ECG Data Reduction Using Computational Geometry and Machine Learning

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by

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Abstract

Cardiovascular disease (CVD) is one of the most widespread health problems. It has become the top cause of 32% death, globally in recent years, responsible for all global deaths annually [1].

The Electrocardiogram (ECG) signal is commonly recorded and used to diagnose cardiac diseases. These signals are recorded continuously, processed, stored and then transmitted via communication networks. This generates huge volume daily. Therefore an efficient and reliable signal compression method is highly demanded to meet the real-time constraints like limited channel capacity, battery - power and memory of remote cardiac monitoring and telecardiology systems. The main objective of compression of the ECG data is effectively storing and transmitting with reduced data rate, without distorting the clinical features in ECG signal.

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Chapter 1: Introduction

Cardiovascular disease (CVD) is one of the most widespread problems in countries. Biomedical signals like electrocardiogram(ECG) are stored and transmitted for diagnosing CVD [2-9]. For effectively diagnosing and detecting CVD diseases the long-term multi-channel ECG signals are recorded with different sampling rates and bit resolutions. The signals are received from recording systems such as 12-lead ECG, the vector-cardiography (VCG) high-resolution ECG, then they are digitized at the sampling rate ranging from 100 to 1000 Hz with resolution between 8 and 12 bits per sample [2–19]. The American Heart Association suggests a conversion rate of 500Hz with a 9bit resolution. The mobile wearable ECG recorder enables the recording and transmission of ECG data to the diagnostic center [14-15]. Thus compression of these signals without distorting the clinical features like PQRST morphologies contained in it is needed.

1.1 Understanding the ECG

The ECG is composed of 5 waveforms. They are the recording of the electrical field generated by his-Purkinje activities producing a signal with an amplitude range of 1-10μV. Some of the waves may not be present in all 12 leads. Ex V1 lead does not contain Q wave.

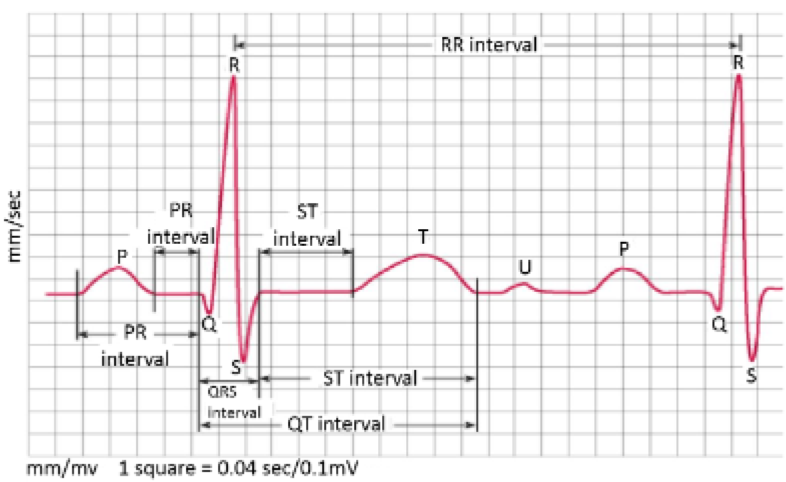

Fig. 1. A period of typical ECG Signal [20]

1.2 Datasets

1.2.1 MIT-BIH Arrhythmia (mita) Database [34]

This database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects. From a set of 4000, 24 hours ambulatory ECG recordings of a mixed population of inpatients and outpatients, 23 recordings were chosen randomly. The other 25 recordings were included from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample.

Over a 10 mV range, the recordings were digitized at 360 samples per second per channel with 11-bit resolution. Each record was independently annotated by two or more cardiologists, with conflicts resolved in order to produce the computer-readable reference annotations for each beat (about 110,000 annotations in total) provided with the database.

1.2.2 BIH Supraventricular Arrhythmia (mitsva) Database [34]

This database includes 78 half-hour ECG recordings chosen to supplement the examples of supraventricular arrhythmias in the MIT-BIH Arrhythmia Database.

1.2.3 The Creighton University Ventricular Tachyarrhythmia (cuvt) Database [35]

This database contains 35 eight-minute ECG recordings of human patients who had persistent ventricular tachycardia, ventricular flutter, or ventricular fibrillation events.

The other records were digitized in real-time from high-level (1 V/mV nominal) analog signals from patient monitors. Record cu01 was collected from a long-term ECG (Holter) recording (played back in real-time for digitization). All signals were digitized at 250 Hz with 12-bit resolution over a 10 V range after passing through an active second-order Bessel low-pass filter with a cutoff of 70 Hz (10 mV nominal relative to the unamplified signals). There are 127,232 samples in each record (slightly less than 8.5 minutes).

Fibrillation is almost usually preceded by a run of ventricular tachycardia in bouts of heart failure, which eventually gives way to the fibrillation itself. In many situations, the onset of fibrillation is difficult to pinpoint. Any therapeutically relevant detector should react to tachycardia runs preceding fibrillation, because medical care is required as soon as possible. As a result, any detector that responds to premonitory tachycardia can have a shorter "time to alarm" than the commencement of fibrillation as documented in the reference annotation files. As a result, the database is referred to as a tachyarrhythmia database instead of a fibrillation database.

The minimal number of non-Ventricular Fibrillation beats prior to the commencement of a Ventricular fibrillation episode in these recordings is 61. The average time from the start of the record and the commencement of Ventricular Fibrillation is 5:47. (with a standard deviation of 2:01). Paced patients were represented by five records (cu12, cu15, cu24, cu25, and cu32) (in some cases, pacing artifacts are not visible, and the pacing is apparent only from the regularity of the rhythm). Many records show repeated attempts at defibrillation.

1.3 Performance Evaluation

The performance evaluation is done using two parameters.

1. Compression Efficiency
2. Signal Quality metrics

1.3.1 Compression Efficiency

The compression efficiencies are evaluated using the following performance measures

1.3.1.1 Sample Reduction Ratio(SRR):

It is defined as the number of samples within the input block divided by the number of the retained samples within the processed block

1.3.1.2 Compression Ratio (CR):

The amount of compression is measured by the compression ratio. The compression ratio is the total number of bits representing the original signal divided by the total number of bits representing the compressed signal.

1.3.1.3 Compression Data Rate (CDR):

It is defined as the ratio of the product between the sampling rate(samples/sec) and the amount of compressed data(bits) to the number of samples taken within a block.

1.3.2 Signal Quality Metrics

In lossy compression methods, different distortion metrics were used for assessing the quality of the reconstructed signal. This can be classified into two groups.

1.3.2.1 Subjective Evaluation

It can be influenced by various factors like knowledge and environmental conditions as it depends on the physician.

So simple mean square error(MSE) and its variants are used.

$$\mathrm{MSE} = \frac{1}{N}\sum_{n=1}^{N}[x(n) - \widetilde{x}(n)]^2$$

where x(n) is the original signal sequence and ˜x is a reconstructed sequence.

1.3.2.2 Objective Evaluation

Every local wave in the ECG signal has a different diagnostic meaning. The objective evaluations can be further subdivided into global measures like root mean square error (RMSE) and Normalized root mean square error (NRMSE). Percentage root means square difference (PRD) and local measures like maximum amplitude error (MAX) or Peak Error (PE).

Chapter 2: Review of Prior Works

ECG signals may exhibit three types of signal correlations: the inter-beat, the intra-beat, and the inter-channel/lead. Fig.1. Illustrates different types of signal correlations. The intra-beat correlation represents the correlation between the successive samples in the ECG cycle. The inter-beat correlation represents the correlation between successive beats in a single-channel ECG signal. The correlation that exists between the signals from different channels is termed as inter-channel correlation.

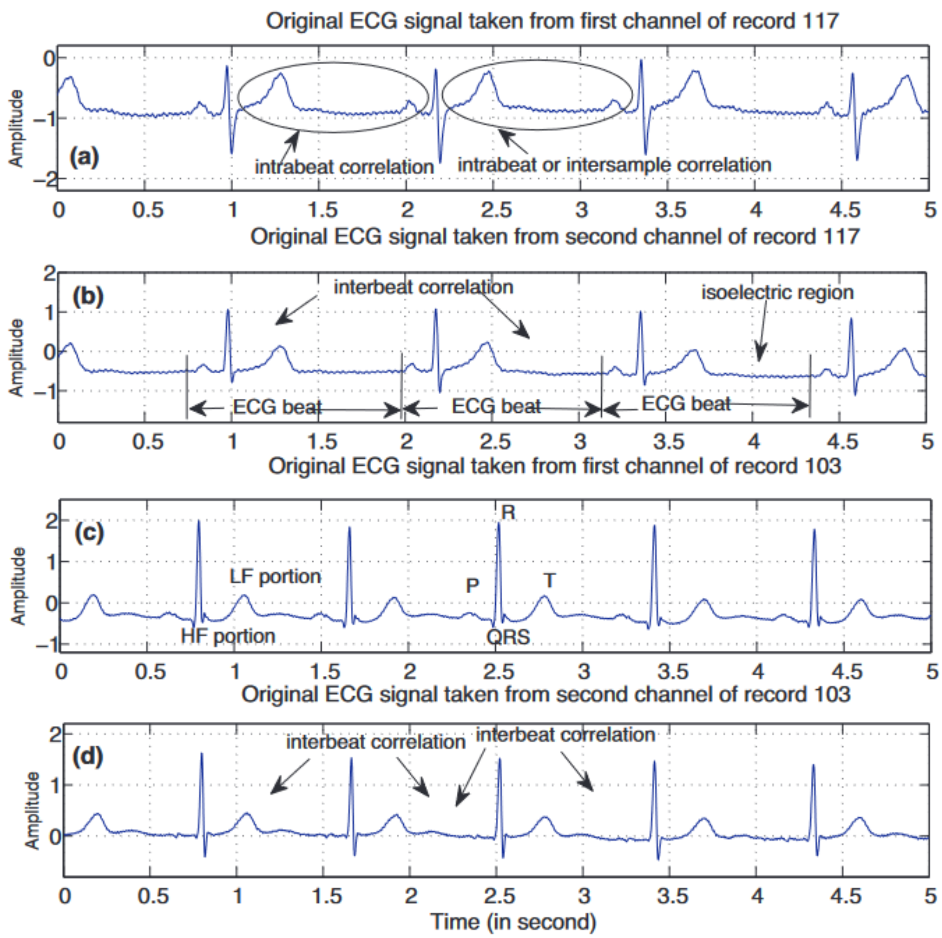

Fig. 2. Illustrates the ECG signal correlations such as intra-beat and interbeat and Low-frequency and High- frequency portions.

The data compression methods seek to minimize the storage size by reducing redundancy [21]. A digital signal is said to have redundancy if all/some of the symbols are dependent on one or more than one other symbol [22]. Data Compression methods that are successful for speech, image, and video signals, can also be applied over ECG signals. Reduced data requires less channel bandwidth for sending a given amount of information in a given time. It also reduces the time required to send the given amount of information in given channel bandwidth. The signal may contain short or long isoelectric regions. ECG signal amplitudes occur in unequal probability [20, 25, 26]. In most compression methods the signal irrelevancy and the redundancy over time and frequency domain are exploited by using signal processing technique.

2.1 Classification of ECG compression methods

ECG data compression should be accomplished without changing the clinical features. The data compression methods are divided into two methods.

2.1.1 Lossy (irreversible compression)

These methods are performed by using quantization of input data. This helps in achieving a high compression ratio. These techniques produce the reconstructed signal with little distortion when compared to the original signal but it is acceptable as long as no significant clinical distortion is introduced in the reconstruction of the signal.

2.1.2 Lossless (reversible compression)

These methods are performed by removing the redundancy which exhibits in terms of statistical dependence. In these methods, there is no loss of information while reconstructing the original signal. The compression ratio is poor hence these are less suitable.

The lossy compression methods are classified into two major groups.

One-dimension ECG compression methods

The 1-D compression is divided into three major categories.

- Time-domain methods work on reducing the transmission time for a given channel capacity.
- Direct data compression techniques try to compress the data using entropy encoding and assigning the variable-length code-words. These code-words are assigned given to quantized data according to their frequency.
- Parameter Extraction compression(PEC) techniques use pre-processing techniques to extract the set of features that can be used to model signals. These parameters are

quantized. It is based upon the notion that the signal is composed of the number of beats repeated at fairly regular intervals.

Two-dimension ECG compression methods

In two-dimension compression methods [27-32]. 2-D transformation is applied to 2D representation of 1-D ECG data. These methods exploit both samples and beat correlation. The methods consist of pre-processing and identifying QRS complex, Period Normalization (PN), amplitude normalization (AN), mean removal (MR) for the reconstruction of the 2D matrix. It may result in a high compression ratio and low reconstruction error but exploits inter and intra-beat correlation. It can be degraded since the PQRST morphologies are time-varying. The performance is directly proportional to the detection of QRS complex which may be affected by low-amplitude QRS complexes. It demands accurate and reliable methods to detect R-peak.

Chapter 3: Computational Geometry

It is a branch of computer science that involves the study of algorithms that can be expressed in geometric forms. It can solve problems like how to find the convex polygon containing all the given points, partition the space according to the points which are closest to given points, etc.[24]

3.1 Algorithms

3.1.1 Convex Hull

Problem:

Given a set of points in the plane. Draw the smallest convex polygon which encloses the set of points such that each point lies within that polygon or on its perimeter. [24]

Pseudo Code:

1. *Find p_0, the point with the minimum y coordinate,*
2. *Sort all the remaining points in order of their polar angle from p_0*
3. *Initialize a stack, S*
4. *push(S,p_0)*
5. *push(S,p_1)*
6. *push(S,p_2)*
7. *for i=3 to n do*
   while (angle formed by topnext(S), top(S) and p_i makes a right turn pop(S)
8. *push(S,p_i)*
9. *return S*

3.1.2 Voronoi Diagram (The post Office Problem)

Problem:

Given a set of n distinct points. Let P := {p_1, p_2, p_3…….. p_{n-1}, p_n} in the plane.

Define a subdivision of the plane into n cells i.e one for each site. The subdivision will have the property that a q lies in the cells according to the site p_i if and only if dist(q, p_i) < dist(q,p_j) for each $p_j \in$ P with $j \neq i$.

Pseudo Code:

The algorithm runs in O(*nlogn*) and uses a storage of O(*n*) [24]

VORONOI DIAGRAM(P)

Input. A set P := {p_1, . . . , p_n} of point sites in the plane.

Output. The Voronoi diagram Vor (P) given inside a bounding box in a doubly-connected edge list D.

1. *Initialize the event queue Q with all site events, initialize an empty status structure T and an empty doubly-connected edge list D.*
2. *while Q is not empty*
3. *do Remove the event with the largest y-coordinate from Q.*
4. *if the event is a site event, occurring at site p_i*
5. *then HANDLE_SITE_EVENT(p_i)*
6. *else HANDLE_CIRCLE_EVENT(γ), where γ is the leaf of τ representing the arc that will disappear*
7. *The internal nodes still present in τ correspond to the half-infinite edges of the Voronoi diagram. Compute a bounding box that contains all vertices of the Voronoi diagram in its interior, and attach the half-infinite edges to the bounding box by updating the doubly-connected edge list appropriately.*
8. *Traverse the half-edges of the doubly-connected edge list to add the cell records and the pointers to and from them.*

HANDLE_SITE_EVENT(p_i)

1. *If τ is empty, insert p_i into it (so that τ consists of a single leaf storing p_i) and return. Otherwise, continue with steps 2– 5.*
2. *Search in τ for the arc α vertically above p_i. If the leaf representing α has a pointer to a circle event in Q, then this circle event is a false alarm and it must be deleted from Q.*
3. *Replace the leaf of τ that represents α with a subtree having three leaves. The middle leaf stores the new site p_i and the other two leaves store the site p_j that was originally stored with α. Store the tuples $\langle p_j, p_i \rangle$ and $\langle p_i, p_j \rangle$ representing the new breakpoints at the two new internal nodes. Perform rebalancing operations on τ if necessary.*
4. *Create new half-edge records in the Voronoi diagram structure for the edge separating V(p_i) and V(p_j), which will be traced out by the two new breakpoints.*

5. *Check the triple of consecutive arcs where the new arc for p_i is the left arc to see if the breakpoints converge. If so, insert the circle event into Q and add pointers between the node in τ and the node in Q. Do the same for the triple where the new arc is the right arc.*

HANDLE_CIRCLE_EVENT(γ)

1. *Delete the leaf γ that represents the disappearing arc α from τ. Update the tuples representing the breakpoints at the internal nodes. Perform rebalancing operations on τ if necessary. Delete all circle events involving α from Q; these can be found using the pointers from the predecessor and the successor of γ in τ. (The circle event where α is the middle arc is currently being handled, and has already been deleted from Q.)*
2. *Add the center of the circle causing the event as a vertex record to the doubly-connected edge list D storing the Voronoi diagram under construction. Create two half-edge records corresponding to the new breakpoint of the beach line. Set the pointers between them appropriately. Attach the three new records to the half-edge records that end at the vertex.*
3. *Check the new triple of consecutive arcs that has the former left neighbor of α as its middle arc to see if the two breakpoints of the triple converge. If so, insert the corresponding circle event into Q. and set pointers between the new circle event in Q and the corresponding leaf of τ. Do the same for the triple where the former right neighbor is the middle arc.*

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