Clinical Evaluation of Generative Model Based Monitoring and Comparison with Compressive Sensing

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ABSTRACT

Generative model based resource efficient monitoring is an emerging data collection technique that has been shown to have compression ratio of around 40 in simulation environment on medical grade data from MIT BIH database. This paper discusses the intermediate outcomes of an ongoing clinical study where GeMREM enabled sensors are deployed on 125 subjects at the St Luke's cardiac hospital. According to the data from 25 patients we see that GeMREM achieves a compression ratio of 33, the reduction attributed to motion artifacts. We also compare the diagnostic accuracy of GeMREM with compressive sensing (CS) based ECG monitoring techniques. The results show that GeMREM although has better resource efficiency, CS is more accurate in representing temporal parameters such as heart rate, standard deviation of heart rate, and heart rate variability. However, interestingly, GeMREM is more accurate in preserving the shape of an ECG beat. Usage of dual basis in CS also cannot achieve shape accuracy comparable to GeMREM. Further, the reconstruction algorithm for GeMREM is almost 20 times faster than that for CS techniques.

Categories and Subject Descriptors

C.2.1 [**COMPUTER-COMMUNICATION NETWORKS**]: Network Architecture and Design—*Network communication*

General Terms

Experimentation, Measurement, Performance, Reliability

1. INTRODUCTION

Resource efficient physiological sensing is essential for non-invasive continuous long term monitoring. Physiological sensors are typically restricted in computation power, storage, communication bandwidth, and energy source. Resource efficiency in sensors boils down to reduction in sensing and communication frequency without degradation of the signal quality. Sensing frequency reduction can be obtained for sparse physiological signals using compressive sensing (CS) [6]. For signals which do not have a suitable sparse representation in some domain, CS may not obtain resource efficiency without significant degradation in signal quality. An alternative for non-sparse signals is to reduce communication frequency using generative model based monitoring (GeMREM). GeMREM exploits periodicity of signals instead of sparsity and learns a personalized generative model for the time domain signal. The sensor only transmits data when collected raw signal does not match the synthetic signal generated by the model. These two techniques are fundamentally different but can provide data compression while maintaining appropriate signal quality. In this paper, we discuss results from a clinical study funded by NIH (Grant # EB019202) and Arizona Technological Enterprise on the efficacy of GeMREM monitoring for cardiac signals in practice and compare with CS in terms of signal quality. We chose CS approach since in our previous work, we have shown that only second to GeMREM, CS obtains the best compression ratio among all other techniques (Table III in [8]).

GeMREM considers that physiological signals may often be represented using a generative model. A generative model is a mathematical function, which when supplied with the correct parameters specific to an individual can generate synthetic signals that are diagnostically equivalent to the raw time domain signal acquired by the sensor. The synthetic and the raw signals although are not same sample by sample, but there is no discernible difference in parameters that are relevant for diagnosis. A generative model has two main parameters: a) rapidly varying time domain (temporal) parameters, and b) fairly static morphological or signal shape parameters. In an execution of GeMREM, the generative model is stored in both the sensor and the data collection device or the base station, as we will call them henceforth. The sensor samples the physiological signal for a given time interval τ. The sensor uses the generative model to regenerate τ time interval of synthetic data. The raw data and the synthetic data are then matched in terms of the diagnostic parameters. If raw data matches synthetic data within a preset error bound, the sensor does not transmit any data to the base station. The base station uses the current model parameters to regenerate the signal. However, raw data may not match synthetic data due to two main reasons: a) mismatch in temporal parameters, when the difference in temporal parameters are passed to the base station and it regenerates using the updated parameters, and b) mismatch in morphological parameters, when the whole raw data is passed to the base station that updates the generative model by learning a new morphological parameter

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set. The idea is that change in morphology of physiological signal is very rare and hence most of the time either there is no data transmission or a very small amount corresponding to the difference in temporal parameters.

Compressive sensing on the other hand, relies on the sparsity of a physiological signal in some transformed domain. A time domain signal is first represented as a linear combination of orthonormal basis vectors. For example, in case of wavelet transforms, the wavelets are orthonormal basis vectors while the wavelet coefficients are the weights of each wavelet in the linear combination. A signal with n samples in the time domain can be compressed to $m << n$ samples if the coefficients of the linear transform only have m non-zero values. The method is to sense at random m samples and send to the base station. The base station then uses linear optimization techniques to derive the transformation coefficients that can represent the m samples with good accuracy. The derived coefficients are then used to estimate n samples of the signal through inverse transformation.

GeMREM and CS both provide good sensor data compression while relying on different characteristics of the physiological signal. GeMREM relies on some static shape properties of the signal, while CS relies on sparsity of the signal in a transformed domain. GeMREM focuses on reduction of communication, while CS attempts to reduce sensing frequency. Therefore, to achieve a fair comparison instead of comparing the two approaches in terms of compression ratio, we compare the two approaches with respect to diagnostic accuracy while keeping the resource efficiency to their maximum. A discussion on their resource efficiency can be found in our previous work [8].

We take the example of electrocardiogram monitoring and implement GeMREM and CS techniques. As a part of a large scale clinical study in collaboration with the St. Luke's hospital we have deployed ECG sensors enabled with GeMREM monitoring algorithm. The sensor was implemented using Shimmer2r [9] platforms and was deployed on 125 patients, we only show results for 25 patients in the ICU. In addition to the GeMREM monitoring system we also installed medical grade Holter monitors to obtain raw data from the patients. CS is implemented in Matlab on the data collected from Holter monitor and we compare the diagnostic accuracy of the two approaches in simulation.

1.1 Overview of Results

Using our experimental results we compare GeMREM and CS with respect to the following important issues:

Shape preserving property: The generative model use in GeMREM has two parts: a) morphological model and b) temporal parameters. The morphological model is a representation of the shape of the physiological signal. The shape of ECG signals in particular is an important diagnostic criteria, which must be preserved. In each beat of ECG signal, there is a high peak, "R" peak, and four other smaller peaks. The CS technique using just the wavelet basis can identify the "R" peak very well however, it fails to replicate the other nuances of the ECG morphology. Usage of discrete cosine basis improves the accuracy in detecting the smaller peaks, but it looses accuracy in detecting the R peaks. A combined basis of wavelet and discrete cosine improves the accuracy but it reduces resource efficiency and increases computational complexity for reconstruction. On the other hand, GeMREM by virtue of a personalized morphological model can preserve the shape of ECG signals.

Resource efficiency: Clinical studies show that GeMREM can increase the lifetime of the ECG sensor 33.5 fold on an average. On the other hand CS can have at most 4 - 5 fold compression before signal quality falls beyond the required diagnostic accuracy. However, GeMREM requires a 3 - 5 minute setup time on each individual to learn a morphological model, during which the raw data has to be collected by the sensor and learned by the base station.

Artifacts: The principal artifact observed in the clinical study with GeMREM based ECG sensor is the apparent existence of Premature Atrial Complex. This occurs due to a fault in the stitching algorithm that is used to regenerate the entire ECG signal at the base station. We have updated the regeneration scheme to get rid of this artifact. For CS, at higher compression rates, the PQ, and ST complexes are often distorted.

Data regeneration complexity: Data regeneration in GeMREM requires computation of a non-linear function and stitching the results to develop a time series. Data regeneration is thus very simple in GeMREM. For CS data regeneration involves solving linear optimization problems and then stitching the resulting solutions. Regeneration in CS typically takes more time for larger signals.

Automated annotations: An interesting advantage for GeMREM is that it can annotate times when the raw data did not meet the model. Typically the main cause for this is motion artifacts, however, morphology also changes when there the patient is undergoing arrhythmia or some form of pathological condition. Such annotations are important for diagnosis and building treatment plans for patients. CS does not have such automated annotation property. GeMREM enabled ECG sensors hence also helps save doctor's time.

Several CS techniques for ECG has been proposed recently [6] however, the reconstructed data have not been previously evaluated in terms of maintaining diagnostic accuracy of ECG signals. A very recent work [5] attempts at such a comparison, however, they only consider temporal parameters and instead of morphological parameters they consider correlation. However, a high signal correlation may not guarantee that important morphological parameters are preserved. This is the first work to our knowledge that compares both GeMREM and CS techniques in terms of diagnostic accuracy of ECG in a clinical setting.

1.2 Public Health Relevance

Nearly 1 in 150 adults in America are suffering from some form of congenital heart disease. A recent survey by the center for disease control has concluded that nearly $2 billion hospital expenditures are related to congenital heart disease. Long term physiological monitoring of the heart is essential in diagnosis, treatment and rehabilitation of congenital heart disease patients as well as determining the optimal time for surgery. The most common physiological signals that are monitored in ICU or at home settings for individuals with heart defects are blood oxygen levels and electrocardiogram (ECG) signals. In a hospital telemetry setting although the focus is on remote monitoring of patients, the initial link from the patient to the monitoring unit is wired. The state of the art medically approved wireless technique to monitor the heart is the Holter monitor which can at most sustain 48 hours of continuous monitoring due to storage and energy limitations. Commercially available heart sensors have been reported to last nearly 84 hours without needing battery replacements. These lifetimes are

clearly not enough since long term monitoring for congenital heart diseases are typically prescribed for months if not years. GeMREM is a novel sensing algorithm that can result in 30 - 40 fold increase in lifetime of ECG sensors allowing them to work for months without battery replacements.

2. PRELIMINARIES

2.1 GeMREM ECG Monitoring

In this paper, we evaluate a novel sensing technology, generative model based resource efficient monitoring, (GeMREM), that promises 40 fold increase in lifetime of ECG sensors [8] allowing them to possibly last for months or years without replacing batteries.

GeMREM deviates from the usual sample by sample monitoring by considering the periodicity of the ECG signal. The ECG signal has two properties: a) temporal features such as heart rate, standard deviation of heart rate and low frequency to high frequency ratio of inter beat times, and b) morphological features, which describe the shape of a single beat of ECG. The common observation is that the temporal features are highly variable while the morphological features remain relatively constant over time. Morphology of the ECG of an individual changes under severe pathological conditions such as arrhythmia or after a heart surgery, whose probability of occurrence is very low.

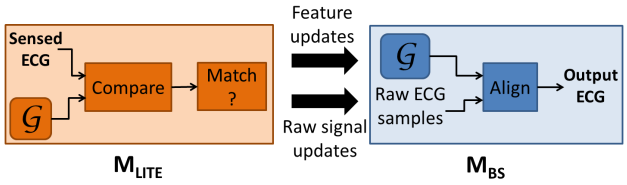

Figure 1: Operation of GeMREM, M_{LITE} is the sensor module, M_{BS} is the base station module, and G is the generative model.

As shown in Figure 1, GeMREM works by first developing a generative model G of a beat of ECG signal. An ECG beat is unique for an individual and can be represented using mathematical equations such as the ECGSYN model [7]. These generative models if provided with the correct inputs can output a synthetic signal that is equivalent to the original signal with respect to *diagnostic features* (Section 2.3.1). These diagnostic features are part of the model and are determined by trained physicians. Both the sensor and the base station keep a copy of the model. At each instant the sensor senses the original signal and compares it with the signal generated from a model. Further, the sensor also derives diagnostic features from the original or sensed and the synthesized signal. If the sensed signal matches the synthesized signal then the sensor does not transmit any data to the base station. The server uses the generative model to regenerate the diagnostically equivalent signal. If the diagnostic feature values do not match then the sensor only sends smaller feature updates, which is used by the base station. However, if the synthesized signal does not match the sensed signal in the beat patterns or morphology then the sensor transmits the entire signal to the base station, raw signal updates.

As shown in Figure 2, a sample by sample monitoring principal would have monitored at high data rate (82 kbps)

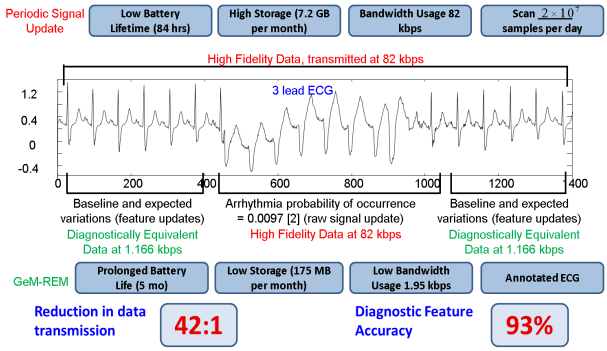

Figure 2: Principle of GeMREM and its benefits.

at all times. However, GeMREM modulates the data rate according to the temporal and morphological changes of the signal. During no change (baseline) or a temporal change the GeMREM sensor sends either a keep-alive signal or just the temporal feature, respectively at a low data rate of 1.16 kbps. However, when there is a change in morphology the GeMREM sensor sends the full data at high data rate (82 kbps). The success of this innovation is invested in the fact that morphological changes are less frequent. For example, arrhythmia occurrence probabilities is only 0.0097.

As opposed to sample by sample monitoring GeMREM only needs to store model parameters and the occasional raw signals in order to regenerate any requested snippet of data. This allows GeMREM to store data in a highly compressed manner if morphologies do not change frequently. An added advantage of this innovation is similar to a Holter monitor, GeMREM can automatically annotate ECG signals for events of interest. The only difference being such annotations is in real time for GeMREM, which can be used to generate critical alarms. Moreover, it can also save considerable time of the doctor who will not be required to scan 20 million samples a day.

2.2 Compressive Sensing

Compressive sensing [6] works on the assumption that a signal that is dense (a lot of non-zero values) in the time domain can have a much more sparse representation if expressed as a linear combination of an orthonormal basis. For example, a sinusoidal signal in the time domain is only a single point in the frequency domain and hence can be represented by only the amplitude of the sinusoidal basis. Mathematically, consider $\vec{x}$ as a signal with n samples a second. Let us consider that in some linear transformed domain the signal $\vec{x}$ can be represented as a linear combination of orthonormal basis $\vec{z} = \{z_1, z_2 \dots z_n\}$. Hence, the vector $\vec{x}$ can be represented using Equation 1.

$$\vec{x} = \mathcal{A}\vec{z}, \tag{1}$$

where, $\mathcal{A}$ is a matrix of dimension $n \times n$ and is independent of x. The vector $\vec{z}$ is assumed to be "m-sparse", which means that it has m values that are much larger than the other $n - m$ values, where $m << n$. CS technique then only considers m random samples of $\vec{x}$ represented by the vector $\vec{y}$ of length m. Such random sampling can be expressed by a index vector $\vec{\phi}$, where $\phi_i = 1$ is sample i if selected and $\phi_i = 0$ if otherwise. With this $\vec{y}$ the vector $\vec{x}$ is estimated using

l_1 norm convex optimization. The reconstruction method comprises of the following optimization -

find $\overrightarrow{z}$ to
minimize (l_1 norm of $\overrightarrow{z}$) such that -

$$\overrightarrow{y} = \langle \overrightarrow{\phi}, \mathcal{A}\overrightarrow{z} \rangle \quad (2)$$

Here $\langle \overrightarrow{x}, \overrightarrow{y} \rangle$, represents element by element multiplication of two vectors resulting in a third vector. The recovered signal $\overrightarrow{x_m}$ can then be obtained simply as: $\overrightarrow{x_m} = \mathcal{A}\overrightarrow{z}$.

2.3 Electrocardiogram signal characteristics

The ECG signal has been extensively studied and used for cardiac diagnosis. A single beat of ECG consists of P, Q, R, S and T waves, with a U wave present in some cases. The Q, R and S waves are often jointly considered as a QRS complex. The shape, amplitude and relative locations of the constituent waves are key features of an ECG, referred to as *morphology features*. The R peak is a sharp peak and has the maximum magnitude, while the P, Q, S, and T waves have much smaller magnitudes and are blunter peaks. The distance between two consecutive R peaks is called the R-R interval, and its reciprocal gives the instantaneous heart rate. The R-R interval typically varies over time, and this variation is described using temporal features such as mean and standard deviation of heart rate, and spectral features such as Low Frequency/High Frequency (LF/HF) ratio [7]. In this paper, we refer to these features as *temporal features*.

2.3.1 ECG diagnostic parameters

The ECG signal has the following diagnostic features [10]:

a) R-R interval: the time difference between two consecutive R peaks, **b) QRS complex width:** the time difference between the Q and the S peaks, **c) QRS complex maximum amplitude**, **c) QRS complex minimum amplitude**, **d) P wave amplitude**, **e) T wave amplitude**, **f) duration of P wave**, and **g) duration of T wave**.

In addition to these metrics we will compare the accuracy of CS and GeMREM algorithms also with respect to standard deviation of heart rate and LF/HF ratio [10], which are although not diagnostic parameters.

3. IMPLEMENTATION

The GeMREM and CS techniques were implemented for monitoring ECG signals.

3.1 ECG generative model for GeMREM

A generative model of ECG can generate synthetic ECG signals, given a set of input parameters. In this paper, we use the widely accepted dynamical generative model ECGSYN, proposed in [7]. For the morphology features, each wave (P, Q, R, S and T) is represented by 3 parameters: (a, b, θ), which determine its height, width and distance to R peak, respectively. A single beat of ECG signal is thus given by -

$$\dot{z}(t) = -\sum_{i \in \{P,Q,R,S,T\}} a_i \Delta\theta_i exp(-\Delta\theta^2/2b_i^2), \quad (3)$$

The parameter $\Delta\theta_R = 0$, while $\Delta\theta_i$ is given by the scaled temporal difference between the i peak and the R peak. For a given patient, the parameters a_i, b_i, and θ_i have to be learned. In our clinical study we use a 2 minute sample of the raw ECG signal to learn the parameters.

Once the parameters are learned, they are transmitted to the sensor. The sensor updates temporal parameters, to the base station. The base station uses the temporal parameters to generate a series of R-R intervals following a random process that matches the heart rate variability. It then makes an ECG beat using Equation 3, scales it in proportion to the current heart rate and places it at the position of each R peak to make a time series signal. In our implementation, we used the reconstruction process to regenerate 1000 samples at a time and then stitched them together. This led to stitching artifacts discussed in more detail in Section 5.

The sensor code was written for TinyOS, while the reconstruction code was written for Android. Code was generated using verified databases available in the Health-Dev tool [2] that are shown to be devoid of common software errors.

3.2 Compressive sensing implementation

ECG morphology has two important characteristics: a) a sharp R peak, and b) four blunt and low amplitude waves. CS for ECG monitoring will need two types of orthonormal basis vectors: a) wavelet basis for capturing the sharp R peak, and b) discrete cosine basis for capturing the blunt waves. The method of using multiple basis can be realized by concatenating the basis matrices of each of the transforms to form a $n \times 2m$ matrix A. For each of the transforms we take the m greatest coefficients. The optimization problem (2) is then solved using the homotopy driven l_1 - penalized least squares regression method (LASSO - homotopy) [4]. In an execution, m samples of ECG are taken at random in a second and is passed through to the base station. For every $2m$ samples, the base station uses the dual basis and estimates $2n$ ECG samples using the LASSO homotopy algorithm. The base station then stitches $2n$ consecutive samples to form the ECG time series.

4. CLINICAL STUDY EXPERIENCE

The clinical study was first started with an initial seed grant from Arizona technological enterprise (AzTE) and then continued with a subsequent NIH grant (# EB019202). The study is performed on patients that volunteer to participate from the St Luke's Cardiac Intensive Care Unit.

IRB approval: A joint IRB was filed with ASU and St Luke's hospital with the full study protocol. Approval was granted for collecting 24 hours data from a medical grade Holter monitor and the GeMREM enabled Shimmer sensor. The sensor installation was performed under the supervision of a registered nurse and clinical studies co-ordinator. Consent forms written both in English and Spanish was prepared by co-ordinator, which was read out to the patients and the subjects were required to provide their consent.

Patient population: 25 patients from the ICU volunteered to participate in the study. Fourteen of them were men while the rest women. One of the patient had frequent atrial fibrillation which was captured by GeMREM through raw data transmission. The age of the patients were not recorded as per IRB clauses. The patients were all bed ridden with limited mobility. The study devices were un-installed when the patients went for procedures such as MRI.

Study Device: The study device is a 3-lead ECG sensor developed by Shimmer Research interfaced with a Google Nexus One Android phone via Bluetooth. The Shimmer ECG device has three Ag-Cl leads attached to it. These leads were attached to the patient's body following the stan-

dard procedure for 3-lead ECG measurement. Double electrodes were used for attachment of the Shimmer as well as Holter monitor ECG leads. This ensures that signal from both devices is equivalent.

Monitoring Regimen: Subjects were monitored for a period of 20 ± 4 hours. ECG monitoring were completed according to the patient's treatment plan. Three double ECG electrodes were placed on the chest area of the individual with an extra ground electrode near the belly (Figure 3). The leads were connected to a Shimmer device through four wires. The Shimmer device is a small and lightweight (28g) plastic box equipped with a MSP-430 microcontroller and a lithium ion battery. The Shimmer device was worn by the patient using a chest strap. The Shimmer device communicated with a Google Nexus One Android phone through a Bluetooth connection. In addition to the study device, a

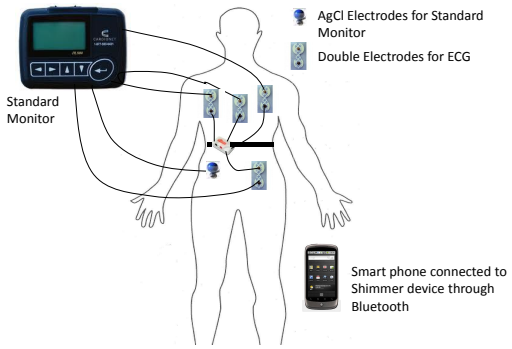

Figure 3: Deployment of the Shimmer device along with the standard ECG monitor.

standard 5 lead Holter monitor was also used to collect ECG signals on a sample by sample basis.

Preparation and Administration of Study Device: Three Ag-Cl electrodes (Figure 3) were placed on the chest of the patient in the form of a triangle to measure ECG using Shimmer sensors. A ground lead was also be placed near the abdomen and away from the triangle formed by the other three leads. To ensure that the spatial distance between the electrodes of the Shimmer sensor and the standard monitor are not significant, we used CardiacDirect double leads [3], which has two solid gel electrodes placed at a distance of 2 in from each other. On the double electrodes, a lead of the standard monitor and a Shimmer lead were attached. This ensured that the measurement artifacts due to separation of lead are minimized. These leads were connected to a Shimmer device which was worn by the patient using a chest strap. The GeM-REM protocol was started and each update from the sensor was time stamped to ensure synchronization between the standard monitor and the Shimmer device. The monitoring was continued for at least 16 hours and maximum up to 24 hrs. Data from both the devices are then stored in a laptop. For maintaining privacy of patients the data was anonymized and the laptop where the data was stored was not connected to the internet.

Data collection method: Prior to deploying the system for a patient, the learning functionality is used to train the generative model using the patient's ECG data. This training process outputs a set of parameter values which are stored on the base station as well as the sensor. These values are intended to be used as inputs for generating synthetic ECG data closely resembling the patient's actual ECG. Thus,

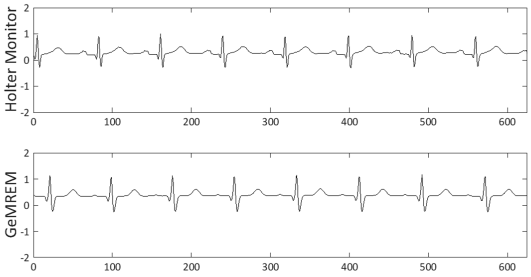

Figure 4: Comparison of raw data between Holter and GeMREM sensors.

data collection was performed in two steps: a) initially a 2 minute sample of ECG is obtained using the Shimmer sensor for training a personalized generative model, and b) the new generative models were manually entered to the Shimmer sensor and then data for 24 hours was collected.

5. ARTIFACTS OF GEM-REM

Stitching artifact: Stitching artifacts are a considerable problem in both GeMREM and CS techniques. This artifact occurs when the signal recovery algorithm has to be used to generate smaller portions of the signal and then stitched to prepare the entire time series. For ECG signals stitching can introduce an untimely ECG beat that can be mistaken by the doctor as a Premature Atrial Complex (PAC). Such a condition can be misleading if it happens frequently. In our clinical studies, we have observed such cases in one of our 25 patients. As a remedy we have updated the GeMREM signal recovery algorithm to avoid stitching. In the updated GeMREM recovery algorithm, we first organize the R peaks of the ECG signal over time. We then introduce each ECG beat with their center at the R peak position. Such a method avoids stitching and hence misleading PAC.

Mobility and Bluetooth interference: An important observation in the clinical study was during scheduled mobility, the patients were unwilling to carry the Android base stations with them. Hence, mobility caused disruption in monitoring. Further, our previous work [1] shows that highly mobile patients can frequently visit parts of the hospital where Bluetooth reception is poor leading to disruption in monitoring. The current system requires manual re- establishment of the connection in case of disruptions which is problematic since the patients either forget or the re- establishment process is too cumbersome. In the ongoing clinical study wireless channel interference is an important issue that causes interruption in monitoring, delay in reconnection, crashing of the base station application, and loss of critical health data. The causes of interference are many fold and are difficult to characterize. We found that in an operational ICU, where proper operation of devices are necessary, interference induced interruptions were the highest.

Motion artifacts: Patient mobility induces motion artifacts in the sensors. Whenever there is motion artifact the morphology of the sensed signal does not match a model. Another major reason of mismatch between sensed signal and a model is occurrence of pathological events such as arrhythmia. Whenever, the ECG sensors finds a mismatch it transfer the raw signal to the smartphone. The GeM-

REM algorithm cannot distinguish between an arrhythmia and motion artifacts. Hence, more often than not it classifies motion artifacts as pathological events and transfers data to the smartphone. This causes loss in compression ratio, battery power and unnecessary usage of bandwidth.

6. COMPARISON OF GEM-REM AND CS

In this section, we compare GeM-REM and CS for ECG signals in terms of their diagnostic accuracy. We do not compare them with respect to compression ratio and resource efficiency, since such research have been already performed in the past and the results are comprehensive showing that GeM-REM achieves around 40 times savings in communication while CS can achieve around 2 - 4 times reduction in sensing frequency and consequently in communication [8].

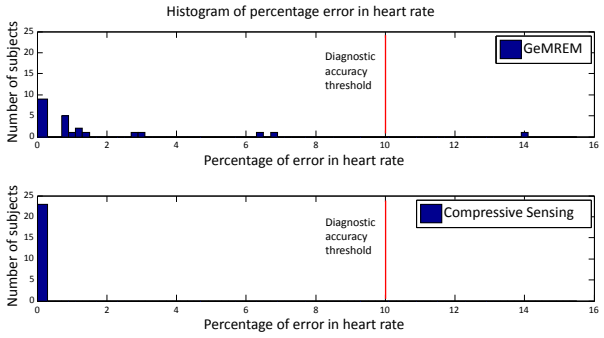

Figure 5: Error in mean heart rates from GeMREM and CS w.r.t Holter device.

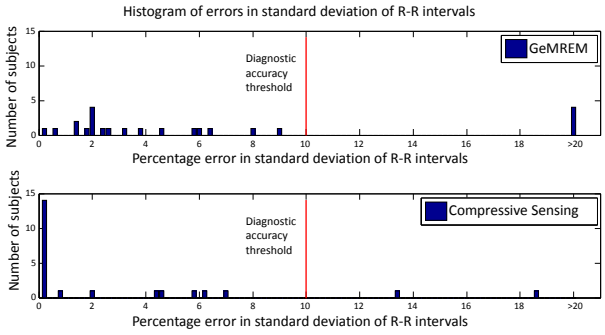

Figure 6: Error in standard deviation of heart rates from GeMREM and CS w.r.t Holter device.

6.1 Setting up

GeM-REM set-up: For each patient, the generative model was trained using 2 minutes of ECG signal collected at 125 Hz frequency. For transmitting data, we use a threshold of 5%. This means that if the temporal parameters such as heart rate, standard deviation of heart rate, and LF/HF ratio changes beyond 5% of the initial value then the original temporal parameters are transmitted to the base station. In addition, if the correlation between a generated ECG beat and a beat from the raw signal sensed by the sensor goes below 0.8, then the whole raw signal is transmitted.

CS set-up: We did not have a practical deployment of CS based ECG sensor. However, we used the technique on data collected by the Holter monitor in a simulation environment implemented in Matlab. Recovery in CS is much more time consuming than GeM-REM, hence we compare the two technique on 1000 samples at a time. In the CS technique, we use a compression ratio of 2, which means the ECG is sampled at the rate of 62.5 Hz. The recovery optimization problem is set-up such that it only tolerates an error of 5%.

6.2 Evaluation metrics

We evaluate GeMREM and CS technique on two sets of metrics: a) error in temporal parameter with respect to data from Holter monitor, which include mean heart rate, standard deviation of heart rate, and low frequency to high frequency ratio of heart rate variation, and b) error in morphological features with respect to Holter monitor, which include the metrics discussed in Section 2.3.1. In the analysis we have divided the entire 24 hour signal into intervals of 1000 samples. For each such interval, we compute the temporal and morphological features and then compare the average error of GeMREM and CS with respect to Holter monitor data over all such intervals.

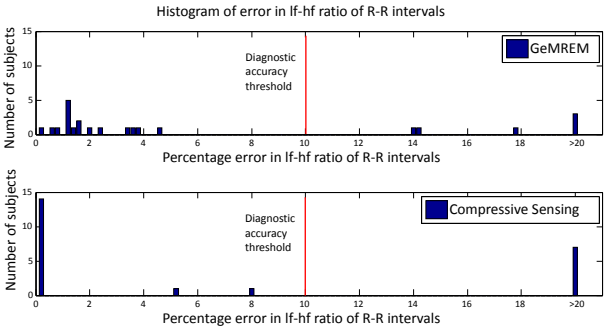

Figure 7: Error in LF/HF ratio from GeMREM and CS w.r.t Holter device.

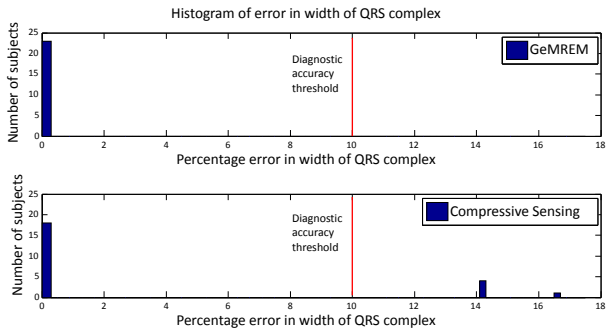

Figure 8: Error in QRS complex width from GeM-REM and CS w.r.t Holter device.

6.3 Evaluation results

We use data from 23 out of 25 patients. Amongst the patients whose data were considered for the analysis, one of them accidentally took off the sensor while for the other

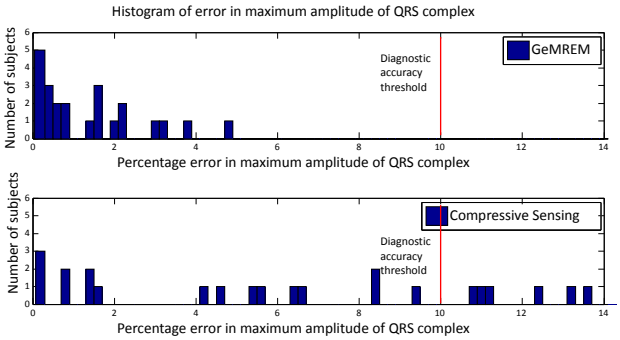

Figure 9: Error in maximum QRS magnitude from GeMREM and CS w.r.t Holter device.

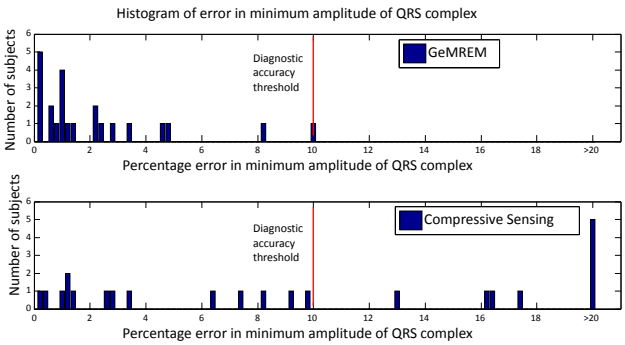

Figure 10: Error in minimum QRS magnitude from GeMREM and CS w.r.t Holter device.

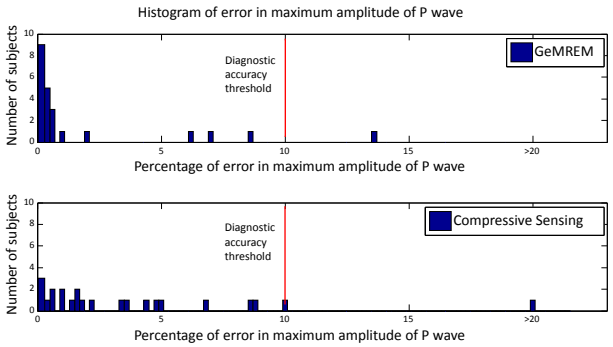

Figure 11: Error in magnitude of P wave from GeMREM and CS w.r.t Holter device.

case the Bluetooth interference inside the ICU room caused the smartphone to abort connection to the sensor. Figure 4 shows a sample comparison of data from Holter monitor and GeMREM ECG sensor from a single patient. According to expert opinion of cardiologist at the St Luke's hospital, each beat of Holter is matched by the GeMREM and both the signals are visually inseparable. On an average GeMREM reduces communication frequency 33.5 times. During procedures such as MRI the study devices had to be re-installed. Often re-installation was done using faulty sensor leads that lead to increased motion artifacts causing raw signal updates. This contributed to a significant loss in resource efficiency.

6.3.1 *Temporal parameter comparison*

Figure 5, 6, and 7 show the histogram of errors in estimation of the temporal parameters for the 23 subjects. Figure 5 shows that while for most of the patients heart rate from GeMREM monitor is within 7% of the Holter reported heart rate CS based approach keeps the error within 0.4% for all patients. Given that doctors are typically not interested in changes less than 10% this error in GeMREM is considered diagnostically negligible.

The same trend is observed in standard deviation (Figure 6) and LF/HF ratio (Figure 7) of heart rate, where CS technique is more accurate than GeMREM. However, the standard deviation and LF/HF ratio are used for comparison of signal quality and are not diagnostic features [10].

In summary, with respect to temporal parameters CS is more accurate than GeMREM, although the degradation in accuracy does not significantly hamper diagnosis.

6.3.2 *Morphological parameter comparison*

Figures 8, 9, 10, 13, 11, 14, 12, show the histogram of errors for the morphological features discussed in Section 2.3.1. For each of these parameters, we see that for all the subjects GeMREM is more accurate than CS. GeMREM keeps the error within 5%, which is much more accurate than required for diagnostic accuracy. The accuracy of GeMREM depends on how well the generative model of the ECG signal has been learned. CS on the other hand has a larger error mostly since it cannot preserve the shape of the P and T waves in the ECG signal.

Interestingly, both GeMREM and CS approach have pretty good accuracy for the QRS complex. P and T waves are however, not very conspicuous features of ECG and needs careful identification and learning enabled by GeMREM. Since they are not sharp peaks and are possibly composed of a large number of wave components, they are not sparse in the wavelet transform domain. Hence CS with the wavelet orthonormal basis often fail to identify such peaks.

Although usage of the discrete cosine transform in addition to wavelet basis is a good solution, it still fails to capture the P and T waves with good accuracy. GeMREM on the other hand, uses a non-linear transformation that uses Gaussian curves to represent the P and T waves. Such non-linear equations can characterize the ECG waves including P and T with good accuracy. Thus in summary,

GeMREM has better accuracy on morphological features that CS, since it uses non-linear transformations to characterize the waves comprising an ECG beat.

6.4 Recovery code execution time

An important factor in real time monitoring is the execution time of the algorithm used for reconstructing the original signal from the compressed information. In case of GeMREM the recovery process includes generation of R peaks that match the statistical properties of the original heart rate from the actual signal and then placing a time scaled version of ECG beat generated using the generative model. In case of CS, to recover or reconstruct n samples of the actual signal a linear optimization problem has to be solved which has n-dimensional output. We implemented the recovery algorithm in a desktop with Intel dual core processor using Matlab for both GeMREM and CS techniques. The results show that (Figure 15), show that the

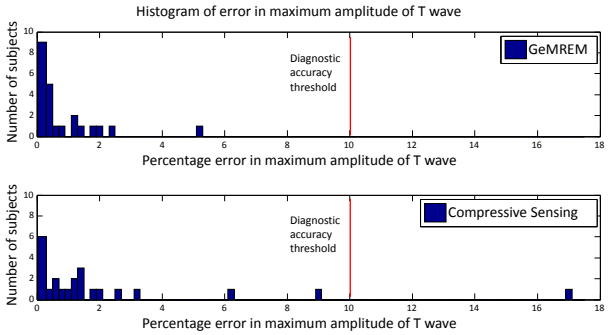

Figure 12: Error in magnitude of T wave from GeM-REM and CS w.r.t Holter device.

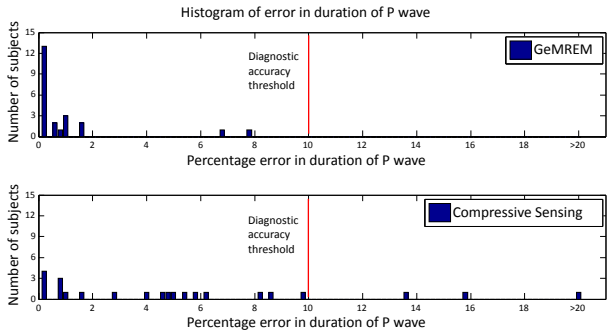

Figure 13: Error in duration of P wave from GeM-REM and CS w.r.t Holter device.

reconstruction algorithm for GeMREM is much faster than CS and hence can be applied in real time. The execution time for recovering 1000 samples from CS was 13.67 seconds. While GeMREM was around 20 times faster than CS to recover signals.

7. CONCLUSION

In this work, we report the effectiveness of generative model based resource efficient monitoring for continuously collecting electrocardiogram data in an ICU environment for 25 patients. The effectiveness measure is obtained by comparing temporal and morphological diagnostic features derived from GeMREM enabled sensor with those derived from Holter monitor data. The results show that in practice GeMREM achieves 33.5 times reduction in communication overhead. We also compare GeMREM and CS techniques with respect to diagnostic accuracy. We observe that while CS is more accurate in terms of temporal parameters, GeM-REM is more accurate in terms of morphological parameters since it uses a shape preserving non-linear generative model.

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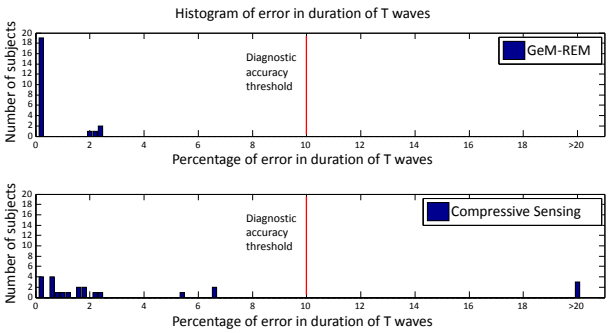

Figure 14: Error in duration of T wave from GeM-REM and CS w.r.t Holter device.

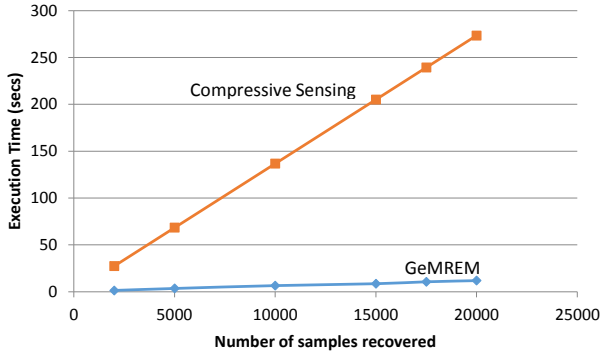

Figure 15: Comparison of execution time for recovering time series signal using GeMREM and CS.

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