NOISY CHANNEL DETECTION USING THE COMMON ANNIHILATOR WITH AN APPLICATION TO ELECTROCARDIOGRAMS

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ABSTRACT

Signal quality assessment is an important issue as noisy channels could mean lost information and unreliable data. In the field of Electrocardiograms (ECG), this is also important as noise could affect the detection of transient cardiac conditions which occur in these noisy channels. In VPW-FRI, the common annihilator is used to decompose multichannel signals with common root locations. Using information from the common annihilating filter, this paper will show that poor quality or noisy signals can be classified from the noiseless signals. This is done through the fact that each channel contributes to the solution of a pulse location and the channels which contribute below a certain threshold are deemed to be noisy or of poor quality. We will show that our algorithm works to the point where VPW-FRI is able to distinguish the features of the signal well despite any noise present.

***Index Terms*—** ECG, Fetal Heart Rate, Finite Rate of Innovation

1. INTRODUCTION

Multichannel sampling and reconstruction for Finite Rate of Innovation (FRI) signals with common support was developed by *Hormati et al.* [4] and extended to the Variable Pulse Width FRI (VPW-FRI) model in [7]. These sampling schemes were developed on the assumption that the various channels contained either Diracs or pulses with common support which means a Dirac would have a single location across all the channels.

This was developed firstly as a solution to MIMO [4] systems and later for Electrocardiogram [7] signals which both fit the assumption of common support. This allowed for accurate estimation of parameters despite noise in any of the channels. For a MIMO system, this would be all that is required given that each Dirac is completely described by its amplitude and location. However, for a signal like an ECG, where each heartbeat consists of a sum of pulses rather than just one pulse, it is not as straightforward.

In [2], *Quick et al.* stated that a sum of seven pulses were needed for accurate reconstruction of an ECG heartbeat and this was later reaffirmed by [3,7]. Therefore, the most prominent features might be detectable, but in noise, the smaller features used by clinicians for diagnosis may not be. The noise in question here would be interference from the muscles which causes a high frequency noise which is hard to separate from the ECG as can be seen in Fig. 1. Also poor contact from electrodes can cause severe distortions of the signal.

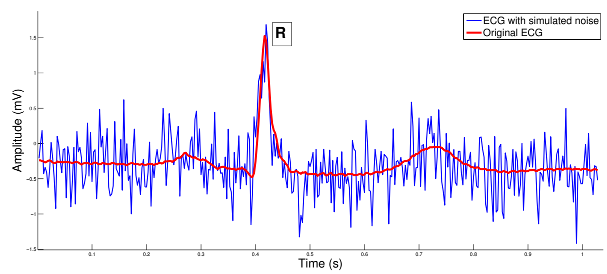

Fig. 1. Original ECG heartbeat vs ECG with simulated EMG noise using 0dB AWGN

Noisy data is usually present when using low quality electrodes, in long term monitoring devices and during ECG monitoring whilst exercising. The clinicians usually tend to discard the noisy segments of data as, depending on the level of noise, they are often unreliable even when denoised.

This poses a problem as firstly large amounts of data are collected in long term monitoring devices so storage would be wasted on noisy and unreadable information and secondly many cardiac conditions are transient in nature and if they occur during these noisy periods they may be lost.

In this paper, we will propose a feature dependent noise detection scheme based on the matrix pencil method in VPW-FRI [3,5,7]. Instead of using frequency bins, mutual information [11] and reference signals [9, 10], we will use the ability of the VPW-FRI algorithm to identify the available features in the ECG. This stems from the fact that although there may be noise, the relative ability of the channel to recognise a particular feature should determine how noisy or usable a signal

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is. This is based on the assumption that within a multichannel environment, there would be at least one noise free channel. This is done without reference signals such as templates or wavelets and the feature itself is derived analytically [7].

The paper will be organised as follows: Section 2 will provide a background on VPW-FRI and the mechanisms used which will be relevant. Section 3 will detail the algorithm used to detect the noisy channels which will be based on the common annihilator principle. Section 4 will contain descriptions of the data used, the experiments and the results obtained. The paper will be concluded in Section 5.

2. VARIABLE PULSE WIDTH - FINITE RATE OF INNOVATION

In this section, only a brief description of VPW-FRI and FRI will be presented which will be sufficient for the purpose of this paper. For a detailed study, please refer to [1–3, 6].

The VPW-FRI algorithm is an extension of FRI which was originally proposed by *Vetterli et al.* [1,6]. The VPW-FRI algorithm expanded the use of Diracs to variable width pusles which were applicable to a wider range of signals. The VPW-FRI algorithm introduced two additional parameters, width and asymmetry which are represented by a_k and d_k respectively. This is in addition to the location,t_k and amplitude,c_k, specified by the original FRI.

The FRI method depended on recovering parameters from at least $2K$ contiguous Fourier coefficients $X[m]$. These coefficients were described by VPW-FRI as

$$X[m] = X^{(1)}[m] + X^{(2)}[m], \tag{1}$$

where

$$X^{(1)}[m] = \sum_{k=0}^{K-1} c_k e^{-2\pi(a_k|m|+it_k m)/\tau} \tag{2}$$

and

$$X^{(2)}[m] = -\sum_{k=0}^{K-1} d_k sgn(m) e^{-2\pi(a_k|m|+it_k m)/\tau}. \tag{3}$$

Finding the t_k parameter is a non-linear problem and therefore uses the annihilating filter, $(A*X)[m] = 0, \forall m \in \mathbb{Z}$ where X is a toeplitz matrix of $X[m]$ values found in Eq. (1). For the multichannel case, the common annihilator is represented by

$$\begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_M \end{bmatrix} \cdot \begin{bmatrix} A[1] \\ A[2] \\ \vdots \\ A[K] \end{bmatrix} = 0, \tag{4}$$

where X_m represents the Toeplitz matrices of the M channels and $A[k]_{k=1}^{K}$ are the coefficients of the common annihilator [7]. This is commonly solved by a Singular Value Decomposition (SVD) described by

$$USV^H = X \tag{5}$$

where U is a $((M \times (2K+1)) \times (2K+1))$ unitary matrix, S is a diagonal matrix containing the singular values and V is also a unitary matrix of size $(2K+1) \times (2K+1)$. The polynomials whose roots are the solution for the common locations are found in the rows of V.

The reconstruction will not be discussed as it is not required in this paper.

3. NOISY CHANNEL DETECTION

In this paper, the signal quality would be defined as the ability to locate a feature within the signal. For the case of ECG, this would be made easier given that ECG generally has quasi periodic heartbeats which mostly contain the same features.

The ability of VPW-FRI to detect the R peak was discussed in [7]. It showed that the common locations of the R peak was found consistently and accurately given that it is the most prominent feature in an ECG signal. The contribution of each signal towards the calculation of the common location however, is still unknown. The features itself can be identified using the method outlined in [8]. The peaks in the twice differentiated singular values can be used to identify which pulses belong to which feature groups.

However, instead of using the V matrix as was done in [7], consider the U matrix. Each column contains M polynomials stacked vertically which correspond to the M channels. This allows us to analyse the polynomial of each channel for a given VPW-FRI pulse and compare them to determine their input towards calculating their contribution towards identifying a particular pulse.

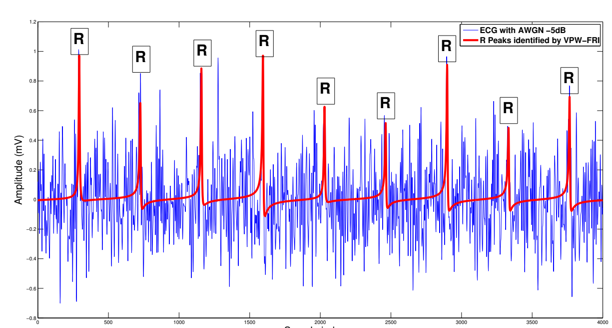

Fig. 2. Example of R peak identification in a noisy ECG signal

In this paper, the first pulse was used since it contains the most energy. The identification of the most prominent feature would guarantee that even in the noisiest case, it would have the best chance of being identified as shown by the ECG example in Fig. 2. This is due to the fact that it has strong common roots. The smaller features would be mistaken for noise and the probability of selecting a noisy channel would not be better than chance. The assumption being made is that there is at least one noiseless channel in each multichannel environment. The algorithm for detecting the noisy channels is as follows:

1. Normalise all signals to the interval $[-1, 1]$.
2. Proceed through the VPW-FRI algorithm as per normal until the annihilating filter step.
3. Circularly shift the X_m stack of matrices in Eq. (4) by one or two blocks for optimal results
4. Use the common annihilator to decompose the stack of Toeplitz matrices.
5. Divide the first column in U into its M constituent vectors, which represent the M channels.
6. Identify the maximum coefficient in each vector, $CMax_m$, where $m = 1 \dots M$
7. Removing the largest and smallest value of $CMax_m$, calculate the mean, μ, and standard deviation, σ, of remaining $CMax_m$ values.
8. The values $CMax_m < (\mu - \sigma)$ are the ones which contributed the least to the common location and thus can be deemed the most noisy or it could also contain a weak signal.

4. RESULTS

4.1. Data

The data used in this paper was a result of a collaboration between NTU and Tan Tock Seng Hospital (TTSH) where TTSH conducted ECG stress tests on treadmills and we were allowed to study the data for denoising and feature detection. All participants voluntarily signed an agreement allowing their data to be used anonymously for research purposes. The data consists of 12 lead ECG with leads I-III, aVR, aVL and aVF and V1-V6. The BRUCE protocol for the stress test was observed, which increased the incline and speed of the treadmill every 3 minutes. The tests were conducted by a physician and the ECG technician. The data was collected using the GE Marquette CASE Stress system with a T2100 treadmill. The data is sampled at $200Hz$.

4.2. Experiment

The experiment conducted was a simple one. Using the 12 lead ECG described in Section 4.1, a clean segment of data was extracted. Additive Gaussian White Noise (AWGN) was added from $-5dB$ to $5dB$ in increments of $5dB$ by randomly selecting 3 channel numbers from $0-12$. If the channel number 0 was selected, then only two channels would have added noise. The variable number of channels added slightly more difficulty to the challenge.At each noise level, 1000 simulations were carried out. The algorithm in Section 3 would be applied and the channel numbers would be compared to gauge accuracy.

	-5dB	0db	5dB	10dB
Hit(%)	100	100	90.4	56.3
Miss (%)	0	0	9.6	43.7
False Detection	0	0	108	521

Table 1. Results of simulation for noisy channel detection

4.3. Results

The performance of the algorithm was measured using three performance metrics, successful hit percentage, miss percentage and false detection. The hit percentage would be the number of simulations where all the noisy channels were identified correctly. The miss percentage would be when one or more channels were identified wrongly. The false detection was calculated as the total number of misclassified channels over the 1000 simulations.

The results of the simulations are presented in Table 1. It shows that at levels of intense noise, $-5dB$ and $0dB$, the algorithm worked perfectly. It was able to identify the noisy or distorted channels with absolute precision. The feature based system worked as even if the second most identifiable feature was used for the noise detection, the algorithm worked perfectly.

As for the simulations conducted at $5dB$, the algorithm suffered in performance as the R peak became easier to detect as the noise becomes milder. Therefore, the noisy channels contributed significantly more to the common roots and therefore increase the chances of misclassification .

At $10dB$, the performance of the algorithm was only slightly better than chance. This is because at this level of noise, the detection of the R peak is almost a trivial problem as can be seen in Fig. 3. Therefore, the noisy channels contribute almost as much as the clean channels. At this level of noise, it won't affect the reconstruction of the feature. The second and third most prominent features of the ECG could be used in this case, but ECG is a special case, given the multiple features it has, and for the sake of generality only the most prominent feature was used.

Conversely, this could be thought of as a measurement of signal quality. The lower quality signals can be identified as their features may be distorted or obscured. This would mean that it is not specific to any particular type of noise and

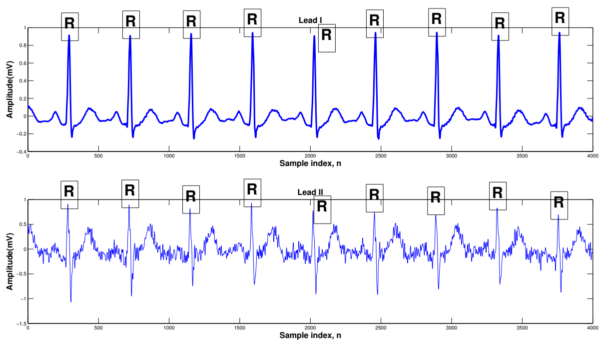

Fig. 3. A noiseless channel (above) and a noisy channel (below).

will be able to classify any channel based purely on how the given noise obscures the features as the algorithm makes no assumptions on the noise model.

A question may arise as to what may happen if all the channels are noise free. For that case, a no reference method would have to be derived, which would either require a more sophisticated method of calculating the thresholds or an empirically derived threshold for specific applications. Also, another subject of ongoing research is to determine the specific level of contribution of each channel rather than just classifying it into usable and unusable. This would broaden the scope of applications.

5. CONCLUSION AND FUTURE WORK

The ability of the algorithm described in Section 3 has uses in the field of biomedical signals where either physiological or environmental noise plays a significant factor when acquiring the signals. In the multichannel environment, in some cases, each individual channels yields specific information for clinicians and researchers and therefore would be lost or deemed unreliable. The method presented in this paper proved reliable for detecting noisy or poor quality channels and can be applied generally to scenarios with a variety of distortions or noise.

Some examples of future work involve feature detection in multimodal signals where each channel is a different physiological signal. By grouping together the channels with common features, relevant channels for those specific features could be identified. An example would be a hospital bedside setting where multiple signals are being recorded simultaneously; ECG, blood pressure, EEG and breathing rate for example. The algorithm could identify the correlated channels and extract relevant features from those channels whilst identifying relationships between the other channels. This is the subject of ongoing research.

In conclusion, the algorithm presented here would work for more applications than just noise detection. Also, given that it was formulated within the structure of the VPW-FRI algorithm, it is convenient to apply when identifying specific pulses within a multichannel signal.

6. ACKNOWLEDGMENT

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