Alignment Methods for Averaging of High-Resolution Cardiac Signals: A Comparative Study of Performance

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***Abstract*—Accurate signal estimation by means of coherent averaging techniques needs temporal alignment methods. A known low-pass filtering effect is yielded when alignment errors are present. This is very critical in the estimation of low-level high-frequency potentials in high-resolution ECG analysis. A comparative study of the performance of three alignment methods (the double-level method, a new time-delay estimation method based on normalized integrals, and matched filtering) is presented in this paper. A real signal and additive random noise for several signal-to-noise ratios (SNR's) are selected to make an ensemble of computer-simulated beats. The relation between the standard deviation of temporal misalignment versus SNR is discussed. A second study with real ECG signals is also presented. Several morphologies of *QRS* and *P* waves are tested. The results are in agreement with the computer simulation study. Nevertheless, the power spectrum of the noise process can affect the results. Matched filter estimation has been tested in the presence of power line interference (50 Hz), with poor results. An application of the three alignment methods as a function of the SNR is proposed. The new time-delay estimation method has been observed to be robust, even in the presence of nonwhite noise.**

I. Introduction

Signal averaging is a classical method for the recovery of low-amplitude potentials in the analysis of biological signals. Such a technique improves the signal-to-noise ratio (SNR), and is based on the time relationship between a reference wave or a stimulus, and the potential that is hidden in the noise. Several applications of signal averaging to evoked responses have been presented by other authors [1], [2]. Signal averaging of cardiac signals, in particular, has allowed high-resolution ECG analysis for noninvasive detection of cardiac micropotentials. Different low-amplitude waves have been studied using this method. Among the most investigated ones are those related to His bundle activity [3], [4] and ventricular late potentials [5], [6].

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A review of coherent averaging techniques published by Rompelman and Ros [7], [8] presents a model of the averaging process, the improvement of SNR, and the effect of trigger jitter. A continuation of the work, more oriented towards late potential detection, has been produced by Craelius *et al.* [9]. The low levels of sensitivity and specificity obtained in clinical studies are studied by them, and it is suggested that these results are due to alignment errors and other technical limitations. In coherent averaging estimation of micropotentials, the accuracy depends mainly on the accurate definition of a fiducial point, and on the constancy of time interval between this point and the signal to be extracted. In particular, in the study of micropotentials linked to *P* or *T* waves, the *QRS* complex alignment does not avoid the jitter effect due to PR or ST segment variability. It is therefore very useful to develop algorithms allowing direct alignment of these *P* or *T* waves in spite of their poor SNR. In signal processing of evoked potentials, an algorithm to align the individual components of the waveform that uses the technique of latency corrected average (LCA) was developed by McGillem *et al.* [10]. As our study is more oriented to cardiac signals, methods allowing direct alignment of waves have been preferred, because ECG structure is better known than evoked potentials.

This paper deals with alignment methods in signal averaging of cardiac signals and their performance for accurate signal estimation, enlarging the work of Koeleman *et al.* [11]. The first part presents three alignment methods: the double-level method, a new time delay estimation method based on normalized integrals, and matched filtering. Several algorithms, directly applying these methods or combining some of them, are then derived. The second part reports on the accuracy of these algorithms for different SNR's in simulated cases. The third part shows the application to real ECG signals with different morphologies and several types of noise.

II. Alignment Methods

Precise synchronization of heartbeats in the process of signal averaging is essential for correct estimation of micropotentials. The existence of trigger jitter in synchronization provokes a low-pass filtering effect in the estimated signal, which seriously limits detection of high-

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frequency low-amplitude components. Below, we present three alignment methods used for the definition of a temporal point of reference for ECG beats in the process of signal averaging.

A. Double-Level Method

The double-level (DL) alignment method is based on a previously fixed threshold level (l). The temporal point of alignment (t_a) for each beat $x(t)$ is defined as the mean point between the first crossing (t_1) of the upward slope of the signal and the last crossing (t_2) of the downward slope through the reference level l. We thus obtain

$$t_a = (t_1 + t_2)/2 \tag{1}$$

where $x(t_1) = x(t_2) = l$. This method has been chosen for its easy computation and for its better performance when compared with other simple methods such as the single level method [12], and because it is more robust in the face of signal variations due to respiration. We now describe certain details relating to the implementation of this method.

The selected value of the threshold level is

$$l = 0.6V_p \tag{2}$$

where V_p is the highest positive or negative peak value of the signal. We have experimentally found that this value permits a precise definition of t_a. Time instants t_1 and t_2 are selected after the definition of a temporal window and a subsequent symmetrical search for the crossover points with reference to the level from each end of the window. This solves certain limitations, in problematical morphologies for this method, which had been noticed in previous studies [11].

B. Normalized Integrals Method

The normalized integrals method (NI) was proposed by Rix and Jesus [13] and has been applied to ECG signals [14]. It is based on calculation of the delay between two signals by measuring the integral of the differences between their normalized integrals. The principle of the method is as follows. Given a positive signal $s(t)$ and its integral

$$\int_{-\infty}^{+\infty} s(t)\, dt = A \neq 0 \tag{3}$$

its normalized integral is defined as

$$S(t) = \frac{1}{A} \int_{-\infty}^{t} s(\tau)\, d\tau. \tag{4}$$

If $s(t)$ is a reference signal and $v(t)$ is another signal of the form

$$v(t) = k \cdot s(t - d) \tag{5}$$

where k is a constant, the delay d of $v(t)$ in comparison to $s(t)$ can be computed by the formula

$$d = \int_{-\infty}^{+\infty} (S(t) - V(t))\, dt \tag{6}$$

where $S(t)$ and $V(t)$ are the normalized integrals of $s(t)$ and $v(t)$, respectively. This relationship constitutes the basis of the NI method.

In the case when the signal $s(t)$ is not positive for all t, the method can be applied to a positive function of $s(t)$ like $s^+(t)$, defined by

$$s^+(t) = \begin{cases} s(t), & s(t) \geq 0 \\ 0, & s(t) < 0 \end{cases} \tag{7}$$

or its square $s^2(t)$. The algorithms based on this method will be denoted NI-P and NI-SQ, respectively.

C. Matched Filtering Method

Matched filtering (MF) is a classical signal detection method for a known signal embedded in noise. In the case of white noise, the impulse response $h(t)$ of a matched filter for detecting the presence of a signal $s(t)$ is

$$h(t) = s(-t). \tag{8}$$

Otherwise, the expression of $h(t)$ involves the power spectral density of the noise. Given a real signal $x(t)$ defined by

$$x(t) = s(t) + n(t) \tag{9}$$

where $n(t)$ is random noise, a temporal point of alignment t_a is defined for synchronization of each wave as the maximum of the matched filter output $y(t) = x(t) * h(t)$. So, t_a is solution of the following equation:

$$\frac{dy(t)}{dt} = 0. \tag{10}$$

If the power spectral density of the noise is constant in the frequency range of the signal, then the matched filter defined before [see (8)] is optimum and therefore provides the greatest possible improvement of SNR [15]. The noise present in the ECG signal frequently fulfills this condition, if it does not include appreciable 50- or 60-Hz interference.

An important requirement of this method is a good knowledge of the ideal signal $s(t)$ to be detected, for an accurate definition of $h(t)$. In this paper, an estimation of the ideal signal was obtained by averaging all the beats of the series studied. The synchronization in this prior averaging was carried out successively with the DL, NI-P, and NI-SQ algorithms. We will denote these algorithms as MF-DL, MF-NI-P, and MF-NI-SQ, respectively.

An alignment method proposed by Woody [16], is based on the cross-correlation between an arbitrary template and a sequence of signals. This method is in essence a matched filter operation. Nevertheless, it first uses a single signal as the template and a repetitive averaging process, each one with the previous average output as the new template, in order to improve the estimated signal.

The method used in our study permits a good estimate of the signal with less processing steps, because a good knowledge of the ideal signal (template) is obtained *a priori*.

III. Analysis of Alignment for Computer-Simulated Waves

A study is presented of the performance of the proposed synchronization methods, applied to various computer-simulated waves for different SNR's. The objective is to establish a ranking of the alignment methods as a function of the SNR and the type of wave considered.

A. Signal and Noise

Given that the alignment methods can be sensitive to the morphology of the waves, a *QRS* complex [Fig. 1(a)] and a *P* wave [Fig. 2(a)] were selected as reference signals for the simulation. Both waves were extracted from real ECG's [Fig. 3(a) and (b), respectively], and contain high-frequency components due to noise. In the simulation study these components can be viewed as micropotentials linked to the reference signals. A collection of beats was generated, formed by these waves as the deterministic components and contaminated by random noise for a specified SNR. The additive noise used in the simulation was white Gaussian, uncorrelated to the signal, with zero mean and a standard deviation dependent on the SNR selected. We used only this type of additive noise, since other factors such as the effect of respiration and wave symmetry variation present effects that are insignificant for the methods tested in this paper [11].

A step signal was then added to each beat [Figs. 1(a) and 2(a)]. By means of averaging all beats as simulated above, an estimation of the deterministic signal present in every beat is obtained. The quality of the estimation will depend upon application of the correct alignment. The existence of synchronization errors leads to a flattening of the averaged signal obtained, as compared with the deterministic signal. Deformation of the step permits this effect to be more easily seen and makes it possible to compare it with the results of Craelius *et al.* [9].

Other published simulation work on the evaluation of various alignment methods did not use real signals. Triangular and cosine-squared signals were used by Koeleman *et al.* [11], and Gaussian signals were used by Rix and Jesus [13]. In this paper, real signals were used for the simulation study, because a more realistic evaluation of performance can then be obtained.

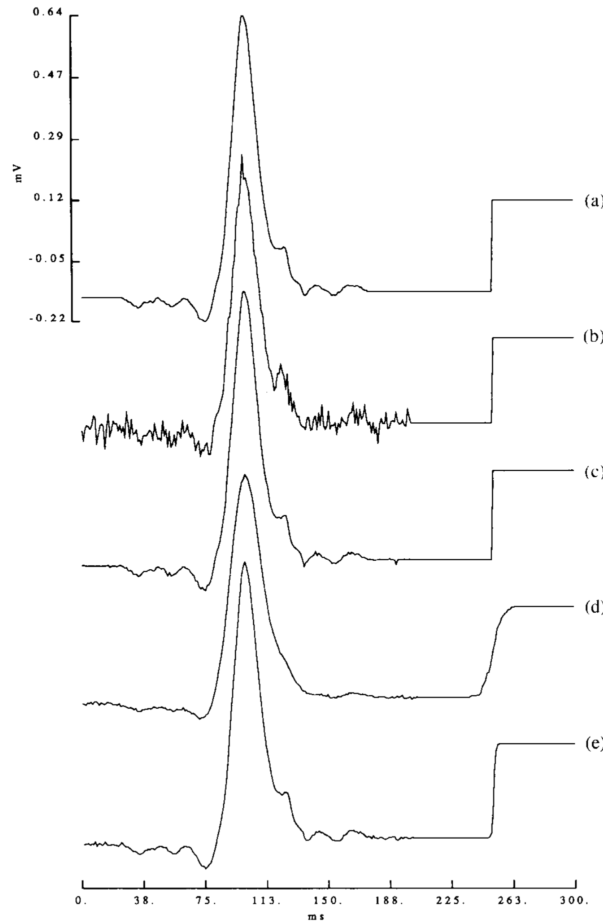

Fig. 1. Compute simulation for *QRS* complex. (a) The deterministic signal for the simulation (extracted from patient P1). (b) A simulated beat with a SNR of 20 dB. Signals estimated by averaging 80 beats (SNR = 20 dB) with (c) perfect synchronization and (d) and (e) with delays normally distributed with zero mean and standard deviations of $\sigma = 5$ ms and $\sigma = 1$ ms, respectively.

B. Results

Estimation of the deterministic signal present in all beats considered was studied by means of signal averaging according to the tested alignment method.

First, we present the effects of incorrect alignment with respect to the hypothetical case of perfect synchronization. Figs. 1(b) and 2(b) show simulated beats (*QRS* and *P* waves, respectively) with an SNR of 20 dB. We take as a reference the estimation of the signal carried out following the average of 80 beats with this SNR by means of perfect synchronization. The signals estimated in this way are shown in Figs. 1(c) and 2(c).

In order to observe the filtering effect produced by the synchronization errors on signal averaging, 80 signals were generated with an SNR of 20 dB and a variable delay d with respect to a point of reference, according to a normal distribution with zero mean and known standard deviation (σ_d). The averaging was then carried out without applying the synchronization methods. The estimated signals for $\sigma_d = 5$ ms and $\sigma_d = 1$ ms are shown in Fig. 1(d) and (e) for *QRS* complex and in Fig. 2(d) and (e) for *P* wave, respectively.

In order to analyze the low-pass filtering effect due to synchronization errors on signal averaging, we consider a record $y_i(t)$ of a random process $\{y(t)\}$. It can be expressed by

$$y_i(t) = s(t - d_i), \qquad i = 1, \cdots, N \tag{11}$$

where d is a random variable and $s(t)$ is the deterministic signal. Then the estimation of $s(t)$ is obtained by the es-

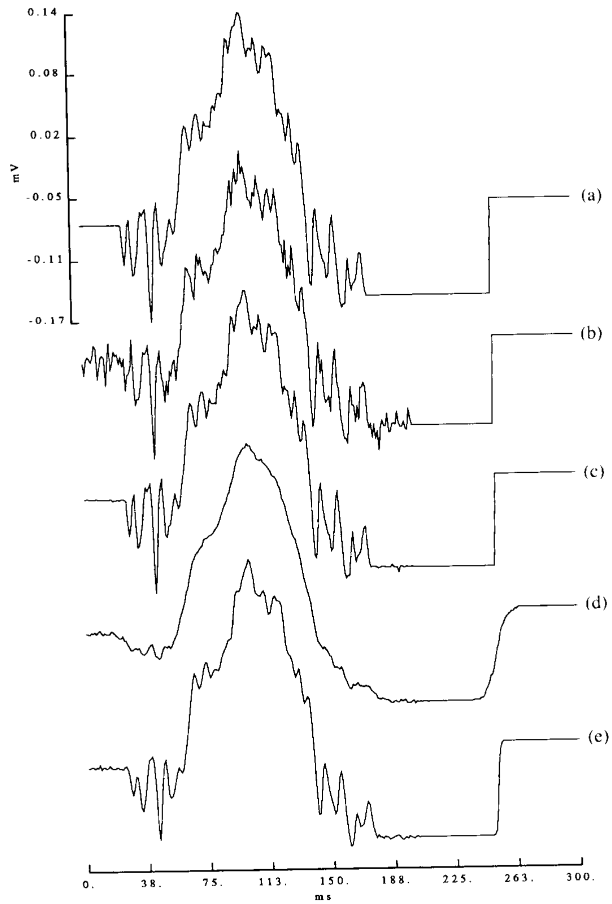

Fig. 2. Computer simulation for P wave. (a) The deterministic signal for the simulation (extracted from patient P2). (b) A simulated beat with a SNR of 20 dB. Signals estimated by averaging 80 beats (SNR = 20 dB) with (c) perfect synchronization and (d) and (e) with delays normally distributed with zero mean and standard deviations of σ = 5 ms and σ = 1 ms, respectively.

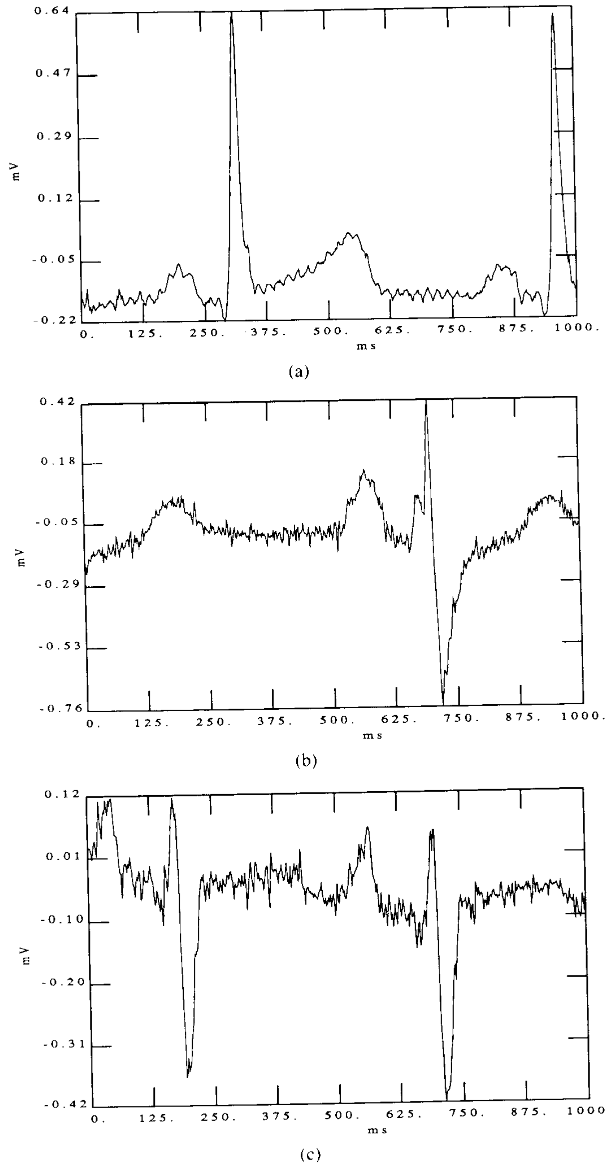

Fig. 3. Real ECG signals selected for analysis of alignment in the simulation study (patients P1 and P2) or in real case (patients P1, P2, and P3). (a) Patient P1. (b) Patient P2. (c) Patient P3.

timate of the mean value of $\{y(t)\}$:

$$\hat{\mu}_y(t) = \frac{1}{N}\sum_{i=1}^{N} y_i(t). \tag{12}$$

In the frequency domain, (11) can be written as

$$Y_i(f) = S(f)e^{-j2\pi f d_i} \tag{13}$$

where $Y_i(f)$ and $S(f)$ are the Fourier transforms of $y_i(t)$ and $s(t)$, respectively.

The expected value of $Y_i(f)$, according to Rompelman and Ros [8], is

$$E[Y_i(f)] = S(f)E[e^{-j2\pi f d_i}] = S(f)C(f) \tag{14}$$

where $C(f)$ is the Fourier transform of the probability density function of d. The effect of synchronization errors (d_i) on signal averaging can be observed as a filtering operation, whose transfer function if $C(f)$. For a zero-mean Gaussian variable, $C(f)$ is a low-pass filter given by

$$C(f) = \exp(-2\pi^2\sigma^2 f^2) \tag{15}$$

where σ is the standard deviation of d. Then this low-pass filtering effect can be characterized by

$$f_c = 132.3/\sigma_d \tag{16}$$

where f_c is the cutoff frequency of the equivalent low-pass filter at -3 dB and σ_d is expressed in milliseconds. Thus for example, we obtain f_c = 26.5 Hz for σ_d = 5 ms.

Once these results were studied as indicators of the characteristics and limitations of the signal averaging technique, the performance of the proposed methods of synchronization was evaluated. Ensembles of 80 signals (QRS and P waves) were generated with perfect alignment

TABLE I
MEAN VALUE AND STANDARD DEVIATION OF OBTAINED DELAYS IN SIMULATED CASE (*QRS* COMPLEX AND *P* WAVE) FOR THE DIFFERENT ALIGNMENT ALGORITHMS

	Signal-to-Noise Ratio (SNR)									
QRS Wave	20 dB		10 dB		5 dB		0 dB		−5 dB	
Alignment Methods	μ_d (ms)	σ_d (ms)	μ_d (ms)	σ_d (ms)	μ_d (ms)	σ_d (ms)	μ_d (ms)	σ_d (ms)	μ_d (ms)	σ_d (ms)
DL	−0.187	0.390	−0.212	0.585	−1.062	2.431	−2.525	7.471	0.097	13.049
NI-P	0.101	0.302	1.240	0.860	2.456	1.456	4.696	2.861	8.139	10.937
NI-SQ	0.000	0.000	0.595	0.516	1.506	0.926	4.341	2.433	14.539	10.041
MF-DL	0.000	0.000	−0.175	0.441	−0.912	0.778	−2.800	1.453	0.737	2.412
MF-NI-P	0.000	0.000	1.225	0.446	2.525	0.741	4.612	1.280	10.662	2.230
MF-NI-SQ	0.000	0.000	0.625	0.484	1.512	0.774	4.375	1.198	12.701	2.629
MF-IS	0.000	0.000	0.062	0.242	0.075	0.608	0.000	0.975	−0.087	1.818
P Wave	20 dB		10 dB		5 dB		0 dB		−5 dB	
Alignment Methods	μ_d (ms)	σ_d (ms)	μ_d (ms)	σ_d (ms)	μ_d (ms)	σ_d (ms)	μ_d (ms)	σ_d (ms)	μ_d (ms)	σ_d (ms)
DL	1.862	0.627	0.825	1.948	0.325	3.577	−0.187	9.875	1.837	20.087
NI-P	0.101	0.302	0.557	0.823	1.063	1.353	2.481	2.449	5.481	4.564
NI-SQ	0.341	0.474	1.430	0.806	2.671	1.403	5.860	2.699	14.610	7.270
MF-DL	2.000	0.000	0.825	0.380	−0.412	2.131	−3.050	3.777	−4.700	6.611
MF-NI-P	0.000	0.000	0.112	0.316	0.500	0.880	0.875	3.124	3.812	5.518
MF-NI-SQ	0.000	0.000	1.075	0.263	2.212	1.114	4.250	2.883	11.275	5.463
MF-IS	1.000	0.000	0.950	0.218	0.850	0.421	−0.062	2.860	−1.575	4.888

and SNR's of 20, 10, 5, 0, and −5 dB. Next, the synchronization methods were applied to each *QRS* and *P* wave, and then the estimated delays, referred to the point of perfect alignment, were calculated. Evaluation of errors introduced by these methods could thus be carried out for each SNR.

In order to apply the NI method, the signal $s^+(t)$ defined by (7) and the squared value $s^2(t)$ were successively considered (NI-P and NI-SQ algorithms, respectively). For the MF method, several signals estimated by the previous algorithms were taken as the ideal signal $s(t)$. Thus we have the results obtained by the algorithms MF-DL, MF-NI-P, and MF-NI-SQ, as defined in Section II-C. The deterministic signal itself was also taken as the ideal signal (MF-IS algorithm) to show the limiting performance of the method. Obviously this situation is not possible in practice.

Table I presents the results of the mean value (μ_d) and standard deviation (σ_d) of computed delays d for each of these situations. These values show the errors produced by application of the alignment algorithms. The σ_d obtained in each case is related to the quality of the estimated signal, and indicates the smoothing effect in the estimation. Therefore, a comparative analysis of performance of the alignment methods for each SNR can be carried out by studying the σ_d values.

The interpretation of the cutoff frequency, as a function of σ_d expressed in milliseconds, is obvious from (16). The influence of the jitter on averaging can also be appreciated using relative values of σ_d defined by $\sigma_r = \sigma_d / w_s$, where w_s is the half-width at half-amplitude of the signals. The parameter σ_r can be considered as an estimation of the mean resolution between two signals randomly picked in the averaged series. The performances evaluated in this study can be compared to previous works [13] using this parameter. For the *QRS* wave selected in the simulation study, w_s is 7.5 ms. Thus, for example, applying DL and SNR = 0 dB (σ_d = 7.471) we can compute a relative σ_r = 0.996.

C. Remarks

The different alignment methods proposed were evaluated by applying them to a collection of *QRS* and *P* waves simulated with SNR in the range of −5 to 20 dB. The results obtained are different for the two waves.

For the *QRS* complex, we should stress that for high SNR values of 20 and even 10 dB, all the three methods show good results. For lower SNR's, the DL method begins to show rather unacceptable results, while NI and MF prove to be robust until SNR = 0 dB. For SNR values below 0 dB, only the MF method achieves good results.

For the *P* wave, the DL method performs poorly below 10 dB. The NI and MF methods have good performance even below 0 dB. For these low SNR's, NI-P gives slightly better results than MF.

Finally, the goodness of the ideal signal estimation for the MF method has been shown to be an important factor for low SNR.

IV. Analysis of Alignment for Real Signals

A. Signals

Six pathological ECG signals (P1, · · · , P6) were selected for evaluating the performance of the different alignment methods as applied to real signals. Diverse signal morphologies were taken, both for the *QRS* complexes and for the *P* waves, contaminated with noise of different spectral characteristics (muscular noise and 50-Hz interference) (Fig. 3). The objective was to obtain a precise estimation of the *P* and *QRS* waves, by means of signal averaging, from a prolonged ECG recording. The results obtained using the various alignment methods were then compared.

B. Signal Processing

The signals were recorded at the Coronary Unit of the Hospital de la Santa Creu i Sant Pau. The instrumentation used was a Mingograf electrocardiograph, a low-pass analog filter with a cutoff frequency of 200 Hz, and a digital data acquisition system based on a PC. The sampling frequency selected was $f_s = 1000$ Hz with a resolution of 12 b. The total gain of the system was 8000.

Once the signal had been digitized, the following processing phases were carried out: a) detection of heart beats, b) high-pass filtering, c) selection of windows corresponding to the *P* and *QRS* waves, d) application of the synchronization methods, and e) calculation of the estimated signal by averaging.

A software *QRS* wave detector was used for detection of beats, this being an adaptation of the algorithm proposed by Pan and Tompkins [17]. It is based on analysis of the slope, amplitude, and duration of the signal, and includes band-pass filtering, differentiation, and integration with a moving window. False detections are thus reduced, so low thresholds may be used and the detection sensitivity increased. This algorithm showed itself to be very robust, and permitted *QRS* selection even in the presence of strong variations in the baseline, muscular noise, and 50-Hz interference.

High-pass filtering was carried out first to eliminate baseline variations. A first-order Lynn filter [18], with a cutoff frequency of $f_c = 1$ Hz, was selected. The occurrence time of the *QRS* complex (t_w) was defined as the maximum absolute value of the band-pass filtered signal. This point was used as the reference for opening the temporal windows of the *P* and *QRS* waves used in the subsequent synchronization process. The point t_w was also the reference for calculation of the standard deviation of the delays obtained with the methods tested. The objective was to find a criterion for quantitative comparison of the performance of the methods.

A collection of windows was defined with a duration of 200 ms for the *QRS* and *P* waves. The *QRS* windows were centered around the point defined by the *QRS* detector, while the *P* wave windows were defined according to the average P-R distance for each subject studied. The different alignment methods DL, NI, and MF were tested on a group of 80 beats for each patient. Averaging was carried out with respect to the temporal point of alignment for each beat. The results obtained for each method follow.

1) The estimated signal after 80 beats.

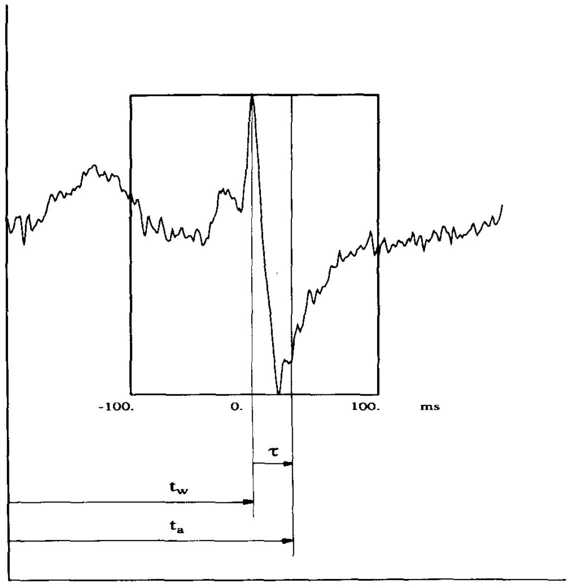

Fig. 4. Definition of the alignment times: the occurrence time of *QRS* complex (t_w) given by the *QRS* detector, the absolute alignment time (t_a), and the relative alignment time (τ).

2) The mean μ_τ and standard deviation σ_τ of the random delay τ defined as $\tau = t_a - t_w$, where t_a is the absolute alignment time. In fact, only the variable τ is measurable instead of t_a, because a relative time basis (with respect to t_w) is used for each beat (Fig. 4). Assuming that t_a and t_w are uncorrelated, we can write

$$\sigma_\tau^2 = \sigma_{t_a}^2 + \sigma_{t_w}^2. \tag{17}$$

The performance of the alignment methods (indicated by σ_{t_a}) may then be studied through the σ_τ values, given that σ_{t_w} is the same in all methods tested.

C. Results

1) QRS Waves: In general, the *QRS* complexes obtained by averaging with the different alignment methods present a similar morphology, although the signals obtained by NI and MF algorithms present better characteristics with respect to amplitude and high-frequency components. Table II compares σ_τ obtained by these methods for the six patients. Fig. 5 shows a comparison of the estimated signals for the patient P3. These signals and their corresponding σ_τ can be classified in the same order of performance as in the simulated study.

2) P Waves: The *P* waves present a very much lower SNR than the *QRS* waves. For this reason, we may expect to obtain much greater differences between the different methods than those obtained in the *QRS* case. In order to synchronize *P* waves, the DL method was also applied to the *QRS* wave of the same beat as the *P* wave (DL-*QRS*). This algorithm provides good results if the P-R interval is

TABLE II
MEAN VALUE AND STANDARD DEVIATION OF DELAYS IN REAL CASE (*QRS* COMPLEX) RELATED TO POINTS DEFINED BY *QRS* DETECTOR FOR THE DIFFERENT ALIGNMENT ALGORITHMS

	Patients											
QRS Wave	P1		P2		P3		P4		P5		P6	
Alignment Methods	μ_τ (ms)	σ_τ (ms)	μ_τ (ms)	σ_τ (ms)	μ_τ (ms)	σ_τ (ms)	μ_τ (ms)	σ_τ (ms)	μ_τ (ms)	σ_τ (ms)	μ_τ (ms)	σ_τ (ms)
DL	0.525	0.547	6.862	0.802	9.683	3.733	−2.000	1.173	−0.700	1.100	−0.150	0.421
NI-P	1.025	0.841	5.886	1.862	0.615	1.619	−1.519	0.912	−3.177	1.260	0.215	0.609
NI-SQ	0.493	0.593	0.987	0.849	0.734	1.177	−0.152	0.618	−1.215	1.659	−0.126	0.512
MF-DL	0.575	0.608	6.687	0.515	10.162	0.431	−2.025	0.632	−0.762	0.939	−0.212	0.438
MF-NI-P	1.025	0.689	5.612	0.512	0.537	0.499	−1.412	0.585	−3.150	0.910	0.225	0.499
MF-NI-SQ	0.500	0.570	0.925	0.494	0.775	0.446	−0.212	0.585	−1.187	0.909	−0.175	0.411

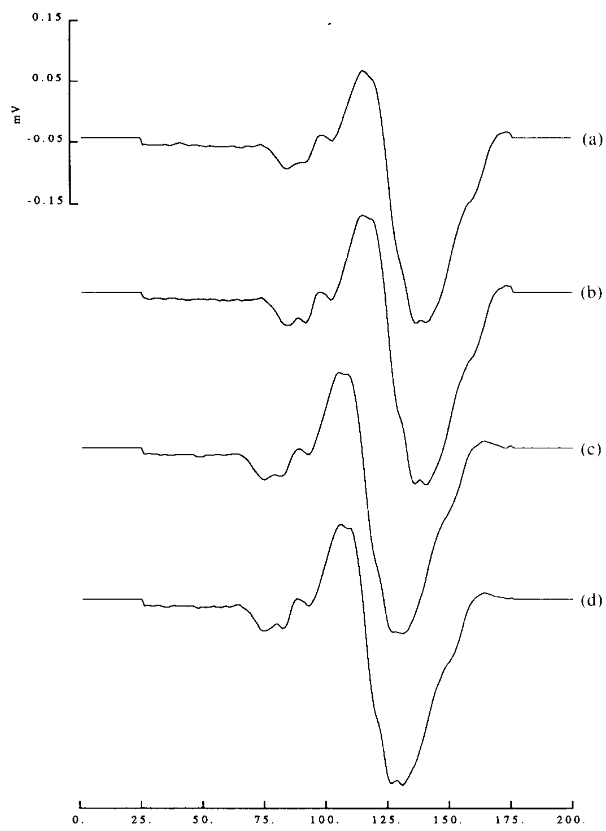

Fig. 5. Signals estimated (*QRS* complex) by averaging 80 beats from patient P3, using the following alignment algorithms. (a) DL. (b) MF-DL. (c) NI-SQ. (d) MF-NI-SQ.

constant. The signals estimated in this way have been used for the MF method (MF-DL-*QRS*).

Table III shows the σ_τ obtained for the six patients using different algorithms. Fig. 6 shows the estimation after averaging 80 beats for signals from patient P1. Patient P1 shows a clear presence of a 50-Hz interference, which causes estimated signals based on the MF method to have a very distorted shape [Fig. 6(d)–(f))].

D. Remarks

The results obtained on real signals agree with those obtained in the simulation studies. Thus for low SNR's, the signal estimations follow the hierarchy obtained in the simulation. The importance of the power spectral density of the noise is also apparent in the results obtained for each alignment method. Thus for cases in which there is a strong presence of 50 Hz, the matched filtering method does not achieve good results.

It is necessary to make a general observation with respect to the calculated σ_τ values. These take as a reference the relative delays obtained (τ) with respect to the absolute temporal position defined by the *QRS* detector (t_w), used for definition of the windows. For this reason they constitute only a comparative result.

The values of σ_τ are a good index to evaluate the relative performance of the alignment methods, given that σ_{t_w} is the same in all tested methods. For the *P* wave signals, the P-R distance was considered constant. Thus the same *QRS* wave reference was used. In spite of some limitations, a study of these standard deviations provides a good quantitative representation of the performance of the alignment methods as applied to real signals. The conclusions presented in this paper are in accordance with the recent published results [19], where an application of these methods for obtaining late potentials was presented.

V. DISCUSSION AND CONCLUSION

A comparative study of the performance of three alignment methods has been presented. Computer-simulated waves and real signals have been considered. Real deterministic signals and additive white noise were selected for the simulation study, and pathological ECG signals were used in the real-signal study.

Several conclusions can be drawn from the simulation study.

1) The double level method shows poor performance for SNR below 10 dB, while the normalized integrals and matched filtering methods give good results down to 0 dB.

TABLE III
MEAN VALUE AND STANDARD DEVIATION OF DELAYS IN REAL CASE (*P* WAVE) RELATED TO POINTS DEFINED BY *QRS* DETECTOR FOR THE DIFFERENT ALIGNMENT ALGORITHMS

	Patients											
P Wave	P1		P2		P3		P4		P5		P6	
Alignment Methods	μ_τ (ms)	σ_τ (ms)	μ_τ (ms)	σ_τ (ms)	μ_τ (ms)	σ_τ (ms)	μ_τ (ms)	σ_τ (ms)	μ_τ (ms)	σ_τ (ms)	μ_τ (ms)	σ_τ (ms)
DL	−4.262	4.155	4.587	2.742	12.218	3.083	0.925	8.264	−4.375	3.641	4.687	2.194
DL-*QRS*	0.525	0.547	6.862	0.802	9.683	3.733	−2.000	1.173	−0.700	1.100	−0.150	0.421
NI-P	1.873	1.898	−1.367	0.732	−1.443	2.243	−0.354	1.387	−1.380	2.552	−1.709	1.692
NI-SQ	1.253	1.906	−1.215	0.687	0.190	1.822	−0.570	1.620	−1.076	2.569	−1.709	1.692
MF-DL	−10.625	7.774	4.512	0.724	12.187	1.534	−1.300	1.584	−4.787	2.644	4.537	1.710
MF-DL-*QRS*	−0.725	4.390	6.625	0.640	10.139	1.477	−3.287	1.811	−1.350	2.460	−0.325	1.253
MF-NI-P	1.062	3.355	−1.550	0.669	−1.387	1.561	−1.575	1.849	−2.062	2.482	−2.087	1.325
MF-NI-SQ	0.187	4.120	−1.425	0.647	0.062	1.638	−1.687	1.907	−1.762	2.556	−2.087	1.325

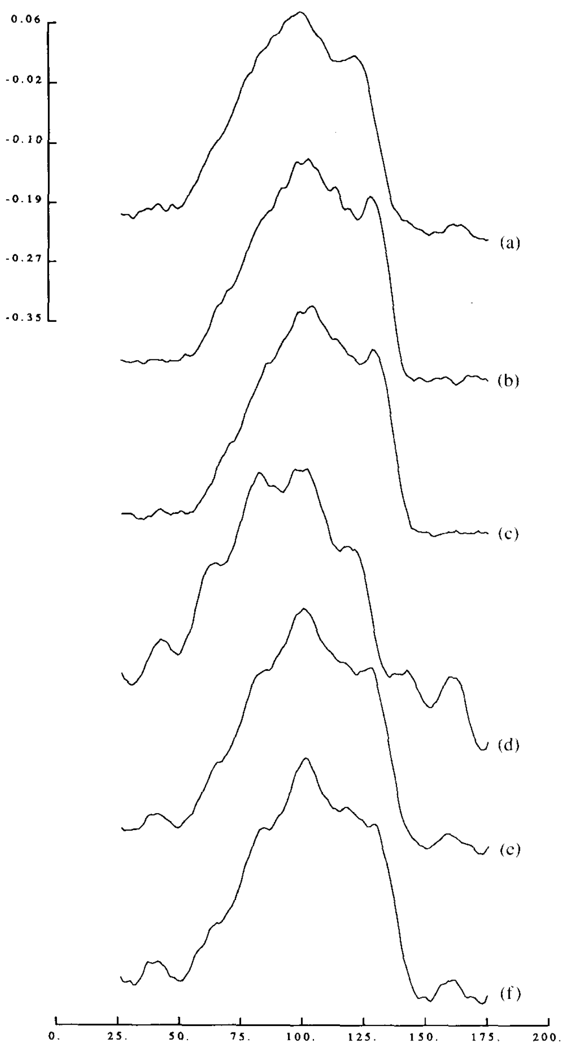

Fig. 6. Signals estimated (P wave) by averaging 80 beats from patient P1, using the following alignment algorithms. (a) DL. (b) DL-*QRS*. (c) NI-P. (d) MF-DL. (e) MF-DL-*QRS*. (f) MF-NI-P. The estimated signal shows a clear presence of a 50 Hz interference when MF method is used [(d), (e), and (f)].

2) The shape of the synchronized wave is an important feature affecting the results obtained in very low SNR's. The normalized integrals and matched filtering methods present similar results for alignment of *P* waves. On the other hand, for *QRS* waves, only the matched filtering method achieves good performance.
3) A combination of the matched filtering-normalized integrals methods gives the best performance. This result proves the influence of the estimated template signal in the application of the matched filtering method.

The following additional conclusions have also been reached from the real-signal study.

4) Alignment methods applied to real signals contaminated by white noise produce similar results to those obtained in the simulation case.
5) For real signals with a strong presence of 50 Hz, the performance is different, and matched filtering does not achieve good results.

Finally, a ranking of the three alignment methods has been obtained as a function of SNR and the type of wave considered (*QRS* or *P* wave). These results will be very useful for obtaining low-amplitude potentials in the averaging of high-resolution real cardiac signals.

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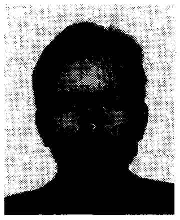

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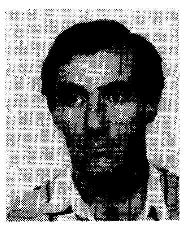

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