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Lost Sample Recovering of ECG Signals in e-Health Applications

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Abstract—**This paper shows the interest of an interpolation method based on parametric modeling to retrieve missing samples in ECG signals. This problem occurs more and more with the emergence of telemedicine applications. The different links (fixed access network (PSTN), mobile access network (GSM/GPRS and future UMTS) or satellite interfacing (DVB-RCS technology)) involved in e-health applications are liable to induce errors on the transmitted data. These errors/losses can occur anytime and anywhere (according to the channel availability, memory overflows, protocols, etc) during a transmission process. Therefore the recovering of missing samples for biomedical signals is of great interest. The method used in this paper is based on a left-sided and right-sided autoregressive model, i.e., the interpolation algorithm uses the samples before and after the sequence of missing samples. An objective measure is used to assess the method performance. Results show that this interpolation method represents a really suitable technique to ECG signal reconstruction in a possible corrupted transmission.**

I. Introduction

Within the frame of telemedicine, mobile e-health applications are using heterogeneous channels for data transmission. When considering the nomadic specificities of future e-health populations, the nominal telecommunication configuration will be patients equipped with wearable sensors for comfortably monitoring various vital signs (as non invasive embedded smart sensors). The transmission of these biomedical data will be made through the various connectionless channels available at the moment and at the place where the patient is. As an example, the OURSES project is part of the French competitiveness cluster named "Aerospace Valley" (http://www.aerospace-valley.com/en/) aiming at validating the use of satellite transmission when transmission are needed in isolated rural areas. The chosen application is medical services for old people living in these areas where no high bit rate is available. Clearly, even if these old people are sometimes living in some specialized structures for the elderly, only nurses are taking care of them. In case of problem, the nurse has to call the physician who is often living far from these isolated areas, maybe 30 minutes far from there. When the physician arrives, sometimes, it is too late. Therefore, the idea of the OURSES project is to equip isolated villages (for example in the Pyrenees, the mountains of the South of France) with a satellite transmission system. Risky people living alone will wear some biomedical sensors (ECG for example), connected to a central unit via a Wi-Fi link and when an alarm is detected by the system, data will be transmitted through satellite links to the correspondent medical doctor who can call the nurse and, based on his diagnosis through ECG analysis, tell the nurse what to do. The same kind of scenario exists for old people living in a specialized structure.

Therefore, the quality of the received biomedical signals is a major key of the success of this experience. The transmission has to be fast, complete and reliable. Satellite transmission is based on the DVB (Digital Video Broadcasting) standard [1]. Within this standard, data to be transmitted are grouped in packets before transmission. These packets are protected against errors produced by the satellite channel. Protection against packet loss is done through the ARQ (Automatic Repeat Request) procedure where retransmissions are based on selective acknowledgments, allowing sender to start retransmission of lost packets with minimal delay. However, no guarantee can be given for the maximum delay necessary to recover from lost packets. There is no way to provide null error rate, excepted if an infinite transmission delay is acceptable which is not the case in this telemedicine context.

Therefore, this paper proposes some solution to recover from lost packets by retrieving missing samples in biomedical signals, without waiting for retransmission of the corresponding packets.

The reconstruction of partially known signals has been widely studied in the signal processing literature. A very good review can be found in [2]. Deeper studies can be found in [3] and [4]. A specific study on the recovery of ECG signals has been made by the same author, using the same kind of algorithms [5], [6]. These algorithms are based on the band-limited spectral property of the signal of interest and provide theoretically exact solution. However, these algorithms present high computational cost for a long sequence of missing samples.

This is the reason why, in this paper, another kind of solution has been investigated for ECG reconstruction. The idea comes from the reconstruction studies in audio processing where the samples loss might be due to the degradation of recording supports and can be recovered by using parametric modeling [7]-[10].

This paper shows the interest of a method based on left-sided and right-sided autoregressive modeling [10] to interpolate missing samples in an ECG signal. The paper is

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organized as follows. Next section describes the interpolation method. Experimental results on real ECG signals are presented in Section III. Conclusion is reported in the last section.

II. Interpolation Method

A. Problem presentation

A previous study has shown that the time out of several ARQ procedures results in 1-2% (for GPRS) and 8% (for satellite transmission) of packet losses [11]. This can induce a long sequence of missing ECG samples. Note that this portion of missing samples can appear everywhere along the received ECG signal and may be prejudicial for ECG interpretation by the physician.

Rather than using iterative techniques, such as the ones proposed in [2]-[6] which can be computationally expensive, we investigate the use of one reconstruction method which has been proposed in [10] for audio signals. This method is based on autoregressive (AR) modeling.

B. Modeling

An autoregressive (AR) model of a signal *x(n)* is defined by [12]

$$x(n) = -\sum_{k=1}^{p} a_k x(n-k) + e(n) \qquad (1)$$

where p is the model order, the a_k 's are the linear prediction coefficients (LPC) and $e(n)$ is the modeling error or excitation signal. This kind of modeling has been extensively used for several applications including spectral analysis, classification, speech coding, prediction, etc.

In order to retrieve audio distorted signals, [10] suggests to use this kind of modeling as a way to interpolate missing samples using backward and forward prediction, around the missing part of the signal. Thus, AR analysis is performed before and after the missing part of the signal. The different corresponding LPC are estimated using a classical error minimizing procedure, through one of the well-known algorithms [12]: the Yule-Walker method, the Burg method, the modified covariance method, etc. Then, the corresponding excitation *e(n)* is computed by inverse filtering. Both models (the one before the missing part and the one after) are used to reconstruct the missing part using (1).

The detailed algorithm is presented in what follows.

C. Reconstruction Algorithm

Let us consider an ECG signal which contains a missing sample sequence of M samples between two segments of N samples each, with $N > M$. The proposed algorithm for the ECG reconstruction consists of the next steps:

1. Estimation of the AR model of a given order p for the segment of N samples **before** the missing part.
2. Computation of the model excitation *e(n)* by inverse filtering.
3. Extension of this excitation by addition of first M samples of the time-reversed version.
4. Filtering of this extended version of the excitation by the AR model. The filtered signal resulting corresponds to the forward signal reconstruction.
5. Steps 1 to 4 are redone in order to obtain the interpolation in the backward way. For this, consider the N samples placed immediately **after** the missing part.
6. The forward and the backward models are affected by a cross-fading window to reduce the interference in the middle of the missing part.

The window used in the cross-fading is defined by [9]

$$w(n) = \begin{cases} 1 - \frac{1}{2}\left(2u(n)\right)^{\alpha}, & u(n) \le \frac{1}{2} \\ \frac{1}{2}\left(2 - 2u(n)\right)^{\alpha}, & u(n) > \frac{1}{2} \end{cases} \qquad (2)$$

where $u(n) = (n - n_s)/(n_e - n_s)$, with n_s and n_e being, respectively, the indices of the beginning and the end of the missing sample part. The parameter α modifies the window's roll-off.

This procedure is illustrated in figure 1.

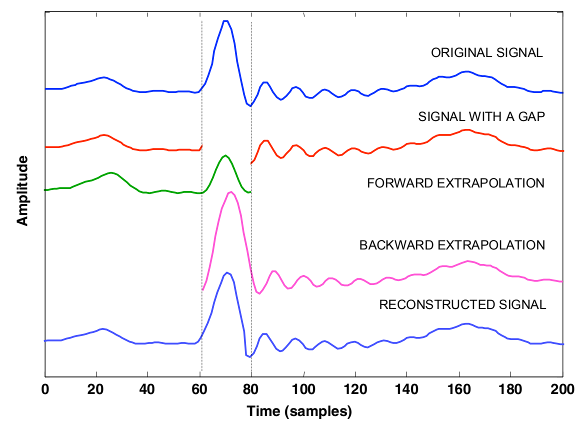

Fig. 1. Different steps in the reconstruction procedure.

III. Experimental Results

This section studies the interest of the algorithm [10] for ECG reconstruction.

A. ECG signals

Test signals were chosen from the MIT-BIH Arrhythmia Database [13]. This well-known database consists of several ECG records for different study cases.

Three different signals were used for the algorithm test. These signals are the records 100, 119 and 200, which present different characteristics. Two minutes of each signal have been used for reconstruction validation.

B. Interpolation parameter setup

The LPC estimation was done using the Burg method. The order of the AR model was fixed to *p=50* after a model error analysis. After this value, the model error variance does not decrease significantly anymore. Note that a classical criterion of modeling order such as MDL or AIC [12] would provide a lower model order. However, since we are not interested in spectral analysis here but only in deriving a liable temporal model of the signal, an overestimation of the model order is preferable. The parameter α (cross-fading window's roll-off) is set to 2.

Real ECG signals from the MIT-BIH Arrhythmia Database were clipped so as to simulate lost samples. The size of the lost sample part varies from *5 to 20 consecutive samples*. This parameter is very important to measure the interpolation method performance. *Position* of the missing part in the signal is another important parameter. Provided that there are no rules for a missing part to happen, these were inserted in a *random way* in order to consider all the possibilities.

C. Reconstruction performance

To assess the performance of the interpolation method, an objective measure has to be used. A natural proposal is to use a *local* Signal to reconstruction Error (Noise) Ratio (SNR) given by

$$SNR = 10\log\left(\frac{\sigma^2_{xgap}}{\sigma^2_{(x-\hat{x})\,gap}}\right) \quad \text{in dB} \qquad (3)$$

where σ^2_{xgap} represents the variance of the original signal in the missing part and $\sigma^2_{(x-\hat{x})gap}$ represents the variance of the reconstruction error also restricted in the missing part. A better criterion would be a subjective one, thanks to a physician who would agree to proceed to ECG analysis and diagnosis in a blind test procedure, dealing with original and reconstructed ECG. However, as a first measure, the SNR seems suitable to assess the interpolation method performance.

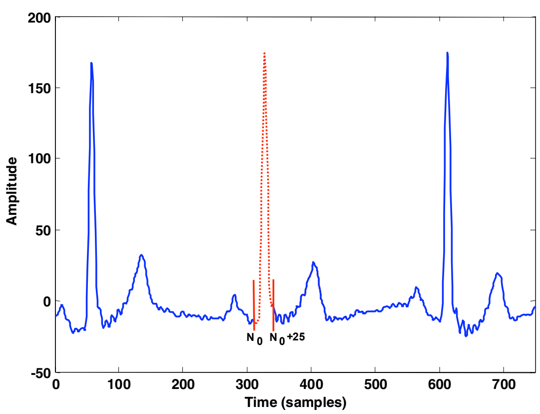

Fig. 2. A QRS complex reconstruction example (record 100).

When processing on real-time signals, this measure will not be possible to give, since the original missing part is not available. Anyway, within the frame of the OURSES project, when lost packets will result in missing samples in ECG signals, the reconstructed signal parts will be displayed in a color different from the received signal part. Thus, the physician will be free to accept or to refuse this signal reconstruction and maybe, to demand a new signal transmission (depending on the emergency situation).

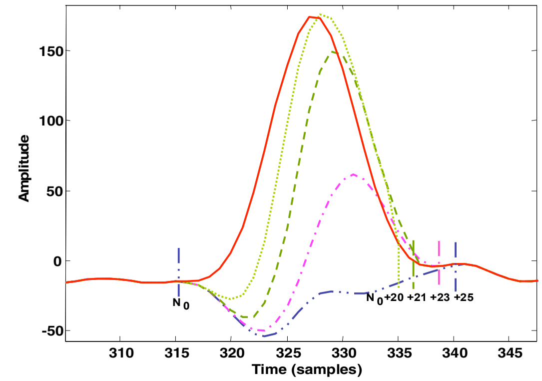

Fig. 3. Influence of the QRS gap length: different end indexes.

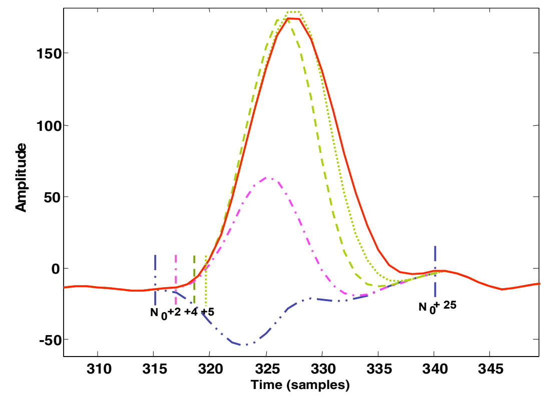

Fig. 4. Influence of the QRS gap length: different beginning indexes.

Figure 2 shows an ECG example where the QRS complex was not received. This example was used to study the missing part position problem and its impact in the method performance. Indeed, this position determines the performance for the AR model. For instance, if we consider a gap in the complex QRS (fig. 2), the AR model before the gap is determined by the P wave and the AR model after the gap by the T wave. Final interpolations for this study case are illustrated in figures 3 and 4. In these interpolations several positions of the beginning and the end of the gap were considered. In figure 3, N_0 is the beginning index of the missing part with a size varying from 20 to 25, centered on the QRS complex. In figure 4, the beginning index is varying from N_0 to N_0+5 and the end of the missing part is fixed to N_0+25. If we consider a maximum gap length of 25 samples, we can observe that the AR model combination of the backward and forward parts (in dashed blue "_.._") is not very reliable for the QRS reconstruction. When reducing the missing part length, the interpolation becomes appropriated to the reconstruction of the QRS complex. Nevertheless, for a same missing part length, it seems more difficult to model the QRS complex using the T wave (backward extrapolation) than the P wave (forward extrapolation). Anyway, except the case where the whole QRS part is missing, this modeling seems well-adapted to the ECG reconstruction and specifically of the QRS part which represents the most important information in the ECG.

Figure 5 shows results in terms of mean local SNR as a function of the missing part length. For each considered ECG and each missing part length, 3800 missing parts have been randomly positioned on the signal. For each reconstructed part, the local SNR (3) has been computed and the mean local SNR has been derived for the considered signal and missing part length.

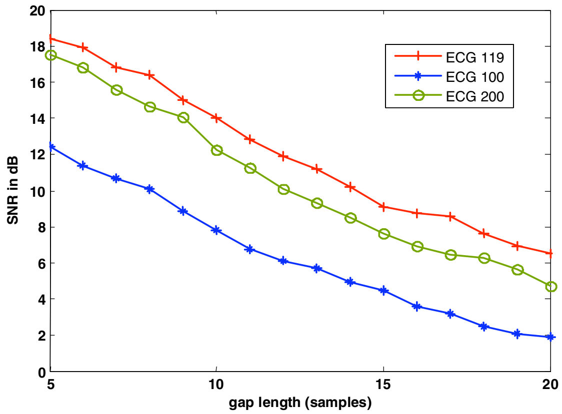

Fig. 5. Performance of the proposed method.

To give a better idea of the interpretation of these local SNR values, a reconstruction example is illustrated in figure 6. This figure shows a segment of the ECG record 200. In this case, the missing parts, generated in a random way, are of 15 samples length each. On the top of the figure, the original signal is shown. Below is shown the corresponding reconstruction signal. For a better comparison between original and reconstructed signals, the original signal is also drawn in a red dashed line. The solid green line corresponds to the reconstructed parts.

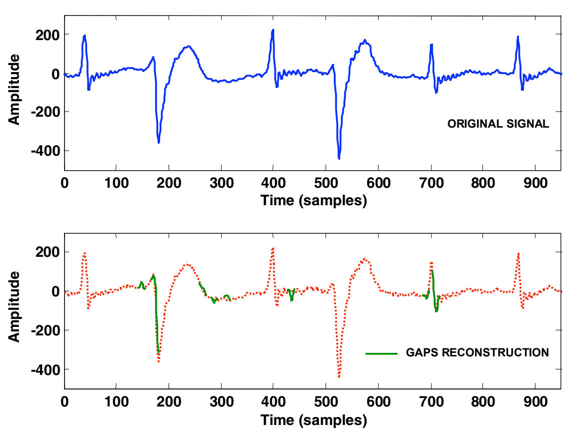

Fig. 6. An example of ECG reconstruction (record 200).

We can observe that this reconstruction corresponding to a mean local SNR of around 7 dB is really reliable and could be accepted by a physician. This example of SNR around 7 dB leads to better understand the preceding figure 5. Therefore, based on these results, the proposed method can be considered as suitable for ECG reconstruction after a wireless transmission or a satellite communication.

IV. Conclusion

In this study, the interest of an AR-based reconstruction method for lost samples in an ECG signal transmission, has been presented. The interpolation method is based on a left-sided and a right-sided AR model and has already been applied to audio signals.

The proposed method was applied to real ECG signals extracted from the MIT-BIH Arrhythmia Database. Different missing part lengths have been considered with a random position within the ECG. The particular and maybe the worst case of a missing QRS part has been studied: except when the whole QRS is missing, the proposed method performs well in the QRS reconstruction. More generally, performance of the interpolation method was assessed considering an objective mean local SNR measure as a function of the missing part length. Results show that this proposed method can be suitable to reconstruct ECG missing parts when transmission errors induce missing consecutive samples in the received signal.

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