Diagnostic Quality Driven Physiological Data Collection for Personal Healthcare

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Abstract—**We believe that each individual is unique, and that it is necessary for diagnosis purpose to have a distinctive combination of signals and data features that fits the personal health status. It is essential to develop mechanisms for reducing the amount of data that needs to be transferred (to mitigate the troublesome periodically recharging of a device) while maintaining diagnostic accuracy. Thus, the system should not uniformly compress the collected physiological data, but compress data in a personalized fashion that preserves the "important" signal features for each individual such that it is enough to make the diagnosis with a required high confidence level. We present a diagnostic quality driven mechanism for remote ECG monitoring, which enables a notation of priorities encoded into the wave segments. The priority is specified by the diagnosis engine or medical experts and is dynamic and individual dependent. The system pre-processes the collected physiological information according to the assigned priority before delivering to the backend server. We demonstrate that the proposed approach provides accurate inference results while effectively compressing the data.**

I. INTRODUCTION

Remote health monitoring is probably one of the most fundamental functionalities that a personalized healthcare system shall provide. Smartphones are fast emerging as the platform for wireless healthcare via affordable medical sensors either embedded in phone or connected through Bluetooth [14][17]. These technologies can not only transform the way healthcare is managed and delivered to individuals, but also enable more accurate aggregation of individual data into health models.

It has been known that real-time collection and transmission of high rate physiological data impose a huge burden on the limited energy resources available to smartphones and sensors. Our tests show that at low data rates (approximately 60bytes/s) and frequent transmissions (once every 0.5-1sec), a cell phone can only last 10-12 hours at most while continually transmitting data over a strong WiFi connection. This means a recharge cycle of every half day for users. It has also been shown that WiFi radios are more energy efficient than cellular radios for infrequent bulk data transfers [26]. Thus, from usability perspective, it is more favorable to reduce the amount of data for transmission to prolong recharge cycle.

We believe that each individual is unique with diverse physical conditions. Automated or semi-automated personalized healthcare shall reflect this uniqueness in physiological signals and associated parameters of an individual. A remote monitoring system shall preserve "important" data features in the related physiological signal for accurate diagnosis during the transmission from user end to server. General data reduction mechanisms either uniformly compress the data or preserve only certain features in the data. The system thus needs a higher-level personalized description to instruct the proper data processing mechanism for each individual.

Medical diagnosis is usually based on inferences drawn, not from raw sensor sample streams, but from the data features extracted from them. The importance of a data feature is best defined in terms of its *diagnostic quality*, or the incremental inference accuracy derived from it. With a notation of priorities encoded into wave segments, we present a diagnostic quality driven framework. The priority is specified by the diagnosis engine or medical experts and is dynamic and individual dependent. The assigned priorities allow a data reduction while maintaining diagnostic accuracy by preserving specific signal features. To demonstrate and assess the concept of diagnostic quality driven bandwidth-scalable physiological data collection, we design and implement a supporting processing framework for healthcare.

II. RELATED WORK

Lossy ECG compression achieves a higher compression ratio by allowing distortion. Various techniques have been well developed [7 - 11]. Quality controlled compression recently has grabbed researchers' attention [19 - 21]. These systems uniformly compress data to a given threshold. [22] developed a compression that is specialized for signal components. We propose to encode priorities into waveforms such that a system can process ECG accordingly in a more personal fashion.

A concept similar to the one discussed in this paper has been explored in the field of image/video compression in the context of "Region of Interest". The JPEG 2000 Standard [23] provides mechanisms to label and compress different parts of a picture into a different degree of fidelity. The MP3 encodes audio based on psychoacoustic models and discards less audible (to human hearing) components [24].

III. DIAGNOSTIC INFORMATION IN ECG

We choose ECG signal, as the subject throughout rest of this study, to investigate the idea of preserving diagnosis-related features while transmitting compressed data. ECG has the benefits that it has been well studied by the medical community and has proven its clinical importance. Besides, everyone has a unique ECG [16] and thus motivates the importance of personalized healthcare. Other types of physiological signals also apply to the same concept in preserving features.

A typical ECG waveform of one normal heartbeat consists of three characteristic waves: a P wave, a QRS complex and a T wave. There is a small U wave that is not always visible. ECG reflects the electrical activity of the heart muscle and is recorded by electrodes attached to the body surface. P wave relates to the depolarization of the atria. QRS complex captures ventricular depolarization and T wave indicates ventricular repolarization of the heart [1, 12]. With different origins in heart, it is natural that each wave segment in ECG has its own

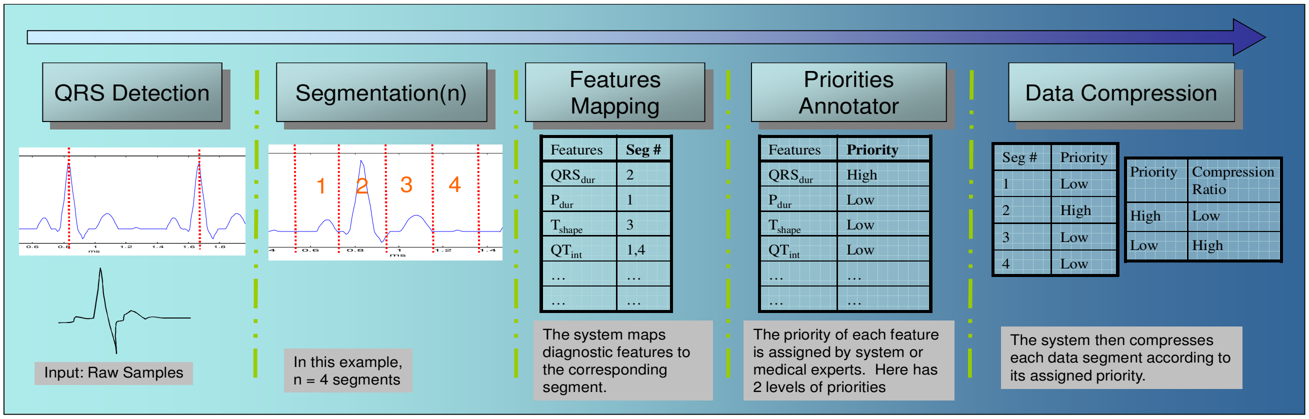


Figure 1. The diagnostic quality driven physiological data collection framework

clinical significance in diagnosis of various cardiac related diseases.

The concept of preserving diagnostic information of physiological signals has been emphasized in medical literatures. Blanco-Valasco et al. showed in [18] that incorrect context can be inferred if the classical percentage-root-mean-square difference (PRD) is exclusively considered. Zigel et al [6] discuss that the PRD does not serve as a "good" distortion measure. They state that "the error criterion has to be defined such that it measures the ability of the reconstructed signal to preserve relevant diagnostic information." Then they introduce weighted diagnostic distortion (WDD) and define 18 relevant ECG diagnostic features in three groups: *duration* (and interval), *amplitude* and *shape*. These data features are well correlated to expert cardiologists' perception. In our evaluation, we focus on these diagnostic features to inspect how the application of lossy compression algorithms on the ECG signal degrades its diagnostic quality.

IV. THE PROCESSING FRAMEWORK

Our system focuses on preserving diagnostic features in an ECG signal while compressing it to a desired ratio. Figure 1 illustrates our proposed mechanism. The key concept is, based on its expert assigned or automated calculated priority, to select a proper compression technique or compress each data segment with different ratio such that a system is able to provide better diagnosis quality even with a low-fidelity signal. Important data features that need to be preserved in the signal are first determined by medical experts or a diagnostic engine. The common diagnostic features in ECG are the intervals, amplitudes and shapes [6]. Medical experts, or the diagnostic engine, can assign priorities to these features according to the cardiac activities of interest. The enabling point is that these features can be mapped back to various wave segments of a cardiac cycle. The system thus has the ECG waveform segments associated with priorities in time domain that are finally used to process the signal accordingly.

The framework of the proposed ECG diagnostic features preservation mechanism includes five stages: *QRS Detection, Segmentation, Features Mapping, Priorities Annotation* and *Data Compression*. In QRS detection stage, the system continuously performs QRS detector algorithm on the collected ECG data to determine the RR interval of heartbeats. Each heartbeat is further segmented into several components in the Segmentation phase. The Feature Mapping phase maps each feature to its corresponding segment, while the Priorities Annotator processes the configuration file or real-time commands to setup priority levels for each data feature. The two resulting mappings are joined by the system to determine the priority of each wave segment. Before transmitting data to the backend server, the Data Compression module compresses each segment with a different ratio based on its priority.

V. IMPLEMENTATION & TEST BENCH

We implement the system by using a Nokia N80 smartphone as the personal base-station, a laptop as the backend server and Alive Heart Monitor [25] as the on-body sensor. The Alive Heart Monitor consists of an ECG sensor and a 3-axis accelerometer and is configured to transmit the collected data via Bluetooth at a pre-defined rate. The Nokia N80 smartphone employs above prioritized processing framework and preserves diagnostic features in compression. The backend server stores the collected data and performs diagnosis. The system components are shown in Figure 2.

For evaluation purposes, we built a test bench to automatically segment the ECG waveform. This ECG segmentation test bench can quantitatively determine the amount of diagnostic information that has been preserved during the information flow. Our approach adapts the Hidden Markov Model [13] for ECG waveforms and uses a Bayesian classifier to segment these waves. To determine its accuracy in ECG segmentation, we choose six recordings in QT Database [27] and then compare the computed results against it. Its accuracy in segmenting fiducial points has a mean of 5.26ms and a standard deviation of 18.26ms, and keeps abreast of the performances as [15].

VI. EVALUATION

A. Diagnostic Quality vs. Compression Ratio

Here, we further investigate the impact of lossy compression on diagnosis quality of an ECG waveform. In the experiment, data features of a raw ECG signal were extracted by using the test bench described earlier. They were compared against features extracted from the signal compressed

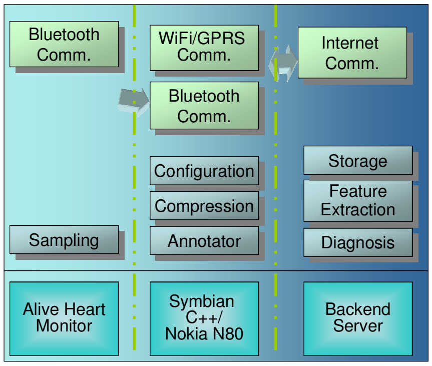
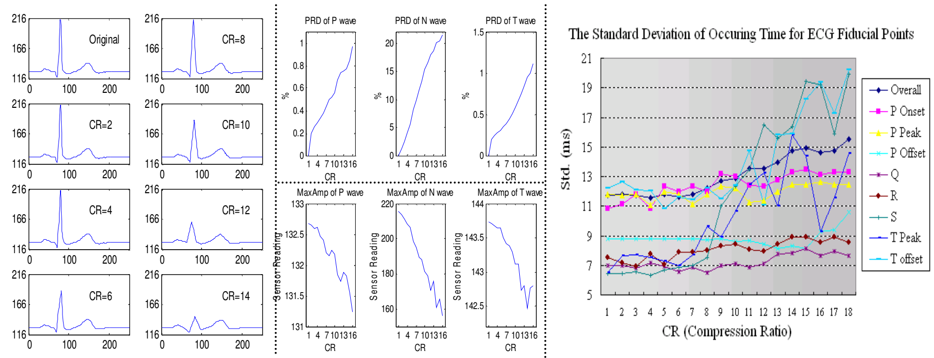


Figure 2. System components.



(a) top (b) bottom (c) (d)

Figure 3. Evaluation of ECG diagnosis quality after compression. (a) Visualization. (b) Shape distortion. (c) Maximum amplitude. (d) Standard deviation of fiducial points.

uniformly at varying ratios to quantify and analyze the degradation of diagnostically relevant features of the signal. The experiment was conducted in a home setting where the author collected approximately 15 minutes (~278K samples) of his ECG trace while watching TV.

The evaluation employs 16 different settings in compressing the data with CR = 1 equals to the original data. We use coarse sampling [5] as the lossy compression algorithm to preprocess collected data samples before transmitting. For "lossy" compression, choosing a different technique does not change the fact that the diagnostic quality drops with the increasing compression ratio.

Figure 3 shows the evaluation results of diagnostic abilities in ECG coarse sampling compression. Figure 3 (a) is a visualization of the ECG waveform of one heartbeat in different CR settings. Figure 3 (b) depicts the PRD between an original ECG and compressed ECG waveforms. This measures the distortion in shape of the characteristic waves in ECG. Figure 3 (c) shows the diagnostic feature of amplitude in ECG. With the increasing CR, the local maximal amplitude of an ECG characteristic wave has dropped accordingly. Figure 3 (d) displays the standard deviation of the occurring time of the fiducial points classified by the test bench described earlier. The increasing standard deviation represents a decreasing precision in determining the durations and intervals.

B. *The Obstructive Sleep Apnea Detection Application*

We use an obstructive sleep apnea detection application (Apdet [2]) from PhysioNet [3], with a real ECG trace obtained from the apnea-ECG database [4] to assess how a general loosy compression affects automatic diagnosis and quantification. *Apdet* is an automated method for diagnosing and quantifying OSA from a single ECG trace. The software employs Hilbert transform on RR interval time series, and then based on the resulting instantaneous amplitude and frequency components, differentiates periods of prolonged OSA from periods of normal healthy respiration.

Figure 4 (f) shows the OSA detection results of Apdet detection application based on original data versus coarse sampling data. Y axis is the sleep time period where blue bar indicates the OSA duration out of total sleeping time. The results show that, in this case, if the CR increases above 6, OSA periods detected by Apdet application become untrustworthy.

For our experiments, we divide each heartbeat (generated through QRS detector) into 4 segments. For each experiment, we select one segment to be the high priority segment and mark the others as low priority segments. The system delivers the high priority waveform with original data fidelity in order to preserve its diagnostic features in time domain. The other low priority waveforms are compressed with CR varying from 2 to 18 in order to ascertain the highest possible compression setting for them. The ECG signal is reconstructed through linear interpolation before application of the Apdet algorithm.

Figures 4 (a), (b) and (d) depict the Apdet results with the high priority segment set to 1, 2 and 4 respectively. For each plot, the leftmost blue line is the result obtained from original data (the highest possible fidelity). The remaining lines in the graphs show results with increasing compression of the low priority segments. All the results show a break point around CR = 8 for the low priority segments. A dramatic improvement takes place when the system sets segment 3 to high priority (Figure 4 (c)). In this case, we can push the compression ratio on the other low priority segments (1, 2 and 4) to CR=18 without compromising the diagnostic accuracy of Apdet. This is because most of the diagnostically significant features to Apdet reside in this segment for this patient. Therefore, if the system preserves data fidelity of this segment, highly accurate diagnosis is possible through Apdet, even when all the other segments are significantly compressed. Figure 4 (e) shows the effect of different compression ratio combinations while maintaining confidence in diagnostic accuracy of Apdet. The resulting overall compression is 8x as compared to the original data with a negligible decrease in accuracy. This corresponds to a substantial reduction in power consumption of cellular transmission.

It is important to note that segment "3" is not a universal magic number that suits everyone for the Apdet application. Because the characteristic waves can differ from individual to individual, the location of the diagnostic features in an ECG waveform also varies. Therefore, the importance of the proposed mechanism is its ability to let the upper tier instruct data pre-processing dynamics in the lower tiers at run-time.

VII. Conclusion

In this work, we propose a diagnostic quality driven framework for personalized health data collection. We show the advantages of accurate diagnosis inference while preserving relevant data features along sensing, preprocessing, feature extraction and diagnosis pipeline. Our implementation evaluates how data compression varies the precision of data features and the accuracy of diagnosis results. We believe that the diagnostic relevant information of any physiological signal shall be maximally preserved during data flow and is individual-dependent. We look forward to increased interests in facilitating the diagnostic driven physiological data collections.

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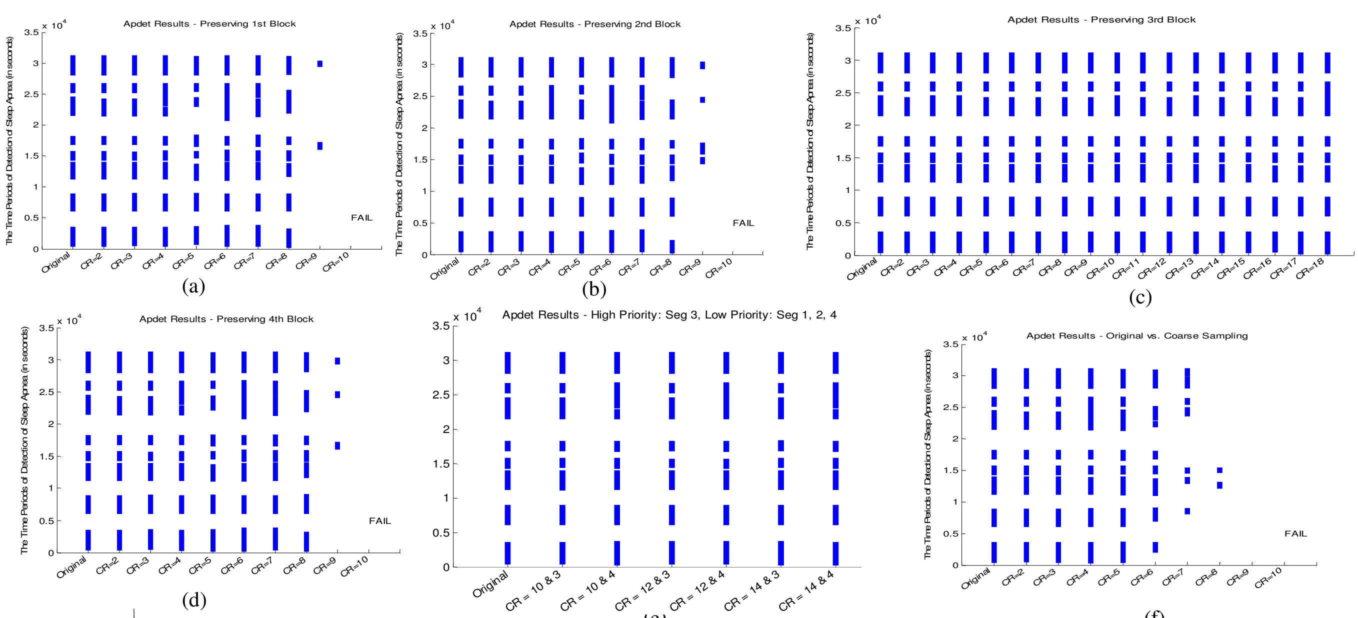

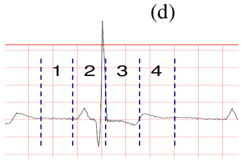

Figure 4. The Apdet diagnosis results when the system preserves **(a)** segment 1; **(b)** segment 2; **(c)** segment 3 and **(d)** segment 4. In **(e),** the system performs hybrid compression. **(f)** shows the original results without assigning priority. The y axis is the detected obstructive sleep apnea periods and the x axis is the compression ratio. The diagnostic features for this patient (Apnea-ECG/a03) reside in block 3.