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Heart Watch: Dynamical Systems Based Real Time Data Driven ECG Synthesis

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Abstract—**Electrocardiogram (ECG) is an important health monitoring signal that is used in various medical diagnosis, especially identifying potential possibility of heart attacks and strokes. Moreover, many patients are in remote places and in many countries the patients to doctors ration is very poor which calls for a miniature hardware that remotely captures ECG and transmits data to the doctors. However, the exact reproduction of ECG requires high bit rate and thus requires transmitting a compressed set of parameters. Further, sending large volumes of annotated raw data to train diagnostic models also compromises the patients privacy. We design and present a system that generates synthetic ECG signals from clinical data in real-time using a highly minimized set of parameters. The system comprises a nonlinear dynamical model whose parameters are trained in real-time to synthesize a signal which matches clinical data with high accuracy. The parameters of the trained system are then transmitted in each cycle of the ECG wave to reconstruct the original signal using the same model at the medical practitioners' location. The parameter learning problem is highly complicated as one needs to solve a nonlinear, non-convex dynamic optimization problem, which usually only converges to local optima. To address this issue, we propose a novel two-stage algorithm that automatically chooses an initial set of parameters in the vicinity of the global optimum and then performs stochastic gradient descent iterations. We perform experiments to demonstrate the accuracy and real-time performance of the system. We show that on average our system processes clinical data of one second in 0.68 s on a microcontroller, with an RMSE error of 0.0038 the average, and 17 parameters per ECG cycle. Our system is also easy to implement, requires minimal storage i.e. only one ECG cycle at any given time, and does not depend on offline training, unlike existing methods.**

Index Terms—**ECG, Non linear dynamics, biomedical signals**

I. Introduction

Electrocardiogram (ECG) signals are a vital feature for analysing cardiovascular activity and detecting heart disease by recording the electrophysiological activity of the heart through the chest cavity via electrodes placed on the skin [1]. The electrodes measure cardiovascular activity that corresponds to a sequence of depolarization and repolarization of the ventricles and atria [2]. Each cycle of the ECG signal contains three main components i.e. the P wave, the QRS complex, and the T wave. Early detection of cardiovascular diseases necessitates long-term monitoring of ECG signals which are wirelessly transmitted to point-of-care devices. However, the difficulty in manually analysing and monitoring ECG data, especially when the patient-to-doctor ratio is small calls for automated diagnosis [3] which requires large volumes of patient data to be transmitted. Further, patients in remote places during emergency need to be monitored continuously and thus large amounts of ECG data need to be transmitted which is not recommended. However, transmitting large volumes of annotated raw biomedical signals poses several challenges in the form of communication bandwidth limitations of the transmission channels for communication, storage on edge devices and nodes, as well as compromises patients privacy [4], [5], [6].

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In order to address the issues stated above, a popular solution has been to develop models that synthesize ECG signals based on clinical data. These models are typically governed by a minimal set of parameters, which correspond to a particular ECG signal. Such a model is trained using clinical data from a particular patient, and the parameters of the trained model are then wirelessly transmitted in lieu of the raw signal, to point-of-care devices, wherein a similar model is used to reconstruct the original signal. Such models typically employ machine learning (ML) methods such as support vector machines [7], decision trees [8], random conditional fields [9], and recently developed deep learning methods networks [10]–[16], [17], [18]. However, existing methods suffer from the following drawbacks:

- These methods usually require large volumes of annotated data and extensive training prior to deployment.
- Training neural-network based models requires expensive, resource stifling hardware such as GPUs, and is unsuitable for devices with constrained computational capabilities like those of edge based microcontrollers.
- Deep learning models are generic and usually lack a direct correspondence with the physiological dynamics, and are also susceptible to adversarial attacks [19].

Another approach to synthesizing ECG signals is to employ mathematical models which have been derived directly from the biophysical dynamics. A few examples of such models are as follows. In [20] and [21], the authors proposed a set of nonlinear ordinary differential equations which model the generation of ECG signals whose features matched those of the clinical signal with a high degree of accuracy. Further, the number of parameters or coefficients of the differential equations were appreciably small. In [22] the authors proposed a dynamical model for generating 12 lead ECG signals, on similar principles. An advantage of these models is that the dynamics could be directly traced to the cardiovascular processes, which enhances their understandability. Further, these models are computationally simple to simulate and also implement in simple hardware in real-time. However, these models required the morphological characteristics of the P,QRS, and T waves and the heart rate to be clearly specified in order to generate synthetic signals. This rendered them, hitherto, ineffective for synthesizing ECG signals which accurately matched the features of clinical obtained data from patients. From the above discussion, it is clear that the following challenges remain open, and thereby form the primary motivation for our system, in the context of IoT/edge devices.

1) Can we develop white-box (explainable), trustable mathematical models for generating ECG signals which are purely data driven (i.e. no requirement of morphological characteristics)?
2) Can the models be trained in real-time using only online clinical data, without the need of *any* offline training?
3) Can such models depend on highly minimal data storage, and use a minimal set of parameters to represent ECG signals with high fidelity feature matching?
4) Can such a model improve computational time and signal error (RMSE) simultaneously, over existing methods?

In order to address the above challenges, we propose a dynamical system model based on a Gaussian mixture vector field as in. This model is based on 15 coefficients which encode the morphology of the PQRST wave, and has been shown to accurately represent ECG signals [20]. Using these dynamics, we design an algorithm to update the parameters such that the model learns from real-time clinical data obtained from the patient, without any offline training. The parameters are updated in each cycle of the ECG signal and are transmitted via a wireless communication channel to point-of-care devices. In order to achieve real-time learning, one needs to solve a global optimization problem, online. This poses severe challenges since the cost function is non-convex and nonlinear, and needs to be minimized in real-time. We propose a novel two-stage optimization algorithm in order to converge to the global optimum. We demonstrate our contributions via extensive experiments that:

1) Our system does not rely on any training data, and uses only one ECG cycle at any given time, thereby minimizing storage and enabling real-time operation.
2) The learning algorithm takes sufficiently less time than the ECG signal rate, which allows enough buffer time for implementing wireless communication protocols for real-time transmission.
3) We show a clear improvement of the learning error (RMSE) over existing methods, while simultaneously minimizing the algorithmic complexity.
4) We also propose a hardware system called *heart watch* which comprises data-acquisition, processing, and wireless communication subsystems.

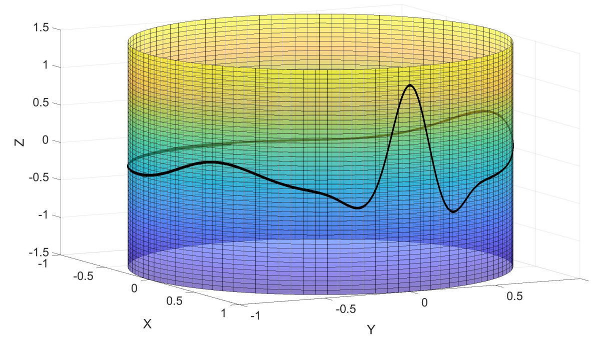

Fig. 1: Gaussian mixture ODE on a unit cylinder describes the PQRST ECG wave

II. Nonlinear model for ECG synthesis

We now describe a nonlinear ordinary differential equations model for generating synthetic ECG signals [20]. The model may be understood as the flow of a Gaussian mixture vector field, on an infinite unit cylinder as shown in Fig. 1. We denote the 3-dimensional state space with Euclidean coordinates (x, y, z) such that (x, y) are constrained to lie on the unit-circle $\mathbb{S}^1$ and $z \in \mathbb{R}$. The mathematical model is given as

$$\begin{aligned} \dot{x} &= (1-\sqrt{x^2+y^2})x - \omega y \\ \dot{y} &= (1-\sqrt{x^2+y^2})y + \omega y \\ \dot{z} &= -\sum_{i\in\{P,Q,R,S,T\}} a_i \Delta\theta_i \left(-\frac{\theta_i^2}{2b_i^2}\right) - (z - z_0), \end{aligned} \quad (1)$$

where $\Delta\theta_i = (\theta - \theta_i) \mod 2\pi$, $\theta = \arctan 2(y, x)$ and ω is the angular velocity of the limit cycle around the unit circle. (Note that the first two equations guarantee that (x, y) stay on the unit circle as long as they are initialized on it). The P,Q,R,S,T waves are described by positive/negative attractors in the z direction which are indicated by the Gaussians within the sum. The trajectory is pushed upwards or downwards towards the stable limit cycle as it approaches the mean of any of these Gaussians. The parameters θ_i encode the location of the waves while a_i and b_i indicate the amplitude and width morphology. The parameter ω corresponds to the RR-interval or ECG cycle length,a and describes its inter-beat variation. In order to capture the baseline wander due to respiratory cycles with frequency f_2, the limit cycle is perturbed from $\mathbb{S}^1$ via the sinusoid

$$z_0 = A\sin(2\pi f_2 t). \quad (2)$$

Fig. 1 illustrates the evolution of the trajectories of the model (1) on the unit cylinder, with a fixed set of parameters. It can be seen that the ECG morphology is quite faithfully represented by this model. In one cycle of the ECG we transmit 15 parameters a_i, b_i, θ_i and the initial phase $\theta(0)$ and frequency ω, using which the clinical ECG is accurately reconstructed.

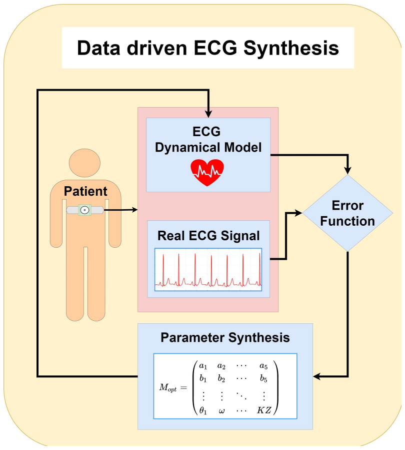

Fig. 2: Real-time parameter learning based data driven ECG synthesis

III. Learning ECG Dynamics

In order to achieve real-time learning, the 17 parameters $M = \{a_i, b_i, \theta_i, \theta(0), \omega \mid i \in \{P, Q, R, S, T\}\}$ are updated with every incoming ECG wave measurement from the patient as illustrated in Fig. 2. The parameters of the model are iteratively updated by minimizing the error between the corresponding synthetic ECG wave and the true signal, in each cycle. We achieve this via a global optimization method described as follows.

A. Cost function

Denote $z_a(t_k)$ as the actual ECG amplitude measurement and $z^M(t_k)$ as the $z-$coordinate signal generated by (1) with the parameters M. Here t_k varies over the set of sampling times N. The optimization problem is formulated as

$$\min_{M} \sum_{k \in N} |(z_a(t_k) - z^M(t_k))| =: J(M). \tag{3}$$

Note that here we have chosen the L_1 error. One may alternatively use the L_2 error instead, however the above choice is motivated by the fact that low amplitude variations are more accurately captured, as will be shown later. Since the dynamics are nonlinear, it is clear that the cost function is also highly nonlinear and definitely non-convex. Due to this, achieving global optimality is indeed a formidable problem since iterative optimization methods are highly sensitive to initial conditions and may indeed converge to local optima.

B. Parameter Optimization

In order to address the above problem we propose a two-stage algorithm. In the first stage, the initial phase $\theta(0)$ for each new ECG cycle is initialized (and correspondingly $x(0), y(0)$) such that the location of the $R-$peak of the synthetic ECG matches that of the actual signal. Note that though θ is a continuous variable, at the end of each cycle there could be a slight discrepancy in the synthetic signal, which though not clinically significant, can cause large errors in the trajectories of the following cycle. Therefore it is necessary to reinitialize this variable in each cycle, along with ω. The parameter learning algorithm is described as follows.

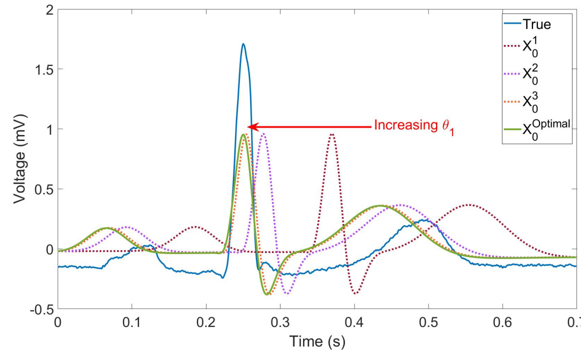

Fig. 3: Illustrations of the iterations in $\theta(0)$ as in step 4

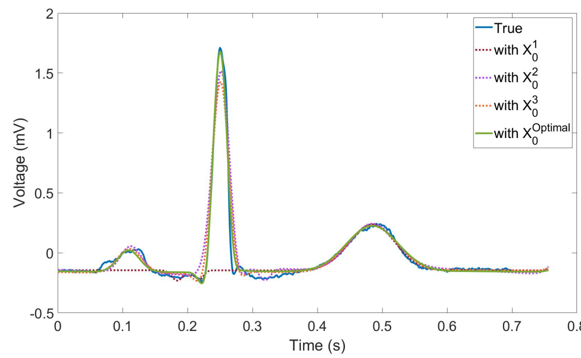

Fig. 4: Comparison between true and synthetic ECG with randomly and optimally initialized $\theta(0)$

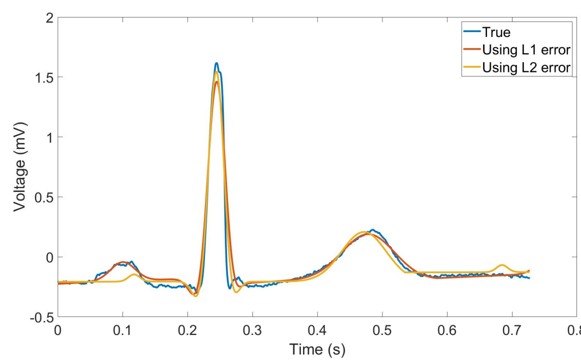

Fig. 5: Effect of L_1 and L_2 optimization for generating synthetic ECG

In Fig. 3 the first part of the algorithm i.e. steps 1-4 to find $\theta^*(0)$ is illustrated. It can be seen that the R-peak of the synthetic signal with initially chosen parameters is displaced from that of the true signal. The iterations of $\theta(0)$ move the synthetic R-peak to the left until its location converges to that of the true R-peak. The need for the two-step algorithm is illustrated in Fig. 4 where it can be seen that without properly initializing $\theta(0)$, the parameters of the synthetic signal may

Algorithm 1: Global parameter optimization algorithm

Result: Determine: M_{opt} such that $J(M_{opt})$ is minimal.

1 Set the initial parameters M_0 such that ω is set by measuring the RR peak length (i.e. heart beat), a_i, b_i, θ_i are chosen randomly and $\theta(0) = -\pi$

2 Compute the synthetic signal z^{M_0}.

3 Determine location of $R-$peak t_{synth} in z^{M_0} and t_{true} in the measured ECG wave z.

4 Update $\theta(0) \in [-\pi, \pi)$ iteratively as follows, until it converges to $\theta^*(0)$.

$$\theta(0)^{i+1} = \theta(0)^i + \lambda(t^i_{synth} - t_{true}), \tag{4}$$

where λ is a chosen learning rate and t^i_{synth} corresponds to the signal genrated using $\theta(0)^i$ instead of $\theta(0)$ in M_0.

5 Update the subset of parameters $\bar{M} = \{a_i, b_i, \theta_i\}$ iteratively as follows, via stochastic gradient descent until it converges to $\bar{M}_\infty$.

6

$$\bar{M}^{i+1} = \bar{M}^i - \gamma \frac{\partial J(\bar{M}_i, \theta^*(0), \omega)}{\partial \bar{M}} + \sigma J(\bar{M}_i, \theta^*(0), \omega) dW, \tag{5}$$

where γ is a iteration step size, dW is a unit normal random variable and σ is a constant. Denote $M_{opt} = \{\bar{M}_\infty, \theta^*(0), \omega\}$.

7 end

settle at local optima where the resulting signal has large error, in fact completely misses the R-peak. Though it is possible occasionally that randomly initialized parameters can converge to global optima, this may not always be true. The effect of using L_1 norm over L_2 norm is illustrated in Fig. 5. Here it can be seen that L_2 optimization performs better near high amplitudes (i.e. R wave) but can cause erroneous artefacts at low amplitudes. Heuristically it can be seen that L_1 optimization performs better in terms of faithfully reproducing the clinical features of the measured ECG signal.

IV. System Design and Communication

The previous sections explained the process including the modelling and algorithmic design of the data driven ECG synthesis block shown in Fig. 2. This block relates to the individual patient level and forms the basis of a network of patients all under the same clinical pathway often monitored and managed by a hospital or healthcare facility. Multiple such patients together form a veritable patient network where wearable medical sensing nodes together communicate the patient data over wireless links (WiFi, cellular or bluetooth) to data aggregators and database servers. It is needless to say that these links raise further questions about privacy and safety and need to be secured. The cardiac information is ultimately retrieved by the medical facility monitoring these patients to provide a care pathway in nursing homes, hospitals, cardiac and heart clinics, etc. This system and its blocks are show in Fig. 6.

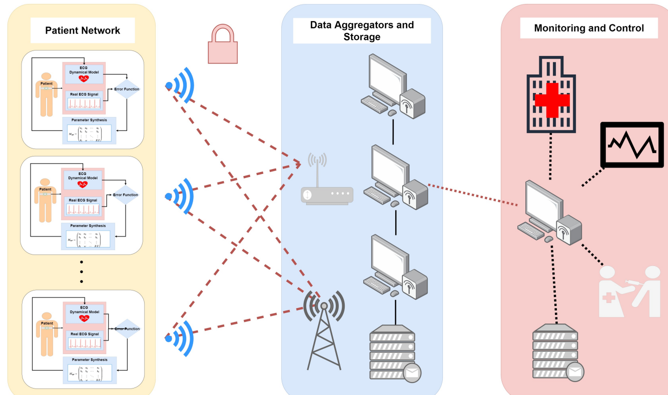

Fig. 6: ECG Synthesis and Wireless Transmission

In order to facilitate the creation of a patient network, we need a hardware platform which can run the ECG synthesis algorithm online and at the same time provide the wireless connectivity required to transmit the synthetic parameters to a data aggregator. To this end we propose a smart wearable ECG monitoring system called "Heart watch". The system consists of two main units - (i) ECG sensing unit and (ii) Processing and communication unit. Though we have chosen AD8233 and nRF52832 chips on the hardware prototype shown in Fig. 7, we impose no restriction on the ECG chip and the processing unit to be chosen. Our proposed algorithm is independent of the number of ECG channels required and the processing platform. However, the processing unit should be able to sense and execute our algorithm in real-time. Additionally, alternate SoCs or RF chips which support WiFi can also be used depending on the required communication mode and frequency.

A. *ECG sensing unit*

The system uses an AD8233 ECG monitoring front-end chip from Analog Devices to record the ECG signals. This chip supports dual channel ECG electrodes and has inbuilt filters to eliminate motion artifacts, signal noise and the electrode half-cell potential often seen when capturing the raw ECG signal. Additionally, the chip is equipped with high gain amplifier circuitry to boost the ECG signal such that it can be easily identified by a processing unit. The signal output generated from this block is in analog form and is connected to the processing unit for analysis.

B. *Processing and communication unit*

The system houses a low power System on Chip (SoC) - nRF52832 from Nordic Semiconductors that embeds a 64 MHz Cortex-M4 micro controller and 2.4 GHz Bluetooth Low Energy communication. One of the main reasons for choosing this chip is that the chip consumes only **0.1 mW** at 64 MHz during processing and a maximum of **0.2 W** during radio transmission over Bluetooth Low Energy (BLE). The chip has

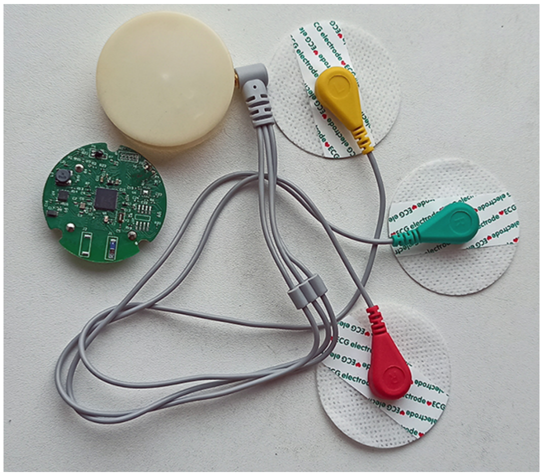

Fig. 7: Heart watch hardware prototype with electrodes and outer case

15 inbuilt Analog to Digital Converters (ADC) which can be leveraged to sample the ECG signals at the maximum sampling rate of 200 kHz which is well within the limit of clinical ECG sampling requirements (1 kHz). Alongside this, the SoC also includes a Floating Point Unit (FPU) which can be further exploited to capture the ECG signals as fast as possible. Our proposed algorithm is executed on this SoC and the processed parameter data is sent over Bluetooth to a receiving unit in the patient's close vicinity such as a smartphone or internet gateway. The output signal from AD8233 is sampled at 1 kHz by nRF52832 and fed into our algorithm every 1 s. The ECG synthesis algorithm is run online and produces the parameter matrix M_{opt} for the captured signal for each cycle. This step is processed in on an average of 0.6 seconds and is then used to transmit the parameter matrix M_{opt} to the smart phone or receiver. The entire system is powered using a coin cell Li-Ion battery.

The system is highly sensitive or large jumps in parameter value and the error function value itself which can indicate an anomaly. This feature can push the system to transmit the raw data on incidences of such anomalous behaviour of the signal based on the discretion of the doctor or health care professional. The same hardware device can be utilized in hospital settings other than the patient' home. The hardware device can be connected over WiFi to the hospital's internal network and act as a high fidelity, low bandwidth ECG transmission module which could be particularly useful in low income economies.

V. Evaluation

The accuracy and real-time performance of the proposed system have been evaluated over 40 cycles of ECG data corresponding to 30 seconds of captured ECG signal from a healthy patient with no prior known cardiac ailments.

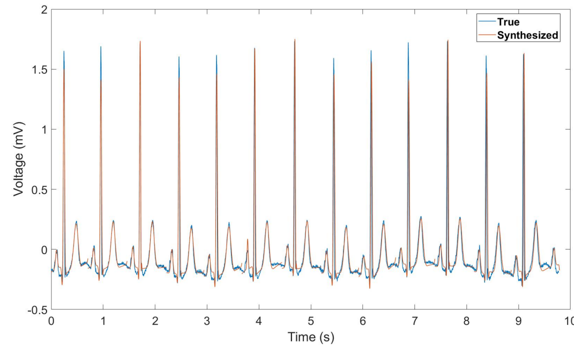

Fig. 8: Comparison between actual and synthetic ECG (10 cycles)

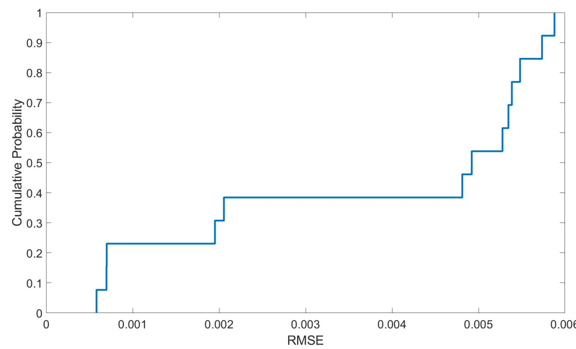

Fig. 9: CDF plot of RMSE (L_2) error

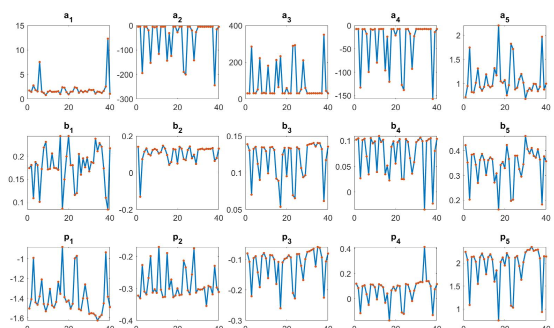

Fig. 10: Evolution of dynamical parameters across ECG cycles

A. Learning Accuracy

In Fig. 8 the actual and synthetic ECG signals have been compared for 13 consecutive cycles. It can be seen that the proposed algorithm generates a signal which consistently matches the actual signal with high accuracy. The CDF plot of the RMSE (L_2) error has been plotted in Fig. 9. The RMSE has been computed for 40 cycles and on average is 0.0038, and within 0.0058 with 90% probability.

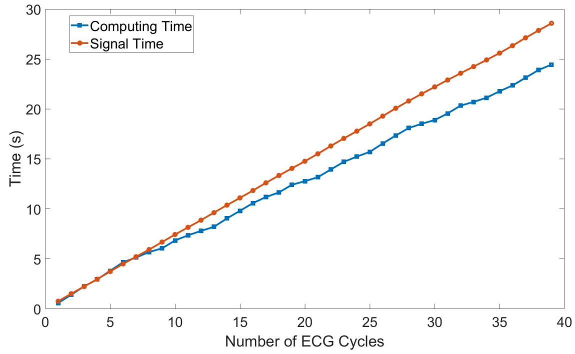

Fig. 11: Comparison between computing time and signal time, shows sufficient buffer for wireless communication

B. Real time Parameter Evaluation

Fig. 10 shows the variation of the parameters M across 40 cycles. Since in each cycle of the 1kHz ECG we only transmit 17 parameters, we achieve a compression ratio of 46.5. Fig. 11 compares the computing time and the signal time across 40 cycles. Here it can be seen that the iterations of the algorithm and other computations complete well before the measured signal. On average, 1s of the signal is processed within 0.68s, and over larger number of cycles there is also sufficient buffer time. This renders our algorithm suitable for implementation on hardware along with wireless transmission protocols.

VI. Conclusion

We proposed a system, Heart Watch, which is a hardware solution that synthesizes ECG signals based on real-time clinical data. The system was based on a nonlinear dynamical systems model whose parameters are updated in real-time with each incoming ECG wave measured from a patient. The system was driven by 17 parameters which encoded the morphology of the ECG wave. The parameters were trained using a novel global optimization algorithm that was proposed in order to handle the complications due to the nonlinear and non-convex cost function. It was shown that the computing time of the algorithm was sufficiently within the signal time which rendered it ideal for deploying on hardware platforms with wireless communication protocols. We also presented a hardware prototype i.e., *Heart Watch* which is capable of data acquisition, processing and wireless transmission. In addition to being computationally simple, the algorithm also showed better RMSE as compared to existing approaches based on machine learning. Our method required no training and only one cycle buffer making it ideally suitable for edge devices. Since the synthetic ECG generator proposed in this paper reproduces the original signal with a high degree of accuracy, it can also be used to generate large datasets of ECG data with various abnormalities in order to train diagnostic models, and for running several other experiments in the area of biomedical signal processing and analysis.

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