Arm-ECG Bipolar Leads Signal Recovery Methods for Wearable Long-term Heart Rate and Rhythm Monitoring

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Abstract

A clinical database of distal electrogram recordings was created in conjunction with the Craigavon Area Hospital Cardiac Research Department. Signal averaged ECG (SAECG) methods were then used to inspect electrograms recorded bilaterally in a pilot study and the evidence based outcome of which directed the WASTCArD research group to consider the left arm as a prime location for a potential long term cardiac monitor.

Empirical mode decomposition (EMD), ensemble empirical mode decomposition (EEMD) and data fusion (DF) techniques were developed due to their ability to extract morphologically intact information from a dynamic data stream and their performance compared to the control SAECG reference method and clinically accepted denoising approach in high-resolution electrocardiography.

EEMD was found to be a robust, low latency denoising technique, in comparison to SAECG performance; achieving signal to noise enhancement figures that, in some cases, improved on the SAECG control method, when used with far-field bipolar leads along the left arm ECG data.

1. Introduction

Cardiovascular disease remains globally the single most common cause of death in developed and developing nations. Sudden death, usually caused by lethal dysrhythmias, accounts for 50% of these deaths [1]. Furthermore, patients with palpitations or loss of consciousness (syncope) account for a large proportion of attendances at hospital outpatients and emergency rooms [2, 3].

Current analysis tools and recording equipment, such as the Omron HCG801 event recorder [4], do not give a good temporal picture because the recording is not continuous.

The effect of drugs on the heart rhythm is widely noted in the literature. An example being those which are linked with QT elongation or torsade de pointes. Domperidone, for instance, has been associated with a small increased risk of serious ventricular dysrhythmia or sudden cardiac death [5,2]. A continuously wearable technology, capable of monitoring patients and implementing a warning strategy during the course of their treatment, would significantly de-risk the administration period.

The purpose of this work is to develop a digital signal processing (DSP) technique that, when fully developed, could be implemented on wearable technology, enabling the capture of a clinical quality ECG signal. The conditioned signal could then be further post processed using contemporary rhythm and pattern recognition algorithms to improve its prognostic value.

2. Methods

2.1. Clinical database

A clinical database of distal electrogram recordings was created. Signal averaging (SAECG) methods were then used as a control reference. A preliminary pilot study on both left and right arms was conducted. It indicated the advantage of the left arm as the preferable site. The low latency techniques of EMD, EEMD and a data fusion (DF) were developed and evaluated against the SAECG method.

2.2. SA ECG – Control standard

The unipolar mapping leads/electrodes of significance are CH1, a reference, high amplitude ECG channel used for temporal alignment in the signal averaging process. Electrodes for the bipolar leads (CH11- CH12) are placed across the biceps on the upper arm. CH10 is placed on the upper forearm and electrodes for the bipolar channel (CH6 - CH2) are located on the wrist. The reference electrode, REF, electrode as depicted in Figure 1 and 2 is also located on the subject's wrist interproximal to CH2 and CH6. The electrodes used were the Ambu Blue Sensor N type, designed for recovery of neonatal ECGs. This electrode type was chosen due to its physical size as a typical adult electrode made use in the wrist area cluttered. The Biosemi recorder was used to recover raw

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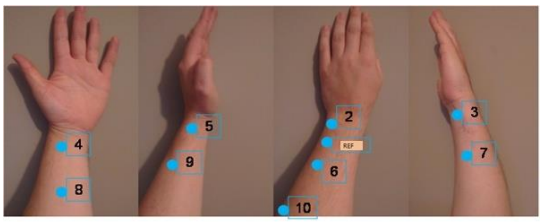

Figure 1. Electrode positions on left wrist enlarged

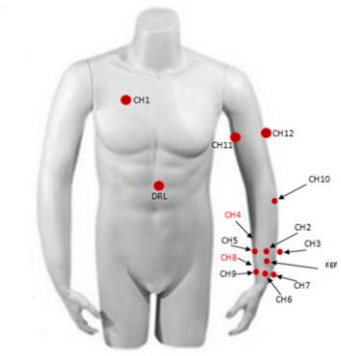

Figure 2. Electrode positions

bioelectric data from the 12 single ended channels simultaneously. A single fiducial point (SFP) was implemented as the marker point for temporal alignment of the signal averaging point. The technique was compared by Escalona et al. (1998) and shown to produce a similar level of accuracy as adopted standard techniques, such as maximum coherence matching (MCM) for example. [6].

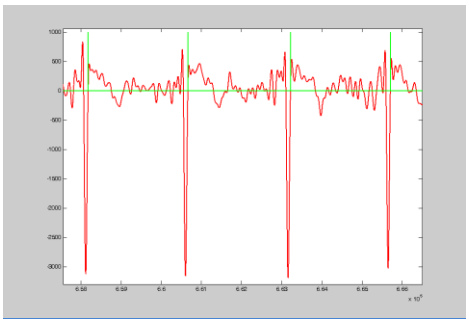

Figure 3. Section of subject 37, channel 1 waveform with fiducial markers in green

Figure 3 shows a typical ECG signal with the single fiducial mark indicated in green across several beats. Once temporal markers have been established, the iterative process of signal averaging can begin. Each fiducial mark is used as a central point for an averaging window. The window spans the time taken to complete a full cardiac cycle – PQRSTu – 550ms.

Each beat that corresponds with a fiducial mark is sectioned into a single dimensional array 1100 points wide. It is then added to a cumulative array until all available beats are processed. To find the Mean average, each point in the cumulative array is now divided by the number of accumulated beat windows (n).

$$\mathcal{X} = \frac{1}{n} \times \sum_{i=1}^{n} \mathcal{X}_i \qquad (1)$$

The resulting waveform is constructed using an average of n waveforms. Any signal that appears consistently in the same temporal space, known as time locked, will remain once the average operation is complete. Random or non-periodic signals are greatly reduced.

2.3. SNR Measurement Method

Signal measured from the isovoltaic area extending between the S wave terminus and the initial inflection point of the T wave is considered to be noise, as there is a pause in cardiac electrical output in this area. The QRS complex is the highest amplitude area of the ECG and is measured as the signal component[7]. Figure 6 shows the measurement areas on an averaged ECG trace. A temporal dispersion method was used, where the standard deviation of the signal was divided by the standard deviation of the noise in order to calculate the overall SNR. The time zones were temporally locked to the fiducial marker point which in itself was fixed to the R zero crossing point. Therefore, the same time zones will apply to all sinus rhythm ECG traces.

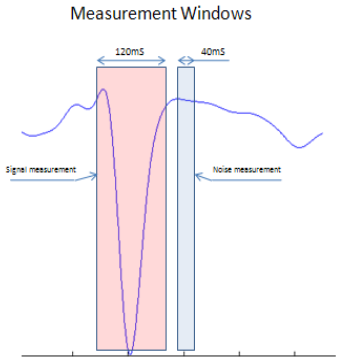

Figure 4. Signal to noise ratio (SNR) measurement windows

The linear SNR was computed as :

$$\text{SNR} = \frac{\sigma\text{Signal}}{\sigma\text{Noise}} \qquad (2)$$

2.4. Empirical Mode Decomposition (EMD)

The EMD algorithm was implemented according to Rato et al. [8] and summarised as follows:

(1) Identify all extrema of x(t)

(2) Using a cubic spline, interpolate between minima and maximawith envelopes e_{min}(t) and e_{max}(t)

(3) Compute the mean envelope$m_k(t) = \frac{(e_{max}(t) + e_{min}(t))}{2}$, where k is the iteration number.

(4) Extract the detail$h_j(t) = x(t) - m_k(t)$.

(5) Repeat (1)–(4) until h_j(t) meets the definition of an IMF, and the IMF converges.

(6) Repeat (1)–(5) to generate a residual r_n(t), r_n(t) = x(t)–h_n(t)

2.5. Ensemble EMD (EEMD)

A uniform distribution of white noise,$w_i(t)$, is added to $x(t)$ before decomposition to reduce the effect of the mode mixing in the EMD process [9, 10, 11].

For EEMD, the ratio of added white noise and the number of signals in the ensemble must be predetermined. Depending on the number of iterations in the ensemble, different white noise w_i(t) with the same amplitude is added N times to an original signal x(t) to generate N modified signals x_i(t).

$$x_i(t) = x(t) + w_i(t) \quad i = 1,2,\dots,N \tag{3}$$

The EMD decomposition is then carried out on each modified signal x_i(t), decomposing it into n units of IMF and one residue. This is replicated for N × n IMF signals and n residue components r_{in}(t). Then, $x_i(t)$can be rewritten as:

$$x_i(t) = \sum_{j=1}^{n} h_{ij}(t) + r_{in}(t) \quad i = 1,2,\dots,N \tag{4}$$

Each set of IMFs $H_j(t)$are averaged causing the noise component $w_{in}(t)$ to trend toward zero.

2.6. Data Fusion

The use of combined approaches to problem solving is not unusual. In this case a method of automating the EMD process is suggested in the form of a fusion between E/EMD and frequency analysis. The FFT is used to assess the spectral content of each IMF prior to partial reconstruction. If the predominant frequency content is outside of the 0.5Hz to 30Hz band the IMF is rejected.

3. Results

Five recordings were rejected (Subjects 14, 22, 29, 33 and 36) due to elevated levels of coherent noise from power line interference. Six recordings were classified as having good recording quality (Subjects 3, 4, 5, 12, 19, and 38). These subjects will be referred to as 'Golden Cases'

3.1 Signal averaging

Subject	Ch1	Ch12-11	Ch10	Ch4	Ch6-2
3	20.972	1.269	1.079	2.233	0.476
4	13.748	4.929	4.667	10.179	1.810
5	55.288	36.865	15.674	1.996	1.852
12	60.588	197.050	22.219	21.225	2.151
19	37.676	1.493	0.248	0.669	0.156
38	98.853	3.672	1.015	0.443	4.989

Table 1. Six best case recordings: SNR mean values along all four distancing bipolar leads along the left arm to the wrist measured using SAECG.

Table 1 shows the mean SNR data along the left arm. The graph of figure 7 shows the data of table 1 in increasing distance along the left arm.

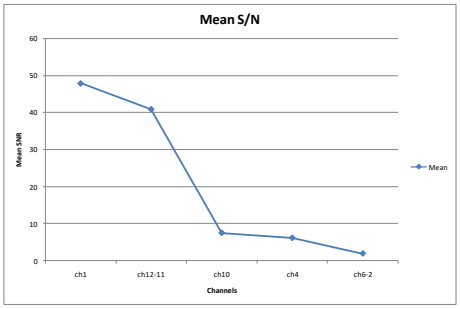

Figure 5. Six best case recordings: plot of mean (N=6) SNR values along the left arm, as calculated in Table 1

3.2 EMD and EEMD comparison

The following data are the result of comparative work carried out on the CAH database. The aim was to identify a data driven technique that could quickly and efficiently extract the cardiac electrical activity from a very deep noise floor. Figure 6 summarises the comparative averages of the golden cases when filtered using 1) SAECG, 2) EMD and 3) EEMD. .

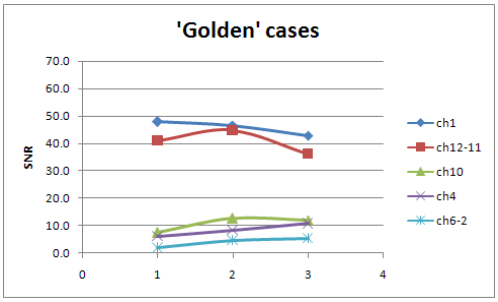

Figure 6. Average SNR of Golden cases.1) SAECG, 2) EMD and 3) EEMD. .

3.2 Data Fusion Techniques

Data fusion of EEMD and FFT has produced the

following result. The graph of Figure 7 shows the comparison across all four discussed techniques when applied to data recovered from each of the 5 distal sites along the left arm. It shows results comparable with the control standard of SAECG in the stronger signal cases of channel 1 (chest lead) and bipolar channel 12-11 (across the biceps). The SNR calculated for the distal channels shows an improvement on that collected using SAECG.

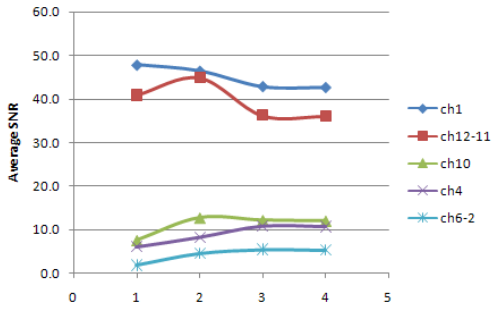

Figure 7.EEMD and FFT fusion comparative SNR data when applied to the 6 best cases from the CAH database. 1) SAECG, 2) EMD, 3) EEMD and 4) Fusion

4. Discussion and Conclusion

A data fusion approach, using EEMD and FFT, that allows automation of the empirical mode partial reconstruction filter method was tested. The results are displayed in Figure 7. They show an almost equal performance to the manual inspection method. The complicating factor of mode mixing is removed leaving only the issue of IMF content unpredictability, which is dealt with using standard frequency analysis - FFT in this case. An average improvement over SAECH of 62.7%, observed for a case of SNR of 1.9. The additional integration of the standard FFT process has shown an advancement by providing a method by which the process may be automated for potential embedded application.

5. Limitations and Future Work

The study has offered an evaluative and data based perspective on the use of a data driven analysis technique in the field of distal ECG signal recovery. The study encountered a number of limitations, which need to be considered.

1) The Biosemi measurement equipment, although battery driven, was very susceptible to mains noise.

2) Lead arrangements were critical to the repeatability of results and would have benefited from more control.

3) No 'live stream' analysis has been carried out at this stage to ultimately prove the levels of latency.

4) Any ECG data recovered using the techniques described herein will exhibit a non standard derivation of that which is currently understood by clinicians.

An implementation of the EEMD – FFT technique on an embedded platform will be required to ultimately prove the level of latency when applied to a 'real life' data stream.

Throughout the study a control signal was available, in the form of a Lead I signal, to allow confirmation of all processing outcomes. In a 'real' device, this would not be available, possibly opening the way for further fusion techniques, using SA assisted by photoplethysmography.

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