Characterization of Fetal Heart Rate Irregularity Using Approximate Entropy and Wavelet Filtering

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Abstract

Approximate Entropy (ApEn) has been used by several researchers as a means to characterize the irregularity of fetal heart rate (FHR), a major contributor to fetal risk assessment. The present work starts by analyzing the influence of accelerative and decelerative (AD) components of the FHR signal in the computation of ApEn. Having shown that the AD components may completely distort the ApEn evaluation we proceed to present two methods of eliminating the influence of the AD components: wavelet filtering; AD detection using specific algorithms based on well-established physiological criteria. We obtained good results with the first method when applied to simulated signals; however it proved unreliable in the practical application of discriminating normal from pathological fetal FHR. With the second method we were able to achieve this discrimination with high statistical significance.

1. Introduction

Since Steve Pincus [1] introduced the approximate entropy (ApEn) measure to assess the degree of randomness of sequences of numbers, ApEn found several applications in the characterization of physiological time series. The good convergence property of ApEn [2] is the major reason of its attractiveness for characterizing the irregularity of physiological time series, since these can only be considered stationary in relatively short time segments. In other words, ApEn does not need the large amounts of data that other competitor measures (spectral, fractal or other types of entropic measures) need. Steve Pincus himself applied ApEn to FHR [3]. Other authors also tried ApEn as a descriptor of heart rate irregularity and compared it with other descriptors [4-8]. Issues such as FHR irregularity during fetal development [4-6], heart rate dynamics in short periods [7], discrimination of normal from abnormal fetuses [8] have been analyzed with ApEn. In all these works the influence of AD components was not addressed. In our previous work [11] we showed that ApEn was able to discriminate three categories of behavioral patterns: calm sleep; calm vigilance; pathological flat-sinusoidal condition. These were expressly chosen because we could analyze sample tracings of these categories devoid of AD components. In the present work we analyze in detail the AD component issue and propose methods to deal with it. One of the methods yielded good results when applied to the discrimination of normal from pathological fetuses in the last intrapartum phase (just before expulsion).

2. The AD component issue

We used 25 tracings of simulated FHR containing several types of accelerative and decelerative events [10]. All tracings were 2000 samples long. To these tracings was added random noise with uniform distribution and with 1, 2, 5 and 10 bpm amplitudes (see Fig.1). The theoretical ApEn values of the noise are (ln(k)): 1.086, 1.6094, 2.3979 and 3.0445, respectively.

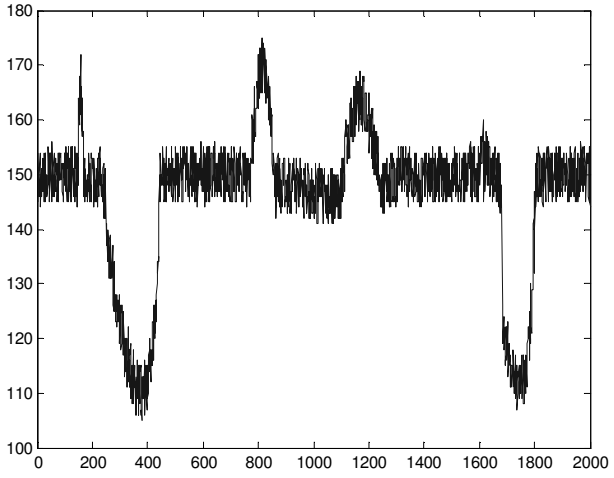

Fig. 1. An example of simulated FHR with added noise. (In all figures the horizontal axis is the sample number and the vertical axis is the FHR value in bpm.)

We next computed the ApEn of AD+noise with the following parameters:

- m (embedding dimension): 1, 2.
- r (noise threshold): 0, 0.1sd, 0.2 sd

Table 1 shows the results for m = 1. Similar results were obtained for m = 2. The ApEn values for the noise alone agree very well with the theoretical values. On the other hand, statistical t-tests for paired samples showed significative ($p \approx 0$) differences between the ApEn values of the noise when compared with AD+noise, independently of the r method being used.

Table 1 mean (standard deviation) of the 25 ApEn values.

	1 bpm	2 bpm	5 bpm	10 bpm
noise	1.097 (.007)	1.605 (.002)	2.376 (.003)	2.955 (.009)
AD+noise (r = 0)	1.483 (.013)	1.890 (.014)	2.473 (.011)	2.806 (.016)
AD+noise (r = 0.1 sd)	0.474 (.150)	0.627 (.113)	1.251 (.008)	1.838 (.011)
AD+noise (r = 0.2 sd)	0.194 (.022)	0.285 (.031)	0.740 (.008)	1.290 (.010)

The conclusions are as follows:

- AD components have a statistical highly significant influence on the computed ApEn values whatever r method is used.
- In our experiments with m = 1 the ApEn value for AD+noise was on average 5.7 times *smaller* than the ApEn of the underlying noise. For m = 2, was on average 8 times *smaller*. Thus, the presence of AD completely shadows the underlying irregularity of the signal.
- The largest average deviations occurred when the ApEn was computed with r = 0.1sd and r = 0.2sd, popular r values used e.g. in [6] and [8].

We also performed experiments with colored noise having several degrees of sample correlation (obtained by filtering the uniform noise by a 1st order autoregressive system). The conclusions were basically the same. The average deviations for the ApEn values computed with r = 0.1sd and r = 0.2sd versus the ones computed with r = 0 were even bigger (30 to 50 times bigger!).

3. ApEn of wavelet filtered signals

A proved method for the efficient linear removal of wide band artifacts (in this case, the AD components) is by means of wavelet filtering. In our case we tried 36 different types of wavelets (from the symlet, coiflet and daubechies families) and decomposition levels. Fig. 2 shows an example of AD estimation obtained by applying a symlet 2 wavelet filtering with 2 decomposition (analysis) levels. For the 25 simulated AD signals with added noise we performed this type of filtering, subtracting afterwards the estimated AD component. The ApEn values computed with m=1 and r=0, on the remaining estimated noise signals, were in tight agreement with the original noise ApEn: an average deviation of 0.0024, i.e., about 0.2% or less. The t-Student p value was 0.86.

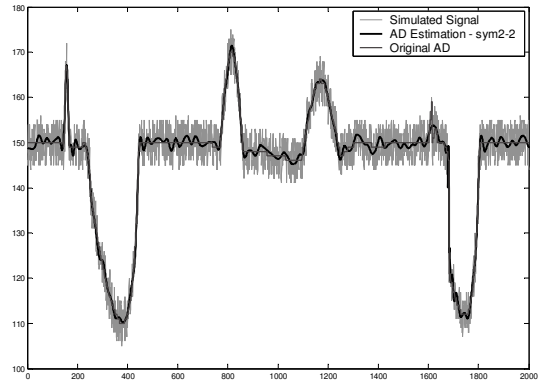

Fig. 2. AD estimation (black) by wavelet filtering (sym2; level2). The estimated AD closely agrees with the original one.

The application of this method to real FHR signals was, however, disappointing. One of the main problems is the systematic overestimation of the AD components by the wavelet filtering method. Since it is a linear method, wavelet filtering is unable to draw a sharp distinction of what it is and is not an AD component. This is exemplified in Fig. 3. The systematic overestimation of the AD component made more difficult the search for the "best" wavelet and yielded unreliable ApEn values.

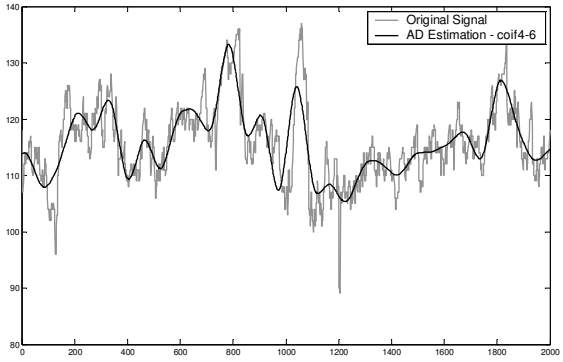

Fig. 3. An overestimated AD component obtained by wavelet filtering with coiflet 4 and using 6 decomposition levels.

4. Discrimination of normal and pathological intrapartum FHR

The second method of AD removal consists of the application of specific algorithms of AD detection. We used the SisPorto system developed at our Center [9] for this purpose. The algorithms are based on well-established clinical criteria, namely the FIGO guidelines of CTG analysis. We had available 37 FHR tracings corresponding to the last 20 minutes before birth: 28 corresponding to normal situations (17 collected in Portugal, 11 collected in Finland); 9 corresponding to pathological situations. All classifications (normal, pathological), performed by expert obstetricians, were based on umbilical pH (respectively pH<7.10 or pH>7.20), fetus weight and Apgar index.

The 37 tracings were processed by SisPorto and all AD components marked in the tracings. All segments corresponding to AD components were removed; all spikes were removed as well. The remaining segments were concatenated (resulting in segment lengths of 1600 up to 3200 samples) and the ApEn values with $r = 0$ computed for embedding dimensions $m = 1$ and $m = 2$. Fig. 4 exemplifies the concatenation process. Table 2 and Fig. 5 summarize the results. The irregularity loss for the pathological cases is completely clear.

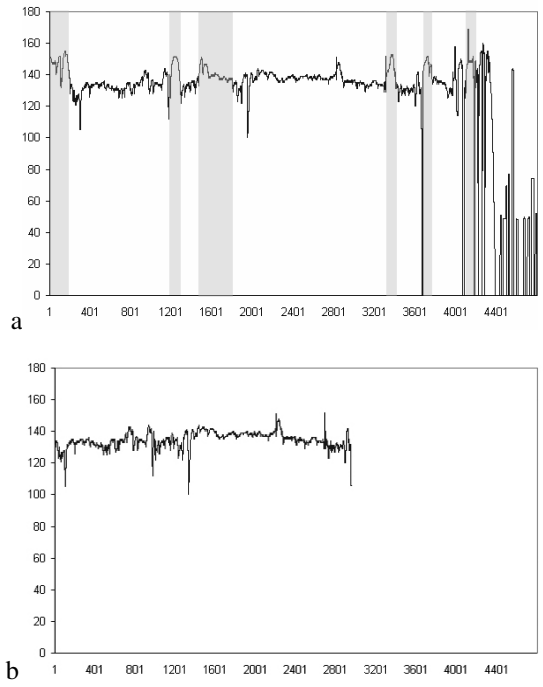

Fig. 4. a) Last 20 minutes of an intrapartum FHR with detected accelerations shadowed gray; b) concatenated FHR after the removal of accelerations and spikes.

Table 2. Mean (standard deviation) of ApEn. The *p*-value is for the Mann-Whitney two-sample test.

m	FHR type	*m* (*sd*)	*p*-value
m = 1	Normal	1.31 (0.23)	0.0134
	Pathological	1.05 (0.26)	
m = 2	Normal	1.06 (0.14)	0.0015
	Pathological	0.83 (0.18)	

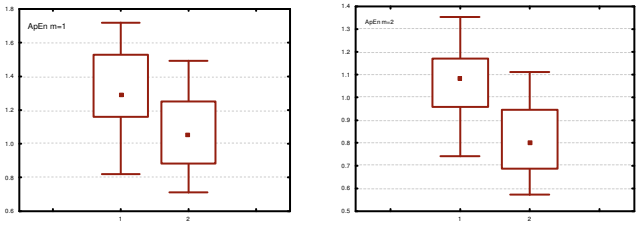

Fig. 5. Box plots of the ApEn values for class 1 (normal cases) and class 2 (pathological cases).

5. Discussion and conclusions

Fetal heart rate, as other types of heart rate, exhibits two sorts of random events: individual bursts of accelerative or decelerative behaviour occurring randomly in time, triggered by external stimulus; a systematic, continuous, random behavior (strictly, a random process) whose internal cause is not yet entirely explained but no doubt related to the highly non-linear dynamics of the heart tissue stimulation. Loss of randomness of this second component is indicative of loss of "plasticity" of the dynamic heart system to adjust to new situations. As shown in other works, using other measures of randomness (viz. spectral and fractal measures), this loss of plasticity corresponds to a loss of heart rate irregularity in old age and/or pathological situations.

We are interested in characterizing the randomness of the second component; not the first one, the AD component. However, if we apply ApEn to the heart rate signal as a whole we cannot escape suffering the influence of the AD component. This issue has been completely overlooked by previous works. We have shown what a dramatic influence the AD component can have in the computation of ApEn, completely shadowing the irregularity one wants to measure. Also, in practically all previous works using ApEn for heart rate characterization a noise threshold $r = 0.1$ sd up to $r = 0.2$ sd has been used. This certainly makes sense if one has reasons to believe the presence of "another noise" besides the irregularity one attempts to characterize. We do not see any justification for such a belief in the present case.

As a matter of fact, in those works retaining the AD component the use of r = 0.1, 0.2 sd even worsens the estimates.

In simulated AD components with added white or colored noise it is possible to determine the ApEn of the noise by first performing wavelet filtering of the AD component. The obtained ApEn values are in close agreement with the target values (deviation on the order of 0.2% or less). The application of the same method to real FHR signals didn't produce, however, such good results. The problem lies in the overestimation of the AD components when dealing with real signals; some of the true irregularity is wrongly filtered out.

We were able to achieve with ApEn (r = 0; m = 1, 2) a high level of discrimination (see Table 2) between normal and pathological intrapartum FHR tracings by "exact" removal of the AD components. By "exact" we mean using the clinical criteria for AD detection as implemented in our SisPorto system (for details on the AD detection algorithms see [9]). These are promising results on the practical usefulness of ApEn.

References

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