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ORIGINAL ARTICLE

A comparison of various linear and non-linear signal processing techniques to separate uterine EMG records of term and pre-term delivery groups

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Abstract Various linear and non-linear signal-processing techniques were applied to three-channel uterine EMG records to separate term and pre-term deliveries. The linear techniques were root mean square value, peak and median frequency of the signal power spectrum and autocorrelation zero crossing; while the selected non-linear techniques were estimation of the maximal Lyapunov exponent, correlation dimension and calculating sample entropy. In total, 300 records were grouped into four groups according to the time of recording (before or after the 26th week of gestation) and according to the total length of gestation (term delivery records—pregnancy duration $\geq$37 weeks and pre-term delivery records—pregnancy duration <37 weeks). The following preprocessing band-pass Butterworth filters were tested: 0.08–4, 0.3–4, and 0.3–3 Hz. With the 0.3–3 Hz filter, the median frequency indicated a statistical difference between those term and pre-term delivery records recorded before the 26th week ($p = 0.03$), and between all term and all pre-term delivery records ($p = 0.012$). With the same filter, the sample entropy indicated statistical differences between those term and pre-term delivery records recorded before the 26th week ($p = 0.035$), and between all term and all pre-term delivery records ($p = 0.011$). Both techniques also showed noticeable differences between term delivery records recorded before and after the 26th week ($p \leq 0.001$).

Keywords Uterine EMG · Electrohysterogram · Pre-term delivery prediction · Linear signal processing techniques · Non-linear signal processing techniques

1 Introduction

Premature labor prediction is an extremely difficult task. This is in part due to the lack of knowledge regarding the exact physiology of the uterus and parturition. Premature labor prediction so far has mostly been based on calculating the risk factors. Although many risk factors were identified such as diabetes, conization, hypertension, smoking, abnormalities of the uterus, short cervix, a positive fibronectin test and others [10, 21, 24], premature labor prediction is far from certain. Any promising technique that could improve the chances of prediction is welcome. Analysis of uterine ElectroMyoGram (EMG), termed as ElectroHysteroGram (EHG), records is one such technique. The EHG records correspond to the activity of the uterine muscles and might therefore be used to predict the premature onset of labor [15, 16]. The signal acquisition is both non-invasive and relatively simple and could therefore easily be introduced into hospital practice. Using the EHG,

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it is possible to detect uterine activity related to contractions during both gestation and active labor [9]. The EHG could therefore supplement the tools currently used to monitor labor [7]. Studies showed that it should be possible to differentiate the EHG during pre-term labor and during active term labor [16], and also the EHG during the pregnancies that resulted in pre-term deliveries as opposed to those that resulted in term deliveries [15].

Most of the signal-processing techniques used were linear techniques which rely on the changes in the frequency power spectrum of the uterine activity as the time of delivery approaches. The techniques studied which consider individual uterine contractions included the following: the calculation of the peak frequency of the power spectrum within bursts of activity [6]; the calculation of burst energy levels [20], the use of the peak frequency, the duration and number of bursts, the means and deviations of the frequency spectrum, combined with neural networks [16]; and the approaches of analyzing contractions using multiple techniques such as the median frequency, the peak frequency and the kurtosis and skewness coefficient, combined with principal component analysis [15]. Other approaches included calculating the root mean square value of the signals and the median frequency value of the power spectrum of the signals for whole 30-min records of uterine activity [13, 25].

It is known that the underlying physiological mechanisms of biological systems are non-linear processes [1]. As the uterus is composed of billions of intricately interconnected cells whose responses are non-linear, it may be regarded as a complex, non-linear dynamic system. To analyze the outputs of such a system, non-linear signal processing techniques are applicable. Therefore, one can hypothesize that non-linear signal processing techniques may yield better results in analysis of the EHG than linear ones. Besides, previous studies on the use of some non-linear signal processing techniques [5], another research in this direction by estimating the fractal dimension of the bursts of uterine electrical activity [18] already produced promising results.

We therefore chose to use and test some of the linear signal-processing techniques already proposed and some non-linear signal processing techniques in order to estimate their ability to separate or differentiate uterine EMG records of term and pre-term deliveries. The following were the linear-processing techniques chosen: the root mean square value of the signal, calculation of the peak and median frequencies of the power spectrum of the signal and determination of the autocorrelation zero-crossing; while the non-linear processing techniques were, estimation of the maximal Lyapunov exponent, estimation of the correlation dimension and calculation of the sample entropy of the signal.

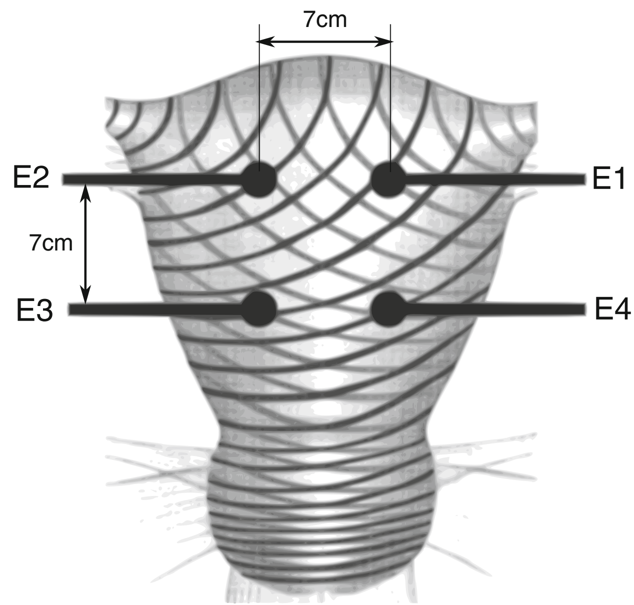

Fig. 1 The placement of the electrodes on the abdomen, above the uterine surface. Signal 1: *E2–E1*, signal 2: *E2–E3*, signal 3: *E4–E3*

2 Methods

2.1 Records

The EHG records used in this research were collected from 1997 until 2006 at the Department of Obstetrics and Gynecology, Medical Centre Ljubljana, Ljubljana. Records were collected from the general population as well as from the patients admitted to the hospital with the diagnosis of impending pre-term labor. One record per pregnancy was recorded. The records are of 30-min duration and consist of three channels. The sampling frequency, f_s, was 20 Hz. The records were collected from the abdominal surface using four $AgCl_2$ electrodes (see Fig. 1). The electrodes were placed in two horizontal rows, symmetrically under and above the navel, spaced 7 cm apart. A special protocol was used during the attachment of the electrodes in order to improve the quality of the measurements [13]. According to the protocol, the resistance between the electrodes had to be lower than 100 kΩ. The first acquired signal was measured between the topmost electrodes (E2–E1), the second signal between the leftmost electrodes (E2–E3) and the third signal between the lower electrodes (E4–E3). Prior to sampling the signals were filtered using an analog three-pole Butterworth filter with the bandwidth from 0 to 5 Hz. The resolution of the scanning system was 16 bits with the amplitude range ±2.5 mV. Due to the large scope of the research, some recording errors were inevitable, e.g., missing accompanying data, signal loss, or broken connection between the skin and the electrodes, or no electrical activity. After a careful visual inspection, and after rejecting those records of pregnancies containing no electrical activity or containing excessive noise, those ended in C-sections and those ended in induced delivery, 300 EHG records (300 pregnancies) ending in term or pre-term deliveries out of a total of 1,211 records were chosen for further analysis. The times of deliveries versus recording times for the 300 EHG records are shown in Fig. 2. The following groups of EHG records were formed:

1. 262 records from pregnancies where the deliveries were term (pregnancy duration ≥37 weeks) of which:
   (a) 143 records were recorded *early*, before the 26th week of gestation;
   (b) 119 records were recorded *later*, during or after the 26th week of gestation.
2. 38 records from pregnancies which ended prematurely (pregnancy duration <37 weeks) of which:
   (a) 19 records were recorded *early*, before the 26th week of gestation;
   (b) 19 records were recorded *later*, during or after the 26th week of gestation.

We put special attention to records recorded *early*. The frequency of contractions early in the pregnancy is relatively low [11]. Therefore, we selected only those records showing some visually detected electrical activity different from noises.

Table 1 describes characteristics of formed groups of EHG records. Average times of recording and times of birth, parity, and age of the mother are shown for the groups of records.

2.2 Preprocessing

The selection of digital filters to remove noise from signals before the processing may greatly influence the results. A band-pass filter is needed. Various frequency bands, such as 0.08–4 Hz (using a Butterworth digital filter) [25], 0.05–4 Hz [16], 0.2–4 Hz [20], and filtering methods including wavelets [3] were used. It was recognized that the uterine EMG content ranges from 0 to <5 Hz [4]. We chose digital Butterworth filters which have a smooth frequency response and are computationally non-intensive. Their major drawback, the phase-shifting, is especially troublesome when using high-pass filtering. Fortunately, the phase-shift can be eliminated by filtering the whole signal twice in different directions, forward and then again backward, thus obtaining a well filtered signal with zero phase shift. The chosen four-pole Butterworth filters were applied bi-directionally to each signal. We used three band-pass filters:

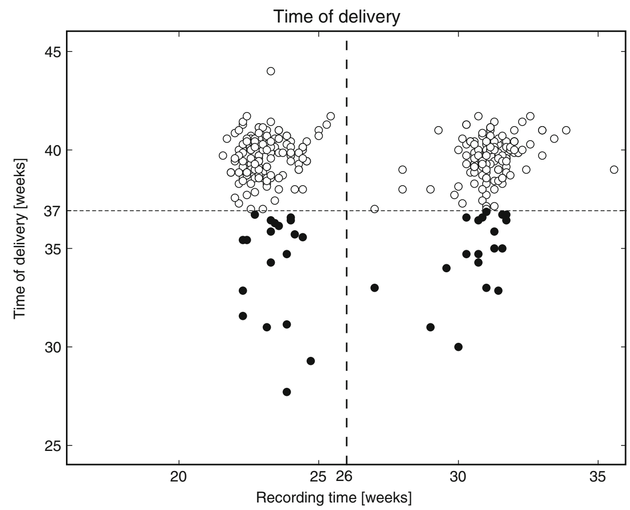

Fig. 2 The times of delivery in relation to the times of recording for the 300 EHG records. *Open circles* term delivery records, *filled circles* pre-term delivery records, the *dashed horizontal line* indicates the boundary (37th week of gestation) between the term and pre-term delivery records, *upper left* group of term delivery records recorded *early* (before the 26th week of gestation), *upper right* group of term delivery records recorded *later* (during or after the 26th week of gestation), *lower left* group of pre-term delivery records recorded *early*, *lower right* group of pre-term delivery records recorded *later*

Table 1 Characteristics of the groups of EHG records

Group	*N*	Recording	Birth	Parity	Age
≥37 weeks, *early*	143	22.7	39.7	0.49	29.7
≥37 weeks, *later*	119	30.8	39.6	0.52	30.1
<37 weeks, *early*	19	23.0	34.2	0.39	29.6
<37 weeks, *later*	19	30.2	34.7	0.64	29.2

N number of records, *recording* average term of recording (weeks), *birth* average term of birth (weeks), *parity* average number of prior pregnancies, *age* average age (years)

(1) 0.08–4 Hz;
(2) 0.3–4 Hz;
(3) 0.3–3 Hz.

The first band (0.08–4 Hz) was chosen so that we could compare results in this study to the results of previous research [13, 25]. However, due to noise in the lower frequencies because of skin stretching and breathing which is often present in the EHG signals, we decided to test filters with a higher low frequency cut-off. Thus, the second frequency band used was 0.3–4 Hz. The third band-pass filter used (0.3–3 Hz) was chosen to test the susceptibility of the methods tested to frequency content in the higher frequencies. The choice of multiple band-pass filters also enabled us to test whether the results yielded by the tested methods depend on the choice of the filtering bandwidth.

2.3 Justification of signal processing techniques

Figure 3 shows two examples of EHG signals from different records. Both records were recorded in the 30th week of gestation. The upper signal is of a term delivery EHG record (delivery in 39th week of gestation), while the lower signal is of a pre-term delivery EHG record (delivery in 32nd week). The signals were filtered using digital a filter with the bandwidth from 0.3 to 3 Hz. Looking at the signals of uterine muscle activities of both signals, one may argue that different physiologic mechanisms are involved. In the signal of the term delivery record, it seems that multiple physiologic mechanisms or non-linear processes are involved in the background, and the muscle activities are less predictable; while in the signal of the pre-term delivery record, it seems that only one physiologic mechanism is involved and the muscle activities are more predictable. According to such an observation, we may expect that non-linear signal processing techniques may separate EHG recorded on women delivering at term or pre-term.

We chose root mean square value of the signal, and the peak and median frequency of the signal power spectrum since we wanted to verify some previous results [13, 25]. The power spectrum reveals periodic components of a signal and it should always be employed in time series analysis whether the primary analysis is statistical or dynamical [1]. Peak and median frequency are suitable estimates of the signal power spectrum. Some previous researches indicate a change in the peak frequency of the power spectrum of the signal as the time of delivery approaches [6, 12]. When observing the power spectrum of uterine EMG signals, researchers have noted the existence of two peaks, one in the lower and one in the higher frequency bands [4]. Unfortunately, the lower-frequency components are always masked by noise. In the higher frequency bands, usually even more than one peak is observable. As these smaller peaks at higher frequencies are likely to contain useful information, completely disregarding them (as done by measuring the peak frequency alone) might not be the best solution. The median frequency of the power spectrum was therefore chosen as an attempt to at least partially capture the information contained in these smaller peaks. The autocorrelation also provides a diagnostic tool for discriminating between periodic and stochastic behavior [1]. Among the non-linear signal processing techniques the maximal Lyapunov exponent and the correlation dimension are prime candidates for dynamic analysis of biological signals [1]. The maximal Lyapunov exponent and the correlation dimension are both properties of non-linear systems. Their calculation is based on a phase space, a construct which demonstrates the changes of the dynamical variables of the system [22, 23]. The motivation to use the maximal Lyapunov exponent was its ability to estimate the amount of chaos in a system [1], while the motivation to use the correlation dimension was its ability to estimate the complexity of time series [1]. The sample entropy, another technique for dynamic analysis of biological signals, is a measure of regularity of finite length time series and estimates the extent to which the data did not arise from a random process [14]. These non-linear techniques seem appropriate quantitative tools to measure the variability of underlying physiological mechanisms and may differentiate EHG signals of term and pre-term deliveries.

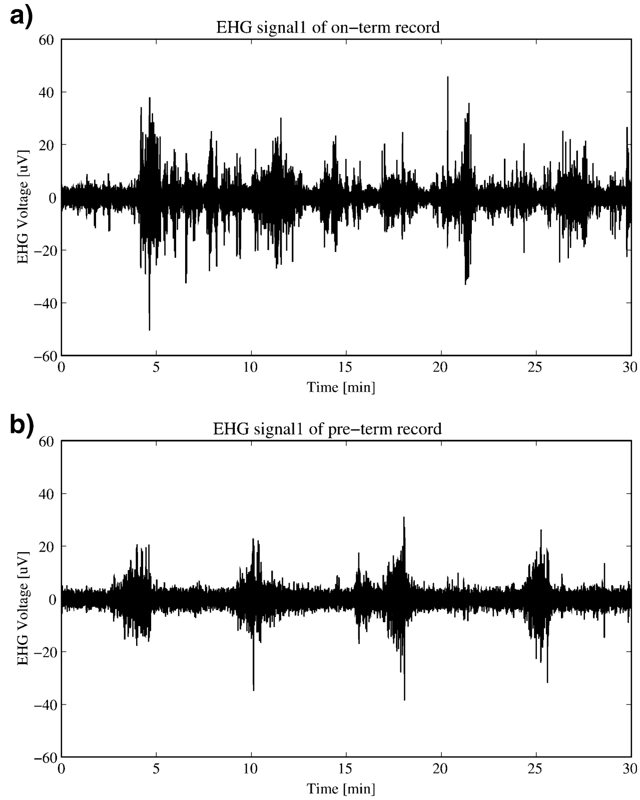

Fig. 3 Examples of EHG signals. **a** Signal 1 of a term delivery record (recorded in 30th week, delivery in 39th week), **b** signal 1 of a pre-term delivery record (recorded in 30th week, delivery in 32nd week)

The main goal of this study was to explore the possibility of classification of term and pre-term delivery EHG records. We applied the techniques to EHG signals as a whole and did not process segmented uterine EMG, i.e., the burst associated to contractile events, as other researchers did [2, 15, 17, 19]. The entire procedure does not involve interactive manual selection of contractile events such as, e.g., Braxton–Hicks contractions, of which the segmentation may also be subjective. The main reason to analyze the records as a whole was to establish a non-invasive and robust procedure which takes a sample of the EHG of length approximately half an hour (which is extreme short in comparison to the total length of gestation) and then processes this record of the EMG fully automatically. Another important reason why we process signals as a whole is the fact that some non-linear techniques, such as estimation of the maximal Lyapunov exponent, the correlation dimension, and calculation of the sample entropy require much larger amount of data than would be available within single contractile events for efficient calculation of phase space or efficient matching in sample entropy method. Besides, it might be difficult to analyze EHG signals in the scope of non-linear processes using single contractions. Each of the techniques was applied to each of the three signals of each EHG record and yielded a single value or a measure for each signal of each record. Due to the transient responses at the beginnings and ends of the filtered signals caused by the low frequency band-stop portion of the filter, and due to the bi-directional filtering scheme, a 1.5 min portion of the signals at the beginnings and ends of the records were not considered. Thus the signal processing techniques were actually applied to the center 27 min of each signal of the records.

Even though there are relatively few effective contractile events early in the pregnancy [11], the electrical activity of the uterus is still detectable [8]. We believe that the indications of excitability of the uterus are not restrained to efficient contractile events. We were therefore reluctant to reject any bursts of uterine activity. Thus we analyzed not only the contractile events but the entire electrical activity of the uterus given time of the pregnancy. The noise was rejected from the records using analog low-pass Butterworth filter and digital band-pass Butterworth filters. Therefore, the signals were noise free at least to this degree.

2.4 Description of the techniques

2.4.1 Root mean square (RMS)

Given a signal, represented by a time-series $x(t)$; $t = 0,\ldots,N-1$ of length N, the root mean square value of the signal, RMS, was calculated as the root of the mean of the squares of all samples in a signal:

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1} x(i)^2}. \tag{1}$$

2.4.2 Peak frequency of the signal power spectrum

For each signal, $x(t)$, the power spectrum, P, was calculated using the fast discrete Fourier transform. Then the peak frequency or the power spectrum (square of the magnitude) was calculated as follows:

$$f_{\max} = \arg\left(\frac{f_s}{N}\max_{i=0}^{N-1} P(i)\right), \tag{2}$$

where f_s and N denotes the sampling frequency and the number of samples, respectively.

2.4.3 Median frequency of the signal power spectrum

The median frequency, f_{med}, was calculated as:

$$f_{\mathrm{med}} = i_{\mathrm{m}}\frac{f_s}{N}, \quad \sum_{i=0}^{i=i_{\mathrm{m}}} P(i) \doteq \sum_{i=i_{\mathrm{m}}}^{i=N-1} P(i). \tag{3}$$

The median frequency was defined as the frequency just above where the sums of the parts above and below in the frequency-power spectrum, P, are the same.

2.4.4 Autocorrelation zero-crossing

The autocorrelation zero-crossing, $\tau_{R_{xx}}$, was defined as the first zero-crossing starting at the peak in the autocorrelation, $R_{xx}(\tau)$, of the signal $x(t)$:

$$R_{xx}(\tau_{R_{xx}}) = 0; \quad R_{xx}(\tau) = \sum_{i=0}^{N-1} x(i)x(\tau + i). \tag{4}$$

2.4.5 Maximal Lyapunov exponent and correlation dimension

Both techniques are based on input data, represented in a phase space. The phase space is a construct which demonstrates or visualizes the changes of the dynamical variables of a system [22, 23]. Each possible state of the system is represented by a single point in the phase space.The recorded time series is influenced by the various factors which represent the state components of the given system. From the recorded time series, the phase space which is "equivalent" to the original phase space of the system, is reconstructed by using time-delayed samples as the coordinates of the new system. This process is called time-delay embedding. Given a time series $x(t)$ of length N, a Q-dimensional phase space is constructed from vectors $\boldsymbol{y}(t)$:

$$\begin{aligned} \boldsymbol{y}(t) &= \{y_d; d = 0, 1, \ldots, Q-1\}, \\ y_d &= (x(t+d), x(t+d+D_{\mathrm{smp}}), \ldots, \\ &\quad x(t+d+(N/Q)D_{\mathrm{smp}})), \end{aligned} \tag{5}$$

where D_{smp} is the sample delay and Q is the embedding dimension. Once the phase-space is reconstructed, the Lyapunov exponents and the correlation dimension can be estimated.

The maximal Lyapunov exponent estimates the amount of chaos in a system and represents the maximal "velocity" with which different, almost identical states of the system, diverge. The (maximum) Lyapunov exponent, λ, is a measure of how fast a trajectory converges from a given point into some other trajectory,

$$\lambda = \lim_{t\to\infty} \lim_{||\Delta \mathbf{y}_0||\to 0} \frac{1}{t} \log \frac{||\Delta \mathbf{y}_t||}{||\Delta \mathbf{y}_0||}, \quad (6)$$

where $||\Delta \mathbf{y}_0||$ represents the Euclidean distance between two states of the system at some arbitrary time t_0 and $||\Delta \mathbf{y}_t||$ represents the Euclidean distance between the two states of the system at some later time t. With noisy data of finite length, the Lyapunov exponent can only be estimated with the accuracy of the estimation dependent on the number of data points and the chosen embedding delay. In order to accurately estimate the maximal Lyapunov exponent, the correlation of the delayed samples must be small. We therefore chose the offset of the first zero crossing, $\tau_{R_{xx}}$, of the autocorrelation, $R_{xx}(\tau)$, of the signal $x(t)$ as the sample delay, D_{smp}, [23]. The embedding dimension, Q, should be larger than twice the number of anticipated underlying factors governing the system under investigation [23]. We simply assumed, without any evidence, that it could be possible to describe the uterus using three underlying factors and therefore used the embedding dimension of $Q = 7$.

The correlation dimension, D_{corr}, is a measure of the complexity of a given time-series. It is proportional to the probability of the distance between two points on a trajectory being less than some r,

$$D_{\mathrm{corr}} = \lim_{r\to 0} \frac{\log(C(r))}{\log(r)}, \quad (7)$$

where

$$C(r) = \lim_{M\to\infty} \frac{1}{M^2} \sum_{i=1}^{M} \sum_{j=i+1}^{M} \Theta(r - |\mathbf{y}(i) - \mathbf{y}(j)|), \quad (8)$$

and

$$\Theta(r - |\mathbf{y}(i) - \mathbf{y}(j)|) = \begin{cases} 1 : (r - |\mathbf{y}(i) - \mathbf{y}(j)|) \geq 0 \\ 0 : (r - |\mathbf{y}(i) - \mathbf{y}(j)|) < 0 \end{cases} \quad (9)$$

To calculate $\lambda_{\max}$ and D_{corr}, we used a practical method described in [23]. As the method yields a series of $\log(r)$ and $\log(C(\log(r)))$ value pairs, the correlation dimension estimate was then calculated as a seven-point least-squares fit of the slope of $\log\ (C(\log(r)))$ around the seventh smallest $\log(r)$.

2.4.6 *Sample entropy*

The sample entropy, *sampEn*, is a measure of the regularity of finite length time series. Less predictable time series exhibit a higher sample entropy. Given a time series $x(t)$ of length N, and patterns $a_j(0,\ldots,m-1)$ of length m, $m < N$, where the patterns a_j are taken from the time series $x(t)$, $a_j(i) = x(i + j)$, $i = 0,\ldots,m-1$, $j = 0,\ldots,N-m$; the part of the time series $x(t)$ at time $t = t_s$, $x(t_s,\ldots,t_{s+m-1})$ is considered as a match for a given pattern a_j if $|x(t_s + i) - a_j(i)| \leq r$ for each $0 \leq i < m$. The number of pattern matches (within a margin of r), c_m, is constructed for each m. The sample entropy, *sampEn*, is then defined as:

$$sampEn_{m,r}(x) = \begin{cases} -\log(c_m/c_{(m-1)}) & : c_m \neq 0 \wedge c_{m-1} \neq 0 \\ -\log((N-m)/(N-m-1)) & : c_m = 0 \vee c_{m-1} = 0 \end{cases} \quad (10)$$

During evaluation of the technique, we varied the parameter m from 2 to 4 in steps of 1, and the parameter r from 0.1 to 0.2 in steps of 0.125.

2.4.7 *Evaluation of the techniques*

In order to evaluate the ability of the investigated techniques to separate groups of records according to the time of delivery (term, pre-term), and according to the time of recording (before or after the 26th week of gestation), we used the Student's *t*-test on the measures produced by each signal processing technique when a technique was applied separately on each of the three signals of the records. Figure 4 shows a schematic representation of the evaluation of each signal processing technique when applied to one of the signals (first, second or third) of the records. M_{TE} and M_{TL} mark the sets of measurements obtained by a signal processing technique when the technique was applied to one of the signals of term delivery records recorded *early* (before the 26th week of gestation) and those recorded *later* (during or after 26th week of gestation), respectively. M_{PE} and M_{PL} mark the sets of measurements obtained by the signal processing technique when the technique was applied to one of the signals of pre-term delivery records recorded *early* and those recorded *later*, respectively. The Student's *t*-test produces the probability, p, that two normally distributed sets belong to the same population. A low value of p is therefore an indication that the technique may be useful for discerning one group of records from another. The probability p_1 indicates how the measures obtained by the signal processing technique, and the analyzed signal, separate term delivery records recorded *early* and pre-term delivery records recorded *early*,the probability p_2 how the measures separate term delivery records recorded *later* and pre-term delivery records recorded *later*, the probability p_3 how the measures separate pre-term delivery records recorded *early* and pre-term delivery records recorded *later*, while the probability p_4 how the measures separate term delivery records recorded *early* and term delivery records recorded

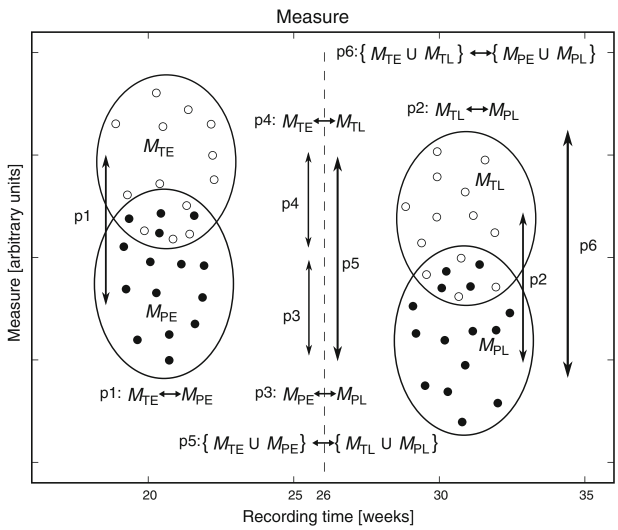

Fig. 4 Schematic representation of the evaluation of each signal processing technique when the technique is applied to one of the signals (first, second or third) for each record. *Open circles* measures obtained by a signal processing technique for term delivery records, *filled circles* measures obtained for pre-term delivery records, M_{TE} set of measurements obtained by the signal processing technique for term delivery *early* records, M_{TL} set of measurements for term delivery *later* records, M_{PE} set of measurements for pre-term delivery *early* records, M_{PL} set of measurements for pre-term delivery *later* records, $p_1,\ldots,p_6$ probabilities according to the Student's *t*-test when applied between the sets of measurements

later. The probability p_5 indicates how the measures obtained by the processing technique, separate all records recorded *early* and all records recorded *later*, while the probability p_6 how the measures differentiate between all term and all pre-term delivery records.

3 Results

Evaluation of the signal processing techniques to separate the groups of uterine EMG records is summarized in Tables 2, 3 and 4. Tables 2, 3 and 4 summarize the results when 0.08–4, 0.3–4 and 0.3–3 Hz band-pass preprocessing filters were used, respectively. We set the significant value of the probabilities, p, to separate the groups to $\leq$0.05. The tables show that the differences between the *early* and *later* groups of records are more pronounced than the differences between the groups of term and pre-term delivery records.

Regarding the separation of term and pre-term delivery records (p_1, p_2, p_6), results indicate that the median frequency performed best among the linear techniques and the sample entropy among the non-linear techniques. The median frequency actually did not show any significant value for the preprocessing filter 0.08–4 Hz (Table 2), but showed significant values to separate all term and all pre-term delivery records, p_6, in the signal 3 for the filters 0.3–4 Hz (Table 3) and 0.3–3 Hz (Table 4). Figure 5 shows the median frequency measurements in the signal 3 and filter 0.3–3 Hz. The median values for term delivery records are higher than those for pre-term delivery records for the groups of *early* and *later* records. The average median value just slightly drops for term delivery records from 0.64 to 0.56 Hz as the time of gestation progresses. The graph also shows that the median frequencies of the pre-term delivery records recorded *later* are relatively low. The sample entropy ($m = 3$, $r = 1.5$) gave much more promising results than the median frequency. The technique showed significant values to separate term and pre-term delivery records recorded *early*, p_1, in the signal 3 and to separate all term and all pre-term delivery records, p_6, in the signal 3 for all three preprocessing filters (Tables 2, 3, 4) as well as in the signal 1 (p_6) for the filter 0.08–4 Hz (Table 2) and for the filter 0.3–4 Hz (Table 3). Besides, the sample entropy also showed significant value to separate term and pre-term delivery records recorded *later*, p_2, in the signal 3 for the filter 0.3–4 Hz (Table 3) and for the filter 0.3–3 Hz (Table 4). Figure 6 shows the sample entropy measurements in the signal 3 for the filter 0.3–3 Hz. The sample entropy values for term delivery records are higher than those for pre-term delivery records for the groups of *early* and *later* records. The average sample entropy value drops for term and pre-term delivery records as the time of gestation progresses.

In the aspect of separating term and pre-term delivery records, the median frequency and sample entropy gave promising results if either the 0.3–4 or 0.3–3 Hz preprocessing filters were used. Other techniques did not indicate significant differences among the groups of term and pre-term delivery records. The correlation dimension, however, indicated a difference between term and pre-term delivery records recorded *later*, p_2, in all signals when the lower band-stop frequency of the filter was 0.08 Hz (Table 2).

Regarding the separation of records recorded *early* and those recorded *later* (p_3, p_4, p_5) a few techniques gave promising results. The root mean square technique gave no useful results. The peak frequency gave some results if the filters 0.3–4 or 0.3–3 Hz were used (Tables 3, 4). The median frequency yielded better results in separation of records recorded *early* and those recorded *later* when using the same two filters (Tables 3, 4). The autocorrelation zero crossing gave some results if any filter was used (Tables 2, 3, 4). The maximal Lyapunov exponent did not give any acceptable value. The correlation dimension gave much better results in separation if the 0.08–4 Hz filter was used (Table 2). Again, the sample entropy gave the best results among all techniques. The technique showed significant values to separate term delivery records recorded *early* and term delivery records recorded *later*, $p_4 \leq 0.001$, in any signal, and significant values to separate all records

Table 2 Evaluation of the techniques to separate groups of records according to time of delivery (term, pre-term) and time of recording when the 0.08–4 Hz band-pass preprocessing filter was used

Technique	Preprocessing filter 0.08–4 Hz						
	Sig	p_1	p_2	p_3	p_4	p_5	p_6
Root mean	1	0.709	0.773	0.415	0.747	0.594	0.954
Square	2	0.448	0.665	**0.035**	0.160	0.061	0.918
RMS	3	0.302	0.712	0.952	0.114	0.121	0.288
Peak	1	0.524	0.326	0.233	0.235	0.299	0.701
Frequency	2	0.094	0.079	0.060	0.069	0.302	0.892
f_{max}	3	0.635	0.467	0.150	0.573	0.338	0.799
Median	1	0.344	0.889	0.251	0.275	0.315	0.375
Frequency	2	0.226	0.079	0.063	0.253	0.694	0.615
f_{med}	3	0.349	0.721	0.070	0.484	0.660	0.491
Autocorrelation	1	0.138	**0.028**	**0.002**	0.526	0.749	0.610
Zero crossing	2	0.169	**0.013**	**0.015**	0.086	0.461	0.340
$\tau_{R_{xx}}$	3	0.295	**0.007**	**≤0.001**	0.480	0.064	0.153
Maximal	1	0.778	0.630	0.441	0.694	0.526	0.897
Lyapunov exponent	2	0.617	0.548	0.227	0.404	0.229	0.933
λ_{max}	3	0.151	0.952	0.679	**0.041**	0.069	0.279
Correlation	1	0.788	0.525	0.136	**0.001**	**≤0.001**	0.490
Dimension	2	0.690	0.529	**0.027**	**≤0.001**	**≤0.001**	0.612
D_{corr}	3	**0.016**	0.536	0.816	**≤0.001**	**≤0.001**	0.211
Sample entropy	1	0.128	0.217	0.379	**0.001**	**0.001**	**0.043**
sampEn	2	0.824	0.572	0.118	**≤0.001**	**≤0.001**	0.501
$m = 3$, $r = 1.5$	3	**0.001**	0.374	0.658	**0.001**	**0.002**	**0.003**

Sig signal number, $p_1,\ldots,p_6$ probabilities according to Student's *t*-tests (refer to Fig. 4); those probabilities ≤0.5 are bold

recorded *early* and all records recorded *later*, $p_5 \leq 0.001$ for the filter 0.3–3 Hz. This technique also showed separability between pre-term delivery records recorded *early* and pre-term delivery records recorded *later*, p_3, in the signal 2, if the filters 0.3–4 and 0.3–3 Hz were used (Tables 3 and 4).

4 Discussion

The results show that the frequency spectra of records recorded *early* and *later* slightly differ. This was expected, as the electrical activity of the uterus is likely to change as the pregnancy progresses. The results regarding median frequency show just a slight drop in the median frequency as time of gestation progresses for term records (see Fig. 5). This means a slight decrease of the power spectra distribution. In some other studies an increase in the power spectra distribution as labor approaches was reported [2, 15, 17, 19]. It is necessary to discuss these differences. It is important to note two facts. Firstly, we processed entire records, the entire electrical activity of the uterus, while in those studies individual contractile events, i.e., the bursts associated to contractions, were processed. Secondly, in those studies significant increase in the power spectra distribution was reported for term and pre-term records within labor [2, 19], or just prior to delivery within 24 h for term records and within 4 days for pre-term records [17], but not earlier. A decrease in the power spectra distribution for pre-term records 10 days prior to delivery was reported as well in [17]. Furthermore, in [15] authors reported an increase of the energy of the band 0.9–1.2 Hz (which might be considered as a decrease of the power spectra) at 6–8.5 weeks before delivery and then a decrease (which might be considered as an increase of the power spectra) at 4.5–5.5 weeks before delivery for term records, and reported an increase of the energy in the bands 0.3–0.6, 0.6–0.9, and 1.2–1.5 Hz (which may be considered as a decrease of the power spectra or shift of the power spectra to lower frequencies) at 6–8.5 weeks before delivery and then a decrease (which may be considered as an increase of the power spectra or shift of the power spectra to higher frequencies) at 4.5–5.5 weeks before delivery for pre-term records. Our records were recorded early prior to delivery (*later* groups) and even much earlier (*early* groups). Of all the records (300) there are 32 records which were recorded within 7 weeks prior to delivery; of these, 21 were pre-term. Similarly, of all the records there are only 15 records which

Table 3 Evaluation of the techniques to separate groups of records according to time of delivery (term, pre-term) and time of recording when the 0.3–4 Hz band-pass preprocessing filter was used

Technique	Preprocessing filter 0.3–4 Hz						
	Sig	p_1	p_2	p_3	p_4	p_5	p_6
Root mean	1	0.536	0.364	0.276	0.932	0.742	0.834
Square	2	0.349	0.139	**0.017**	0.255	0.058	0.633
RMS	3	0.715	0.617	0.435	0.092	0.060	0.500
Peak	1	0.534	0.117	0.053	**0.007**	**0.002**	0.153
Frequency	2	0.477	0.144	0.589	0.067	0.074	0.320
f_{max}	3	0.997	0.192	0.232	**0.011**	**0.005**	0.535
Median	1	0.427	0.052	**0.005**	**0.001**	**≤0.001**	0.066
Frequency	2	0.695	0.704	0.456	0.077	0.054	0.559
f_{med}	3	0.051	0.142	0.266	**0.001**	**≤0.001**	**0.013**
Autocorrelation	1	0.375	0.967	0.828	**0.024**	**0.024**	0.475
Zero crossing	2	0.095	0.355	0.309	0.733	0.590	0.066
$\tau_{R_{xx}}$	3	0.282	0.468	0.632	**0.012**	**0.021**	0.646
Maximal	1	0.467	0.527	0.378	0.704	0.966	0.916
Lyapunov exponent	2	0.515	0.179	0.061	0.517	0.209	0.612
λ_{max}	3	0.811	0.759	0.515	0.105	0.077	0.660
Correlation	1	0.107	0.610	0.200	0.545	0.360	0.137
Dimension	2	0.479	0.585	**0.043**	**≤0.001**	**≤0.001**	0.892
D_{corr}	3	0.569	0.644	0.364	0.054	**0.036**	0.508
Sample entropy	1	0.214	0.086	0.569	0.117	0.087	**0.035**
sampEn	2	0.692	0.148	**0.005**	**≤0.001**	**≤0.001**	0.338
$m = 3$, $r = 1.5$	3	**0.029**	0.226	0.591	**0.001**	**0.001**	**0.014**

Sig signal number, $p_1,\ldots,p_6$ probabilities according to Student's *t*-tests (refer to Fig. 4); those probabilities ≤0.5 are bold

Table 4 Evaluation of the techniques to separate groups of records according to time of delivery (term, pre-term) and time of recording when the 0.3–3 Hz band-pass preprocessing filter was used

Technique	Preprocessing filter 0.3–3 Hz						
	Sig	p_1	p_2	p_3	p_4	p_5	p_6
Root mean	1	0.586	0.349	0.247	0.838	0.529	0.769
Square	2	0.361	0.141	**0.016**	0.210	**0.044**	0.615
RMS	3	0.636	0.612	0.445	0.069	**0.045**	0.450
Peak	1	0.630	0.100	0.051	**0.020**	**0.005**	0.146
Frequency	2	0.252	0.201	0.371	0.093	0.256	0.705
f_{max}	3	0.138	0.176	0.416	**0.012**	**0.007**	**0.044**
Median	1	0.371	0.059	**0.012**	**0.002**	**≤0.001**	0.055
Frequency	2	0.696	0.568	0.480	0.217	0.163	0.496
f_{med}	3	**0.030**	0.212	0.661	**0.007**	**0.005**	**0.012**
Autocorrelation	1	0.085	0.897	0.526	**0.033**	0.053	0.146
Zero crossing	2	0.089	0.340	0.223	0.658	0.499	0.059
$\tau_{R_{xx}}$	3	0.327	0.614	0.650	**0.045**	0.069	0.624
Maximal	1	0.543	0.518	0.339	0.991	0.726	1.000
Lyapunov exponent	2	0.533	0.175	0.056	0.421	0.156	0.591
λ_{max}	3	0.670	0.743	0.540	0.068	0.051	0.554
Correlation	1	0.150	0.961	0.131	0.413	0.209	0.334
Dimension	2	0.676	0.377	0.069	**≤0.001**	**≤0.001**	0.568
D_{corr}	3	0.790	0.976	0.446	0.113	0.079	0.882
Sample entropy	1	0.326	0.172	0.272	**0.001**	**0.001**	0.084
sampEn	2	0.882	0.184	**0.017**	**≤0.001**	**≤0.001**	0.323
$m = 3$, $r = 1.5$	3	**0.035**	0.165	0.334	**≤0.001**	**≤0.001**	**0.011**

Sig signal number, $p_1,\ldots,p_6$ probabilities according to Student's *t*-tests (refer to Fig. 4); those probabilities ≤0.5 are bold

were recorded within 5 weeks prior to delivery; of these, 14 were pre-term. Since we did not take records frequently during gestation and prior to the delivery (our goal was not predicting the beginning of labor nor following the changes in spectra prior to delivery, but differentiating groups of term and pre-term delivery records recorded before and after the 26th week of gestation to see whether it is possible to differentiate these groups early during the pregnancy), it would be difficult to match our results to the results discussed above. We therefore may conclude, that if entire records are processed and records are taken more than 7 weeks prior to delivery, a slight decrease of the power spectra distribution is observed for term records.

The results also indicate that early prediction of pre-term labor is less achievable through the use of the techniques used in this research. The differences between the groups of records recorded *early* and *later* were noticeable with all techniques, with the sole exception of the maximal Lyapunov exponent, both for term and pre-term delivery recording groups. This confirms that the electrical activity of the uterus changes during pregnancy. It also implies that the EHG may be useful as one of the tools used by obstetricians to assess the probability of the onset of early labor, as noted in [6]. By using multiple techniques, the reliability of the detection of the onset of labor should improve. Additional techniques may be use of model for risk assessment in the beginning of pregnancy and during pregnancy [24], where the main risk factors are previous preterm delivery, conization, bleeding in pregnancy, as well as other risk factors such as psychological and social evaluation, bacterial vaginosis, and measurement of cervix.

According to the results, a high value of median frequency *later* during the pregnancy may be associated with term delivery (see Fig. 5). A low value of median frequency does not appear to have any predictive value.

The maximal Lyapunov exponent and the correlation dimension, however, did not perform as expected. Furthermore, while feasible, their calculation requires significantly

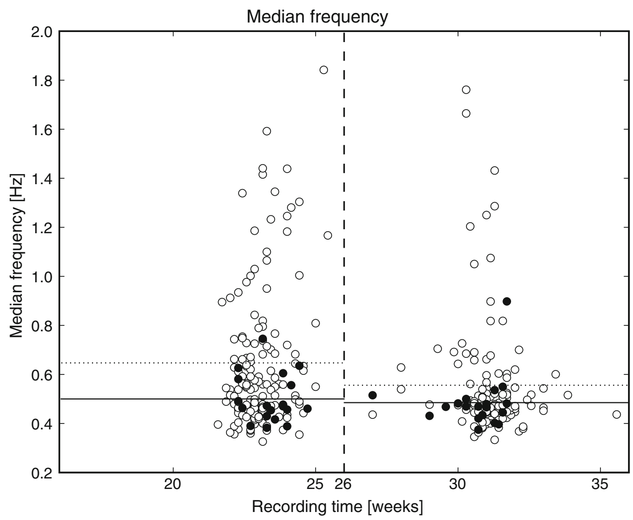

Fig. 5 The median frequency measurements (signal 3, preprocessing filter 0.3–3 Hz), *open circles* measures obtained for term delivery records, *filled circles* measures obtained for pre-term delivery records, the *dotted horizontal lines* the average median values for term delivery records (0.64 and 0.56 Hz), the *full horizontal lines* the average median values for pre-term delivery records (0.50 and 0.49 Hz), separation of groups of *early* term and pre-term delivery records: $p_1 = 0.03$, of *later* term and pre-term delivery records: $p_2 = 0.212$, of all term and pre-term delivery records: $p_6 = 0.012$, of pre-term delivery records recorded *early* and *later*: $p_3 = 0.661$, of term delivery records recorded *early* and *later*: $p_4 = 0.007$, and of all records recorded *early* and *later*: $p_5 = 0.005$

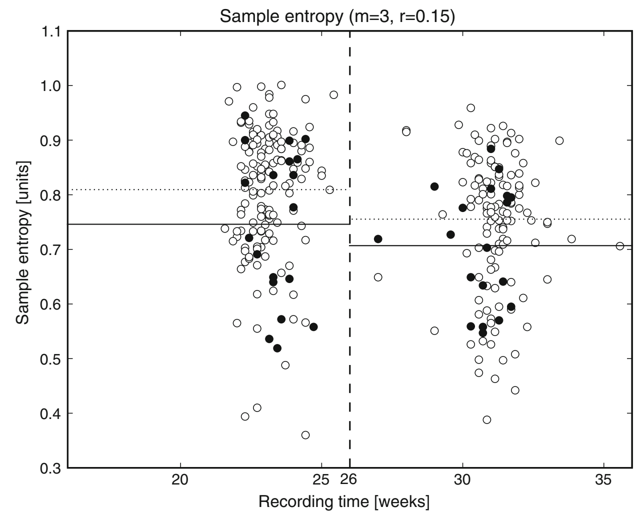

Fig. 6 The sample entropy measurements (signal 3, preprocessing filter 0.3–3 Hz, $m = 3$, $r = 1.5$). *Open circles* measures obtained for term delivery records, *filled circles* measures obtained for pre-term delivery records, the *dotted horizontal lines* the average sample entropy values for term delivery records (0.81 and 0.76), the *full horizontal lines* the average sample entropy values for pre-term delivery records (0.75 and 0.71), separation of groups of *early* term and pre-term delivery records: $p_1 = 0.035$, of *later* term and pre-term delivery records: $p_2 = 0.165$, of all term and pre-term delivery records: $p_6 = 0.011$, of pre-term delivery records recorded *early* and *later*: $p_3 = 0.334$, of term delivery records recorded *early* and *later*: $p_4 \leq 0.001$, and of all records recorded *early* and *later*: $p_5 \leq 0.001$

more resources than the linear techniques. The correlation dimension only produced some encouraging results in separation of delivery records recorded *early* and *later* when used with a preprocessing filter of 0.08–4 Hz.

Sample entropy showed promising results. The problem with sample entropy, however, lies in its extreme susceptibility to the parameter settings. If the matching pattern length, *m*, is too large, or if the sensitivity margin, *r*, is too low, within some time signals, no pattern matches can be found. The sample entropy in these cases depends solely on the length of the signal and is much higher than usual. The outliers caused by this anomaly also affected the Student's *t*-test, producing a low *p*. To avoid such erroneous results, we limited our search for suitable *m* and *r* values to those that were found to be safe while using any of the three preprocessing filters. Noticeable differences were found between the groups of records recorded *early* and *later* (see Fig. 6). The technique indicated a difference between the term and pre-term delivery groups of records. As the time of gestation progresses, the average sample entropy values for term and pre-term delivery records drop indicating higher predictability of the signals as the delivery approaches. The average sample entropy values are lower for both *early* and *later* pre-term delivery records and indicate that the signals of pre-term delivery records exhibit higher predictability than the signals of term delivery records. Higher predictability may be observed in the example in Fig. 3. The signal of the pre-term delivery record shows higher predictability than that of the term delivery record.

The differences in the median frequency and in the sample entropy between *early* term and *early* pre-term delivery records and for all term and all pre-term delivery records, with the 0.3–3 Hz preprocessing filter, were most pronounced when the measurements were calculated for the signal 3, which was measured lower on the abdomen, i.e., closer to the cervico-isthmic section. Differences for the signal 3 when using these two techniques and the same preprocessing filter were not significant for *later* term and *later* pre-term delivery records when (due to the increase in the size of the uterus) the electrodes were placed nearer to the uterus fundus. (The electrodes were always placed approximately 3.5 cm below the navel.) These differences may be due to the fact that the uterus has two functional entities. However, there were also noticeable differences in the median frequency and in the sample entropy, with the same preprocessing filter, for the groups of records recorded *early* and *later* during pregnancy; but these differences were significant for the signals 1 and 3 in the median frequency and for all three signals in the sample entropy, indicating that the position of the electrodes does not affect the effectiveness of the methods to separate groups of records recorded *early* and *later*.

The median frequency technique showed separability between *early* term and *early* pre-term delivery records for the preprocessing filter of 0.3–3 Hz, while the sample entropy techniques showed separability between these two groups for each preprocessing filter. This strengthens our assumption that early during the pregnancy there actually is some electrical activity of the uterus and not noise only, and that this activity differs for the two groups.

The choice of preprocessing filters and electrode placement also greatly influenced the results. The results obtained using the root mean square value and median frequency with the 0.08–4 Hz preprocessing filter are quite in accordance with the results of previous research [13, 25]. The success of the median frequency greatly depended on the lower band-stop frequency. With the 0.08–4 Hz filter, no separability among the groups was found. Sample entropy seems to be less affected by the choice of a preprocessing filter, yielding good results in the signal 3 regardless of the filter. In this signal, differences among the term and pre-term delivery groups of records were detected, regardless of the length of gestation for *early* records, for all records, but not for *later* records. The band-pass preprocessing filter of 0.3–3 Hz seemed to perform well for both the median frequency and sample entropy.

Visually, the differences between the term and pre-term delivery groups of records are only detected relatively late in the pregnancy. The methods investigated in this study might help to distinguish between records leading to term or pre-term delivery. The indication for oxytocin antagonist use may be confirmed sooner in the process of preterm delivery. Even when the differences are noticeable, the values obtained by the various techniques were dispersed. The differences between measures for different records within a group are in all cases much larger than those between groups, making classification of records difficult. Any future work regarding classification should therefore focus on using multiple techniques, with the median frequency and the sample entropy being among the prime candidates. Even if these methods are not yet useful for hospital work, they do bring new insight into physiology of parturition.

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