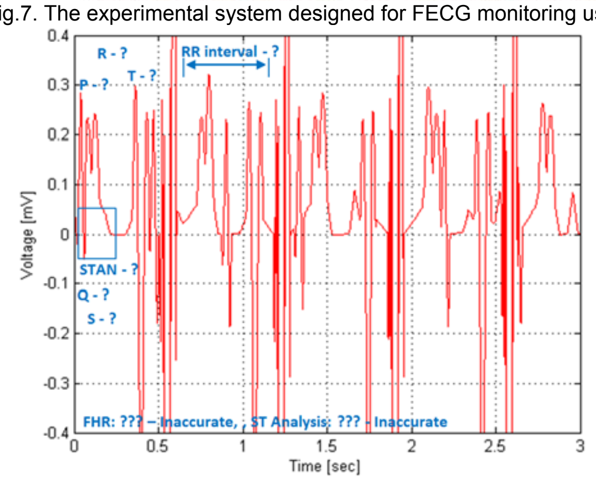

Fig.9. The result of direct subtraction of Mreal(n) from Freal(n)

The results of the experiments

Within the experiments carried out, various structures of ANFIS were examined. An overview of the structure models used for this purpose is in Table 1. In order to build the ANFIS model the ANFIS functions were used [16] and for the training (estimation) the EVALFIS functions were applied [16]. A detailed description of the work with the ANFIS and EVALFIS function in MATLAB [17] is available in [16], [17].

Figures 10 to 13 present the results of the performed experiments. In the graphs the particular segments (components) of the FECG signal are identified (P, Q, R, S and T). Then the FHR is determined including a statement whether we are able to make an ST analysis. If there is a question mark (?) in the graph near the segment under examination, it means that we are not able to identify this segment (determine it unambiguously).

Table 1. ANFIS info

ANFIS info				
Building the ANFIS Model	A	B	C	D
Number of nodes	21	35	53	75
Number of linear parameters	12	27	48	75
Number of nonlinear parameters	12	18	24	30
Total number of parameters	24	45	72	105
Number of fuzzy rules	4	9	16	25

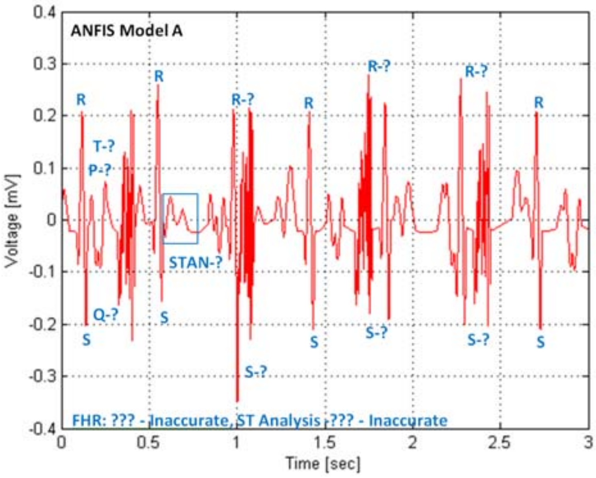

Fig.10. The results of the experiments for ANFIS A Model

The ANFIS A Model shows only a partial improvement of the diagnostic quality of FECG. If this model is applied, it is not possible to identify the FHR. The model is not able to plausibly determine the R-R interval; see Fig. 9 (there are R segments which are impossible to identify without doubt). Making an ST analysis, while applying this model, is out of the question.

In case of applying the ANFIS B Model (Fig. 11), we are able to determine the value of FHR (determination of the R-R interval). This model enables precise (unambiguous) identification of the FECG segments (R, Q and S). Although the recording is not precise enough to enable making an ST analysis, the system utilizing this model is able to serve as a genuine cardiotocograph [5].

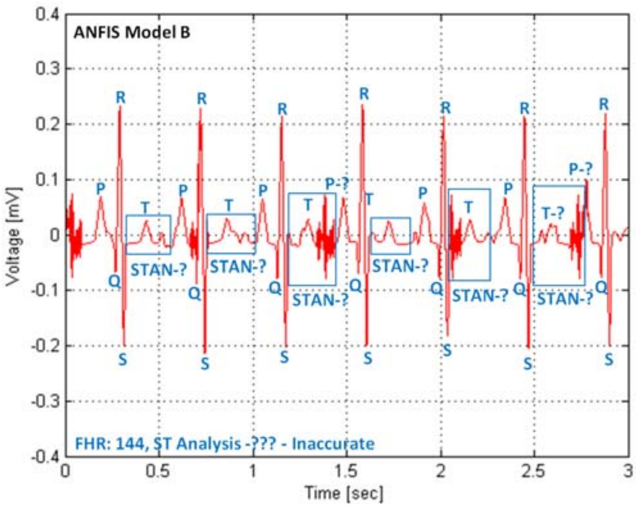

Fig.11. The results of the experiments for ANFIS B Model

The ANFIS C Model (Fig. 12), allows for determination of FHR. This model enables precise identification of all segments of the FECG signal (P, Q, R, S and T). However, the recording is not conclusive enough to enable an ST analysis (the ST segment is still distorted to a great degree).

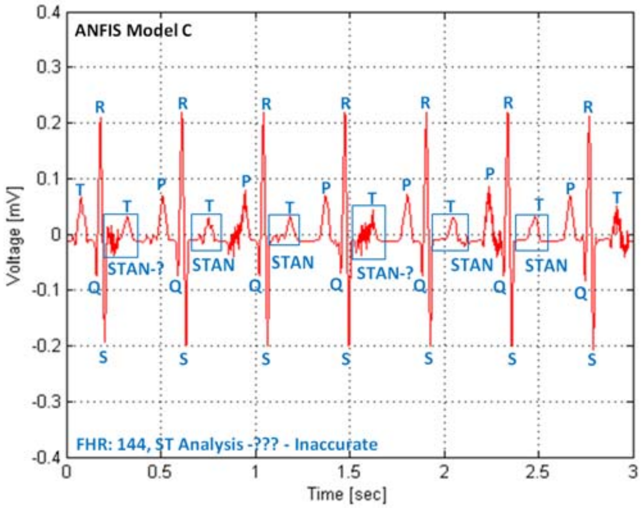

Fig.12. The results of the experiments for ANFIS C Model

The results of the experiments indicate that if the ANFIS D Model (Fig. 13), is applied, it is possible to make an ST analysis because we can precisely analyse the T wave elevation as well as the ST segment.

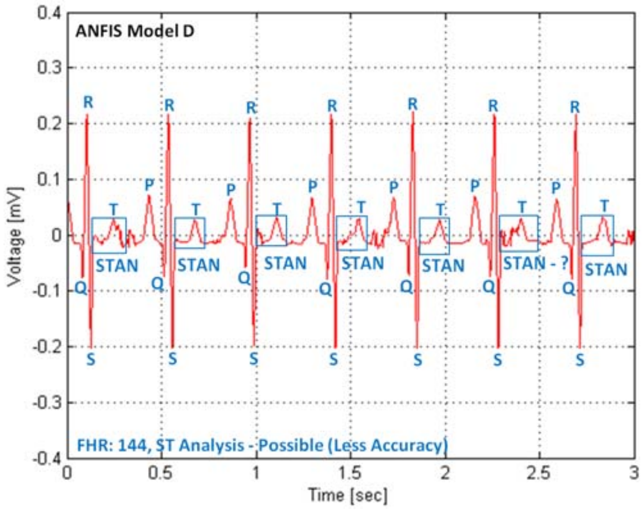

Fig.13. The results of the experiments for ANFIS D Model

Table 2 shows the ability of the examined ANFIS models to improve the value of SNR (the distance of the signal from the noise). In terms of the performed experiments, first the SRN value of the contaminated FECG was determined and then the value of the signal after its passage through the designed system was identified. The difference between these two values reveals what improvement was reached by applying each model. The SNR ratio is defined by the equation [17]:

$$SNR = 10\log\frac{P_s}{P_n}[dB], \quad (12)$$

where P_s and P_n determine the signal output (*s* means signal) and noise (*n* means noise). If the SNR value = 0 dB, it means that both the signal and the noise have the same output. If SNR > 0, then the signal output is greater than the noise output and if SNR < 0, then it is vice versa.

Table 2. The results of the experiments in the form of SNR

Improvement of the SNR value			
Building the ANFIS Model	SNR_{in} [dB]	SNR_{out} [dB]	SNR improvement [dB]
ANFIS Model A	-17.3014	-6.6157	10.6857
ANFIS Model B	-17.3269	1.1349	18.4618
ANFIS Model C	-17.4686	3.2987	20.7673
ANFIS Model D	-17.2959	4.3245	21.6203
ANFIS Model E	-17.5413	4.4568	21.9981
ANFIS Model F	-17.4598	4.4324	21.8922

Conclusion

This article deals with the utilization of the ANFIS system for refining the diagnostic quality of the abdominal fetal electrocardiogram FECG. The ANFIS system was implemented in order to identify (learn about) the non-linear relation between the thorax and the abdominal MECG (the source of contamination of the examined FECG).

The experiments carried out have proved the functionality of the designed technology. They have shown that the designed technology can successfully extract the FECG even if it is completely contaminated by the mother's MECG. The results of the study indicate that in case of applying the ANFIS D Model it is possible to identify the individual segments of the FECG signal; see Fig. 13.

The results have also revealed that the system utilising ANFIS shows better experimental results than the conventional systems based on the LMS and RLS adaptive algorithms [1]. The designed system has the ambition to clear up the doubts in evaluation of the results of the ST segment analysis while applying the non-invasive external monitoring.

The authors of this article are still involved in intensive research in this field. The next step will be a verification of the designed technology on a large sample of the real FECG records. For this purpose the authors started cooperating with The University Hospital Brno, Czech Republic.

Acknowledgement

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