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Fully Digital Pacemaker Detection in ECG Signals Using a Non-Linear Filtering Approach

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Abstract— **This paper deals with the detection of pacemaker pulses in an electrocardiogram (ECG) waveform. In order to realize a pulse detector that is robust to a wide-band electromyographic (EMG) noise, we propose a (patent pending) fully digital approach that exploits a two step filtering strategy, followed by a threshold comparison. By resorting to computer simulations which employ a synthetic and realistic ECG signal model, we show that our approach is particularly effective and it significantly outperforms a well known patented algorithm.**

I. Introduction

The detection of pacemaker pulses in electrocardiogram (ECG) signals is requested to appropriately classify and interpret the pacemaker interaction with the cardiac rhythm in the diagnostic bandwidth (DBW) (up to 150 Hz) [1].

A pacing pulse that is subject to a low-pass (LP) filtering in the DBW, can be significantly widened depending on the filter impulse response; similarly when it is subject to a high-pass (HP) filtering, a tail at the end of the pulse can be created [2] [3]. Thus, in order to not overwhelm the physiological ECG signal, it is necessary to detect and remove pacing pulses before applying any analog filter, which are typically used in ECG systems and typically work in the DBW.

Due to the high frequency nature of the pacemaker pulses, many devices, like those proposed in [4] [5] [9], use dedicated analog circuitry to detect and replace pacing pulses before the signal is passed to an analog-to-digital converter (A/D) (250-500 Hz). Other approaches, such those in [6] [7], combine analog and digital detection systems, while others [1] [2] propose fully digital detection systems. Specifically Helfenbein et al. [1] propose a digital detection algorithm for signals sampled in the DBW. Although the Helfenbein's algorithm works quite well for almost all the signals tested in [1], due to its sensitivity to electromyographic (EMG) noise it is also prone to missed and false detections and faces even further problems with pacemakers using shorter pacing pulses. Conversely, Herleikson suggests in [2] to up-sample the ECG signal and to detect the pacemaker pulses exploiting their high frequency content.

In order to provide a flexible and upgradable architecture, we propose, as in [2], a (patent pending) fully digital detection algorithm that does not require any analog filtering in the DBW before the ECG A/D conversion. To this end, Section II focuses on the overall ECG system architecture, Section III presents the digital signal filtering approach, while Section IV describes the proposed algorithm. The detection performance are shown in Section V, where they are also compared with the performance of the algorithm proposed by Herleikson in [2].

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II. ECG System Architecture

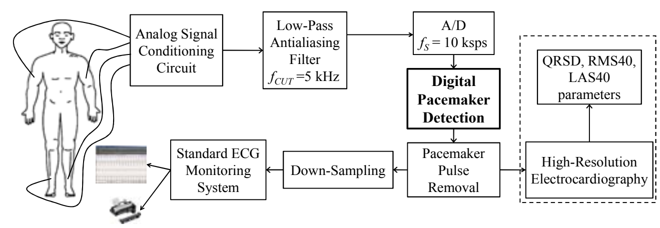

Figure 1. Overall block diagram of a possible ECG system

Fig. 1 represents a possible architecture for an ECG system that is capable to employ the algorithm we describe in Section IV. The ECG signal of a patient with a pacemaker is processed by a wide-band analog circuit whose aim is to amplify the signal and adjust its dynamic range to the A/D input. After the signal is LP filtered in order to avoid aliasing, and digitally converted employing a sampling frequency $f_S = 10\,\text{kHz}$ that prevents the pacing pulses widening, we identify the pacemaker pulses using the algorithm described in Section IV. Once the pacing pulses are detected, they can be easily removed at the high sampling frequency f_S by simply replacing a portion of the signal before and after the time instant of the detected pulse with a signal average over the recent past, similarly to what described in [2]. Successively, it is possible to down-sample the digital signal for a standard ECG monitoring system, and/or to exploit its high sampling rate to detect late potentials, as explained in [13].

III. Signal Model and Filtering

Consider a patient with a pacemaker, whose discrete ECG signal $s[n]$, at sampling frequency f_S, is expressed by

$$s[n] = x_{ECG}[n] + p[n] + w[n], \qquad (1)$$

where $x_{ECG}[n]$ is a typical noiseless ECG, $w[n]$ the additive noise, and $p[n]$ the potentially present pacemaker signal.

In order to correctly detect the pacemaker pulses, it is important to exploit their structure and statistical characterization, as well as those of the noise and the ECG. To this end, it is well known [1] that the most relevant frequency content of an ECG signal is within the [0, 150] Hz DBW and its dynamic range is approximately 1 mV, with its local maximum at the R wave peak. Additionally, the ECG may be corrupted by different noises, such as

- the baseline wander (BW) $w_{BW}[n]$, due to the patient respiration and movement (0.05 Hz to 1 Hz) [10],

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- the power-line interference (PLI) $w_{PLI}[n]$, which consists of a 50/60 Hz pickup,
- the electromyographic (EMG) noise $w_{EMG}[n]$, introduced by the muscle electrical activity (wide-band content).

Consequently, the overall noise can be modeled as

$$w[n] = \sigma_{BW} w_{BW}[n] + \sigma_{PLI} w_{PLI}[n] + \sigma_{EMG} w_{EMG}[n], \quad (2)$$

where σ_{BW}^2, σ_{PLI}^2, σ_{EMG}^2 are the powers of each noise.

The pacing pulses in $p[n]$ are conversely characterized by significant high frequency energy due to their sharp amplitude transitions at the rising and falling edges of the pulse. With a certain approximation, the pulse can be represented by a square wave, whose typical duration lies within 0.1 to 2 ms, and whose amplitude is bigger than 0.5 mV [2].

Thus, in order to identify the pulses by exploiting their structure, we propose the following 3-step procedure:

S1) HP filtering of the overall signal $s[n]$ in order to remove great part of $x_{ECG}[n]$, as well as the noise contribution due to the BW and to the PLI;

S2) pacing pulse enhancing with respect to the wide band EMG by means of a non-linear transformation;

S3) final detection of the pacing pulses by comparing the obtained signal with a given threshold V_T.

A. *Linear High-pass Filtering (S1)*

A possible approach to remove the natural ECG signal $x_{ECG}[n]$ is a simple differential filtering, as proposed by Herleikson in [2]. This approach has the nice property to enhance the rising and falling edges of the pacing pulse, by generating the filtered signal $s_{HP}[n]$, as expressed by

$$s_{HP}^{(H)}[n] = s[n] + s[n-1] - (s[n-2] + s[n-3]), \quad (3)$$

which is nothing but an average of two consecutive two-step finite differences (derivatives). Exploiting (3), the information about the presence of a pacing pulse resides mostly on the two samples located at the rising and falling edges of the pulse, which are typically characterized by opposite amplitude and by a distance equal to the pulse duration.

In order to improve the robustness of the pulse detection to the noise contribution, we propose to generalize (3) by extending the time observation window, as expressed by

$$s_{HP}^{new}[n] = s[n] + s[n-1] - (s[n-2-k] + s[n-3-k]). \quad (4)$$

Denoting with T_D the pulse duration and with $d = T_D f_S$ the corresponding number of samples, Fig. 2 shows that each pacing pulse in $s[n]$ generates in $s_{HP}^{new}[n]$ two trapezoidal waves with opposite amplitude, whose discrete duration l_F and distance d_F (total duration $d_{TOT} = 2l_F + d_F$) are

$$l_F = \min(d+1, k+3); \quad d_F = \max(d, k+2) - l_F. \quad (6)$$

Clearly, the parameter k in (4) controls the filter time-span and, consequently, the cut-off frequency f_C of the associated HP frequency response $H_{HP}^{new}(\omega)$ that is expressed by

$$H_{HP}^{new}(\omega) = \sum_{n=-\infty}^{+\infty} h_{HP}^{new}[n] e^{-j\omega n} = 4j\, e^{-j\omega\frac{3+k}{2}} \sin\left(\omega\frac{2+k}{2}\right)\cos\left(\frac{\omega}{2}\right), \quad (5)$$

where $h_{HP}^{new}[n]$ is the filter impulse response of (4). The frequency response $H_{HP}^{new}(\omega)$ is shown in Fig. 3, where $k=0$ represents the Herleikson filter in (3).

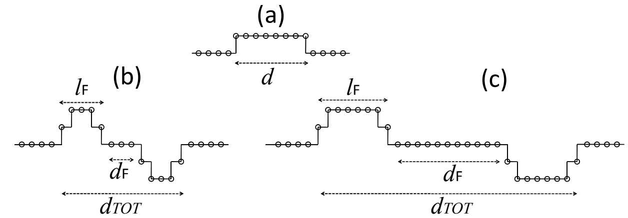

Figure 2. (a) ideal pacing pulse; (b) filtered signal $s_{HP}^{new}[n]$ with $k < d$; (c) filtered signal $s_{HP}^{new}[n]$ with $k > d$

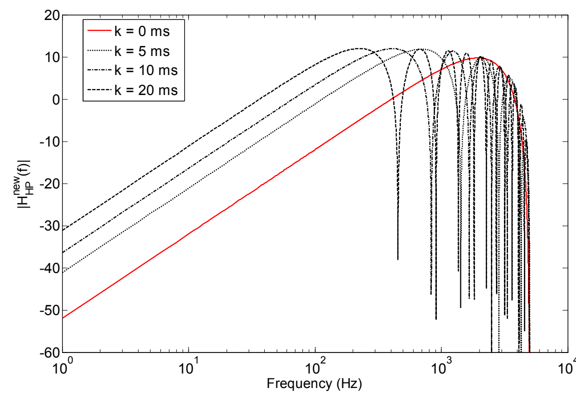

Figure 3. Magnitude of the linear filter frequency response.

It is clear from Figs. 2 and 3 that higher values of k make the pulse detector more robust to wide-band EMG noise, and conversely worsen the removal of the LP natural ECG signal. This fact suggests to choose k as a good trade-off among these two competitive aspects, as confirmed by simulations in Section V, where we clarify how to choose k to optimize the detection performance in several scenarios.

B. *Non-Linear Filtering (S2)*

Our aim is to detect pacing signals that are potentially embedded in $s_{HP}[n]$, whose time-domain structure is characterized by a rapid raise followed by a rapid fall (as in Fig. 2), and is different from the structure of the wide-band EMG noise. A simple idea is that a pacing event can be identified by comparing the amplitude $s_{HP}[n]$ with its surrounding samples, as better clarified in the next section. To this end we consider an observation window with a time-domain support $\mathbf{w}_N^{(-)} = [n-N, \ldots, n]$, where the apex $^{(-)}$ means that the window is extended towards the past samples that we use to define the $(N+1)$-dimensional vector

$$\mathbf{s}_N^{(-)}[n] = \left[s_{HP}[n-N],\ s_{HP}[n-N+1],\ \cdots,\ s_{HP}[n]\right]. \quad (7)$$

The associated variational series $\mathbf{v}_N^{(-)}[n]$ is defined as the sorted version of the vector $\mathbf{s}_N^{(-)}[n]$, by

$$\mathbf{v}_N^{(-)}[n] = \left[s_{HP}^{(1)},\ s_{HP}^{(2)},\ \ldots,\ s_{HP}^{(N+1)}\right], \quad s_{HP}^{(1)} \le s_{HP}^{(2)} \le \ldots \le s_{HP}^{(N+1)}. \quad (8)$$

In order to improve the detection robustness to the noise contribution, similarly to what we proposed by (4), we consider a support window $\mathbf{w}_{N,k_2}^{(-)} = [n-k_2-N+1, \ldots, n-k_2, n]$ and the corresponding vector $\mathbf{s}_{N,k_2}^{(-)}[n]$, composed by the current sample and by N contiguous past samples at a discrete temporal distance $k_2 + i$, $0 \le i \le N-1$, as expressed by

$$\mathbf{s}_{N,k_2}^{(-)}[n] = \left[s_{HP}[n-k_2-N+1], \cdots, s_{HP}[n-k_2],\ s_{HP}[n]\right], \quad (9)$$

and, similarly to (8), we name $\mathbf{v}_{N,k_2}^{(-)}[n]$ its variational series. The vector signal $\mathbf{s}_{N,k_2}^{(-)}[n]$ in (9) and $\mathbf{v}_{N,k_2}^{(-)}[n]$ permit to compare the current sample $s_{HP}[n]$ with the past ones and consequently to enhance the rising edges of a pacing pulse with respect to the noise. In order to avoid a false pulse detection induced by a sudden voltage rise caused by an electrode-skin contact loss, we consider also the vector $\mathbf{s}_{N,k_2}^{(+)}[n]$ in the support window $\mathbf{w}_{N,k_2}^{(+)}$, and its variational series $\mathbf{v}_{N,k_2}^{(+)}[n]$, composed by the current sample and other N samples in the future, as expressed by

$$\mathbf{s}_{N,k_2}^{(+)}[n] = [s_{HP}[n]\ ,\ s_{HP}[n+k_2]\ ,\ \cdots\ ,\ s_{HP}[n+(k_2+N)-1]] . (10)$$

We define $R(\mathbf{v}_N^{(-)}[n],\ i)$ ($R(\mathbf{v}_N^{(+)}[n],i)$) as the position (*rank*) of the sample $s_{HP}[n-i]$ ($s_{HP}[n+i]$) in $\mathbf{v}_N^{(-)}[n]$ ($\mathbf{v}_N^{(+)}[n]$) and $V(\mathbf{v}_N^{(-)}[n],m) = [\mathbf{v}_N^{(-)}[n]]_m$ ($V(\mathbf{v}_N^{(+)}[n],m)$) as the *value* of the sample whose *rank* is m in $\mathbf{v}_N^{(-)}[n]$ ($\mathbf{v}_N^{(+)}[n]$). Instead of considering only the signal derivative in the time domain, we propose to analyze the derivative in the sorted domain. Specifically, we compare the amplitude of the current sample $s_{HP}[n]$, with the closest neighbor in the variational series $\mathbf{v}_{N,k_2}^{(-)}[n]$ and $\mathbf{v}_{N,k_2}^{(+)}[n]$. Thus, similarly to what proposed in [8] in a different context, we define the *differential rank signal* $dr(\mathbf{v})$ of a vector $\mathbf{v}$ as

$$dr(\mathbf{v}) = \begin{cases} s_{HP}[n] - V(\mathbf{v}, R(\mathbf{v},0)-1), & \text{if } R(\mathbf{v},0) > (N+1)/2 \\ s_{HP}[n] - V(\mathbf{v}, R(\mathbf{v},0)+1), & \text{if } R(\mathbf{v},0) < (N+1)/2 \\ 0, & \text{otherwise} \end{cases} , \quad (11)$$

and we propose to use $dr(\mathbf{v}_{N,k_2}^{(-)}[n])$ and $dr(\mathbf{v}_{N,k_2}^{(+)}[n])$, rather than $s_{HP}[n]$, to determine by a simple threshold approach if $s[n]$ corresponds to a pacing pulse or not.

In a wide band noise environment, the two differential rank signals $dr(\mathbf{v}_{N,k_2}^{(-)}[n])$ and $dr(\mathbf{v}_{N,k_2}^{(+)}[n])$ can increase the detector performance with respect to the use of $s_{HP}[n]$. Indeed, if we would simply use the filtered signal $s_{HP}[n]$, some noise spikes that occur into the support window $\mathbf{w}_{N,k_2}$ could produce some false detections. On the contrary, the differential rank signal, which represents the signal derivative in the sorted domain, allows the detector to avoid false detections because it would compare, with a high probability, a noise spike with another noise spike of quite the same amplitude. It is clear that if there is only a single noise spike into a support window $\mathbf{w}_{N,k_2}$, the detector may occurs in a false detection also with the differential rank signals. Clearly, the false detection probability is reduced by a wide support window $\mathbf{w}_{N,k_2}$, which decreases the probability to collect a single noise spike. However N has to be optimized because a too wide support window $\mathbf{w}_{N,k_2}$, would also increase the probability of a noise spike with amplitude similar to the pace pulse, which could cause a missed detection.

The time-guard k_2 in the variational series $\mathbf{v}_{N,k_2}^{(-)}[n]$ and $\mathbf{v}_{N,k_2}^{(+)}[n]$ avoids the comparison of a pace pulse sample with other pace pulse samples in the sorted domain. Thus, a higher k_2 increases the detector robustness, although it is useless a value higher than the pulse discrete duration d_{TOT}, defined by (6). Section V will clarify this points by showing detection performance for different values of k_2 and N.

IV. PACING PULSE DETECTION (S3)

A simple approach, consists in comparing $s_{HP}[n]$ with a fixed threshold V_T. In order to avoid multiple detections associated to a single pulse, possibly induced by the discrete pulse duration l_F in Fig. 2, we identify as the pulse position the first value $\bar{n}$ that satisfies $dr(\mathbf{v}_{N,k_2}^{(-)}[n]) > V_T$ *and* $dr(\mathbf{v}_{N,k_2}^{(+)}[n]) > V_T$. Successively, we inhibit the search for a pulse for a refractory period $n_R \geq d_{TOT}$. In order to minimize the pulse position error, we want to force the discrete instant $\bar{n}$ as close as possible to the correct pulse position, which is the rising edge of the trapezoidal wave shown in Fig. 2. To this end, and to use a single positive threshold, we force the first trapezoidal wave to be always positive, which may not be true because the pacemaker pulse may appear negative for some ECG leads. Thus, we apply the non-linear filtering to the absolute value $|s_{HP}[n]|$ of the signal, rather than directly to $s_{HP}[n]$.

Summarising, once the overall ECG signal $s[n]$ has been filtered by (4), the proposed detector identifies a pacing pulse at the discrete instant $\bar{n}$ if both the differential rank values $dr(\tilde{\mathbf{v}}_N^{(-)}[n])$ and $dr(\tilde{\mathbf{v}}_N^{(+)}[n])$ overpass a positive threshold V_T, as expressed by,

$$dr(\tilde{\mathbf{v}}_{N,k_2}^{(-)}[\bar{n}]) > V_T \quad AND \quad dr(\tilde{\mathbf{v}}_{N,k_2}^{(+)}[\bar{n}]) > V_T . \quad (12)$$

Specifically, $\tilde{\mathbf{v}}_{N,k_2}^{(-)}[n]$ and $\tilde{\mathbf{v}}_{N,k_2}^{(+)}[n]$ in (12) represent the variational series, defined as in (8), for the absolute values $|\mathbf{s}_{N,k_2}^{(-)}[n]|$ and $|\mathbf{s}_{N,k_2}^{(+)}[n]|$ of the vector $s_{HP}^{new}[n]$, respectively. It is obvious that a high value of V_T increases the robustness to false detections induced by noise contributions, but it also increases the probability to miss the detection of true pacing pulses, as verified by simulation in the next section.

V. SIMULATION RESULT

In order to assess the performance of the detection algorithm, we use two standard parameters that are namely the Sensitivity (S) and the Positive Predictivity (PP) [1], defined as $S = TP/(TP+FN)$ and $PP = TP/(TP+FP)$, where the false negative (FN) denotes the number of missed detections, the false positive (FP) represents the number of extra false detections, and the true positive (TP) is the number of correct detections. Practically S represents the fraction of real events that are correctly detected, and PP represents the fraction of detections that correspond to real pacing events.

The detection algorithm considers a refractory period $t_R = n_R / f_s = 20$ ms, which is a trade-off between the request to avoid multiple detections of the same pulse, and the need of detecting closely pulses produced by dual chamber pacemakers. We consider a detected pulse to be a correct detection if its discrete instant $\bar{n}$ belongs to a 12 ms window centered in the discrete instant of the correct pacing pulse. This choice depends on the fact that this time interval would corresponds to less than 0.5 mm in a standard 12-lead ECG thermal printing and because we can potentially replace the 12 ms portion of the signal before and after the time instant of the detected pulse with the signal average over the past 2 ms, similarly to [2].

To check the performance of the proposed solution, we consider that the signal $x_{ECG}[n]$ in (1) is synthetically generated according to the dynamical model proposed in [12]. We do not consider herein the contribution of the BW to the noise, e.g. $\sigma_{BW}^2 = 0$ in (2), because its LP frequency distribution cannot affect the detector performance after the HP filtering described in Section III.A, as we also verified by simulations, that are not shown herein. The PLI $w_{PLI}[n]$ is generated as a sinusoid whose frequency f_{PLI} is modeled as a Gaussian random variable with mean $m_f = 50$ Hz, variance $\sigma_f^2 = 1\ \text{Hz}^2$, and phase uniformly distributed in $[0, 2\pi]$. We model the EMG noise $w_{EMG}[n]$ as a zero mean AWG noise that is LP filtered at a cut-off frequency f_{cut}^{EMG}.

We evaluate the performance of the pacemaker detector for different noise-to-signal ratios (NSR) associated to each noise component and defined as $NSR_{EMG} = \sigma_{EMG}^2 / \sigma_{ECG}^2$ and $NSR_{PLI} = \sigma_{PLI}^2 / \sigma_{ECG}^2$.

Finally, the pacing pulse is modeled as a square wave with short duration $T_D \in [0.1,\ 2]$ ms, very low duty-cycle (<2 pulses/240 ms) and quite high amplitude $a = 0.5$ mV, as summarized in [2] and [11]. All the waveforms have been simulated assuming a discrete-time band resolution of 5 kHz, which means a sampling frequency $f_S = 10$ kHz.

In order to highlight the best values of the parameters k, k_2, N and V_T for the algorithm we proposed and described in Section IV, we simulated S and PP for different values of each parameter. By means of what we define as the "equal S and PP criterion" (ESPP), we consider a parameter value as "good" when it provides good performance for both S and PP. To facilitate the interpretation of the parameters k, k_2, and N, we use their continuous counterparts $T_k = k / f_S$, $T_{k_2} = k_2 / f_S$ and $T_N = N / f_S$ in the figures legends. When it is not differently specified, we use the following set of parameters values: $T_D = 1$ ms, $T_k = 1$ ms, $T_N = 10$ ms, $T_{k_2} = 4$ ms and $V_T = 0.35$ mV.

In Figs. 4-8 we first check the algorithm behavior with respect to the wide-band noise, and we show the detection performance versus NSR_{EMG} for different values of the parameters k, k_2, N and V_T, when $\sigma_{PLI}^2 = 0$ in (2).

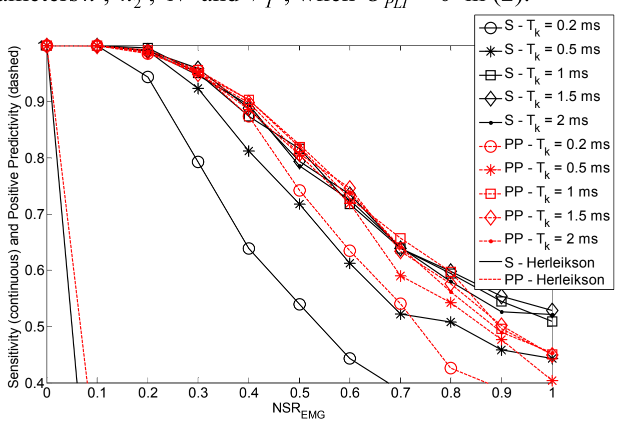

Figure 4. Performance for different values of T_k.

Specifically Fig. 4 shows how the performance are influenced by the discrete time-span k of the HP filter in (4). Fig. 4 demonstrates that a higher value of T_k gives a better S, because it makes the detector more robust to wide-band noise, but it also demonstrates that for a T_k higher than the pulse duration T_D, both the sensitivity S and the positive predictivity PP cannot improve, as motivated in Section III. Fig. 5 shows the detection performance for different T_{k_2}, which represents in (9) and (10) the time distance of the current sample $s_{HP}[n]$ from the past and the future samples.

It is clear that the choice of k_2 does not significantly affect the PP, while the sensitivity S improves by increasing T_{k_2}. However, it is easy to understand that the detection performance cannot further improve when k_2 becomes higher than the total distance d_{TOT} defined by (6).

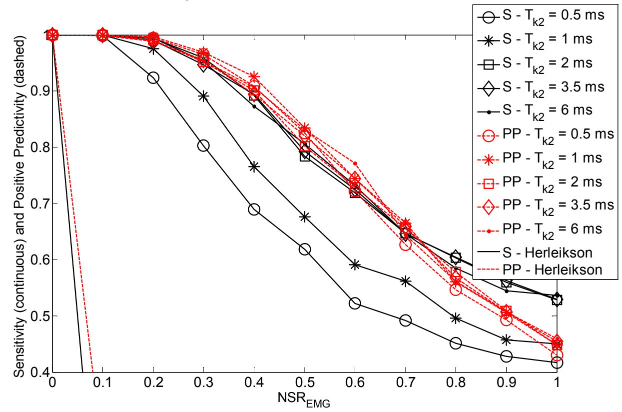

Figure 5. Performance for different values of T_{k_2}.

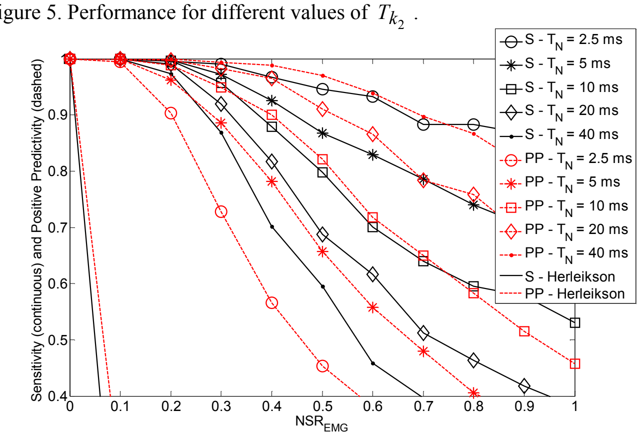

Figure 6. Performance for different values of T_N.

Fig. 6 shows the performance of the proposed algorithm for different sizes T_N of the two time windows defined in (9) and (10). It can be observed that, for a given NSR_{EMG}, a bigger T_N improves the PP, while on the contrary, it gives a worse S. The ESPP criterion we previously introduced would suggest $T_N = 10$ ms as the right choice.

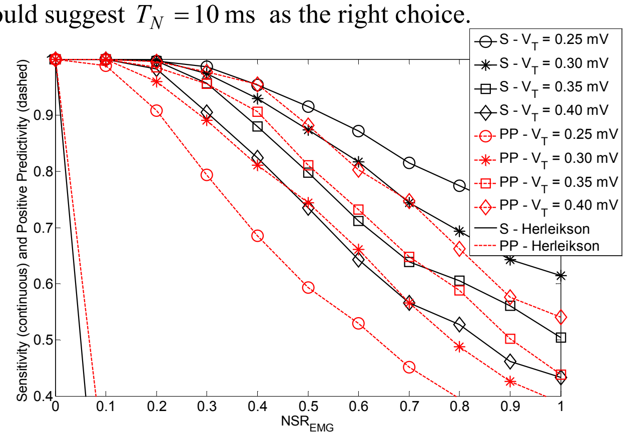

Figure 7. Performance for different values of V_T.

Fig. 7 shows the detection performance for different values of the threshold V_T. The ESPP criterion would suggest $V_T = 0.35$ mV as the best choice. However this fact could be misleading because we have been using in this set of simulations the optimal parameters values identified in Figs. 4-6 by the ESPP criterion, when the threshold was exactly $V_T = 0.35\,\text{mV}$. Thus, as suggested by Fig. 6, if for instance we increase V_T, which favors PP with respect to S, we should at the same time reduce T_N. This multiple parameter optimization problem is however not considered herein, due to lack of space. Summarizing, Figs. 4-7 highlight that, in a white wide-band EMG scenario, the Herleikson approach fails to correctly detect pacing pulses, whereas our method works quite well even at high NSR_{EMG}.

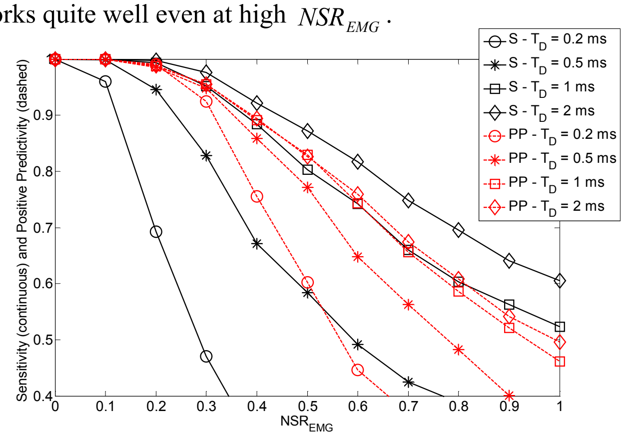

Figure 8. Performance for different values of T_D.

Fig. 8, which shows the algorithm sensitivity to the pulse duration T_D, highlights that a wider pacemaker pulse facilitates the detection performance.

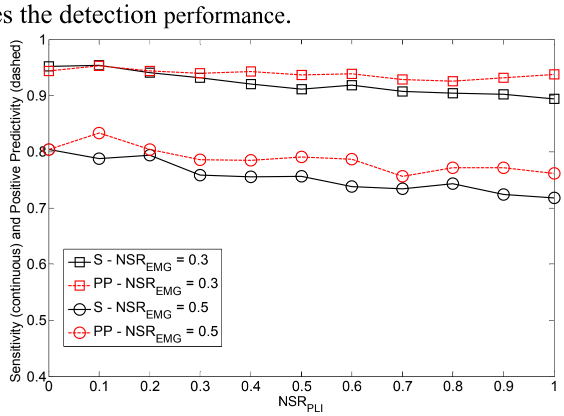

Figure 9. Performance with respect to NSR_{PLI}.

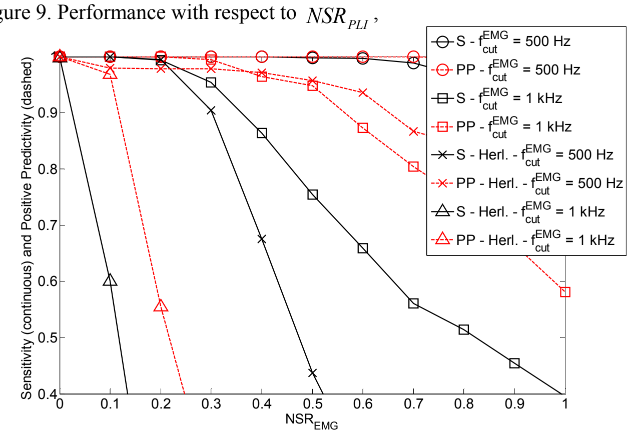

Figure 10. Performance for $f_{cut}^{EMG} = 500$ Hz and $f_{cut}^{EMG} = 1$ kHz.

Fig. 9 shows the performance versus NSR_{PLI}, for fixed $NSR_{EMG} = 0.3$ and $NSR_{EMG} = 0.5$, where it is clear that the PLI does not significantly influence the algorithm performance. This is true in all the scenarios, if k is not too high.

Fig. 10 compares the proposed algorithm with Herleikson algorithm [2] when $\sigma_{PLI}^2 = 0$ and for a band-limited EMG noise, with a maximum frequency $f_{cut}^{EMG} = 500 \div 1000$ Hz. We choose $k = 0$ because, by means of Fig. 3, it is obviously the best choice for a noise that is already LP band-limited, as we also verified by simulations not shown herein. Fig. 10 shows that, when the EMG noise has a limited bandwidth, although Herleikson algorithm [2] performs quite well, it is completely outperformed by the proposed solution. It is interesting that $k = 0$ means using the same HP filtering of [2], which consequently highlights the effectiveness of the non-linear filtering we introduced.

VI. Conclusions

This paper has presented a new algorithm for the detection of pacemaker pulses in ECG signals, based on a 3-step procedure. In order to identify the pacemaker pulses, in the first-step a linear filter removes the natural ECG signal, in the second-step a non-linear filter enhances the pace pulses with respect to the wide band noise, and in the third-step the detector simply compares the filtered signal with a threshold. The main characteristic of the proposed method, which always outperforms a widely used patented algorithm [2], is the detection robustness in wide-band noise environments. Moreover, by a reduced set of parameters the algorithm can be flexibly adapted to several different scenarios. Future works will focus on automatic and adaptive selection of these parameters, and on the exploitation of the potential correlation between the ECG complex and the pacemaker pulses positions.

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