Continuous Health Condition Monitoring by 24x7 Sensing and Transmission of Physiological data over 5-G Cellular Channels

Amitabh Mishra
Center for Distributed and Mobile Computing, EECS
University of Cincinnati,
Cincinnati OH 45221-0030 USA
mishraab@mail.uc.edu

Dharma P. Agrawal
Center for Distributed and Mobile Computing, EECS
University of Cincinnati,
Cincinnati OH 45221-0030 USA
dpa@cs.uc.edu

***Abstract* —A novel architecture tested exclusively for instantaneous sensing and 24x7 transmitting important physiological signals over cellular networks has been introduced in this paper. Pulmonary Artery Pressure (PAP) and Electrocardiogram (ECG/EKG) are selected as two preliminary physiological signals for this exercise as these two can help diagnose Cardio-Vascular Diseases (CVDs), the major silent killer of modern days. We use a Wireless Body Area Sensor Network to get the physiological data from a user's body and transmit them to a WBAN coordinator. The coordinator compresses received data from the body sensors, modulates it using bi-phase modulation scheme and sends it to a GSM module for remote transmission over existing cellular network. The GSM module receives the data and sends it to a remotely located tiny server for subsequent demodulation and reconstruction of the original signals. We explain details of different techniques used for data compression of this methodology and provide efficient transmission of data considering allowable range of perturbation in the information content in maintaining original characteristics. For the transmission of physiological data, we visualize to have a dedicated channel in upcoming fifth generation mobile technology, as more bandwidth for everybody is anticipated for services like data on demand, and would make 24x7 health-monitoring a reality in the near future. The novelty of our approach lies in the fact that it would enable online, round-the-clock health watch for the cellular system subscribers at very low power consumption by collaborating with the underlying sensor networks.**

Keywords—Bit-error-rate (BER); body sensor nodes, wireless body area network (WBAN), coordinator and sink station (CSS), IEEE 802.15.6; telehealth; mHealth; Wireless Body Area Sensor Network (WBAN).

I. INTRODUCTION

Two of the major challenges in world health today are: increase in the life expectancy causing an increase in the number of geriatrics, and rise in the cost of healthcare. Studies indicate that based on current trends [1], the overall healthcare expenditure of developed and developing countries is projected to reach 20% of the Gross Domestic Product (GDP) of these countries by 2022. This could adversely affect the global world-wide economy.

It has been proved by research that an early detection in the initial stages can prevent most of the ailments and diseases. This fact advocates that a proactive wellness management with such a focus should be ensured by the health care systems of the future. Wearable monitoring systems starting to appear in the healthcare market could offer a possible solution to proactive and more affordable health care systems. These systems can affect early detection of abnormal conditions and provide substantial betterment in the quality of human life.

Wireless Body Area Networks (WBANs) form an important prong of such wearable technology that involve the use of low power, low radio range sensor nodes for sensing of physiological and bio kinetic parameters and transmission of sensed data using wireless link hops over a network. WBANs envisage a human-centric use of wireless technology for personalized telehealth and telemedicine, and remove the compulsion to stay confined to bed or under the care of medical attendants or doctors. Apart from monitoring the physiological and bio kinetic parameters of patients and athletes, the concept can also be used in life-saving applications, especially the personnel who work in hazardous environments, like first responders, fire-fighters, divers and astronauts. The rise in the cost of healthcare around the world has proportionately increased the need for integrating WBAN systems into the upcoming information technology and telecom infrastructure.

WBANs can drive the cost-savings and improve the efficiency of healthcare by effecting proactive concepts. In addition to monitoring of vital signs, seizures or organ implants, WBANs can provide proactive cardiovascular monitoring by identifying potential heart ailments before they occur.

A battle for WBAN standards have been among Wi-Fi, Zigbee and low power Bluetooth until the IEEE 802.15.6 standards for WBANs emerged on the scene in late 2012 [2]. The new standards come with QoS provisioning for WBANs, apart from other important specifications. While the standards define the essentials and protocols for various layers, compatibility of transmission of the WBAN data utilizing the various available telecommunication networks is still a gray area. Our position in this regard is that the aforementioned interworking standards between IEEE 802.15.6 and the evolving 5G standards need to be developed. To advocate this further, we have experimented with encoding and communicating vital sign data corresponding to two parameters via a GSM network and obtained encouraging results. Our position emphasizes enormous emerging opportunity for mobile health sector that holds great promises of reducing the cost of healthcare monitoring. Such a move could be a great initiator for novel business models in this nascent sector that would generate a vibrant consumer base. Mature and powerful consumer mobile technology is capable of handling the challenges of innovative healthcare applications, and its emerging standards like 5-G should be further developed with such applications in mind.

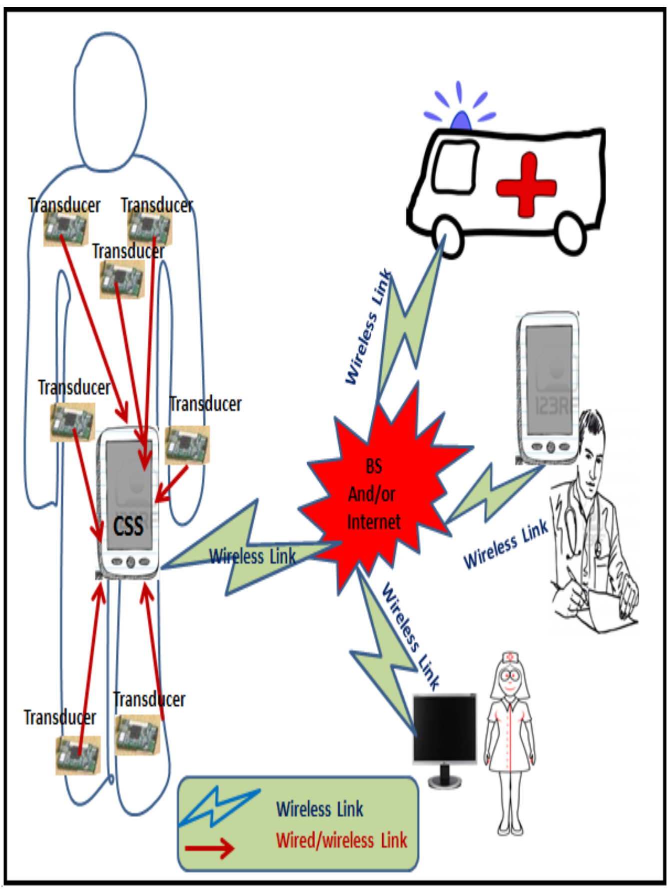

Figure 1: A typical WBAN with links from Body Sensor Nodes to the end users via the Coordinating Sink Station (CSS)

II. BACKGROUND AND MOTIVATION

WBANs contain an important hidden proficiency to remodel the future of health care monitoring not only by doing away with the need for costly in-hospital monitoring of patients, but also by diagnosing several life threatening diseases [3]. It is estimated that by 2020, cancer death rates might increase by 50%, taking the toll up to 15 million [4]. WBAN based cancer cell monitoring can affect early tumor diagnosis without a biopsy and offers a timely analysis for early treatment. Yet another dominant causes of death is the cardiovascular disease, which is assessed to cause nearly 30 percent of deaths worldwide [5, 6]. We decided to focus our work on cardiovascular signals for this reason.

One of the major challenges related to WBANs involves the energy-fidelity tradeoff. WBANs have to transform and transmit the sensed parameters into valuable information of acceptable and appropriate fidelity level, in an energy efficient manner. This feature calls for selective processing of varied physiological data samples.

Due to the constraint of a small sensor node size and even smaller batteries, increasing the lifetime of sensor nodes and consequently that of the networks is always an issue [5, 6]. Body Sensor Nodes (BSNs) are similar to their wireless sensor networks counterparts [7, 8], but smaller in size, and lower in battery capability, and hence suffers from severe constrained. The sensor nodes need to keep collecting data samples and relay them to the CSS. A large number of data samples corresponding to the physiological parameters are collected. However, the number of samples collected does not take into account the frequency and nature of variations in the physiological parameter. In this paper, we have also tried to reduce this data content in order to address the energy-fidelity tradeoff [9] by signal processing methods involving excluding of some sample data from transmission and recreation of missing samples using prediction.

IEEE 802.15.6 standards lay down the specifications for WBANs, but they treat WBANs as standalone networks of a distinct type. Interworking between the IEEE 802.15.6 and the other existing wireless systems like GSM, WCDMA, WiMAX, ZigBee and HomeRF etc. is an important issue that still needs to be worked on. In our work, we explore the possibilities of WBAN functions if the mentioned standards and protocols are developed in the future telecom standards like 5G and provisions of such interworking are developed.

III. RELATED WORK

Wagner *et al.* [10] use ZigBee links and a cable connection for BSN data collection and processing in an embedded system from which the data is sent over Bluetooth links to the smartphone for presentation. The approach by Ogunduyile *et al.* [11] utilizes a GPRS/Internet connection for uploading the BSN data to a Medical Health Server for analysis. Baviskar and Shinde's approach [12] uses BSNs for data logging, processing and analysis that send the results to the CSS over Bluetooth links. The system proposed by Bourouis *et al.* [13] uses GPRS/UMTS link for beaming up BSN data to a server.

Although all the approaches involve a WBAN and suggest the use of a smartphone as the CSS, none focuses on data compression for energy saving and improving on BSN as well as WBAN life-time, which we address in this paper.

Our work presented in this paper is different from these schemes in that none of the afore mentioned approaches explore the possibility of transmitting the sensor data by means of encoding as a text message or sending it as a voice coded signal by means of digital phase modulation. We compress and encode vital parameter data and package it for transmit it as a short text messages. Our follow up scheme encodes compressed BSN data as a digital phase modulated voice signal for transmission over regular voice channels.

We have enhanced sensor network design discussed in [14] by adding the capability of communicating over commercial wireless voice/data networks to WBANs. The benefit of our architecture can be directly useful in mitigating inter and intra-WBAN interference issues, by adding to the solutions proposed by Jamthe *et al.* [16]. None of the previous works proposes such a solution for dealing with WBAN interference.

IV. ANALYTICAL MODEL AND PROBLEM FORMULATION

A.SAMPLE REDUCTION

Transmitting all the physiological sensor data samples would increase the fidelity of data and the accuracy of information contained therein. Such a sampling would satisfy the Nyquist criterion but it would also mean transmitting a lot of such data which could be rendered redundant through signal processing techniques.

If an emergency medical condition occurs for a human subject being monitored by a WBAN, our proposed architecture can send medical data updates to the concerned medical personnel by means of short messages or encoded in a voice call. While such updates might not be able to send BSN data corresponding to continuous monitoring, they would still help the medical personnel in an early diagnosis, preparation or decision on the course of action about the subject.

B.ENCODING AND ERRORS INVOLVED

In order to encode the PAP and ECG Lead-II data as short text messages, the first challenge faced pertains to the limitation that any single message of the mentioned type cannot contain more data than what would be needed for encoding 160 textual characters. Not much of uncompressed sensor data can be packaged in a single text message. Multiple text messages in a sequence could be a possible solution, but a lot of such messages would still need to be packed in a limited amount of uncompressed data. If the sensor data is compressed, more amount of information could be packaged in the same number of short messages. Energy-fidelity tradeoff would need to be kept in mind in the process of cutting down and compressing the data.

For this work, we chose sets of 3600 samples covering 10 seconds of sensor data for PAP and ECG signals. A standard short text message can hold 160 encoded textual characters. If we tried to encode our sample sets as text messages, 3600/160 = 24 text messages would be required. It is important to note that this would be for raw/unreduced 10 second data. However, if the sample frequency was reduced, data corresponding to more time could be packaged in the text messages. A reduction in sample size by a factor of five in samples could encode 10 seconds in 720 samples, which can be contained in just 5 text messages if each sample was encoded in 8-bits, corresponding to the ASCII code for the text messages. However, we are not bound to follow such encoding, and resort to compression in encoding in order to squeeze in even more data in every message pack.

One such compressed encoding scheme could be delta modulation. One bit difference delta encoding could approximately hold 160x8 = 1280 data samples in one short text message pack. This would mean that 10 seconds of data could be encoded in three text message packs. Lossless compression techniques applied on top of such an encoding could yield a further tight packaging of data.

However, there would be a compression-fidelity tradeoff involved. Maximum allowable error in an approximation that would result from such a compressed encoding is debatable and the tradeoff can be best decided by physicians and specialists. The maximum error in encoding is decided by the step size and the maximum can be half the step size. In case of PAP, the lower and higher ranges of the signal are 20mV and 45mV respectively, consequently making the signal span to be 25mV. Encoding this signal into eight bits yields a step size of 25mV/256 = 97.6 μV, thereby limiting the maximum allowable encoding error to 48.8μV. The error in case of ECG lead-II signal, similarly, is 3.42μV, because the signal-range from -0.75 mV to 1.0 mV gives a step size of 6.83 μV.

V. PROPOSED ARCHITECTURE AND FRAMEWORK

Before we try packaging BSN data in the form of a text message, we need to reduce the amount of sample data by cutting down the quantum of transmissions. The number of samples in the data can be reduced if the missing sample values can be predicted within the limits of acceptable error by signal processing techniques. Dual prediction techniques as proposed by Mishra *et al.* [16] can then be utilized at the receiving end for missing sample reconstruction apart from the technique used by us in this paper. We reduced the amount of data by skipping those samples from the original set that can be predicted at the receiving end. We also applied delta encoding to further pack more amount of data in every message packet containing encoded BSN data.

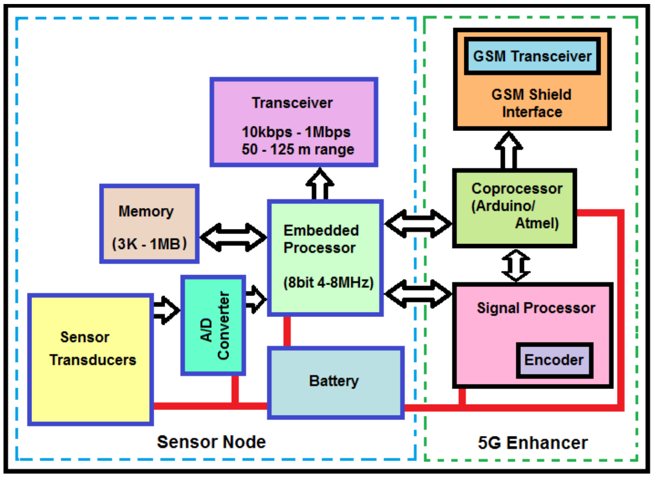

Figure 2: 5-G Enhancement for a typical WBAN BSN.

Our proposed architecture, shown in Figure 2, involves enhancement of body sensor nodes discussed in [17], with a coprocessor which is an additional microcontroller. This microcontroller facilitates ease of data logging, processing and temporary storage of data samples from the sensor nodes. The microcontroller has a wireless extension/add-on that makes the sensor node capable of communicating with the CSS or any other similar device over GSM or other commercial voice/data network, in addition to IEEE 802.15.6 radio. We call this addition in the extended architecture as the 5G extension for the sensor node, with a proposal and assumption that the 5G standards would envisage dedicated channels for communication and processing of sensor data from WBANs. Such an enhancement would benefit a WBAN by enabling the sensor nodes to communicate with CSS, which could be a smartphone itself, thus obviating the need for a dedicated CSS device. We use a smartphone as the CSS in our architecture as smartphones have become very common these days, with a variety of applications available for them which could also be custom made. This also means that, if needed, the WBAN would then have the capability to send its physiological data directly to any other smartphone with the physician, or with emergency or nursing services using the GSM/WCDMA or similar voice/data network.

Hence the architecture works as follows. The sensor nodes sense and then process the physiological data. The data is then encoded, packed in the desired format, say a text message or as a voice-coded data message, and passed on to shield. The shield then transmits the data to the smartphone functioning as the CSS, or any other smartphone as required. The WBAN CSS can make decisions regarding a need-based use of voice/data network instead of internal WBAN wireless links running on IEEE 802.15.6 depending on the current scenario with respect to interference, QoS, throughput requirements and urgency of communication.

Along with the text-message encoding, another important functionality in our architecture is to use a speech signal encoding of the physiological sensor data using PSK, and then transmitting the data as a voice call. The coprocessor sends the related encoding request to the signal processor block in the architecture. The signal processor block acknowledges the request and generates a digitally modulated output of the compressed sensor data using BPSK. An important aspect of this encoding is the use of human speech frequencies (100 Hz – 3.3 kHz) in digital modulation so that the generated output can be treated as a voice signal by the further processing stages. This allows the coded signal to be transmitted as a voice call to the receiving smartphone. The received call can be directed to the right application in the smartphone for decoding and presentation.

VI. RESULTS

We reduced the sample data sets from the PAP and ECG signals obtained from *Physionet* [18], progressively, into four different subsets of each of the original sets. The first subset contained just the alternate samples, the second contained every third sample, the third set had every fourth sample and the fourth had every fifth sample. Consequently, the sample sizes of the first, second, third and fourth sets were a half, a third, a fourth and a fifth of the original set, respectively. These four sets are transmitted and the original is recreated from these four sets by numerical interpolation at the receiving end and compared with unreduced set of samples. The results of the recreation are plotted in Figure 4 for the ECG-Lead II signal. Similar work has been done on the PAP signals as well. The signal specifications for the two signals have been shown in Table 1.

Table 1: Signal specifications for the two vital sign BSN parameters

Characteristics	PAP (mV)	ECG-II (mV)
Signal Minimum	21.4119	-0.5296
Signal Maximum	43.3432	0.8143
Signal Span	21.9313	1.3439

The recreated signals were compared with the original sets and an error analysis has been presented in Table 2.

Table 2: Maximum Error with sample reduction for PAP and ECG

Sample Reduction	PAP	%Error	ECG-II	%Error
Halved	0.183	0.835	0.051	3.773
1/3rd	0.263	1.200	0.083	6.154
1/4th	0.443	2.018	0.130	9.666
1/5th	0.481	2.194	0.202	15.001

From Table 2, it can be seen that the error is less for the PAP signal as compared to the ECG signal. This is because of the signal span range and wave nature of the ECG signal that has more and subtle variations compared to PAP, that get encoded due to smaller step size.

The reduced PAP and ECG signals were then compressed, encoded as text messages and transmitted over GSM network. Our set up for this comprised of an Arduino microcontroller board with a GSM shield extension. Using the setup we successfully received the encoded message signal as a short text message.

The text messages sent by the Arduino were successfully received at the other end by a GSM cellular handset. The encoded and compressed BSN data was then available for decoding and rebuilding of the original, uncompressed data samples out of the receiving handset. For rebuilding the missing BSN sample data at the receiving end, we applied numerical interpolation techniques. We tried five such techniques, and offer a comparison between the techniques for the two vital sign parameters in Table 3.

Table 3: Percentage error values for ECG-Lead II from the five numerical interpolation techniques

Reduced	Linear	Near	Spline	Pchip	Cubic
½	3.773	14.495	3.691	3.668	3.698
1/3rd	6.154	16.445	6.392	5.447	5.447
1/4th	9.666	25.017	9.078	9.316	9.346
1/5th	15.001	32.971	9.309	10.202	11.727

From the Table, it is obvious that apart from the nearest neighbor interpolation algorithm, the other four are comparable, and yield lesser error. Of the four, linear spline interpolation performs better across the various reduced sample sets.

We selected twenty random sets of samples (3600 samples for 10 seconds in each set) of the PAP and ECG Lead-II signals from healthy individuals and multiple patients for evaluating the performance of prediction algorithms. PAP and ECG Lead-II parameters are different in terms of wave-shape, range, and nature of variations. The two vital sign parameters have been chosen for evaluation just to offer diversity in choice. We reconstructed the signals at the receiving CSS smartphone end by applying the nearest neighbor interpolation, linear interpolation, linear spline, and two flavors of cubic spline algorithms for comparison. The results of error evaluation of one such set using linear interpolation are shown in Figure 3 for the ECG signal. ECG signal has been chosen for representation here because the signal span is the lowest for this signal, thus posing maximum constraints pertaining to fidelity and error.

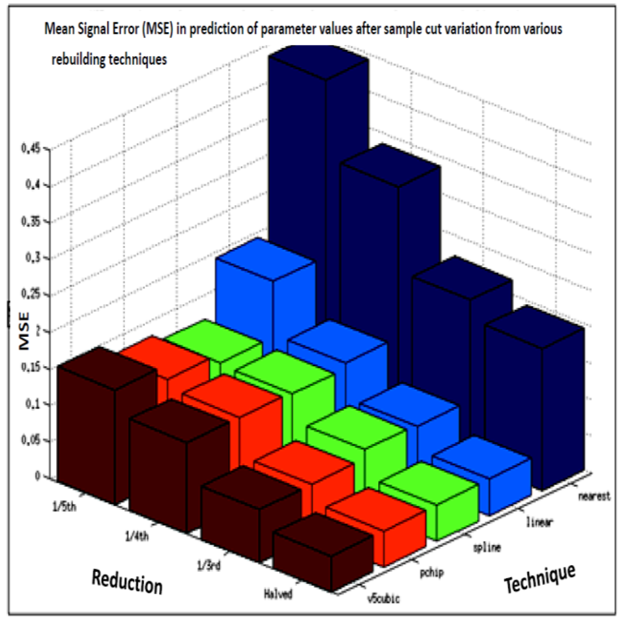

Figure 3: Plot of mean square error in the prediction of ECG signal

The first column of graphs in Figure 4 shows the signal sets with stepped reduction in the number of samples. The second column shows the rebuilding of missing samples for the corresponding row at the receiving end. The figure shows the rebuild using linear interpolation as the prediction algorithm. For the sample analysis and graphical evaluation, we wrote the programs in MATLAB r2012 [19] and in Java 1.7 [20].

The discussed results are a part of our ongoing work. We are working on encoding of BSN data as a voice signal and transmitting the data over a GSM voice call. Our focus is on the comparison of various digital voice modulation schemes so as to find out the one that yields most efficient packaging and transmission of BSN data. We are also trying to develop smartphone applications for decoding and processing of this data and then presenting it to the end user for immediate consumption.

Figure 5 shows the error plots between the original signal waveforms and their reconstructed versions for different amounts of sample cuts in the ECG signal as depicted in the four cases shown in Figure 4. It is observed that the error increases with rise in the amount of reduction in the sample size from the original set. We showed the results to practicing physicians who said that their diagnosis would not have changed for the signals and the error observed would have therefore been tolerable.

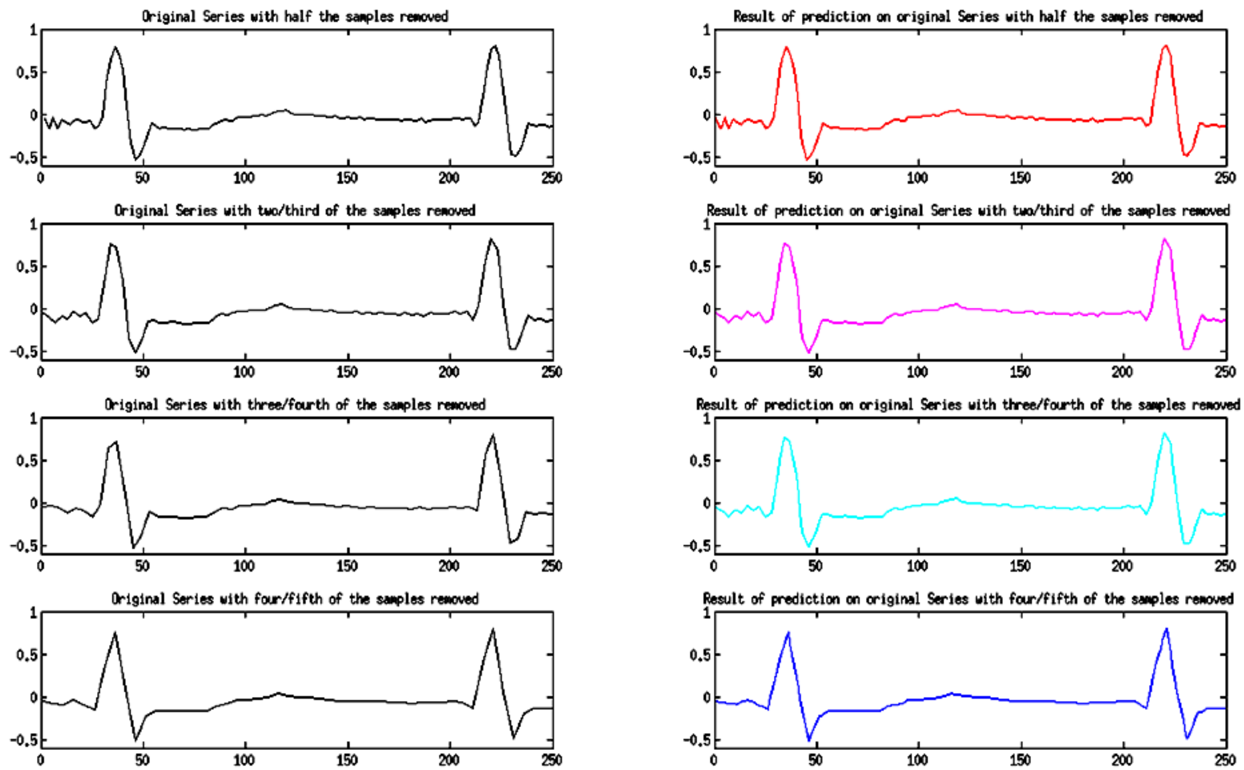

Figure 4: Plots for linear interpolation based predictive rebuild of the ECG Lead-II signal

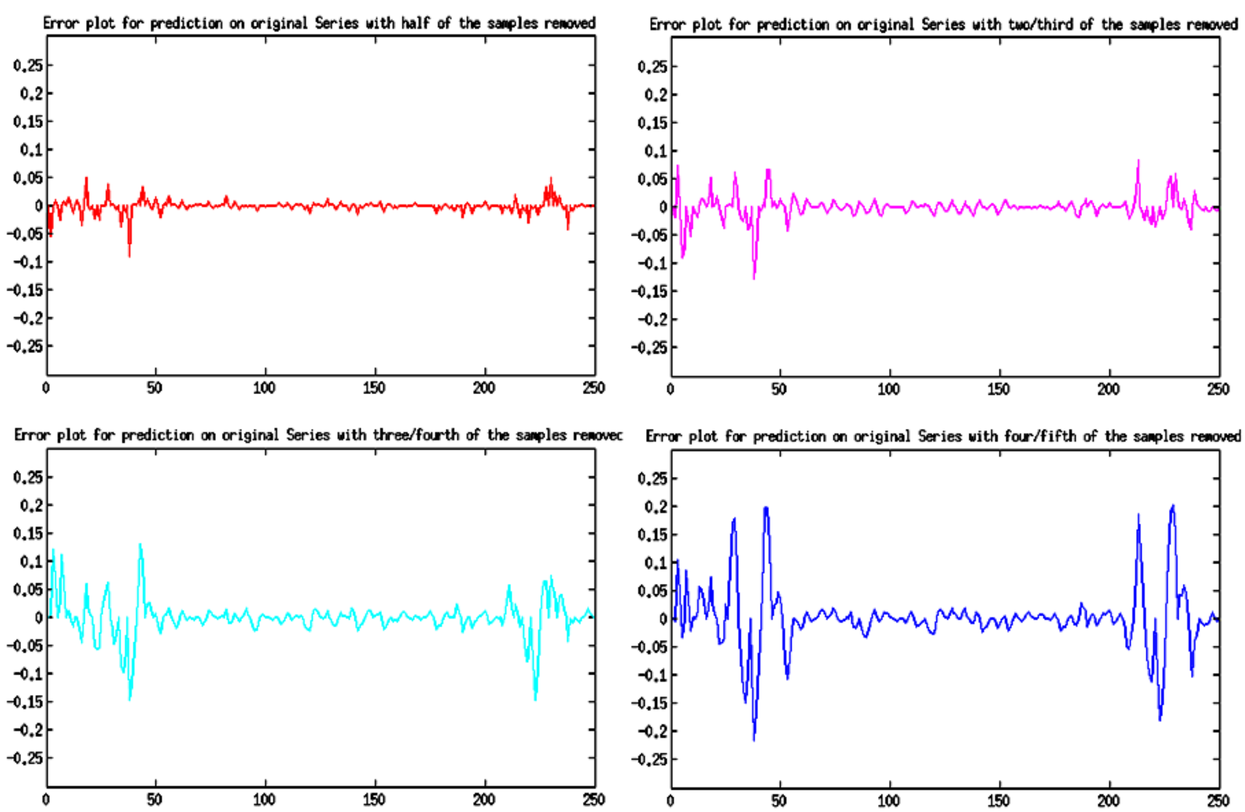

Figure 5: Plots for error for the linear interpolation based predictive rebuild of the ECG Lead-II signal for the four reduced sample sets

VII. CONCLUSION

We have presented architecture of WBAN sensor nodes with potential 5G enhancement that would offer additional functionality of routing BSN data through voice/data channels in conventional wireless communication networks. We have experimentally tested the feasibility of realizing this enhancement by means of extension circuitry for processing and transmission and are still working towards making the system more efficient and diverse. Dedicated channels in 5G would demarcate the slots for important BSN data that would not be denied service in the event of a busy network. Such data would be encoded in the form of text/voice and would open an option of getting routed through GSM voice and control channels.

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