Accurate ECG R-Peak Detection for Telemedicine

Yangdong (Jack) Liao, Ru-Xin (Tony) Na, and Derek Rayside
Electrical and Computer Engineering
University of Waterloo, Canada
jackliao07@gmail.com, naruxin220@hotmail.com, drayside@uwaterloo.ca

***Abstract*—Electrocardiograms (ECGs) are usually recorded in a clinical setting by medical professionals using twelve leads attached to the patient. Our industry partner has developed a single-lead ECG machine for use by patients at home. Patients can then send these readings to remote doctors. The goal of the machines is to make medical expertise more accessible, affordable, and convenient.**

The ECGs recorded by patients with a single-lead suffer greatly from baseline wandering and high frequency noises, as compared to ECGs recorded with twelve-leads in a clinical setting.

Accurate R-peak detection is an important step in ECG analysis. A variety of methods have been proposed in the past against standard clinical twelve-lead ECG recordings. In this study, we propose a new R-peak detection algorithm for single-lead mobile ECG recordings. Our area-based approach is built on the understanding that QRS complexes are typically narrow and tall, resulting in large areas over the curve around these locations. Our algorithm is simple to implement, computationally efficient, and does not require any signal pre-processing. This conceptual simplicity is a quality that distinguishes our approach from existing solutions.

We evaluated our algorithm against data collected by patients from single-lead portable devices, and yielded 99.4% precision and 99.4% recall. The MIT/BIT Arrhythmia Database of twelve-lead clinical ECG recordings was also used to verify our algorithm. On this dataset we obtained a precision of 99.3% and recall of 98.6%.

I. Introduction

Electrocardiograms (*a.k.a.* ECG and EKG) record the heart's electrical activity and are used by medical professionals in clinic for a variety of monitoring and diagnostic tasks.

Our overseas industrial partner has developed four models of a small, inexpensive, and simple ECG machine for patient use at home. Our partner is the top vendor of such devices in their domestic market, where they have been selling these machines since 2005. In that time they have shipped hundreds of thousands of units and established partnerships with dozens of hospitals. Patients take ECG readings at home, which they send in to the hospital for interpretation by medical staff.

Fig. 1 Areas over the curve (blue shading) for each local maximum (P, R, T) in an ECG pulse.

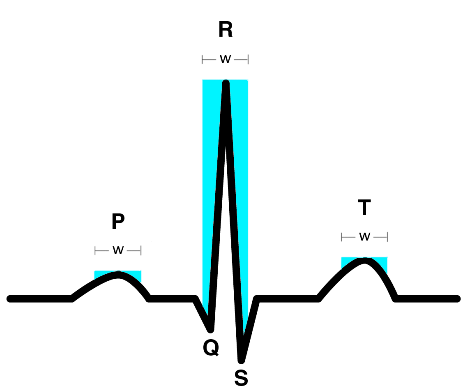


Fig. 2 ECG with severe baseline wandering and interruption

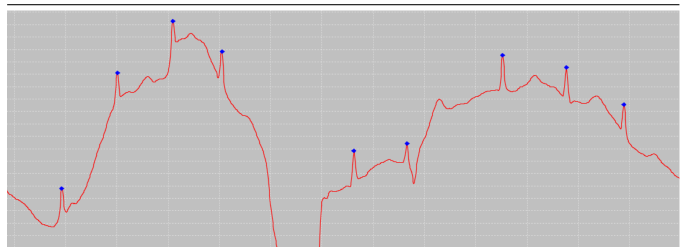
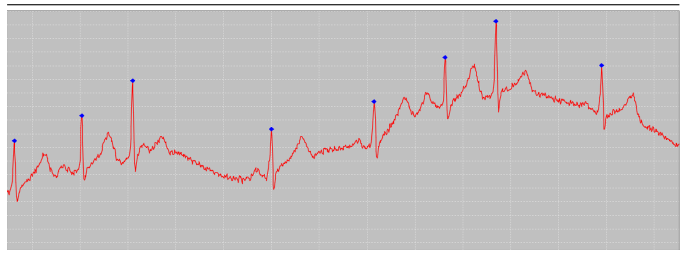


Fig. 3 ECG with small b. wandering and high frequency noise



Each ECG pulse comprises five points, known as P, Q, R, S, and T (Figure 1). Computer algorithms are sometimes used to automatically identify these points (*e.g.*, [1–16]).

We have developed a new algorithm for identifying R-peaks by computing the area over the curve. Our algorithm performs competitively on both the standard MIT-BIH clinical dataset [17], and a dataset of over 1000 patient-collected ECG readings from our industrial partner. Our algorithm is easy to understand and implement, does not require preprocessing the signal, handles both high and low frequency noise, and is not fooled by peaked T waves (a medical condition in which the T waves are sharp, and are abnormally higher than the R peaks).

The quality of the ECG data produced by these inexpensive portable machines used by patients is lower than what one would get from an expensive machine operated by professionals. The data typically suffer from baseline wandering, high frequency noise, and arbitrary interruption. (Refer to Figure 2 and Figure 3, where R peaks are labelled by blue dots.)

The devices have a single lead that the patient holds against

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Fig. 4 Normal ECG with R-peaks labelled by blue dots

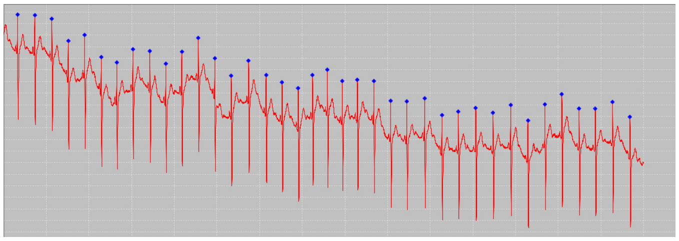
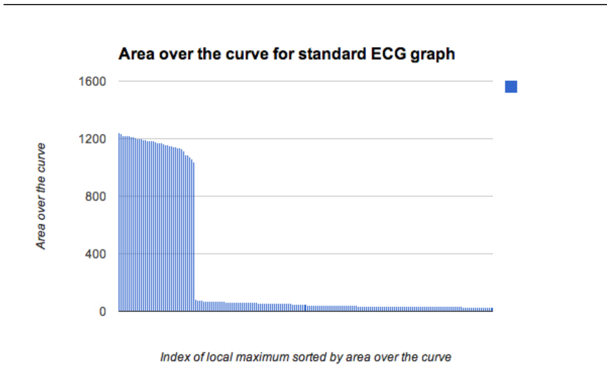


Fig. 5 Sorted over curve areas for local maxima in Figure 4.



their chest. Patients typically cannot maintain constant pressure on the lead, which introduces much of the noise.

II. Area Over The Curve

The inspiration of our algorithm came from the fact that it is extremely easy for humans to perceive where the R peaks are located, even when the T waves have higher amplitudes and relatively sharp peaks. We believe that this is due to the fact that QRS complexes are very narrow and tall (some T waves may have higher amplitudes, but they are much wider towards the base). Using this hypothesis, we came up with the notion of *area over the curve*, which stems from the idea that if something is narrow and tall, it must have a lot of empty spaces around it, as illustrated by Figure 1.

Given that the typical QRS complex can last up to 120ms, for each local maximum M, we define the neighbors N of M as the set of points within 60ms of M. Then, M's area over the curve is defined as the sum of the magnitude of M minus the magnitude of every point in N. The peaks are then sorted by their area under the curve, and those with the greatest areas are considered R-peaks.

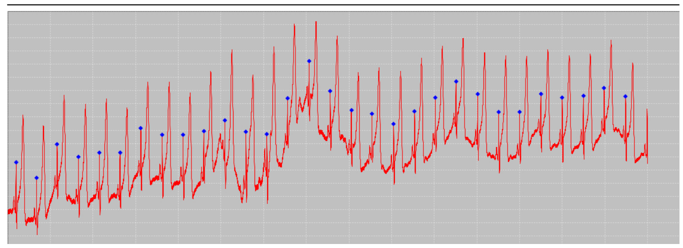
Figure 4 shows an ECG reading from a healthy individual taken with one of our partner's portable devices. The R-peaks are labelled with blue dots. Figure 5 shows the local maxima points from this ECG sorted by their area over the curve. Note the discontinuity in the graph: the R-peaks have much higher area over the curve than the P and T peaks do.

Figure 6 lists pseudocode for finding the R-peaks by computing the area over the curve. This algorithm does not require any preprocessing of the ECG data: it is impervious to both high and low frequency noise, as low frequency noises have little effect over the short window; while peaks from high frequency noises have small areas over the curve. Other techniques require pre-processing with Fourier transforms [1],

Fig. 6 Pseudocode for getRIndexes(points)

```
duration ← duration of ECG in seconds
window ← number of points corresponding to 60ms
rIndexes ← []
areaList ← []
for i = window to points.length - window - 1 do
  isLocalMax ← true
  current ← {index = i, area= 0}
  for j = -window to window do
    delta ← points[i] - points[i + j]
    if delta < 0 then
      isLocalMax ← false
      break
    else
      current.area+ = delta
    end if
  end for
  if isLocalMax then
    areaList.add(current)
  end if
end for
sort areaList by area in descending order
medianArea ← areaList[duration / 2].area
thresholdArea ← medianArea / 2
for i = 0 to areaList.length - 1 do
  if areaList[i].area < thresholdArea then
    break
  else
    rIndexes.add(areaList[i].index)
  end if
end for
return rIndexes
```

Fig. 7 High-T syndrome ECG with R-peaks labelled by dots



Hilbert transforms [4, 10], wavelet transforms [6], *etc.*

Figure 7 shows an ECG reading from a patient with peaked T waves: the T-peaks are higher than the R-peaks. Nevertheless, the R-peaks still have a greater area over the curve because the T-peaks are wider, as shown by Figure 8.

By contrast, the windowed filter technique [1] struggles with high T waves. Figure 9 shows the windowed filter technique successfully identifying R-peaks in a normal ECG. Figure 10 shows the windowed filter technique erroneously identifying T-peaks as R-peaks on an ECG from a patient with peaked T waves.

III. Evaluation

We evaluate our algorithm in terms of precision, recall, and conceptual simplicity. We measure precision and recall on the standard MIT-BIH [17] ECG dataset, as well as on a dataset

Fig. 8 Sorted over curve areas for local maxima in Figure 7.

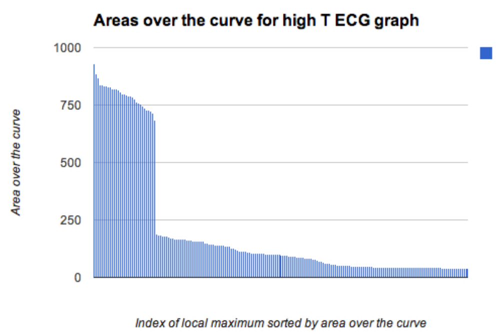
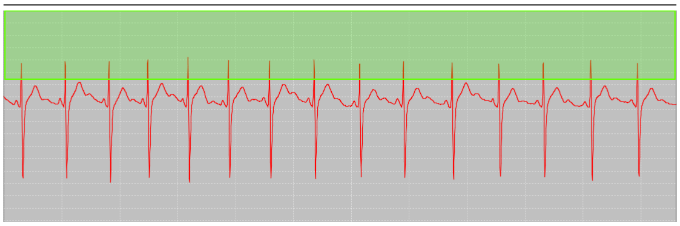


Fig. 9 Windowed filter [1] applied to a normal ECG. R-peaks are the local maxima in the filter (green shaded area at top).



from our industrial partner.

A. *Precision and Recall on Industrial Partner's Dataset*

Our industrial partner provided us with 1000 unlabelled ECG recordings taken by patients using their portable devices at home. These ECGs are 250Hz format for 30s duration, and have roughly 50 pulses each. We selected a random sample of fifty ECGs and manually labelled the R peaks (2526 pulses).

Our area-over-the-curve technique obtained a precision of 99.4% and a recall of 99.4% on these ECGs.

For comparison, we also implemented the double difference technique [2] and evaluated it on this dataset, resulting in slightly lower precision than area-over-the-curve (99.0%), and equivalent recall (99.4%). Applying a pre-processing step to filter high frequency noise improved the double-difference scores to 99.4% precision and 99.5% recall, but did not change the area-over-the-curve scores.

B. *Precision and Recall on the MIT-BIH dataset*

The MIT-BIH dataset [17] contains 48 ECGs collected in a clinical setting and annotated by a team of cardiologists. These

Fig. 10 Windowed filter [1] applied to an ECG with high-T syndrome. T-peaks are now the local maxima in the filter (green shaded area), and the R-peaks are below the filter.

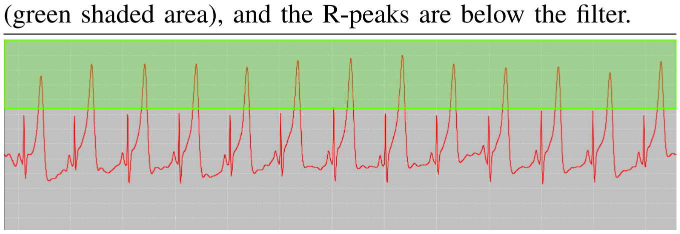


TABLE I Comparison of conceptual simplicity

Description	*Adv. Math*	Pre.	Constants
Hilbert transform [5]	$\surd$	.	.
Wavelet transform [6]	$\surd$	.	.
Mode decomposition [8]	$\surd$	.	.
Slope deflection [3]	$\times$	$\surd$	3
Shifting window [15]	$\times$	$\surd$	4
Adaptive threshold [16]	$\times$	$\surd$	~ 6
Area over the curve	$\times$	$\times$	2

TABLE II Precision and recall on the MIT-BIH dataset

Description	*Prec.*	*Recall*	*Subset*
Shifting window [15]	99.9%	99.9%	$\sim$ 15%
Wavelet transform [6]	99.8%	99.5%	$\sim$ 23%
Hilbert transform [5]	99.9%	99.8%	$\sim$ 98%
Adaptive threshold [16]	99.7%	99.6%	All
Mode decomposition [8]	99.8%	99.9%	All
Slope deflection [3]	99.9%	99.9%	All
Area over the curve	99.3%	98.6%	All
Area over the curve	99.7%	99.4%	$\sim$ 94%

ECGs were recorded in the late 1970's and have been available to the research community for over thirty years. Each ECG is 30 minutes long, and digitized at 360Hz. The dataset contains approximately 110,000 pulses.

Table II summarizes the results of our algorithm on this dataset, as well as some other techniques that report these results in their papers. Some papers report results on only a subset of the MIT-BIH dataset, as indicated in Table II. Our technique is competitive, but not quite as good as the top three: adaptive threshold [16], mode decomposition [8], and slope deflection [3].

We observed that our technique struggled with ECGs that display premature ventricular contractions (PVC), which have the form of a wider QRS complex, resulting in a smaller area over the curve and a higher chance of false classification. If we remove these PVC ECGs then the precision and recall scores for area-over-the-curve improve.

C. *Conceptual Simplicity*

While our algorithm is able to perform competitively with existing algorithms, our approaching stands out in terms of its simplicity. A simpler algorithm is easier to implement, requires less advanced software technology, and is less error-prone. We consider three measures of simplicity in Table I: whether advanced mathematics (*e.g.*, Fourier transform, Hilbert transform, wavelet transform, *etc.*) are required; whether pre-processing is required; and how many constants are named in the code. Most other techniques seem to require either advanced mathematics or pre-processing, whereas our technique requires neither. Implementing advanced mathematics or pre-processing is likely to be easier using advanced software technology such as Matlab. Our technique, by contrast, can be easily implemented in any general purpose imperative programming language. Moreover, our technique requires fewer named constants than others.

Other measures of conceptual complexity include the maximum depth of nested control structures and the cyclomatic complexity [18]. Most papers do not list their pseudocode, so it is difficult to make these measurements. In any case, our algorithm (Figure 6) has a nested control structure depth of 3 and a cyclomatic complexity of 6.

IV. Related Work

There are a fair number of prior approaches to R-peak detection, some of which we have compared our technique with above. A more comprehensive comparison with the following works remains for future work. We categorize the related work here into techniques that specifically look for R-peaks and those that looks for QRS complexes. We sort each list by year of publication.

A. *R-peak detection:*

- RR interval detection algorithms (mobile devices) [13]
- empirical mode decomposition [11]
- shifting window difference threshold and forward-backward difference threshold (for real-time applications) [15]
- preprocessing techniques for R peak detection [9]
- variable threshold method [12]
- a combination of wavelet transform, Hilbert transform, and adaptive thresholding [10]
- Hilbert transform [4]
- Hilbert transform and moving average filter [5]
- windowed filter [1]
- a sorted metric relating to slope [2]
- tensor decomposition and Kalman filtering [14]

B. *QRS complex detection*

- wavelet transform [6]
- empirical mode decomposition [8]
- empirical mode decomposition in MATLAB [7]
- positive negative deflection (corresponds to slope) [3]

V. Conclusion

The area-over-the-curve approach to R-peak detection performs competitively, achieving precision and recall rates of over 99% on both the standard MIT-BIH [17] clinical dataset and the dataset of patient-gathered ECG recordings from our industrial partner. One of the main advantages of the area-over-the-curve approach is its conceptual simplicity: it does not require advanced mathematics; it does not require advanced software technology (*e.g.*, Matlab); it can be implemented with any general purpose programming language; it has low cyclomatic complexity; it has a low number of nested control structures; it has a low number of named constants; and it is robust to both high and low frequency noises without preprocessing. This conceptual simplicity makes it a suitable candidate for mobile computing, in particular, low-cost portable ECG recorders.

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