Adaptive ECG Sampling – A Minimum-Error Approach

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Abstract

Adaptive sampling, also known as arbitrary or compressed sensing is an interesting form of concise representation of the process in a series of samples non-uniformly distributed in time. When fed with some a priori knowledge of the signal (e.g. physiological limitation) it may provide efficient usage of the data carrier, improve precise representation of selected phenomena and increased immunity to noise. In this paper we propose a smart iterative downsampling procedure to optimize sampling timepoints for best signal fidelity at given sampling rate. The method starts with identifying and sorting local extrema and then iterates the interpolation process taking alternately one half of samples as reference and minimizing the reconstruction error by adjusting timepoints' positions of the other half. The algorithm was tested with 41 records from MIT-BIH Arrhythmia Database. We found that even with 20 sps the R-peak time precision is sufficient for accurate heart rate measurement and with only 80 sps the signal reconstruction error drops below 0.1% of the full measurement scale.

1. Introduction

Adaptive sampling of the ECG, yet attractive as digital crowd reducing technique, involves a compromise of diagnostic quality and data size. Statistics-based approaches (i.e. compressed sampling [1]) are challenged by the noise and ECG model-based approaches poorly correspond to inter-individual variability.

Adaptive sampling of the ECG [2], while appealing as a method for reducing data size in digital processing, inherently entails a trade-off between maintaining diagnostic quality and minimizing data volume [2]. This compromise is particularly evident in real-world applications, where the need to balance efficient data management with accurate clinical information is critical. Statistics-based approaches, such as compressed sampling, have shown potential in reducing data size [1, 3, 4]; however, they face significant challenges when dealing with noise, which can severely impact the quality of the reconstructed signal. Furthermore, these approaches often struggle to capture the unique variations in ECG waveforms that occur between different individuals, leading to potential inaccuracies in diagnosis [5].

On the other hand, ECG model-based approaches, which attempt to predict missing data points based on predefined models of ECG behaviour, often fall short in accurately representing the wide range of inter-individual variability seen in actual patient data [6]. This variability is influenced by numerous factors, including age, gender, health status, and the presence of specific cardiac conditions, making it difficult for a one-size-fits-all model to achieve reliable results across diverse populations [7].

To make thinks even more complex, it should be noted that subtle but diagnostically important signal components are difficult to identify using statistical values. Parameters such as amplitude, time, variance usually do not allow distinguishing useful components from noise. Finally, in real world-recorded signals, noise is always present, regardless of the quality of the equipment, method or care of the measuring person. Only mathematical models of phenomena and signals are noise-free, but the conclusions drawn from their use will not always apply in the real world.

Given these challenges, the reconstruction of a diagnostically reliable ECG from missing sample points using adaptive sampling techniques becomes crucial [8]. Accurate reconstruction is essential not only for preserving the integrity of the ECG signal but also for ensuring that both occasional and experienced ECG readers can confidently interpret the data [5, 9]. For non-experienced readers, reliable reconstruction allows for more straightforward, accurate interpretation of the ECG, reducing the likelihood of diagnostic errors. For experienced readers, it enhances the diagnostic process by providing a clearer, more consistent signal that can be analysed with greater precision, thereby supporting better clinical decision-making [9]. Ultimately, the development of advanced adaptive sampling and reconstruction techniques holds the promise of improving ECG diagnostics by balancing data efficiency with high diagnostic quality, enabling broader and more effective use of ECG technology in diverse healthcare settings [6].

In this work we propose a data resampling method based on local minimization of reconstruction error able to flexibly assign a given data stream. Additionally, we study the trend of changes in the error rate depending on the data stream intensity.

2. Smart downsampling of signals

For a time frame of 1 s given in the signal and a fixed number N-1 of samples to be optimized in target non-uniform representation, our method starts with identifying signal extrema and sort them by descending absolute value of amplitude. Then a half of samples (i.e. N/2) are assigned to time points of most prominent extrema in the original ECG, what results in N/2-1 non-uniform intervals between them. This yields a first approach to the non-uniform time series, which is then iteratively refined. Next, the remaining N/2-1 samples are assigned one to each interval so as to minimize the cumulative distance between signal values in original data points and their counterparts calculated with linear interpolation from the non-uniform series (fig. 1). The algorithm iterates through a loop up to 20 times, updating either even- or odd-indexed samples based on minimum distances and handling edge cases effectively. The consecutive values of reconstruction error are compared and if they stop decreasing the iterations are ceased prematurely.

The proposed iterative refinement of non-uniform series yields the optimal ECG representation in a given time frame which is saved (or transmitted) as output data stream. Unlike in uniform signals, each sample bears information of the value and the distance from preceding sample. In theory, the time distance is real-valued, but to comply with integer value machine representation, the aggregate consists of fixed-length value- and distance bits.

The only additional information needed by the reader is the data format specified above. The reconstruction algorithm bases solely the non-uniform series of sample points that represent ECG beat to recover high-resolution information of the ECG. First it reads the consecutive data points and separates value- and time distance-related bits. Next the signal value is found at a given distance with linear approximation and the algorithm ends with calculating values in evenly spaced time points.

The algorithm depicted in the flowchart (Fig 1) follows a structured approach to reconstruct ECG signals. It begins by preprocessing the input data to remove noise and artifacts, then employs error minimization techniques to reduce discrepancies between the reconstructed and original signals. As long as the error exceeds a predefined threshold and decreases, advanced error minimization methods are applied iteratively to further refine the reconstruction. In a complementary reconstruction method, linear interpolation is used to fill in missing points, and the final reconstructed signal is outputted as the result. This algorithm effectively combines preprocessing, error minimization, and interpolation to ensure accurate ECG signal reconstruction.

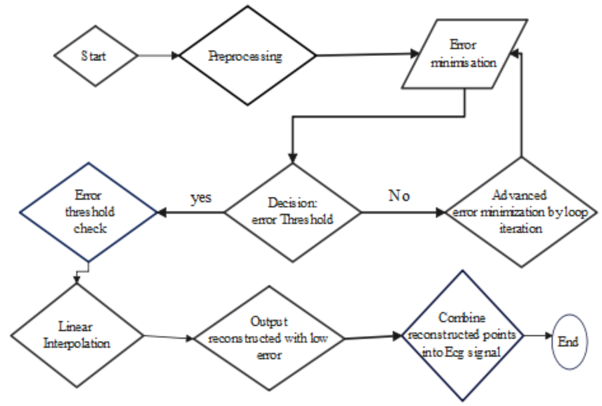

Figure 1. Block diagram of the smart downsampling-reconstruction algorithm.

3. Tests and results

The aim of this study was to propose and test the performance of smart ECG downsampling method and to recover the uniform ECG from its non-uniform representation in order to check the error induced by missing information to the signal at various data rates. To this point we used a subset of 41 half-hour ECGs from MIT-BIH Arrhythmia Database. The signals of both leads, originally sampled at 360 sps were independently processed to reduce the data rate to a range from 20 to 120 sps. An example of original signal and overlaid respective non-uniform representation with only 20 sps (extreme case) is presented in Fig. 2. For each average data stream value in the range from 20 to 120 sps we calculated the reconstruction error. As error metrics we adopted the Mean Squared Error (MSE) referred to the full measurement range. The dependence of reconstruction error on the number of samples per second is presented in Fig. 3.

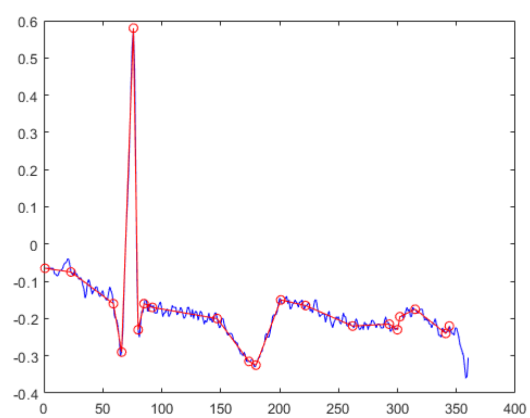

Figure 2. Non-uniformly distributed ECG samples: blue – original uniform representation, red – corresponding non-uniform representation in 20 samples

Our results showed (Fig. 3) that squared error decreased as we set increasing number of non-uniform representation sample points. Surprisingly, even a small number of samples allows for obtaining low value of the representation error MSE. Using the smart subsampling algorithm, the vast majority of ECG information can be represented and reconstructed by presenting it in small number of significance-prioritized non-equidistant ECG samples.

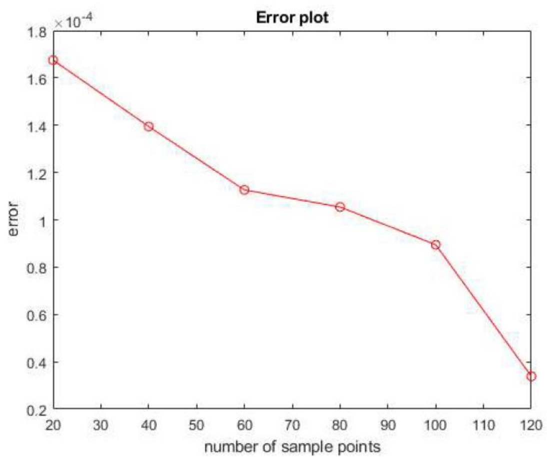

Figure 3. Dependence of reconstruction error on number of signal samples

The graph in Figure 3 clearly demonstrates a decreasing trend in error as the number of sample points increases, indicating that the accuracy of the ECG representation improves with more data and broader bandwidth. Initially, when the number of sample points is low (around 20), the error is relatively high at approximately 1.7×10^{-4}. As the sample number increases to 60, the error decreases significantly to about 1.1×10^{-4}, showing that adding more sample points initially has a strong impact on reducing error. This range ends at around 60 sps where the error minimization procedure guarantees acceptable distortion level of 0.1%.

Table 1. Reconstruction error for tested data rates.

Number of Sample Points per Second	Reconstruction Error ($\times 10^{-4}$)
20	1.7
40	1.45
60	1.2
80	1.1
100	0.7
120	0.3

In the mid-range, between 60 and 100 sample points, the error continues to decline but at a slower rate. For instance, as the number of sample points increases from 60 to 100, the error decreases from roughly 1.1×10^{-4} to 0.7×10^{-4}. This gradual reduction in error indicates that while the accuracy is still improving with more data, the rate of improvement slows compared to the initial phase.

As the number of sample points approaches 120, the error drops more sharply again, reaching around 0.3×10^{-4}. This suggests that beyond a certain threshold (around 100 sample points), the addition of more sample points significantly enhances accuracy, leading to a steeper decline in error.

The trend also highlights the concept of diminishing returns in data subsampling. Initially, in the range of 20 – 60 sps adding more sample points reduces the error significantly, but then at 60 sps as more points are added, the improvement in accuracy becomes less pronounced. This suggests that there is an optimal range of sample points where error minimization is most efficient. Beyond this range, while accuracy continues to improve, the benefits may not justify the additional cost and effort. Thus, it is crucial to select an appropriate number of sample points to balance the accuracy and resources expenditure.

Table 2. Features and Trends of Reconstructed ECGs sample points.

ECG Parameters	Parameter Values
Mean Error	1.075×10^{-4}
Standard Deviation	0.472×10^{-4}
Range	1.4×10^{-4}
Trend	Decreasing

4. Discussion and conclusions

Our research proves that non-uniform ECG sampling may efficiently adapt to the local features of the signal with no a priori model. The decreasing trend in the error with an increasing number of sample points (i.e. broadening bandwidth) highlights the importance of adequate sampling in achieving high accuracy. It suggests that to optimize the performance and minimize errors, it is crucial to select an appropriate number of sample points, balancing the trade-off between accuracy and the resources required to gather more data.

To simplify the presentation, we assumed the data stream intensity is fixed in one second time frame. Indeed, the data stream can be freely adjusted depending on medical content or occurrence of important cardiac events (e.g.: Atrial Fibrillation). Further studies are necessary to identify the optimal data stream for various heart beats' morphologies and values of signal-to-noise ratio.

The medical interpretation of ECG waves relies heavily on the fidelity of the signal, which is directly influenced by the number of sample points per second. With fewer sample points, the reconstruction process might miss essential details, leading to distorted or incomplete ECG waveforms. This could result in missed or incorrect identification of cardiac events, such as arrhythmias. However, as the sample points increase, the reconstruction process becomes more robust, capturing the finer details of the ECG waves more accurately. This leads to a more precise representation of the heart's electrical activity, which is critical for clinical decision-making.

As the MSE applied as error metrics does not distinguish cardiac components and noise, the question arises to what extent the non-uniform series represents the noise. One of the plausible interpretation of the mid-range plateau is that at 60 sps cardiac components are already sufficiently well represented and further increase of data rate makes the representation more and more noisy. This hypothesis, however needs further studies with precisely controlled data and noise models.

Our results also demonstrate that appropriate selection of data rate not only saves the data carrier, but also increases the signal fidelity in regions with short sampling interval and at the same time reduces the presence of noise in regions with long sampling interval. Therefore, the proposed non-uniform ECG representation significantly enhances the accuracy of ECG waveform reconstruction by reducing error and shows improved ability to handle noise. This leads to more reliable and precise ECG signals, which are essential for accurate diagnosis and monitoring of cardiac health.

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