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Real-Time Wearable Telecardiology From Representative Signals

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***Abstract*— Electrocardiograms and other similar techniques (e.g. Photoplethysmograph) are very effective tools for the detection of cardiac abnormalities. Automated analyses of ECG signals may be used for this purpose, but due to their complexity—often involving a Neural Network or Principal Component Analysis—the signal needs to be transmitted to be analysed on a powerful device. Thus, even if signals are compressed before being sent, a significant amount of non-critical information is transmitted, unnecessarily consuming bandwidth and resulting in delays. This is problematic as lives may depend on how fast and accurately an ECG signal can be analysed.**

We present here a fast, simple and accurate technique that works in real time to detect some ECG abnormalities. We base our analysis on correlations of the time sequence with a Representative Signal (RS) to detect abnormal behaviour. We have implemented this scheme on a standard, inexpensive portable device, so abnormalities may be automatically detected immediately on the device itself, without the need for transmission.

I. INTRODUCTION

Cardiovascular disease (CVD) has long been the leading cause of death in Australia [1], [2]. Until recently, patients with Coronary Heart Disease (CHD)—a type of CVD—would present to a hospital to have an electrocardiogram (ECG) test, which cardiac specialists would use to diagnose the disease based on their ECG (time sequence) signal. A typical ECG signal is shown in Fig. 1.

Technological advancements in the field of Body Sensor Networks (BSN) and mobile telephony now make it possible to monitor remotely a patient's ECG signal, in both time and frequency, and send the data from the monitoring device to a remote server. Traditionally, remote server analysis is needed to detect abnormalities because the complex pre-processing and post-processing techniques used require processing power and memory capacity not available on inexpensive mobile devices. Naturally, this results in all the signal information—both relevant and irrelevant—being sent to the server for analysis.

Many remote server analysis approaches have been proposed previously [3]–[8], which include the use of Wavelet Transforms (WT) [5], Neural Networks (NN) [6], WT and NN [3], [4], Principal Component Analysis (PCA) and K-Means Clustering (KMC) with compressed ECG signals [7] and a sequential combination of FCM $\rightarrow$ PCA $\rightarrow$ NN [8]. All of these techniques require heavy analysis at the server side to detect abnormalities.

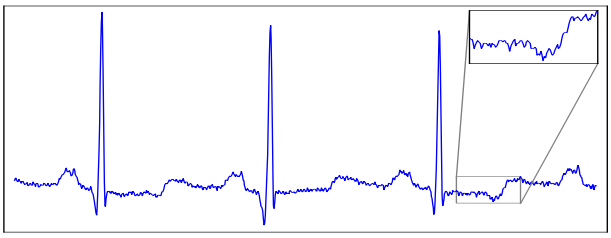


Fig. 1. Normal ECG Signal, Zoom in of the Noise

Further work in the area of mobile based approaches [9]–[13], include R-R peak detection on standard mobile phones [9], R-R based arrhythmia detection [10], heart rate, R-R interval, R peak amplitude, and normal/abnormal beat detection [11], a mobile phone-based monitoring system with PVC detection [12] and a CVD prevention and detection system known as HeartToGo [13]. The authors describe the HeartToGo system as an experimental prototype, with unknown accuracy and performance. The remaining client-side approaches perform limited analysis and most do not identify particular arrhythmias.

II. REPRESENTATIVE SIGNALS

The previous section shows that these state of the art diagnostic techniques are either incomplete or not suitable for mobile device based approaches. Furthermore, mobile based diagnostic approaches appear to be limited in comparison to tele-monitoring approaches.

A. Representative Signal (RS) Construction

We introduce here a technique based on the construction of a signal representative of a sequence of normal heart beats. In this way, our analysis does not use all the heart beats present in the ECG sequence, but only a representative pattern which carries the essential signal information. We extract the fundamental signal information by de-noising and calculating an average signal using a clustering algorithm. The complete sequence of steps to construct the RS follows[1]:

1) Collect a continuous sequence of 12 normal sinus rhythm (NSR) heart beats.

[1]The set of parameters selected produce the best results.

2) Remove the baseline drift by applying a 8 level Discrete Wavelet Transform using the Biorthogonal 6.8 wavelet and zeroing out the 8th level approximation coefficients [14].
3) De-noise the sequence of beats by applying a 3 level One Dimensional Wavelet de-noising function[2] using the Daubechies 2 wavelet. See Fig. 2(a) and 2(b).
4) Split the sequence into individual beats, by detecting the R-R interval and dividing the interval in half.
5) Superimpose the beats, such that they are aligned at the R-Peak[3].
6) Apply the K Means Clustering (KMC) algorithm to the superimposed beats, using 250 clusters.
7) Using the cluster centers found in step 5, reconstruct the signal.
8) De-noise the reconstructed signal by applying a 2 level One Dimensional Wavelet de-noising function[2] using the Daubechies 3 wavelet.

The baseline drift removal technique is based on prior research by R. von Borries et al. [14], though we use the slightly smoother Biorthogonal 6.8 wavelet instead. For de-noising, we use the Daubechies 2 and Daubechies 3 wavelets, as they are appropriate for the desired noise being removed.

Our approach takes advantage of the fact that heart beat morphology is specific to each patient. That is, two patients will have a slightly different normal sinus rhythm morphology, but the morphology remains consistent for each patient. This coincides with recent research by Sufi and Khalil, which demonstrates that ECG signals can be used as biometrics [15]. Moreover, we have found that even arrhythmia beats seem to be alike for each patient. See Fig. 3.

A graphical illustration of the RS construction steps can be seen in Fig. 2. The construction technique is applied to a sequence of 12 heart beats classified as normal sinus rhythm for that patient by a medical professional. See Fig. 1.

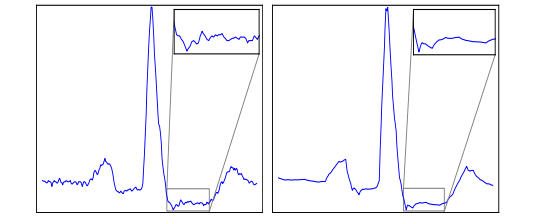
B. Detecting Abnormalities

After calculation, the RS is re-sampled to match the sampling rate of the ECG recording. In our case, the MIT-BIH database, sampled at 360Hz. The RS is then stored as a sequence of digital points.

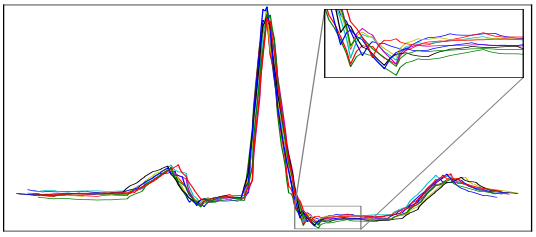
To detect abnormalities, the RS is superimposed onto the patient's beat ensuring that the beats align at their R-Peaks. To make both signals the same length, the shorter signal to the left and right of the R-Peak is zero padded. After this, the signals are both normalised to create an upper-bound whilst maintaining their relative sizes. The final step is to split the

[2]One Dimensional Discrete Wavelet de-noising applied using (wdencmp) function from the MATLAB Wavelet Toolbox, using default values generated from the (ddencmp) function.

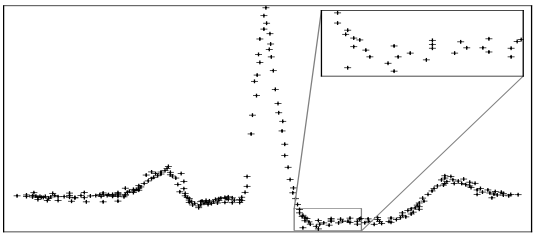
[3]To detect the R-Peaks, each ECG record is run through a script which locates the R-Peak using the annotations from each record as a reference.



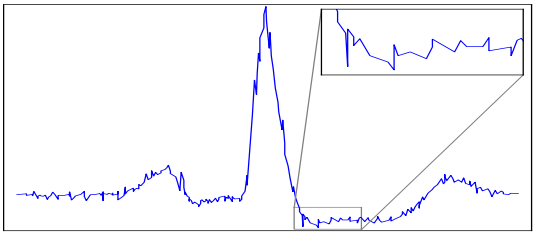
(a) Original Signal (b) De-noised Signal



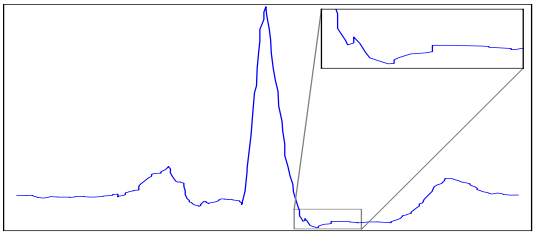
(c) Superimposing ECG Beats



(d) Applying K Means Clustering



(e) RAW RS



(f) Filtered RS

Fig. 2. RS Construction Steps

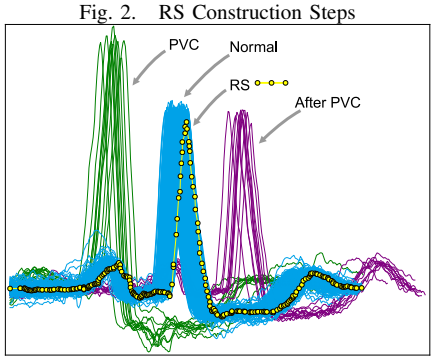


Fig. 3. RS Superimposed with a Subset of PVC Beats

signals into windows of 10 samples. Once the beats are ready, the following calculations are performed per window:

$$ERS\&EUB = \sum_{i=1}^{10} {Y_i}^2 \quad (1)$$

$$ED = \sum_{i=1}^{10} (Y_{RSi} - Y_{UBi})^2 \quad (2)$$

$$R = \frac{ERS}{EUB} \quad (3)$$

$$SIG = \frac{ED}{ERS + EUB} \quad (4)$$

For each window, the signal energy ERS of the RS pattern and the signal energy EUB of the unclassified beat are calculated (Eq. 1). A third energy value ED of the difference between RS and the unclassified beat is also calculated (Eq. 2). Equation 3 determines the size of the energies relative to each other. Finally, the SIG calculation establishes the sizes of the energies relative to the size of the signal itself (Eq. 4).

The energy values ERS and EUB have minima of 0 and maxima of 10, because the beats are normalised between 1 and -1 and the window size is 10. Therefore from Eq. 1 $\sum_{i=1}^{10} {Y_i}^2 <= \sum_{i=1}^{10} 1^2 = 10$.

Similarly ED will have a minimum of 0 and a maximum of 40 if both signals were flat at 1 and -1 for the duration of the window.

R ranges from 0 to $+\infty$ which is a result of ERS being 0 or EUB being infinitely small. An R value closer to 0 indicates that EUB is much larger than ERS. A value closer to 1 indicates that both signals are approximately close to each other, while a very large value of R—close to infinity—indicates that ERS is much larger than EUB.

The SIG value determines whether this difference is significant with respect to the size of the signals (i.e. the size of the difference relative to the size of the signals). We have concluded experimentally that a SIG value of 0.1 or higher, as in this case, means that the difference between RS and the unclassified beat, relative to their mass distribution is significant for our purposes.

Based on these values, together with the window divisions, we can determine the size, shape and location of significant differences between the RS pattern and unclassified beat.

C. Classification

We have applied our technique to 21 patients from the MIT-BIH Arrhythmia Database, who have Premature Ventricular Contraction's (PVC). The requirement for each patient selected is to have at least one PVC beat, at least 12 normal consecutive beats and for the majority of the patients beats to have a morphology similar to that of a normal sinus rhythm beat. See Fig. 1.

Our rule-based classifier for PVC detection, consists of:

1) Only check the window if it is on or past the R-Peak and before the 4th quarter. Essentially this rules forces the classifier to concentrate on the 3rd quarter region when the total number of windows is divided into 4.
2) **Abnormality Rule 1**
   a) The R-Peak for the unclassified beat will be significantly larger $R < 0.5$ or significantly smaller $R > 6$ in the window containing the R-Peak.
   b) The ED must be less than ERS or EUB. This makes sure that both R-Peaks are on the same side of the X axis.
3) **Abnormality Rule 2**
   a) The window will have a negative mean value for the unclassified beat. This ensures that the classifier detects abnormalities below the X axis.
   b) ED is less than EUB and R is less than 0.5. The rule is checking that the RS is also below the X axis and that EUB is significantly larger than ERS.
   OR
   c) ED is larger than ERS and ED is larger than EUB. This accounts for the instances where the unclassified beat is below the X axis but RS is above the X axis.
   d) $EUB > 0.7$ and $SIG > 0.4$. With this rule, the classifier detects instances where the unclassified beat dips down deeply.
   e) $EUB > 0.32$ and $SIG > 0.1$. With this rule, the classifier detects PVC instances where the unclassified beat has a shallow but wider dip.

The rules 2, 3d and 3e have a weighting of 1, 3 and 1 respectively. The classifier uses these weightings to identify two distinct types of PVC. The first is a deep ventricular contraction which lasts for the duration of 1-2 windows. The second is the shallow and wider ventricular contraction.

A final judgement is made based on the collective weightings for the abnormal windows. A weighting of at least 3 is required with two or more consecutive windows showing indications of PVC to classify a beat as PVC, or a single window with a deep PVC indication is also adequate.

The thresholds in these rules have been derived from our optimisation cycle, where each threshold is incremented and then the results compared using a heat map to determine the improvement in accuracy. The optimum threshold is selected once no further improvements in accuracy can be identified[4].

[4]The thresholds have been manually revised since the initial optimisation

TABLE I
PVC CLASSIFICATION RESULTS

Patient	# Beats	# PVC Beats	Se	Sp	PPV	NPV
100	2271	1	100.00	99.96	50.00	100.00
105	2570	41	68.29	94.74	17.39	99.46
106	2025	520	88.46	100.00	100.00	96.17
114	1877	43	100.00	98.36	58.90	100.00
116	2410	109	99.08	99.83	96.43	99.96
119	1985	444	100.00	100.00	100.00	100.00
121	1861	1	100.00	99.19	6.25	100.00
123	1516	3	100.00	99.93	75.00	100.00
200	2599	825	97.70	98.65	97.11	98.93
201	1998	198	99.49	97.56	81.74	99.94
202	2134	19	94.74	98.77	40.91	99.95
205	2654	71	98.59	100.00	100.00	99.96
208	2953	992	98.89	92.71	87.28	99.40
209	3003	1	100.00	99.80	14.29	100.00
213	3249	220	78.18	98.81	82.69	98.42
215	3361	164	97.56	99.06	84.21	99.87
223	2603	473	90.27	99.48	97.49	97.88
228	2051	362	99.72	98.28	92.56	99.94
230	2254	1	100.00	99.69	12.50	100.00
233	3077	830	99.28	99.33	98.21	99.73
234	2751	3	66.67	99.89	40.00	99.96
Avg	51202	5321	96.00	98.78	90.15	99.53

D. Data Analysis

The statistical measures used to evaluate the accuracy of our approach are:

- `Se` (Sensitivity): The `Se` value is a measure of the likelihood of PVC beats being detected as PVC beats.
- `Sp` (Specificity): `Sp` is a measure of the likelihood that a normal beat will be detected as normal.
- `PPV` (Positive Predictive Value): `PPV` is a measure of the likelihood that a beat detected as PVC is actually a PVC.
- `NPV` (Negative Predictive Value): Measures the likelihood of a beat not classified as PVC actually not being PVC.

E. Results

From Table I, we can see a high `Se` and `Sp` rate, close to 100% for the vast majority of patients. High `Se` and `Sp` show that the classifier correctly classifies PVC beats as PVC and healthy beats as healthy with very good accuracy.

Although the average `PPV` result (90.15%) can be considered very good, the `PPV` measure varies greatly, ranging from 6.25% to 100%, where the classifier incorrectly classifies healthy beats as PVC beats. These `PPV` values are further exaggerated by the effects of prevalence.

Prevalence is the ratio of sick patients to the total number of patients. In our dataset the number of mis-classifications is exacerbated by low PVC prevalence values. As expected, the prevalence ratio is low as the general population will not all have a particular arrhythmia. In our case, some patients—such as patients 100, 121 and 209—have a low ratio of PVC. As discussed by Altman and Bland [16], when the prevalence ratio is low, the `PPV` values will not be close to one (100%), even if the `Se` and `Sp` values are close to one (100%). This is so because only a small number of false positives are needed to overtake the number of PVC cases for some patients. For this reason the `PPV` values are not as high as the `Se` and `Sp` values.

The `NPV` values for each patient are also considerably close to 100%, showing that the majority of the beats classified as normal we true normals.

The low `PPV` and high `NPV` values indicate a high number of false positives and a low number of false negatives respectively. False positive errors occur when a beat is classified as PVC when it was really normal. This type of error occurs frequently which is the reason why the `PPV` values are low; a significant number of beats are being classified as PVC when they are normal. In a life or death situation, this would not be a big problem when compared to false negative errors.

False negative errors occur when a PVC beat is classified as normal. This can be a fatal mistake. We can see from the very high `NPV` values that the classifier is very good at classifying normal beats, and that it is unlikely that a PVC beat will be classified as normal.

F. Efficiency

To measure performance the technique was implemented in Java and timed on a HTC Dream mobile device running the Android operating system, using embedded timestamps in the classification code. On average, the technique requires 18.71ms to perform all the required calculations based on an average of 30.10 windows per beat.

According to Jones [17], the normal sinus rhythm rate is between 60–100 beats per minute, resulting in a duration of approximately 600–1000ms. Therefore the time taken to classify each beat with our approach is much less than the 600ms limit, making this approach and implementation perfectly suitable for real-time monitoring[5].

III. COMPARISON WITH EXISTING TECHNIQUES

Table II provides an in principle comparison of the existing techniques discussed above with our approach. From the table, we can see that our approach has higher accuracy than [6] (bearing in mind [6] classifies multiple arrhythmias) and is comparable to the majority of other approaches. However, most approaches do not use the same dataset, hence these results are not general across all datasets. As for performance, the majority of the mobile based approaches do not perform arrhythmia diagnoses, nor they provide performance results. In addition, the heterogeneity of the mobile devices used would make direct comparisons very difficult.

[5]The timing was performed with pre-loaded recordings from the MIT-BIH Arrhythmia Database. An additional penalty may be incurred from any delay between the ECG leads and the mobile device.

[6]Se and PPV values recalculated from data provided in literature to suit our interpretation of TP,TN,FP,FN.

TABLE II
ACCURACY AND PERFORMANCE OF EXISTING TECHNIQUES

Approach	Accuracy		Performance
	Se	PPV	
Ebrahimzadeh et al. [3]	95.40		N/A
Shyu et al. [4][6]	98.95	69.03	N/A
Ranjith et al. [5]	87.50	93.30	N/A
Barro et al. [6]	82.41	84.22	N/A
Ibaida et al. [7]	100.00		N/A
Ceylan et al. [8]	99.00		N/A
Sufi et al. [9]	N/A	N/A	<= 8ms
Fensli et al. [10]	99.20		?
Chung et al. [11]	?	?	?
Chen et al. [12]	93.29	94.41	?
Jin et al. [13]	?	?	?
RT WTRS	96.00	89.71	18.71 ms

? = Data not provided in literature

IV. DISCUSSION AND FUTURE WORK

We have introduced and implemented in Java—making it portable—a new approach for the classification of ECG signals. The technique is fast and has very good accuracy, so it is suitable for real-time use on standard, inexpensive mobile devices. Our real-time analysis removes the need for transmission to a remote location, reducing network traffic and making possible the raising of the alarm immediately in the presence of an abnormal episode.

Further work with this technique is currently progressing:

- **Periodic re-generation of the Representative Signal:** In its current form, the technique requires manual re-generation of the representative signal with a 24 hour period. Thus, the technique is to be used in a 24 hour holter monitoring scenario. Further work will allow the automatic re-creation of a representative signal on the device itself using a subset of the patient's recorded ECG. One approach is to re-create the representative signal by identifying a normal sinus rhythm beat in real-time in which there is a very high correlation, and then replace the representative signal with this new beat. Another approach is to reduce the complexity of the representative signal creation algorithm to be executable on the device.
- **Adaptation to patient state:** Currently, as discussed above, the technique requires manual representative signal re-generation on a periodic basis, in the order of 24 hours. The ECG signals used for our experimentation where recorded with the patient in a resting state, so the RS is only suitable for when the patient is in a resting state. Thus, when the patient moves from a resting state into a stressed state—e.g. an exercise workout, climbing stairs—the representative signal cannot adapt in real-time, which may cause a increase in false positives until the patient moves back into a resting state. There are two possibilities to solve such a problem:
  - Create a second representative signal with the patient in a stressed state. Thus, the technique could switch representative signals when an increase in heart-rate is detected, partially adapting to the patient's changing state.
  - The second alternative is to frequently re-generate the representative signal in real-time, as discussed in the point above, thereby fully adapting to the patient's changing state.

Finally, this technique is also being tailored to other heart conditions, such as ST segment deviation.

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