

# ECG Quality Measures in Telecare Monitoring

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**Abstract**—We analyze the use of unsupervised ECG acquisition in the home environment. An algorithm for automatically marking ECG recordings for sections of obvious artifact is described. The algorithm was validated against a set of 150 records randomly chosen from a database of ECGs and manually annotated to identify sections of artifact. Using this algorithm 4751 single lead-I ECG recordings from 24 home-dwelling patients were examined. The ECGs were collected using a remote home monitoring system. The participant ages (N=24) ranged from 54-92 years and were suffering either chronic obstructive pulmonary disease and/or congestive heart failure. Percentages of amplifier saturation, high frequency artifact, low signal power and the maximum continuous section of useable ECG are quoted. 1344 records were found to contain no artifact, while 3506 records contained 10 seconds or more of uninterrupted ECG (including the 1344 with no artifact). The results show that in the majority of cases, the capture of ECG in an unsupervised home environment is achievable.

## I. INTRODUCTION

TELECARE is rapidly becoming a preferred solution to the challenge of reliably monitoring subjects suffering chronic disease from remote locations [1-4]. Physiological measurements are routinely taken in the home environment and returned via a communications link to a central database, where they can be accessed by the treating physician, or ideally, analyzed for deviations from normal ranges, in order to generate alerts and recommendations.

However, guaranteeing the validity of signals recorded in an unsupervised environment is a challenge in itself. While subjects are educated in the use of the technology, one is still required to guarantee the quality of such signals if features extracted from these signals are ultimately destined for use in decision support and alert generation subsystems [5, 6].

One physiological measurement of interest is the Electrocardiogram (ECG), and a common ECG derivative – the heart rate. Reliably estimating the heart rate ideally requires an extended uninterrupted epoch of ECG.

While there is an extensive literature base dating back 30 years on feature extraction algorithms and noise mitigation when applied to the ECG [7], interestingly, there appears to be a paucity of literature on these issues when applied to unsupervised or remote collection of ECGs. There is some literature referencing ECG feature extraction in telecare [8,

9] but the underlying assumption is a signal of reasonable quality and an effective patient measurement technique.

The following paper reviews a cohort of single lead ECG signals acquired remotely from a group of 24 home-dwelling patients and describes an approach for algorithmically estimating the signal quality that can be used to determine the reliability of the derived signal parameters and also in assessing patient measurement technique. Such quality measures are critical in telehealth applications in general when determining remotely the need for intervention based upon a set of abnormal measurements.

## II. METHODS

### A. Database

4751 single lead-I ECG recordings were collected on 24 home-dwelling patients using a remote monitoring system called the TeleMedCare Health Monitor – TMC-HM (TeleMedCare Pty. Ltd. Sydney, Australia). The participant ages ranged from 54-92 years and were suffering either chronic obstructive pulmonary disease and/or congestive heart failure. The participants were monitored from February 2007 to January 2008.

After a brief training period, participants recorded their ECG measurements in an unsupervised manner approximately daily in their homes using the TMC-HM. Taking an ECG signal typically involved the participant placing their hands on a specially designed plate with embedded metal contacts for recording a lead-I ECG signal. The patient must press a button to start the recording and then place their hands on each of the plates until recording stops. The condition to stop recording is based on an internal algorithm which waits a period of 25 seconds after it believes it has detected an ECG signal. After this time the recording will cease automatically. Hence the shortest record length is 25 seconds. We will examine only the first 25 seconds of each record since we are interested in the average effectiveness of the technique applied by patients during this initial recording period. The signal is acquired with a sampling rate of 500 Hz using a 12-bit analog-to-digital converter (ADC) with a dynamic range of  $\pm 5$  mV.

The TMC-HM automates all aspects of data collection and transmission of the ECG signal to a central server database for further analysis.

### B. Signal Masking

The following steps describe the process of determining which sections of the ECG signal clearly contain artifact, or obviously do not contain an ECG signal. The three major features utilized to identify such events in the ECG signal are outlined below.

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### 1) Rail Contact Mask

Any samples, of the raw unfiltered ECG, which pass within 1% of the rail voltage are marked. These locations constitute a rail contact mask, which identifies where the acquisition amplifier has saturated. In order to ensure the saturation event is adequately identified, one second before and after each event are also deemed as saturation. Fig. 1 contains a plot of a raw unfiltered ECG signal. Shown is the rail contact mask, where the amplified signal is within 1% of the rail voltage. Also, shown is the rail contact mask after being dilated by 1 second.

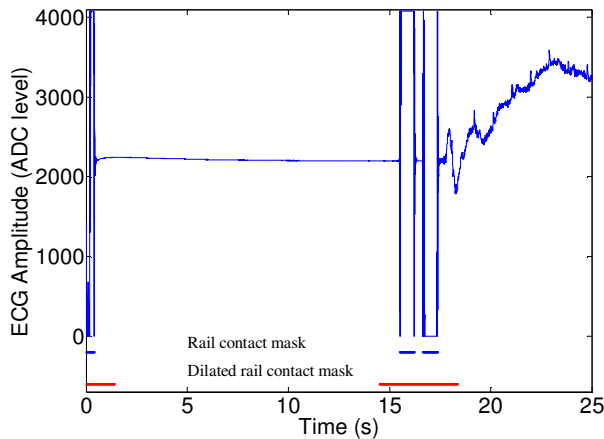


Fig. 1: Shown is the raw ECG signal. Also shown is a mask which marks the locations where the ECG signal passes within 1% of the rail voltage. Also shown is the augmented rail contact mask, which is the original rail contact mask dilated by 1 second.

### 2) HF Mask

Any movement of the patient's hands during recording will typically manifest itself as high frequency muscle artifact and electrode-tissue contact noise on the ECG signal. We can detect these artifacts using a simple estimate of the high frequency content of the signal, over time, combined with a fixed value threshold.

The signal is first notch filtered at 50Hz to remove line noise. The signal is then high-pass filtered using a 5<sup>th</sup> order elliptic filter with a cut-off of 40 Hz, -80 dB gain in the stop-band and 0.5 dB ripple in the pass-band. Forward-backward filtering is employed to ensure a zero-phase response.

An estimate of the instantaneous high frequency power is then obtained by squaring this high-pass signal and then low-pass filtering the result with a 0.05 second normalized hamming window FIR filter. This low-pass filtering is required to smooth the power estimate over time. Finally, the instantaneous power estimate is square-rooted to obtain the original units of mV. This power estimate is compared to a fixed threshold of 30 (noting the dynamic range, 0 to 4095, of the ADC corresponds to  $\pm 5$  mV), which was manually tuned for apparent optimal performance.

Fig. 2 shows the notch and high-pass filtered ECG signal. Also shown is the high frequency (HF) mask, where the power estimate breaches the threshold assigned for high frequency artifact.

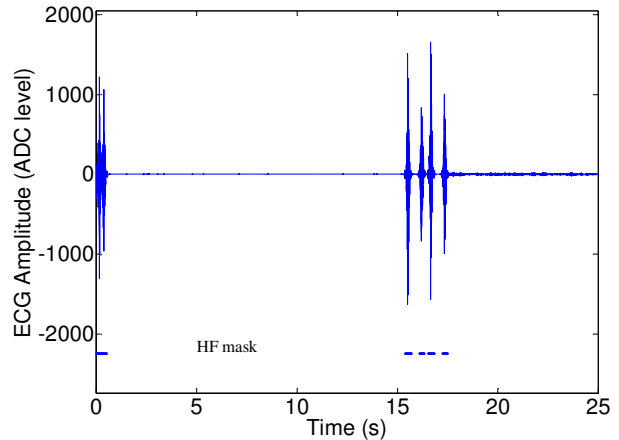


Fig. 2: Shows the ECG signal after being notch filtered at 50 Hz and high-pass filtered at 40 Hz using a 5<sup>th</sup> order elliptic filter. Also shown is the HF mask identified by thresholding the squared integrated version of this signal.

### 3) Low Power Mask

To detect sections of low power in the ECG signal, the signal is first band-pass filtered, with a pass-band of 0.7 – 33 Hz, using an IIR filter with a cut-off of 33 Hz, a gain of -60 dB in the stop-band and a near linear phase response in the pass-band. Since the ECG is known to predominantly occupy the 0 – 40 Hz band, any signal power above 40 Hz can be assumed as not attributable to ECG activity.

Again, this signal is squared and smoothed, by filtering the squared signal with a normalized 0.05 second hamming window FIR filter. This squared, smoothed signal is finally square-rooted. As with the HF power estimate signal, the estimate of the power in the 0.7 – 33 Hz range is compared to a fixed threshold of 10. Where the power estimate falls below the threshold is marked as belonging to the low power mask.

As a post-processing step, any section of the low power mask less than 3 seconds in duration is removed to give the trimmed low power mask. This is required since sections between QRS complexes often meet the criteria to be marked as low power.

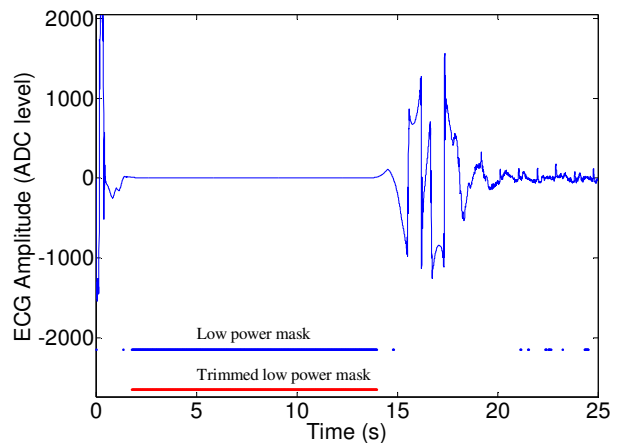


Fig. 3: A plot of the ECG signal after band-pass filtering with a pass-band of 0.7 - 33 Hz. Also shown is the low power mask and the same mask after trimming sections less than 3 s.

Fig. 3 shows a plot of the band-pass filtered signal with the low power sections marked. Also shown is the augmented low power mask, where short sections have been trimmed.

#### 4) Final Signal Mask

Finally, all three masks (dilated rail mask, HF mask and the trimmed low power mask) are combined. In a post-processing step, any continuous section of signal which has not been marked by the combined mask, but which is less than 5 seconds is also included in the final mask. Fig. 4 presents an illustrative example.

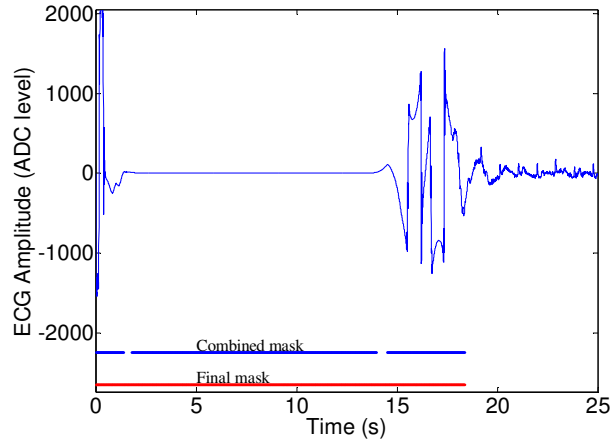


Fig. 4: For illustrative purposes, the 0.7 - 33 Hz band-pass filtered ECG signal is shown. Also shown is the combined mask and the final mask, with short unmasked sections included in the final mask.

#### C. Masking Algorithm Validation Data Set

To validate our signal masking algorithm, 150 ECG recordings were randomly selected from the data set of 4751 recordings; unfortunately, more were not manually scored due to the time consuming nature of this task. The gold-standard signal mask was manually annotated by the authors, using a MATLAB graphical user interface to simultaneously examine the raw ECG and the 0.7 - 33 Hz band-pass filtered ECG, denoting sections of HF artifact, low power and rail contact. The final post-processing step, which removes sections of unmasked signal less than 5 seconds in duration, was performed automatically.

#### D. Quality Measures

From the automatically masked signals, we examine a number of quality measures. Namely, the percentage of the signal which has not been marked by the final mask (this is effectively the percentage of useful signal in each record), the percentages of signal marked by the HF, low power and dilated rail contact masks, and the length of the longest uninterrupted segment in each record.

### III. RESULTS

#### A. Masking Algorithm Validation Results

Table I shows the positive predictivity, negative predictivity, sensitivity and specificity results for a comparison between the automated masking algorithm and the manually annotated data for 150 ECG records. The comparison between the gold-standard and the automatically generated

mask was performed on a sample-by-sample basis for each record. Also shown is the number of records,  $N$ , for which each parameter was calculable. For example, the sensitivity cannot be calculated for a record which the gold-standard indicates to contain no artifact, since the both the number of true positives and false negatives must be zero for such a record, and the calculation would involve a division by zero.

TABLE I  
PERFORMANCE RESULTS FOR AUTOMATED MASKING ALGORITHM

| Measure               | Mean | Standard Deviation | $N$ |
|-----------------------|------|--------------------|-----|
| Positive Predictivity | 98%  | 10%                | 112 |
| Negative Predictivity | 97%  | 19%                | 141 |
| Sensitivity           | 89%  | 20%                | 114 |
| Specificity           | 98%  | 14%                | 143 |

Comparison results for the automated signal masking algorithm versus the manually scored gold standard for 150 ECG recordings.  $N$  is the number of records for which each parameter was calculable.

#### B. Signal Quality Results

Fig. 5 through Fig. 9 show histograms of the various signal quality measures mentioned in Section II.D.

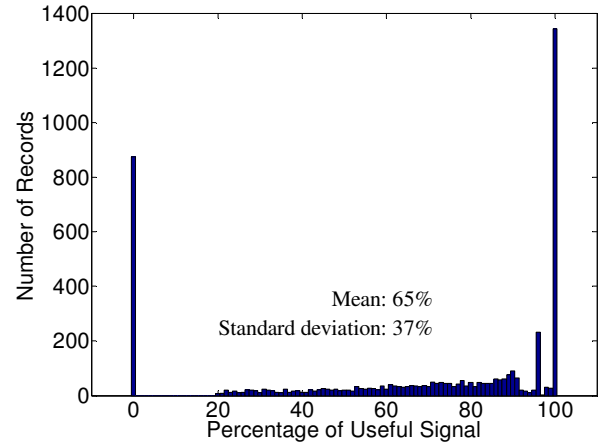


Fig. 5: Histogram of the percentage of each record which was deemed to be useful, according to the final signal mask.

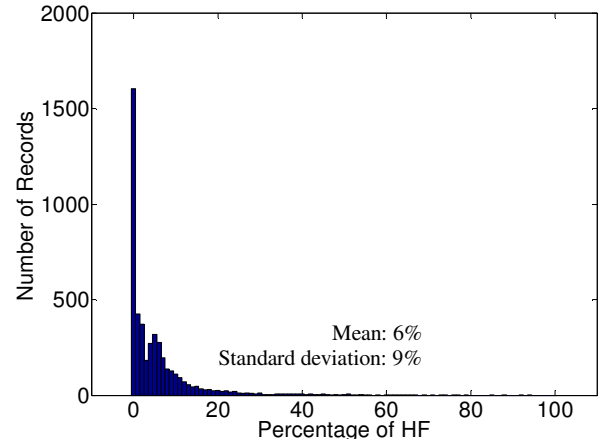


Fig. 6: Histogram of the percentage of each record which was deemed to contain high frequency artifact, according to the HF mask.

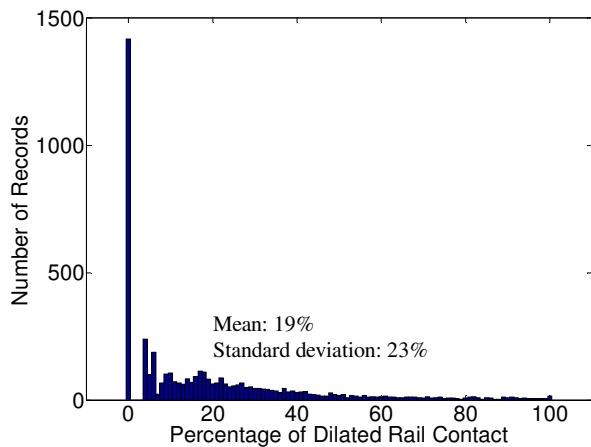


Fig. 7: Histogram of the percentage of each record which was marked as rail contact, according to the dilated rail mask.

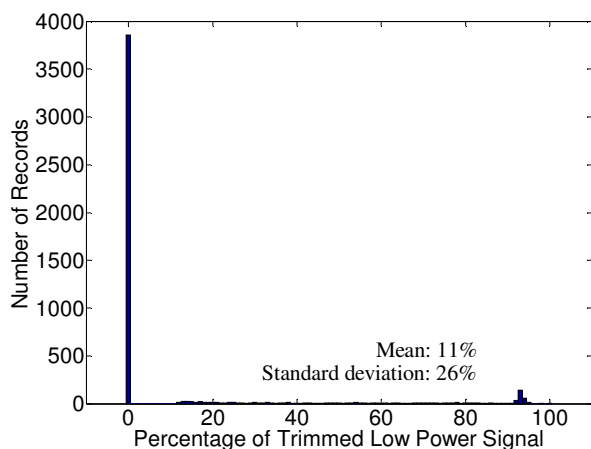


Fig. 8: Histogram of the percentage of each record which was deemed to contain low power signal, according to the low power mask.

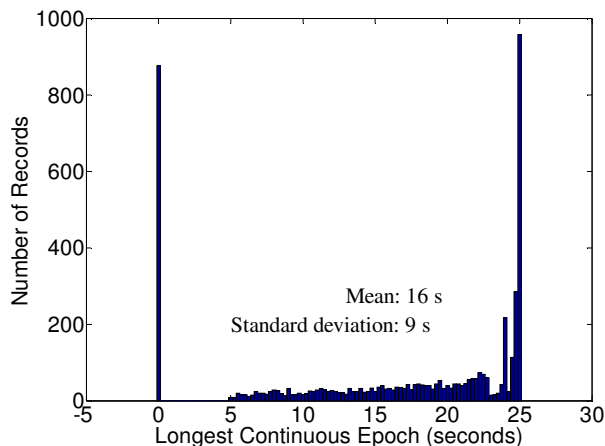


Fig. 9: Histogram of the longest continuous section of useful signal in the final mask.

#### IV. DISCUSSION AND CONCLUSIONS

We have developed a scheme for automatically marking ECG recordings for sections of obvious artifact. The algorithm was validated against a set of 150 records randomly chosen from the database and manually annotated to identify sections of artifact. The average positive and

negative predictivity, the specificity and the sensitivity were calculated; with the minimum value being a sensitivity of 89%. This technique is expected to generalize well, with some adaptation, to ECG obtained with other acquisition systems.

This algorithm was used to examine all 4751 single lead ECG recordings made by patients in the home environment, in an unsupervised manner. We note in Fig. 9 that, of all 4751 records, 3506 (74%) contained 10 seconds or more of continuous ECG. From Fig. 5 we see that 1344 (28%) records contained no artifact, while 875 (18%) were considered completely unusable, with the remaining records distributed quite uniformly over the remaining percentages.

The most dominant form of artifact was the dilated rail contact, which occupies, on average, 19% of the recording. The least significant artifacts were low power events greater than 3 seconds in duration.

The results indicate that, in the majority of cases, the capture of ECG in an unsupervised home environment is achievable. In this paper we have presented what we believe to be one of the first reports of ECG quality measures in unsupervised telecare environments. However, future work is required to identify a graduated scale of quality indicators, for the remaining unmasked sections of signal which, while they do not exhibit the characteristic traits of artifact, may not be of adequate quality for the extraction of QRS complexes and the analysis of QRS morphology and ECG rhythm.

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