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Detecting Missing Signals in Multichannel Recordings by Using Higher Order Statistics

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Abstract — **In real world applications, a multichannel acquisition system is susceptible of having one or many of its sensors displaced or detached, leading therefore to the loss or corruption of the recorded signals. In this paper, we present a technique for detecting missing or corrupted signals in multichannel recordings. Our approach is based on Higher Order Statistics (HOS) analysis. Our approach is tested on real uterine electromyogram (EMG) signals recorded by 4x4 electrode grid. Results have shown that HOS descriptors can discriminate between the two classes of signals (missing vs. non-missing). These results are supported by statistical analysis using the t-test which indicated good statistical significance of 95% confidence level.**

I. Introduction

Electrophysiological signals are believed to carry detailed information relative to the system that generates them [1]. Over the years, these signals have been the subject of extended research in a variety of directions including signal acquisition equipment to areas such as digital signal processing, and pattern recognition. The analysis of these electrophysiological signals has completely changed the way various diseases previously were diagnosed in clinical routine. As a result, many of the problems confronting health professionals can be solved today by analyzing these signals recorded noninvasively from the patients [1].

The non-invasive acquisition of an electrophysiological signal is usually done through the attachment of a minimum of two electrodes to the body surface. However, multiple electrode configurations are commonly used in clinical practice to obtain a spatial description of the underlying bioelectrical phenomenon. The major applications in non-invasive multichannel electrophysiological signal acquisition would be those of the electroencephalogram (EEG) [2, 3], the electrocardiogram (ECG) signals [4] and the uterine electromyogram [5]. Studies have shown that, although there is a correlation between the electrical activities recorded at different sites, the characteristics of the recorded signal depend on the position of the recording electrode [1]. With the use of multiple electrodes, it has become possible to look deeper into the electrophysiological activity of a system, evaluate the correlation between signals recorded from spatially distributed regions and characterize it by new features such as the synchronization and the propagation velocity. Moreover, it was shown that the joint use of spatial data from different spatial sensors has the potential of solving difficult pattern recognition problems including the classification of electrophysiological signals [6].

However, in clinical practice, continuous recording of all channels is often cumbersome especially when a continuous monitoring for prolonged durations is to be performed. As a result, one or multiple signals can be lost, masked by noise or even corrupted during an ongoing recording session due to electrode displacement issues. In fact, there is always risk of electrode drift, misplacement, displacement or even complete detachment, leading to the corruption of the desired data and therefore misdiagnosis. Herein, corrupted signals of all sorts are termed missing signals for the sake of generalization.

Hence, the detection of missing signals in multichannel recordings represents a crucial objective of biomedical signal processing so as to mitigate the influence of the misleading results of their analysis in biomedical research.

In this paper, we present an approach for detecting missing signals in multichannel recording by using higher order statistics (HOS) descriptors since these descriptors are known to be sensitive to the shape variation of the amplitude distribution of a signal. Indeed, shape variation is expected to occur following the loss or the corruption of the recorded signal. Our approach is then tested on real uterine electromyogram (EMG) signals recorded by a matrix of 16 electrodes placed on the abdominal wall of pregnant women. Herein, we use the absolute values of kurtosis and skewness derived from the recorded channels in order to discriminate between contraction signals and missing signals found in the database. The values of the above stated parameters are compared between the 2 classes (non-missing vs. missing signals). Finally, the obtained results are discussed.

II. Materials and Methods

A. Uterine Electromyogram (EMG):

Uterine EMG signal, also called electrohysterogram (EHG), is the bioelectrical signal recorded noninvasively from the abdominal wall of pregnant women during their gestational period. It represents the noninvasive space-time recording of the uterine electrical activity with one or multiple independent sensors that capture some aspect of

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physiological events related to pregnancy and labor. It was proposed that, by analyzing this signal, pregnancy can be monitored and labor can be detected [7, 8]. More important, uterine EMG provides a highly useful characterization of preterm labor since many pathological processes are manifested by alterations in the signal properties. These findings have been confirmed experimentally on several species, including human [9].

B. Database description

Uterine EMG signals used in this research were recorded from 10 women. Our database consists of 30 pregnancy contraction signals and 30 labor signals. Recordings were made in the University Hospital of Amiens in France by using a protocol approved by the ethical committee (ID-RCB 2011-A00500-41). Recordings were performed by using a 16 electrode grid, arranged in a 4x4 matrix positioned on the women's abdomen with interelectrode spacing of 2 cm (fig.1). The ground electrodes were placed on each hip. Signals were sampled at 200 Hz. The recording device has an anti-aliasing filter with a cut-off frequency of 100 Hz. In all the patients, uterine activity was also recorded by a TOCO in order to correlate it with the uterine EMG signals. The bursts of uterine electrical activity corresponding to contractions were then manually segmented. In this study, in order to increase the signal to noise ratio, we considered vertical bipolar signals instead of monopolar ones. Our signals form thus a rectangular 3x4 matrix. Interfering artifacts were minimized by using a bandpass filter set at 0.1 - 3 Hz [7].

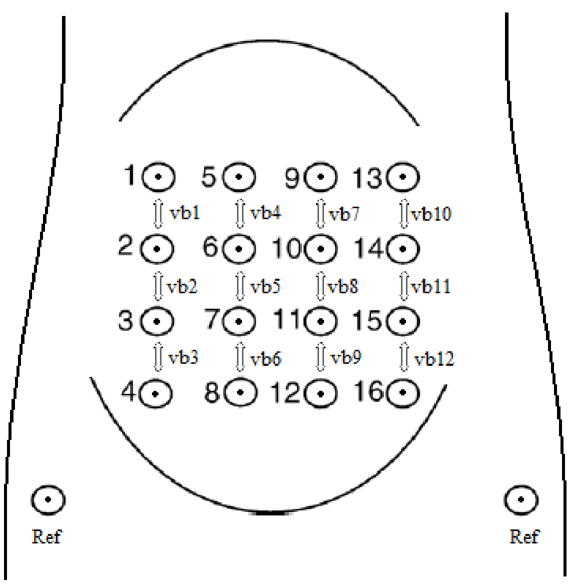


Figure 1- Electrodes configuration on the woman's abdominal wall. Vb_i represent the derived bipolar signals.

C. Higher Order Statistics (HOS):

Herein, 2 HOS descriptors (skewness and kurtosis) are used to evaluate the shape variation of the amplitude distribution of the signals in our database. The normalized 3rd order central moment or skewness, given by (1), describes the degree of deviation from the symmetry of a Gaussian probability density function (PDF), whereas the normalized 4th order central moment or kurtosis, given by (2), describes the peakedness of the PDF around the mean value.

$$S = \frac{E[(X-\mu)^3]}{\sigma^3} \quad (1)$$

$$K = \frac{E[(X-\mu)^4]}{\sigma^4} \quad (2)$$

where X represents a random process, μ and σ are the mean and the standard deviation of this process, respectively, and E() is the expected value.

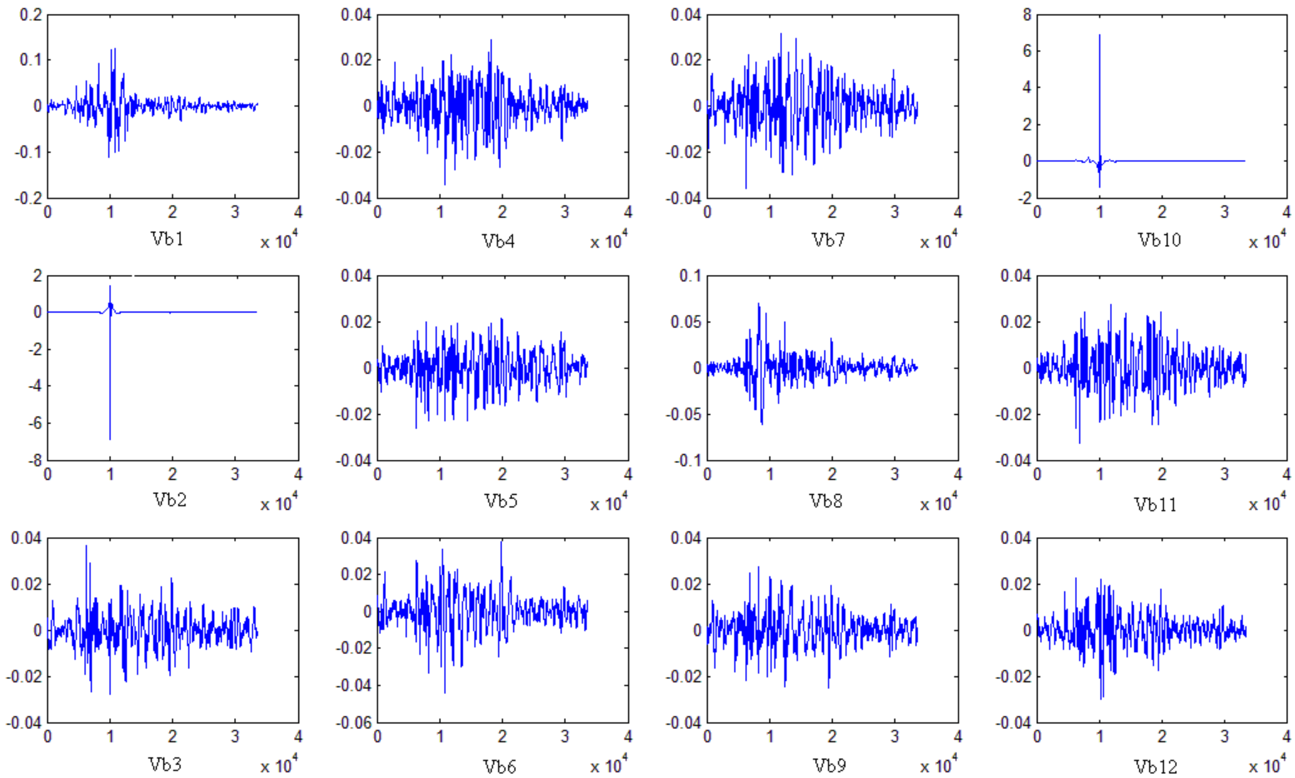
It is important to note that a normal distribution has a skewness value equal to 0 while a nonzero value of the skewness index reflects the presence of a right or left tail elongation of the distribution. A kurtosis value equal to 0 indicates a normal distribution while a positive value corresponds to a more peaked than the normal distribution and a negative one to a more flattened distribution.

Noteworthy, uterine EMG can be considered as a stochastic process whose samples are not normally distributed [10].

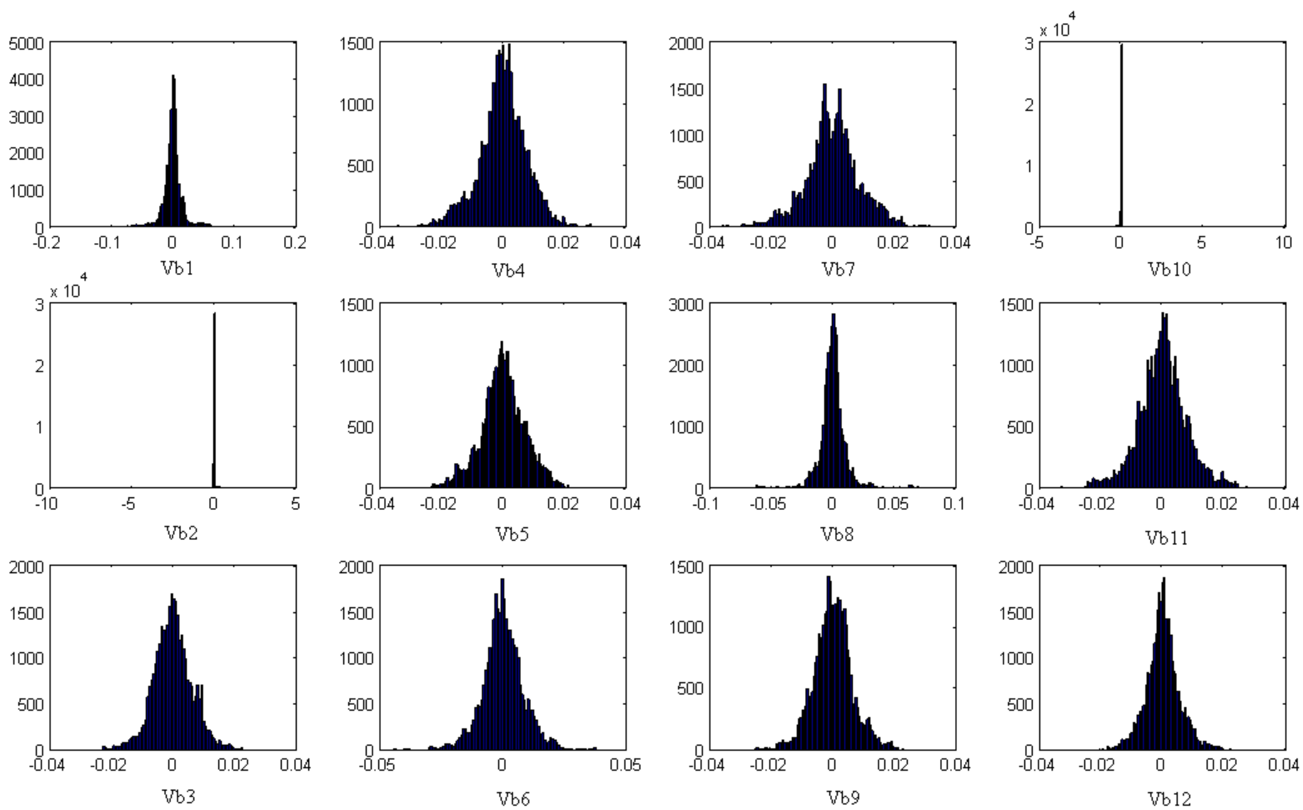
III. RESULTS

Uterine EMG signals were post-processed after the multichannel data acquisition. A total of 30 pregnancy and 30 labor contractions were used in this work. As mentioned above, each contraction has a 12 bipolar signals resolution. First, the recorded signals were divided into 2 datasets representing the 2 classes of signals: normal or non-missing (633 signals) vs. missing or corrupted signals (87 signals). Noteworthy, 25% of the missing signals were pregnancy contractions while 75% were labor contractions. An example of the 12 signals recorded during a burst of electrical activity that occurred at the onset of a term labor is illustrated figure 2.a. This figure shows that not all the signals were successfully recorded during the contraction. Some signals (i.e., Vb_1, Vb_2 and Vb_{10}) should be considered as missing. The corresponding PDFs of the 12 signals are illustrated in figure 2.b. This figure shows that the shape of the distribution may be a powerful indicator when a loss or corruption of a signal has occurred.

Next, the absolute values of skewness and kurtosis were calculated for the 2 groups of signals by using (1) and (2) respectively. The mean and standard deviation values of the 2 descriptors for each class of signals were calculated and compared. The mean value of the skewness calculated from all the non-missing signals was 0.26 (standard deviation = 0.2). However, for the missing signals, the mean value of the skewness was 2.89 (standard deviation = 2.9). As for the kurtosis, its mean value for the non-missing signals was 2.21 (standard deviation = 2.22) and 40.23 (standard deviation = 60.57) in the case of missing signals. Figure 3 shows the comparison between the values of the skewness (fig.3.a) and the kurtosis (fig.3.b) respectively for the 2 classes of signals.



a)



b)

Figure 2 –a) 12 uterine EMG signals recorded during labor contraction; b) the corresponding power density functions (PDF) of the 12 signals

IV. DISCUSSION

The acquisition of bioelectrical signals is today accomplished by means of relatively low-cost equipment which appropriately records, amplifies and digitizes the signal. As a result, several clinical procedures based on bioelectrical signals are in widespread use in hospitals around the world. Such equipments may include one or several sensors. In situations where the recording is performed by using multiple sensors, a missing signal detection algorithm can be of valuable help in the analysis of multichannel recordings. Missing signals can therefore be excluded from the analysis or even reconstructed from the other recorded signals.

Herein, we compared the PDFs of the normal signals with those of the missing signals by means of HOS descriptors in order to detect the missing ones. Based on the fact that the loss of a signal alters its amplitude distribution, HOS analysis can discriminate between normally recorded signals and missing signals. In fact, missing signals showed either higher peakedness or a distribution shift, i.e. long distribution tail. The performance of the proposed approach was evaluated on multichannel uterine EMG signals. Results have shown that missing signals may be detected with more than 95% confidence (using *t*-test).

Although still to be tested, we believe that this approach may be applied to other types of signals usually recorded by multiple electrodes. However, more tests are required to draw a final conclusion. We also believe that the use of a combination of the 2 parameters considered in this study (skewness and kurtosis) may be used as the input of a classifier that can be used to classify the signals between the 2 considered classes (missing or non-missing).

Finally, we believe that this technique is of great importance for enhancing the quality of the database, thus, the confidence and the reliability of the results.

V. CONCLUSION

The higher-order statistical evaluation of both normal and missing multichannel Uterine EMG signals was performed over 30 pregnancy signals and 30 labor signals. From this study, we may conclude that normal physiological signals may be separated from missing signals by means of kurtosis and skewness calculation. Indeed, missing signals are characterized by either high kurtosis, or high skewness, or both in rare cases. The results shown in this paper are of high importance for the assessment of signal quality before any classification and diagnosis process.

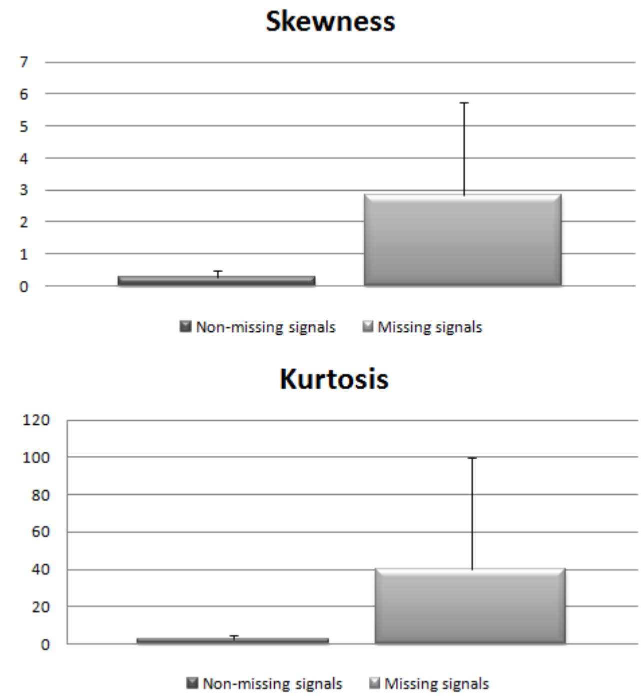


Figure 3 - Average of the absolute values of skewness (top) and kurtosis (bottom) obtained from the two studied classes: non-missing vs. missing signals

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