EEG ANALYSIS: IMPROVEMENT OF SIGNAL AVERAGING AND COMPARISON
WITH A BEAT TO BEAT APPROACH USING ADAPTIVE IDENTIFICATION

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The purpose of this paper is fine analysis of High Resolution ECG recorded on body surface. Two approaches are investigated: signal averaging and beat to beat estimation. The results presented show the efficiency of a new triggering method with this method the T wave can be chosen as triggering signal. In the second approach, each cardiac beat is assumed to be the impulse response of an ARMA model in a state variable form. Model parameters and signal estimation are adaptively performed by a particular smoothing algorithm: the Generalized Partitioned Algorithm (GPA).

In conclusion we can say that beat to beat estimation gives information which must be completed by the one coming from averaging.

1. INTRODUCTION

In this paper we discuss fine ECG analysis by High Resolution methods [1, 2, 3]. We are interested in either the fine structure of classical ECG waves (specially P wave) or the extraction of cardiac micropotentials. ECG records are made on body surface with classical acquisition systems.

Usually signal-to-noise ratio improvement is made by signal averaging. The efficiency of this method mainly depends on signal alignment accuracy and on shape constancy. To improve alignment accuracy we brought out a new method of time delay estimation (TDE) [4, 5]. We present here applications to light exercise ECG. Signal averaging allows the only extraction of recurrent signals and shows what is permanent in a beat series. In such a way, eventual variations from one beat to another are rubbed out. Therefore we apply smoothing, filtering and adaptive algorithms in order to obtain a beat to beat estimation. Finally we discuss the application of these two approaches.

2. THEORY

2.1. Signal Averaging

To perform synchronous signal averaging a fiducial trigger point is currently generated by detecting QRS complex. Signal alignment accuracy depends on the trigger point stability and the constancy of the distance between the trigger point and the signal to extract. With R waves detection good results are obtained for the extraction of low potentials near the QRS complex and physiologically linked to it (e.g. His bundle potential).

Our TDE method enlarges possibilities for choosing other waves than the R one, to ensure synchronisation (e.g. P or T waves). Then the jitter phenomenon influence is reduced when extracting low potentials near P or T waves.

TDE method: Consider two signals having same shape \(s(t)\) and \(v(t) = k \cdot s(t-d)\) assumed to be positive on the interval \([a, b]\), and let \(S(t)\) and \(V(t)\) be their normalized integrals \((S(a)=V(a)=0; S(b)=V(b)=1)\). One can compute delay \(d\) by the formula:

\[
\begin{align*}
    d &= \int_{a}^{b} (S(t)-V(t)) \, dt \\
    &\text{Consider now} \quad V_{\tau}(t) = V(t-\tau). \text{ Application of (1) to } S(t) \text{ and } V_{\tau}(t) = S(t-(d+\tau)) \text{ gives} \\
    Q(\tau) &= \int_{a}^{b} (S(t)-V_{\tau}(t)) \, dt = d+\tau
\end{align*}
\]

So, without noise \(Q(\tau)\) is a straight line with a zero crossing at \(\tau = -d\). In presence of noise, the estimation \(\hat{d}\) of \(d\) makes use of this linearity. \(\hat{s}(t)\) and \(\hat{v}_{\tau}(t)\) representing noisy quantities, for a series of values \(\tau_i\), (2) becomes:

\[
\begin{align*}
    \hat{Q}(\tau_i) &= \int_{a}^{b} (\hat{s}(t)-\hat{v}_{\tau_i}(t)) \, dt \\
    \text{The linear regression } y = mx + b \text{ of } \hat{Q}(\tau_i) \text{ versus } \tau_i \text{ gives the estimation } \hat{d} \text{ of } d: \\
    \hat{d} &= \hat{b}/\hat{m}
\end{align*}
\]

2.2. Every Beat Estimation

For immediate diagnostic and prognostic application, extraction of cardiac activity on a beat to beat basis is highly desirable [5, 6]. The problem under consideration is the estimation of a deterministic unknown signal corrupted by an additive noise (SNR< 0dB). In such a case, standard Automatic Control techniques are poor of
results [7]. Recent researches [8] show a new smoothing identification approach to solve this problem.

**Signal modeling:** The deterministic signal is assumed to be the impulse response of a linear invariant system represented by an ARMA model in a state variable form. Consider the signal \( z(k) \) defined by

\[
(5) \quad z(k)=a_1 z(k-1)+\ldots+a_n z(k-n)+b_1 u(k-1)+\ldots+b_n u(k-n)
\]

Where \( u(.) \) represent the impulse input. One can consider that the desired signal \( z(k) \) is generated by a "autonomous" system starting from non-zero and unknown initial conditions. So (5) can be written in the following state form:

\[
(6) \quad\begin{cases}
 x(k+1)=J x(k) + \theta(k) z(k) ; x(0)=x_0 \neq 0 \\
 y(k)=C x(k) \\
 y(k)=z(k)+v(k)
\end{cases}
\]

Where

\[
 J = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \\ \end{bmatrix}, \quad \theta(k) = \begin{bmatrix} -a_1 \\ -a_2 \\ \vdots \\ -a_n \\ \end{bmatrix}
\]

and \( v(k) \) is assumed to be a white gaussian noise. In such a case both estimates of the parameter vector \( \theta(k) \) and the initial state \( x(0) \) can be achieved by a particular smoothing algorithm: the Generalized Partitioned Algorithm (GPA) developed in [9].

The GPA: in the GPA the initial state vector is partitioned into a nominal state and a remainder assumed to be independent and gaussian

\[
(7) \quad x(0) = x_n(0) + \Delta_x(0)
\]

In the augmented model defined in [9] a particularly interesting partitioning choice is

\[
(8) \quad x_n(0) = \begin{bmatrix} x(0) \\ -\theta(0) \end{bmatrix}, \quad \Delta_x(0) = \begin{bmatrix} 0 \\ \tilde{\theta}(0) \end{bmatrix}
\]

This choice gives separate smoothing equations of \( x(0/N) \) and \( \tilde{\theta}(0/N) \). At each iteration \( j \) a reference trajectory is generated by a nominal Kalman filter conditioned on \( \tilde{\theta}_{j-1}(0) \) and starting with \( \tilde{x}(0) \) and \( P(0) \). Convergence is reached when \( \|
\begin{bmatrix} \tilde{x}_{j-1} \\ \tilde{\theta}_{j-1} \\ \end{bmatrix} - \begin{bmatrix} \tilde{x} \\ \tilde{\theta} \end{bmatrix}\| \leq \epsilon \) is fulfilled. Notice that only a \( n \times n \) matrix inversion is necessary. Signal reconstruction is obtained by the application of a Kalman filter starting with the last smoothed values of the initial state \( x(0/N) \) and the error covariance matrix \( P(0/N) \).

3. RESULTS AND DISCUSSION

ECG signals have been recorded at the "Laboratoire de Cardiologie - Hôpital Pasteur (Dr. A. VARENNE). After a linear amplification \((x10^5)\), the signal has been passed through a bandpass filter \(0.5-300 \text{ Hz.} \) Then signals were recorded on to magnetic tape. Data acquisition was made using a sampling rate of \(1000 \text{ Hz} \) and a 12 bits quantization for an input level of \( \pm 10 \text{ V.} \)

Before QR6 detection, signals have been pre-processed by a digital moving average band-pass filter as that proposed in [10]. The number of samples in the two averagers were chosen in order to remove base line variations and high noise frequencies (above \(60\text{Hz} \)). Records were made in the recovery phase after a light exercise in normal and healthy young persons (car-

![Fig.1. Averaged P wave of 20 and 80 signals](image)
3.1. Signal averaging

In order to check our triggering method we compare the averaged signals obtained by:

1st - R wave detection using a standard level threshold technique.

2nd - triggering on P wave (fig.1) and on T wave (fig.2) using our method.

Figure 1 shows an example of P wave averaging. In figure 2 we can compare an averaged TP interval using as triggering signal: R wave (a), P wave (b) and T wave (c). Comparing Fig. 1 (a) and (b) one can verify that mean shape is preserved better in (b) than in (a). Moreover "low potentials" pre and post P can be seen in (b) and are rubbed out in (a) by the jitter phenomenon due to PR variations. The example of fig. 2 shows how recurrent "low potentials" on TP interval linked to the T wave can only be extracted by triggering on T wave itself (c) and not on R(a) or next P wave (b).

3.2. Beat to beat estimation

We applied the GPA to the same records as those processed in fig.1. Figure 3 shows in (a) three P waves before processing and (b) the same three waves estimated by the GPA. Notice that we assume no a priori knowledge: $g(0) = 0$ and $x(0) = 0$. Convergence was reached in 5 or 6 iterations. Like in [11] we verify a rather good reconstruction of the desired signal, nevertheless the simplicity of the chosen model: second order and time invariant.

3.3. Discussion

In this paper we tried to improve two weak points of the signal averaging technique: alignment accuracy and shape constancy.

We proposed a new synchronization method which improves signal alignment and allows stable triggering on low SNR signals.
Fig. 3a. Three noisy P waves before processing.

To analyze shape variability we applied a particular estimation method leading to the extraction of the desired signal on a beat to beat basis.

According to the results, our time delay estimation method provides:

1st - a better mean shape of P wave
2nd - the extraction of "low potentials" physiologically linked to P or T wave.
3rd - a sorting between low potentials by successively synchronizing on R, P and T waves. TP interval is the principal investigation field.
4th - a rather good estimation of the probability distribution for PR or ST interval.

Second approach results show that a fine structure of P wave can be obtained.

Second approach provided smoothed P waves; on such signals the shape evolution from beat to beat is more obvious. But permanent low potentials cannot be distinguished from noise. Therefore the two approaches, are really complementary; signal averaging shows what is permanent in the majority of records, independently of any model. This mean information allows, in a beat to beat analysis, to point out time evolution and peculiarities of one beat.

REFERENCES