NON-INVASIVE FETAL HEARTBEAT DETECTION USING THIRD-ORDER CUMULANT SLICES MATCHING AND ANN CLASSIFIERS

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ABSTRACT

Many techniques have been introduced to detect fetal heartbeats during labour. In this paper, the advances in higher-order statistics, non-linear filtering, and artificial neural networks are exploited to propose a hybrid technique to improve the non-invasive detection of fetal heartbeats during labour. The proposed hybrid system uses the mother and fetal third-order cumulants (TOCs), which carry the signature imprints of their respective QRS-complexes, in the signal processing phase. Quadratic and cubic Volterra filters with LMF updates have been employed to synthesise the signal into linear, quadratic, and cubic parts, and retain only the linear part. The classification phase employs an LMS-based single-hidden-layer perceptron. The sensitivity, specificity and classification rate have been calculated. The technique has been evaluated for diagonal, wall, or arbitrary TOC slices, employing both the LMF-based quadratic and cubic Volterra filters. Results have shown a detection rate of 86% of fetal heartbeats during labour.

KEY WORDS

Third-order cumulants, ECG signal, neural network classifiers, non-invasive detection, fetal heartbeats

1 INTRODUCTION

The fetal heart rate (FHR) is a useful tool in the assessment of the condition of the fetus before and during labour [1]. There are several different non-invasive methods used in medical practice for the measurement of the FHR; The ultrasound cardiotocography (CTG), Fetal Magnetocardiography (FMCG) [7], phonocardiography [8-9], and Fetal Electrocardiography (FECG) [1]. FECG uses non-invasive surface electrodes placed on the maternal abdomen is another tool for FHR recording. The fetal signal is very weak relative to the maternal signal and to the competing noise. Widrow et al. [2] proposed an adaptive filtering and adaptive noise cancellation method to extract the FECG from the composite maternal ECG signal. A variant of the same approach was used by Longini et al. [3]. Auto-correlation and cross correlation techniques [4] and spatial filtering techniques [5-6] have been proposed. These methods require multiple maternal thoracic ECG signals. Other methods were proposed for the rejection of the disturbing maternal ECG signal [1]. The automated long-term evaluation of FECG is regarded as less robust than CTG. A failure rate of approximately 30% is quoted as an almost unanimous norm [10]. The advantage of FECG is that it can be implemented in small and relatively low-cost devices [11].

A proposed technique employing wavelet transform [14] exploits the most distinct features of the signal, leading to more robustness with respect to signal perturbations. The algorithm is validated using data with high SNR. Dynamic modelling has been proposed [15]. The data has comparatively high SNR and the fetal heartbeats can be detected by an adaptive matched filter and requires much shorter data samples than the dynamic modelling. Thus, the dynamic modelling apparent success at high SNR is offset by the required lengthy data. Due to the beat-to-beat fluctuations of the shape and duration of the ECG waveform, the normal ECG cannot be considered to be deterministic. Determinism is found in adult and fetal ECGs for data lengths of 10,000 samples [16].

The independent component analysis (ICA) which has been carried out under assumptions [12], the validity of each has been challenged [13]. A third-order cumulants (TOCs) technique for non-invasive fetal heartbeat detection has been proposed [17]. The ECG signal is processed using a Volterra filter. To improve the performance of the Volterra filter, quadratic and cubic LMF Volterra filters have been proposed [18].

This paper proposes incorporating an adaptive cubic LMF Volterra and an artificial neural network classifier to improve the detection rate. The cubic Volterra filter has been shown to improve the performance of some biomedical signals such as electromyographic signals during labour [19]. Cross validation has been done by comparing the results of the detection to QRS peaks of the fetal heartbeat extracted from the fetal scalp electrode which is the goldstandard. The paper is structured as follows. Section 2 describes the theory of TOCs and Volterra filters. Section 3 describes the proposed hybrid technique and the detection operation. Section 4 discusses the implementation of the hybrid technique and shows
typical results for fetal ECG signals. Conclusions are drawn in Section 5.

2 BACKGROUND

2.1 Third-order cumulants and 1-d slices in ECG

Consider a non-Gaussian signal \{X(k)\} with TOCs given by [21]:

\[
\mathbf{C}_3(\tau_1, \tau_2) = \text{Cum}\{X(k), X(k + \tau_1), X(k + \tau_2)\}. \tag{1}
\]

The calculations of the TOCs are implemented off-line due to the large CPU time required to calculate the lags in different dimensions. One way of reducing this load is to use 1-d slices of the TOCs. One-dimensional slices of \(\mathbf{C}_3(\tau_1, \tau_2)\) can be defined as [21]:

\[
r_{21}^x(\tau)\text{Cum}\{X(k), X(k), X(k + \tau)\} = \mathbf{C}_3^x(0, \tau), \tag{2}
\]

\[
r_{22}^x(\tau)\text{Cum}\{X(k), X(k + \tau), X(k + \tau)\} = \mathbf{C}_3^x(\tau, \tau), \tag{3}
\]

where \(r_{21}(\tau)\) and \(r_{22}(\tau)\) represent 1-d wall and diagonal slices, respectively. The former can be obtained from Eq. (1) by assuming \(\tau_1 = 0\), whilst the later obeys the condition \(\tau_1 = \tau_2\). Employing 1-d slices will have the effect of reducing the CPU time by reducing the complexity of the operations. The calculations of TOC slices are comparable to those of autocorrelation and take CPU time of approximately 1 msec unlike TOCs, which take 1 sec to calculate. For a sampling rate of 0.5 KHz and an FHR of the order of 120 bpm, a real-time system can be easily implemented. An algorithm which calculates any arbitrarily chosen off diagonal and off wall one-dimensional slice, and hence reduce the CPU time by 99%, has been developed [18].

Adequate knowledge of the TOC of both the mother’s and fetal ECG signals must first be acquired in order to pave the way for fetal QRS-complex identification and detection. There are several motivations behind using TOC in processing ECG signals; (i) ECG signals are predominantly non-Gaussian [22], and exhibit quadratic and higher-order non-linearities supported by third- and fourth-order statistics, respectively. (ii) Gaussian noise diminishes in the TOC domains if the data length is adequate [21]. This implies that it is possible, under certain conditions, to process the ECG signal in Gaussian noise-free domains. For ECG signals a minimum length of 1 sec is adequately long to suppress Gaussian noise in the TOC domains, whilst not long enough to violate Hinich’s criterion of “local” stationarity [23]. In general, ECG signals are non-stationary in the statistical sense, but relatively short data can be successfully treated with conventional signal processing tools primarily designed for stationary signals. For example, when dealing with individual cardiac cycles, non-stationarity is not an issue but when one takes on board the heart rate time series which is chaotic and multi-dimensional then it is not wise to assume stationarity for analysis purposes [16], (iii) In the TOC domain all sources of noise with symmetric probability density functions (pdfs), e.g., Gaussian and uniform, will vanish. The ECG signals are retained because they have non-symmetric distributions [17]. (iv) ECG signals do contain measurable quantities of quadratic and, to a lesser extent, cubic non-linearities [13]. Such measurable quantities of non-linearity if not synthesised and removed before any further processing for the purpose of signal identification and classification could lead to poor performance with regard to fetal QRS-complex detection rates.

2.2 LMF quadratic and cubic Volterra

The Volterra structure is a series of polynomial terms [24], which are formed from known values of a given time sequence \(y(k)\). The output of the filter is expressed in the form

\[
y(n) = \sum_{i=1}^{N} a_{1i} x_{k-i+1} + \sum_{i=1}^{N} \sum_{j=1}^{i} a_{ij} x_{k-i+j} x_{k-2i+j} + \ldots \tag{4}
\]

Adaptive conventional Volterra is updated using the least-mean squares (LMS) criterion. The least-mean-square (LMS) algorithm minimises the expected value of the squared difference between the estimated output and the desired response. A more general case is to minimise \(\mathbb{E}[e(n)]\) [25]. \(N = 1\) is the Least-Mean-Square (LMS) and \(N = 2\) is the Least-Mean-Fourth (LMF). The LMF algorithm updates the weights as follows:

\[
a_i(n + 1) = a_i(n) + 2\mu_i . e(n) . x(n). \tag{5}
\]

The LMF has, in general, a faster convergence than the LMS algorithm. It has generally a lower weight noise than the LMS algorithm, with the same speed of convergence. It was shown to have 3 dB to 10 dB lower mean-squared error (MSE) than the LMS algorithm [25]. Adaptive LMF-based quadratic and cubic Volterra structures have been developed and shown to outperform LMS-based Volterra by 6-7 dBs [18].

2.3 Neural Network classifiers

A major limitation of the back-propagation algorithms is the slow rate of convergence to a global minimum of the error-performance surface because the algorithm operates entirely on the gradient of the error-performance surface with respect to the weights in the single-hidden-layer perceptron. The back-propagation learning process is accelerated by incorporating a momentum term. The use of momentum introduces a feedback loop which prevents
the learning process from being stuck at a local minimum on the error-performance surface of the single-hidden-layer perceptron. The classifier is a single-hidden-Layer Perceptron based on a modified Back-Propagation technique [13]. The modified back-propagation algorithm has a momentum term which helps to avoid local minima [13]. One hundred and sixty one-dimensional TOC slices have been used as templates for the desired signals in the Artificial Neural Network (ANN) classifier.

3 THE PROPOSED HYBRID TECHNIQUE

3.1 Detection operation

3.1.1 Creating ECG cumulant database

3.1.2 Detecting the maternal QRS-complexes

This step includes sequential reading of the ECG recording and processing each of the 90% overlapping windows (length 250 msec) to compute the diagonal or wall slice TOC. The slice is then matched to the templates until a maternal QRS-complex is detected. Once the first maternal wall and diagonal TOC slices have been detected, an auxiliary subroutine is used to accurately pinpoint the position of the R-wave. If the second successive segment detects a maternal QRS-complex then it is discarded because it is the same complex detected twice in two adjacent windows. The whole process of window TOC template matching technique is repeated until the second maternal QRS-complex is detected and its R-wave is pinpointed. The maternal heart rate is accurately calculated from the knowledge of the current and previous R-wave positions.

3.1.3 Detecting the fetal cardiac cycles

The search for the fetal cardiac cycle begins from the position of the detected maternal R-wave. Window overlapping, each with fetal cumulant template matching, continues until the first, second, and possibly third fetal ECG TOC diagonal and wall slice signatures have been matched to at least one corresponding template for each one of them. Once the slices have been template matched, the window will be flagged as a detection window. If the next overlapping window detects a fetal heartbeat, it will be discarded because it is the same fetal heartbeat that has just been detected in the previous window. The number of fetal heartbeats detected within the maternal cardiac cycle is counted. The instantaneous maternal heart rate is previously known with some degree of accuracy, and the relative fetal to maternal heartbeat is also known within the maternal cardiac cycle. Hence, the averaged fetal heart rate can be calculated within each maternal cardiac cycle. Operations 2 and 3 are repeated for all individual maternal cardiac cycles.

3.2 ECG segmentation and window minimum length

The duration of the fetal cardiac cycle varies from 250 msec to 500 msec for a range of fetal heart rate between 240 bpm and 120 bpm. The fetal QRS-complex itself occupies between 50 msec and 70 msec. The fetal heartbeat is detected in a flag window of length 250 msec. This window length serves two criteria; (i) it is the minimum length yielding an acceptable upper threshold of both the deterministic and stochastic noise types inherent in the higher-order statistics of the ECG signals encountered, and (ii) this window length allows the detection of one, two, three, or four fetal heartbeats (FHBs) within one maternal transabdominal cardiac cycle. For example, for maternal heartbeats of 60 bpm, the R-wave-to-R-wave = 1000 msec, and four segments x 250 msec = one maternal cardiac cycle = possible four fetal cardiac cycles.

3.3 Window overlapping

When detecting the fetal heartbeat within the maternal transabdominal cardiac cycle, 90% overlapping windows, each of 250 msec duration, are scanned at a rate of 100 Hz with a sampling rate of 0.5 KHz. The overlapping percentage should be carefully chosen to compensate for the apparent loss of temporal resolution due to a lengthy window which is dictated by the maximum threshold of the variance of the TOCs. Assuming that the average fetal QRS-complex duration is 60 msec, this may be encountered at the beginning, middle, or end of the flag window. Hence by using a window overlapping of 90%, any fetal QRS-complex which may be missed because it starts to evolve, say, 20 msec before the end of a window, can definitely be picked up by the next one or two overlapping windows when it completes its full duration of 60 msec and has definitely reached its full peak (the R-wave). If this particular QRS-complex has enough strength to be picked up by two successive overlapping windows, the algorithm will count it as one FHB. It has been found that reducing the overlapping below 90% yielded missed fetal heartbeats.

3.4 Calculation of an averaged fetal heart rate

The instantaneous fetal heart rate is calculated by measuring the interval between two successive R-waves and this requires pinpointing accurately the R-point of the QRS-complex. Although the ECG TOC template matching technique is very effective in detecting the occurrence of the QRS-complex as a whole even when it is completely buried in noise, it cannot locate the R-wave over a window length of 250 msec which satisfies the criterion for the variance threshold. In most transabdominal ECG recordings (85%), the fetal QRS-complexes cannot be seen as they are completely masked by other signals and motion artefact. This obscurity accounts for the lower success rate of fetal heartbeat
detection in all other reported and appropriately assessed fetal heartbeat detection techniques [1].

The adult heartbeats can be measured accurately and the instantaneous heart rate for adults can be calculate. Hence, by counting the number of fetal heartbeats (FHBs) that have occurred between two successive maternal R-waves, one can easily calculate the averaged FHR within the maternal cardiac cycle. On average, the maternal cardiac cycle is 1000 msec. Two maternal cardiac cycles measure 2 sec. So, detecting and displaying up to eight FHBs will take less than 2.000030 sec which is well within the manufacturers’ detection-to-display interval of 3.75 sec.

4 DATA COLLECTION AND RESULTS

4.1 Data collection

The AEMG measurement included data obtained from pregnant women at various stages of gestation [18]. This was achieved, with the consent of women, using a pair of electrodes, Sonicaid 8000, a Pentium IV PC and an interface card. The software used for the attractor calculations was MATLAB 8.0. Ag-AgCl Beckman electrodes of 8 cm in diameter, and 25-cm spaced centres were positioned on the abdominal wall after careful preparation of the skin, which lowers the interelectrode impedance of 10 kΩ. The electrode pair is set over the umbilicus, and lined up with the median vertical axis of the uterus. The ground electrode is located on the woman’s hip.

The training data involves using third-order cumulants and their slices of segments of fetal scalp electrode measurement. These are used to compare with results obtained from the transabdominal ECG recording. The testing data is the transabdominal ECG recording.

4.2 Results

4.2.1 TOCs and their diagonal and wall slices

An optimised third-order Volterra structure is employed to decompose the ECG signal into its linear, quadratic, and cubic parts and retain only the linear part. Fig. 1 depicts five maternal transabdominal ECG signals with segmentation and their corresponding TOCs and their diagonal and wall slices for predominantly maternal QRS-complexes, the first fetal heartbeats with maternal contribution, QRS-free ECGs, and the second fetal heartbeats with maternal contribution. The diagonal and wall TOC slices of the maternal QRS-complexes, segment (I) in Fig. 1, are easily distinguished from the diagonal and wall TOC slices of segments (II), (III), and (IV). Furthermore, the diagonal and wall TOC slices of the fetal heartbeat segments, (II) and (IV) in Fig. 1, are distinguishable from the corresponding diagonal and wall TOC slices of the QRS-free ECG segments (III). However, in some cases, those of segments (II) and (IV) could be mistaken for QRS-free ECG segments. Note that the peaks of the QRS-free ECG segments are much narrower and more related to motion artefact than a signal.

4.2.2 The NN classifier

A single-hidden-layer perceptron is used for the classification of the TOC slices of the maternal QRS-complexes, the first fetal heartbeat with maternal contribution, QRS-free ECG, and the second fetal heartbeat with maternal contribution from maternal transabdominal ECG segments. This is achieved using a standard back-propagation with momentum algorithm [20]. Each of the input and output layers has a dimension of 8 x 8 and the hidden layer has a dimension of 5 x 5. The input to the first layer is the TOCs diagonal and wall slices. The network is trained using TOC slice templates obtained from the maternal chest and fetal scalp electrode ECGs as well as previously detected and earmarked transabdominal ECG segments. The latter training sequences are templates of the diagonal and wall slices of the TOCs of four segments from maternal transabdominal full cardiac cycles. The input to the network is eight template patterns. These are the TOC diagonal and wall slices of four segments from one transabdominal cardiac cycle. For example the first pair are maternal slices, the second pair are fetal slices, the third pair are QRS-free slices, and the fourth pair are fetal slices. The network is trained over the eight patterns. The training terminates when the worst error in all patterns in one pass is less than 0.1. Typically the average error will be in the range of 0.001.

The TOC slice templates are used as input to the classifier. Each one of the 10 templates in each set is used as an input and the weights of each neuron in the classifier are optimised by changing the learning rate and the momentum constant until the error is minimised. Then the transabdominal ECG signal with 250-msec window is used as an input to the classifier. The instantaneous weights of the input signal are compared to those of the templates which are stored in the memory. The two sets of parameters are correlated. Once a signal is classified the output will be set to 1. The classification of the four segments involves a pattern-by-pattern updating rather than batch updating for the weight adjustments. This is more suitable to speed up the performance. Pattern-by-pattern updating tends to be orders of magnitude faster than batch updating. However, it should be noted that pattern-by-pattern updating is harder to parallelise.

4.2.3 Cumulant matching of the fetal heartbeats

Each one of the four transabdominal ECG segments (data length 250 msec) has ten corresponding templates used for matching. An optimised cubic Volterra structure is employed to synthesise the four transabdominal ECG segments and the corresponding templates.
4.2.4 The maternal heartbeat classification rates

The classification rate is 100% for maternal QRS-complexes using the TOC template matching technique with single-hidden-layer classification. To calculate the maternal heart rate an auxiliary method to pinpoint the R-wave employing an adaptive thresholding has been used. Note that this is not accurate when one deals with deformed QRS-complexes in heart patients. The data obtained include all mothers’ ECGs exhibiting normal-to-the-patient QRS-complexes. The instantaneous maternal heart rate is calculated by dividing 60 by the R-to-R interval (in seconds). The application of this auxiliary routine leads to a maternal heart rate with an accuracy of 99.85%.

4.2.5 Classification rate for the hybrid technique

Table 1 shows the fetal heart detection quality and classification rate using transabdominally-measured ECGs and their respective TOC diagonal or wall slices with and without linearisation. The combined diagonal and wall slices improve the classification rate by about 1% over and above that achieved by either slice. A further improvement of about 1% is achieved by using two off-diagonal and off-wall slices. A second-order Volterra synthesiser results in a higher detection rate of 83.49%. The highest achievable classification rate for non-invasive fetal heartbeat detection using the first hybrid system is 86.16% when a third-order Volterra synthesiser is employed in conjunction with single-hidden-layer classifiers. Note that the classification rate for coincident mother’s and fetal QRS complexes is 0%.

Table 1

<table>
<thead>
<tr>
<th>TOC matching template slice type with and without linearisation using Volterra and in conjunction with ANN classifiers</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>False Positives</th>
<th>False Negatives</th>
<th>Classification Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOC Diagonal/Wall slice</td>
<td>76.24</td>
<td>79.38</td>
<td>24744</td>
<td>28512</td>
<td>77.81</td>
</tr>
<tr>
<td>TOC Diagonal and Wall slices</td>
<td>77.13</td>
<td>80.24</td>
<td>23712</td>
<td>27444</td>
<td>78.74</td>
</tr>
<tr>
<td>TOC Diagonal, wall, diagonal &amp; wall, and an off-diagonal 22.5° slice</td>
<td>78.04</td>
<td>81.18</td>
<td>22584</td>
<td>26352</td>
<td>79.69</td>
</tr>
<tr>
<td>Linearised diagonal/Wall slice using 2nd order adaptive LMF Volterra synthesiser</td>
<td>82.37</td>
<td>84.61</td>
<td>18468</td>
<td>21156</td>
<td>83.49</td>
</tr>
<tr>
<td>Linearised diagonal/Wall slice using 3rd order adaptive LMF Volterra synthesiser</td>
<td>84.46</td>
<td>87.85</td>
<td>14500</td>
<td>18648</td>
<td>86.16</td>
</tr>
</tbody>
</table>

Fig. 1. (a) Transabdominally-measured ECG (Code: 16-23) showing segmentation (segments I, II, III, and IV, each 250 msec). (b) The TOCs and their diagonal and wall slices (insets) for the QRS-free ECG (l.h.s.) and the second fetal heartbeat with maternal contribution (r.h.s.). \( \tau_0, \tau_1, \) and \( \tau_2 \) are, respectively, the reference, first and second time lags of the TOCs.
5 CONCLUSION

5.1 Parameters of the single-hidden layer perceptron

The network has been optimised in terms of its learning rate, momentum constant, and hidden layer size to achieve the minimum mean-squared error. The optimum learning rate is found to be 0.8. The optimum momentum constant is found to be 0.99 and 0.90 for the maternal QRS-complex and the fetal heartbeat with maternal contribution segments, respectively. The single-hidden-layer has an optimum dimension of 5 x 5. The input to the first layer is the TOCs diagonal and wall slices. The network is trained using TOC slice templates. The input to the network is eight template patterns. These are the TOC diagonal and wall slices of four segments from one transabdominal cardiac cycle. The network is trained over the eight patterns. The training terminates when the worst error in all patterns in one pass is less than 0.1. Typically the average error will be in the range of 0.001.

5.2 The classification rate for fetal heartbeat segments

The results of the first hybrid system indicates that a linear combination of diagonal and wall slices of the TOC can improve the detection rate by up to 1% over and above the 77.8% obtainable using only either slice. Using two more arbitrary slices off-diagonal and off-wall would result in a further improvement of up to 1%. Using two slices instead of only one results in an two-fold increase in the CPU time of 1 msec using Unix WS.

Further improvement of 6% to 8% is attainable with maternal transabdominal ECG signal linearisation employing second- and third-order Volterra syntheses, respectively. Based on the first hybrid system using TOC slices for signal processing and subsequent single-hidden-layer classification, 100% and 86.16% classification rates have been achieved for maternal QRS-complex and fetal heartbeats, respectively. Note that the classification rates for coincident and non-coincident mother’s and fetal QRS-complexes are 0% and 95.55%, respectively. The remaining undetected 13.84% fetal heartbeats include 9.8% overlap with the maternal QRS-complexes and 4% occur during depolarisation of the maternal T-waves. Those events unavoidably lead to significant distortion of the fetal TOCs. This means that the cumulant signatures will not be close to the TOC template signature stored in the database. Examples of false negatives and false positives have been found in the following cases, respectively, (i) a fetal heartbeat with maternal contribution TOC diagonal slice was wrongly matched to a QRS-free ECG TOC diagonal slice template, and (ii) a QRS-free ECG TOC diagonal slice was wrongly matched to a fetal heartbeat with maternal contribution TOC diagonal slice template.

REFERENCES