

*uterine contractile activity,  
tocography,  
automated contraction detection*

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# EFFICIENCY OF AUTOMATED DETECTION OF UTERINE CONTRACTION USING TOCOGRAPHY

Monitoring of uterine contractile activity enables to control the progress of labour. Automated detection of contractions is to be an integral part of the signal analysis implemented in computer-aided fetal surveillance system. Evaluation of efficiency of three algorithms for automated detection of uterine contractions in the signal of uterine mechanical activity is presented. These algorithms are based generally on analysis of the frequency distribution of signal values. The reference data in form of beginning and end of contraction episodes were obtained from human expert. Obtained results showed high efficiency of the algorithms tested where the best one ensured the sensitivity and positive predictive value equal to 92.2 and 97.2, respectively.

## 1. INTRODUCTION

During the last decade the computer-aided systems have become a standard approach to accomplish the cardiotocographic (CTG) monitoring both during pregnancy and labour [1], [7], [10]. The main task of the fetal monitoring system is quantitative analysis of the signals acquired from bedside monitors in order to help clinician in a fetal state assessment [2], [6]. Bedside monitor measures the mechanical uterine contractile (UC) activity by means of strain-gauge transducer attached to maternal abdomen with elastic strap. Signal of uterine activity may be printed by bedside monitor or presented in computer-aided system in a graphical form as a tocogram, where the contractile episodes are reflected by temporary amplitude increase. Although the essential information on the fetus condition is obtained from monitoring and analysis of the changes of the fetal heart rate variability, such situation when the fetus responds to contraction with decrease of its heart rate is considered as a valid sign of fetal distress [3]. Additionally, monitoring of uterine contraction activity enables to control the progress of labour. Thus automated detection of contractions is to be an integral part of the signal analysis implemented in computer-aided fetal surveillance system [4], [5]. What's more, automated method is able to provide detailed description of contractions which comprises: onset time, duration, amplitude and area under tocogram waveform. In this paper we compare three automated methods for UC analysis in relation to the reference information provided by the

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human expert. These three algorithms were developed in different stages of our studies on automated analysis of fetal and maternal biophysical signals.

## 2. METHODS

Research material comprised intrapartum cardiotocographic recordings obtained from the archives of MONAKO Systems that are used in many polish hospitals. There were no personal data in the signals files, only the samples of the acquired signals: fetal heart rate and uterine contraction activity (UC), which constitute the cardiotocographic recording. We selected 80 signals from 80 patients. Minimum duration was 22 minutes, whereas maximum one was limited to 40 minutes. That established duration range was caused on the one hand by the time the expert has to spend on analysis of a certain trace, and on the other hand by our assumption that the material should comprise rather shorter signals but of different characteristics. Total duration of all recordings was 2786 minutes, whereas the average duration of recording was  $34.8 \pm 6.3$  minutes.

In the fetal monitoring system the signals of both the fetal heart rate and the mechanical uterine activity are stored just as they are provided to the system by a bedside monitor via its digital output [9]. The sampling frequency is 4 Hz, and the UC sample values are expressed in arbitrary units in the range of 0 to 100 with resolution of 0.5.

Dedicated software tool was created in LabView (National Instruments) which enables the expert to enter the markers of recognized contractions. Each cardiotocographic record was read in and presented in the same scale and proportion as they were used in the computer-aided fetal monitoring system. After the expert had marked the beginning and end of a given contraction by pressing the mouse button, those pointer positions were captured, converted into the number of sample with resolution of 2.5 s, and saved into the reference data files. Expert recognized 869 contractions (from 4 to 22 for particular recordings).

Contractions detected by using all the three automated algorithms were compared with the reference data provided by the expert. The contraction detected by a given algorithm is assumed as referring to the pattern recognized by the expert if their onset times differ by no more than 15 seconds and additionally at least 50% of contraction duration determined by a given algorithm is covered by the expert's contraction. As the automated algorithm is aimed at detection of contractions which are recognized by the expert, the sensitivity and positive predictive value (PPV) were used to estimate the efficiency of the algorithms tested:

$$Sensitivity = \frac{Detected\ contractions}{Detected\ contractions + Not\ detected\ contractions} \quad (1)$$

$$PPV = \frac{Detected\ contractions}{Detected\ contractions + False\ contractions} \quad (2)$$

The essential step in automated detection of contractile patterns in UC signal is estimation of the so called basal tone (BT). The basal tone refers to resting strength exerted on strain-gauge transducer by uterine muscle when the contractile activity does not occur. Thus, when patient's monitoring starts, it is important to set the zero level of the basal tone when the fetal monitor is measuring none contractile activity [13]. During monitoring the basal tone varies, usually from 0 to 20 units [11]. The contractile activity is represented by an increase of the contraction wave above the basal tone, and it is classified as valid contraction episode when both its amplitude  $A$  and duration  $T_D$  exceed the established minimum values (in this study we assumed  $A_{min} = 20$  units and  $T_{Dmin} = 30$  seconds). The detection threshold (DT) is set at constant value above BT, which enables to start detection procedure every time the UC signal

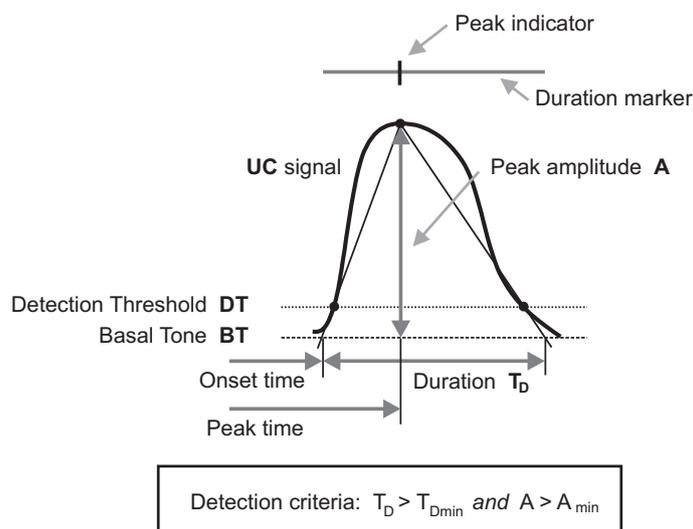


Fig. 1. Parameters for detailed description of the contraction episode detected in UC signal according to the established minimum criteria for: duration  $T_{Dmin} = 30$  s, and amplitude  $A_{min} = 20$  units.

crosses the DT (Fig. 1). All detected contractions are represented by the onset time, duration, amplitude and the time when the maximum amplitude occurs. In the fetal monitoring system these contraction parameters are listed on request of clinician evaluating the CTG record, and additionally the contractions are graphically marked on the UC trace.

In general, all tested algorithms are based on analysis of the frequency distribution of the UC values within the window of established width. The first algorithm runs on original 4Hz samples, whereas in case of the two others the input signal is obtained by averaging the UC signal in non-overlapping windows of ten-sample width that leads to an increase of the sampling period to 2.5 s. Such time resolution was set for the timing parameters (onset time, peak time and duration) of contractions detected by the algorithms and recognized by the expert. That enabled to perform their comparison and other operations on discrete signals.

*Algorithm #1.* This algorithm was created for the task of our studies on comparing two alternative methods for uterine activity monitoring – mechanical and electrical [8]. It is based on original 4 Hz samples. The preliminary low-pass filtering at 0.04 Hz is used to suppress the maternal breathing movements. The tocogram is analysed in the four-minute window of one-minute step. Such window comprises labour contraction (duration about 1.5 minute) together with the non-activity segment. The one-minute step is enough taking into account the very low variation of the basal tone. Within each window the histogram of UC samples is created with values ranging from 0 to 100 in one-unit classes. The modal value of the histogram is taken as a basal tone BT value. In that way each consecutive BT sample is determined every minute. The threshold level DT was established at 10 units above the basal tone.

*Algorithm #2.* This algorithm has been used in the fetal monitoring system. It has been upgraded recently due to limited efficiency that has been reported for late antepartum and intrapartum recordings [15]. At first, the input signal is smoothed by moving average over 10 samples, and next up to three steps of the baseline tone determination are performed. In the first step the frequency distribution is determined in forty-minute windows, and the one-unit class is searched to split the area of histogram in proportion one to nine. This class is taken as a consecutive value of the basal tone. Then, using the DT set at 5 units above the BT the candidate segments are detected and each segment is classified as contraction if it lasts more than the established minimum duration  $T_{Dmin}$  and exceeds the minimum amplitude  $A_{min}$  above

the BT. However, due to temporary increase of the strength exerted on UC transducer, which can take place during maternal deep breath or changing position, the real resting level also increases, that should be reflected in the basal tone estimated. Thus, among all the recognized contractions those of duration exceeding 3 minutes undergo reanalysis. Like in the first step the frequency distribution is determined within such segment, but now the BT refers to the class which splits the histogram area in proportion one to four, in the segment being analysed. Again, the contractions are detected using established minimum values for duration and amplitude. In most cases two steps are enough, however for some recordings, especially intrapartum ones, the third step has to be applied which relies on repeating the second one for these candidate segments which are still too long.

*Algorithm #3.* This algorithm is intended to use in future instrumentation for home fetal telemonitoring [12], [14]. The basal tone is determined in one step to compromise between power consumption and efficiency of uterine activity monitoring. Like in the previous algorithm the input signal undergoes preliminary moving average over 10 samples. This signal is analysed in four-minute (96 samples) window, which is shifted every one 2.5 s sample. The time position of the BT sample being determined in each step relates to the middle of the window. Each consecutive window is divided into two parts comprising the same number of 48 samples. In each part the minimal value is determined. Selection of one of them is based on analysis of frequency distribution of sample values within analysed window. If the area of histogram below the mean of these two minimum values is higher than the area above, the lower minimum value is taken as the BT value in this window, otherwise the higher minimum value is taken as a valid one.

### 3. RESULTS

Obtained results listed in Table 1 show that the best efficiency of the automated contraction detection is provided by the Algorithm #2, which is based on three-step analysis of UC samples frequency distribution. This algorithm ensures the highest sensitivity equal to 92%, which means the highest ability to detect true (recognized by expert) contractions.

The sensitivity of the simplest Algorithm #1 is significantly lower – 83.8%, while the Algorithm #3 ensures satisfying value close to 90%. The values of PPV obtained for all algorithms are very high – close to 100%, which indicate that automated approach does not cause a detection of patterns that were false contractions. The signals have been found of full consistency with the expert, which means that a given algorithm detected all and only those contractions being recognized by the expert. The highest number of such cases (45%) has been noted for the Algorithm #2 of the best efficiency.

Figures 2 and 3 show how the sensitivity and PPV differed for particular records. The best Algorithm #2 ensures a quite limited dispersion of the sensitivity, with the lowest value of 72%. For two other algorithms noticeable dispersion was observed. The lowest sensitivity of

Table 1. Efficiency of three algorithms for automated detection of contraction patterns, in relation to the expert who recognized 869 contractions in 80 signals.

	Number of all contractions detected	Sensitivity [%]	PPV[%]	Signals with full consistency with the expert [%]
Algorithm #1	750	83.8	97.1	28.8
Algorithm #2	<b>823</b>	<b>92.2</b>	<b>97.2</b>	<b>45.0</b>
Algorithm #3	789	89.4	98.5	41.3

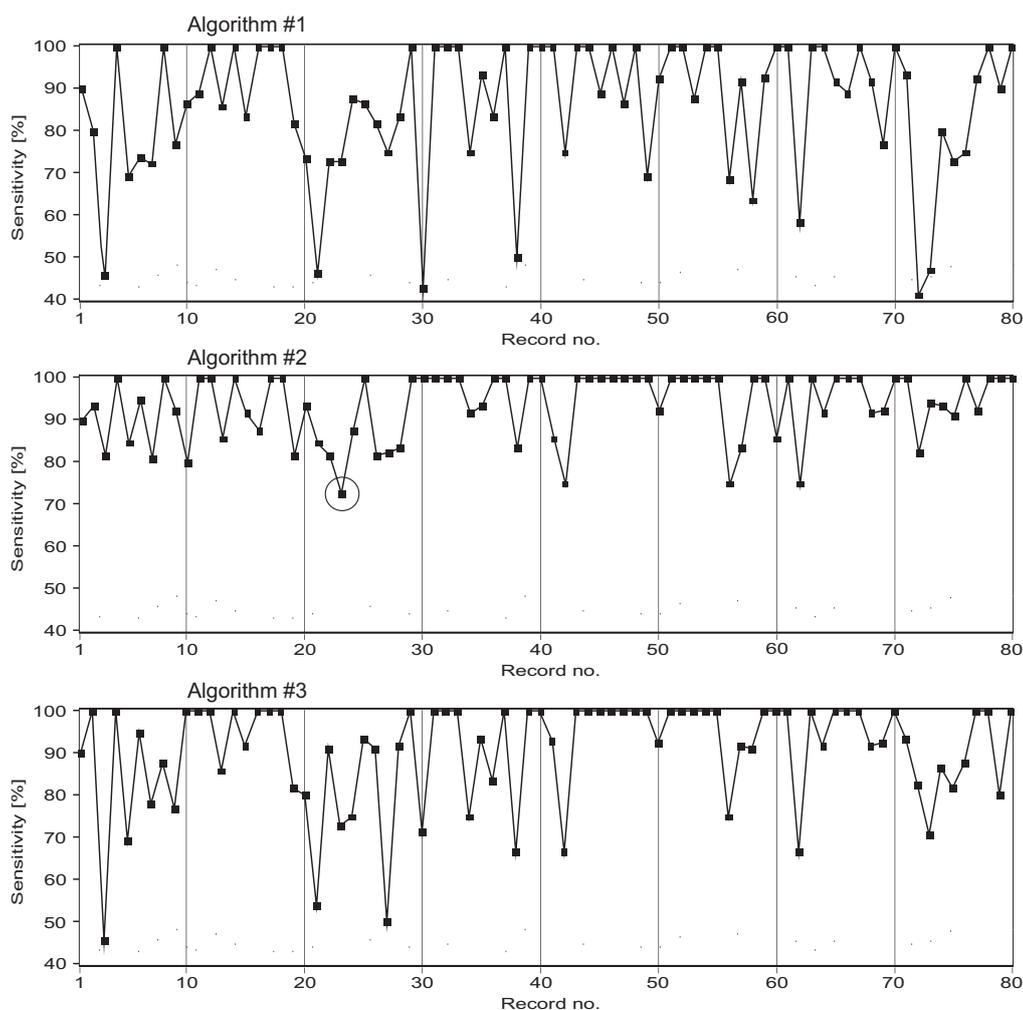


Fig. 2. Changes of sensitivity obtained by the investigated algorithms across all of 80 signals. Contractions detected in signal trace no. 23, for which the lowest sensitivity was noted using the best Algorithm #2, are presented in details in Fig. 4.

42% was noted for the Algorithm #1. In turn, the PPV obtained for all UC signals is much more stable. For most of the recordings the PPV is equal to 100% and only for a few records it is lower than 90%.

When analysing closer the signal no. 23 of the worst sensitivity obtained for the best Algorithm #2 (Fig. 4), we can note that despite a very good quality of UC signal, the algorithm did not detect two first expert's contractions. It is mainly caused by applying the strict criteria for minimum amplitude and duration for contraction validation. Then, even slight difference in amplitude and/or duration may reject the contraction, especially if its amplitude and duration are rather small and therefore close to minimum values. On the other hand, in case of poor quality signals, like the signal no. 30 in Fig. 5, the expert is able to differentiate between true uterine contractile activity and interferences, analysing the shape of neighbouring occurrences.

Whereas the algorithm just measures an increase of UC trace above the basal tone and if this increase matches the criteria the algorithm recognizes false contraction (first detected contraction in Fig. 5). Furthermore, if longer contraction occurs when the basal tone increases, which took place between 6<sup>th</sup> and 12<sup>th</sup> minute in Fig. 5, the expert marks one and the most evident but shorter episode. In that case the automated method tends to split such long episode into several contractions – three in the case considered. These reasons mainly led to the PPV = 70% obtained for the signal no. 30 being processed by the best Algorithm #2.

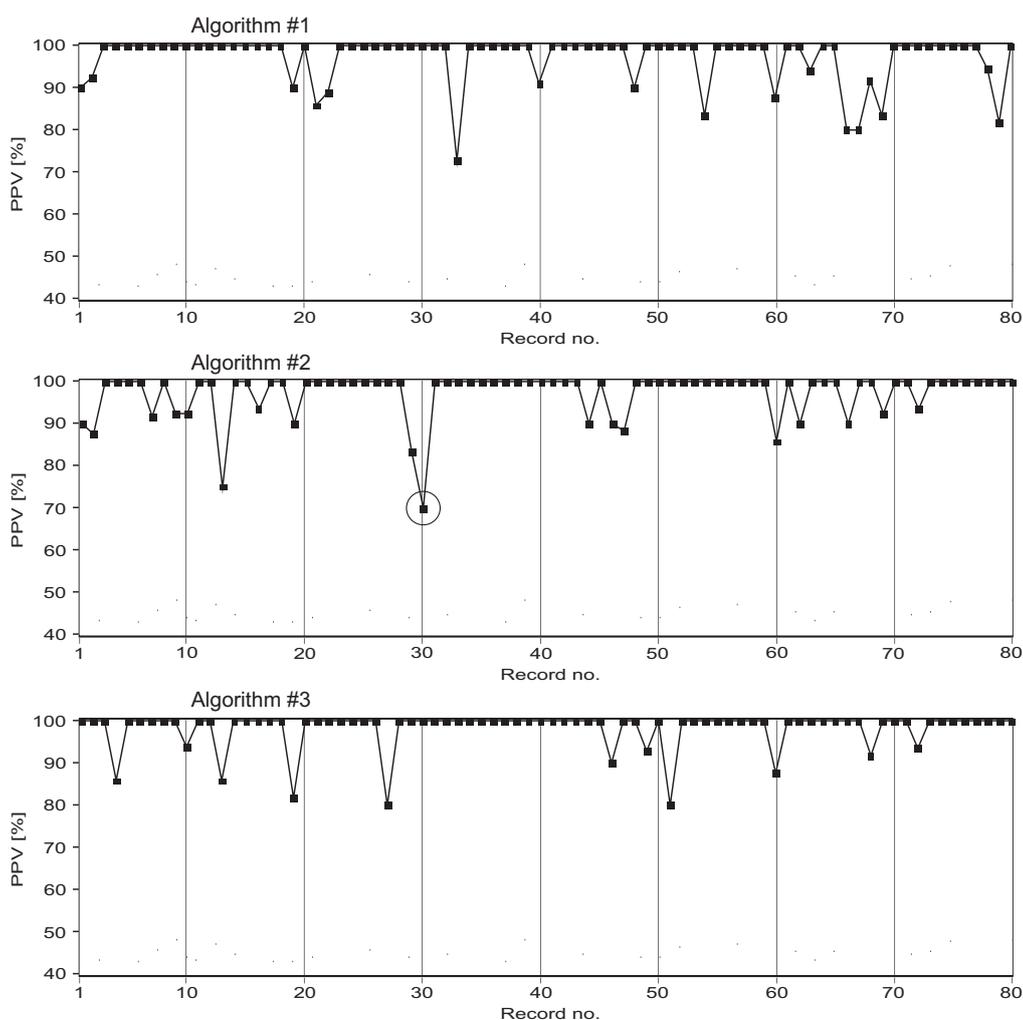


Fig. 3. Changes of the positive predictive value PPV obtained by the compared algorithms across all signals. Contractions detected in signal no. 30, for which the lowest PPV was noted using the best Algorithm #2, are presented in details in Fig. 5.

#### 4. CONCLUSIONS

Three various algorithms for automated detection of uterine contraction in the signal provided by fetal monitor were tested. All the methods showed high efficiency in relation to the expert when using 80 intrapartum signals. The best results were provided by the algorithm currently implemented in the computer-aided fetal monitoring system, but satisfying results have been also ensured by the algorithm intended to use in monitoring instrumentation for home pregnancy monitoring.

We noted that the algorithm sensitivity depends more on the uterine contraction signal quality than the positive predictive value does. Generally, none of the algorithm incline to detect the false contractions i.e. contractions not recognized by the expert, which has been confirmed by high positive predictive values obtained. However, an increase in the signal UC, which is caused by maternal movement or position change signal with interferences caused by maternal movement or position change, may be classified as contractions by the automated method, if only it matches the detection criteria. Whereas according to the human expert it does not originate from uterine contractile activity.

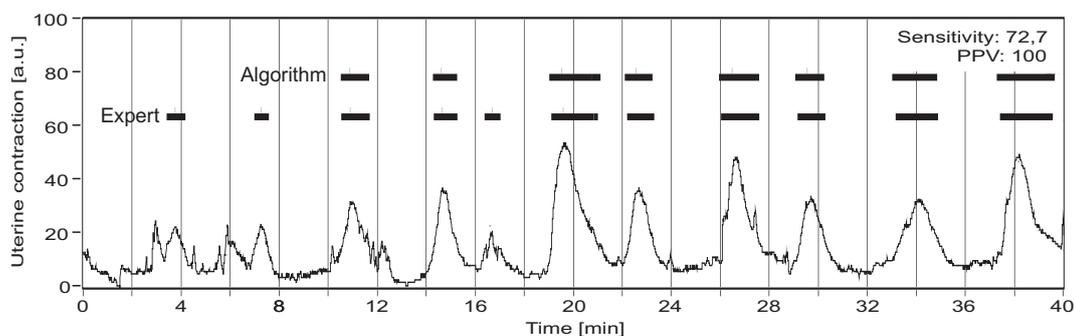


Fig. 4. Uterine contraction signal no. 23 with the lowest sensitivity (72.7%) provided by the best Algorithm #2, because the algorithm detected only eight from ten contractions recognized by the expert. None false contractions led to the PPV = 100%.

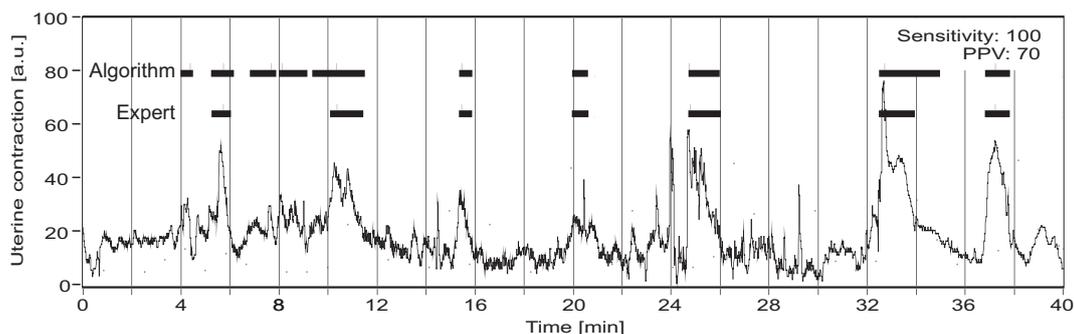


Fig. 5. Uterine contraction signal no. 30 with the lowest PPV (70%) provided by the best Algorithm #2, because the algorithm detected three false contractions. Detection of all of the seven contractions recognized by the expert led to maximum sensitivity of 100%.

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