Energy Conservation and Lifetime Optimization of Wireless Body Sensor Networks for 24x7 Physiological parameters' Monitoring

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Abstract — We introduce and propose a new architecture tested solely for a prompt sensing and anytime-connected wireless body area network for the transmission of important physiological signals over cellular networks. Our work considers signals related to cardiac diagnostics for transmission and energy based evaluations in such a network. The physiological data from cardiac parameters is sensed and transmitted over a Wireless Body Area Sensor Network (WBAN) to a coordinator and sink station (CSS). The CSS compresses the data received, processes it and sends it through GSM communication over the cellular network to a remote base station. The GSM receiving unit receives the data and directs it to a dedicated remote server for demodulation and decompression. We have discussed the methods used for the compression of data in this scheme and tried to keep the transmission error low. We propose a dedicated channel in upcoming generations of mobile communication technology for the transmission of vital physiological data. We have also tried to evaluate the network lifetime using common battery models. Our methodology would facilitate round-the-clock health monitoring for the subscribers of a cellular communication system by working in partnership with the underlying body sensor networks consuming low power.

Index Terms— Bit-error-rate (BER), body sensor nodes, wireless body area network (WBAN), coordinator and sink station (CSS), IEEE 802.15.6, telehealth, mHealth, Internet of Things

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. Recent developments in wireless technologies can be used to address these challenges ably.

A. Need for proactive wellness management

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 healthcare 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.

B. Internet of Things (IoT) and Wireless Body Area Networks (WBANs)

The Internet of Things is an innovative paradigm that conceptualizes a pervasive presence of a variety of objects with unique identification and communications capability such as Radio-Frequency IDentification (RFID) tags, sensors, actuators, and mobile phones around us at home, in workplace, or anywhere we go [2]. Through unique addressing schemes and communications capability, such objects would be able to interact with each other and cooperate with their neighbors to reach common goals [3]. It is anticipated that in the next ten years, Internet nodes may reside in everyday things – furniture, paper documents, supermarket articles, food packages, and more. For the business users, the most obvious outcomes will be visible in fields such as automation, intelligent transportation of people and goods logistics, industrial manufacturing, and. In this context, domestics, e-health, assisted living, enhanced learning are only a few examples of possible application set-ups in which the IoT paradigm will play an important role in the near future [1]. The WBANs of the future are anticipated to be an important subset within the IoT paradigm.

Wireless Body Area Networks (WBANs) form an important prong of such wearable technology that involve the use of low power, small radio range sensor nodes for sensing physiological or 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

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confined to the 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, including the IoT.

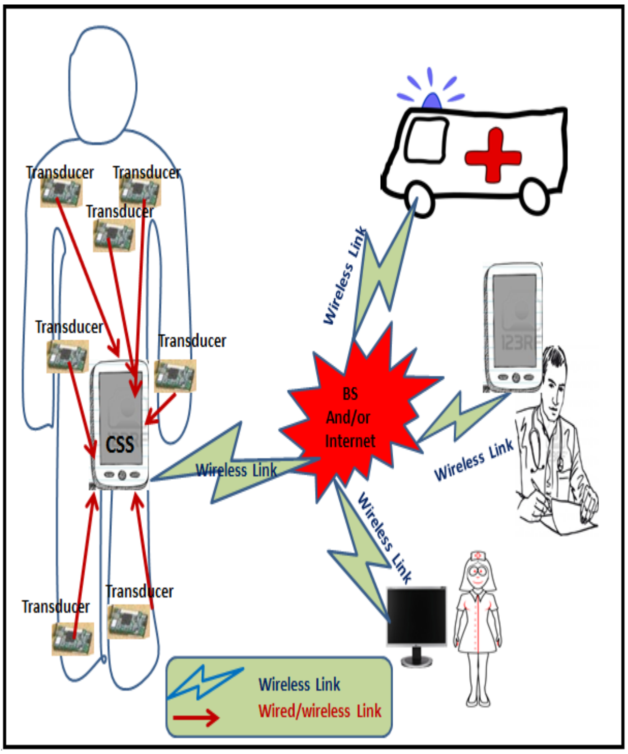

Fig. 1: A typical WBAN with links from Body Sensor Nodes to the end users via the Coordinating Sink Station (CSS)

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 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 an important initiator for novel business models in this nascent sector that would generate a vibrant consumer base. Mature and powerful consumer mobile technology of today is capable of handling challenges of innovative healthcare applications and its emerging standards like 5-G should be further developed with such applications in mind. None of the previous phases of mobile telecommunications architectures have considered the need to incorporate the handling of healthcare applications so far, and hence the authors look towards the 5-G for not missing on this opportunity while the standards are still being framed.

II. BACKGROUND AND PRIOR RESEARCH

WBANs contain an important hidden proficiency to remodel the future of healthcare monitoring not only by doing away with the need for costly in-hospital monitoring of patients, but also by helping in the diagnosis of several life threatening diseases [4]. It is estimated that by 2020, cancer death rates might increase by 50%, taking the toll up to 15 million [5]. 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 in the world is the cardiovascular disease, which is assessed to cause nearly 30 percent of deaths worldwide [6, 7]. We have decided to focus our work on cardiovascular signals for this reason.

A. *Energy-Fidelity tradeoff in WBANs*

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 [7, 8]. Body Sensor Nodes (BSNs) are similar to their wireless sensor networks counterparts [9, 10], but smaller in size, and lower in battery capability, and hence suffers from severe constraints. 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 by the BSNs. 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 [11] by signal processing methods involving the exclusion of some sample data from transmission and restoration 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 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 compatibilities between such interworks could be maintained.

B. Related Work

Wagner *et al.* [12] 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.* [13] utilizes a GPRS/Internet connection for uploading the BSN data to a Medical Health Server for analysis. Baviskar and Shinde's approach [14] 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.* [15] 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 present work is different from these schemes in that none of the 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 modulation. We compress and encode vital parameter data and then package it for transmitting it as a sequence of short text messages. Our follow up scheme encodes compressed BSN data as a digital modulated voice signal for transmission over regular voice channels.

We have enhanced the sensor network design discussed in [16] by adding the capability of communicating over commercial wireless voice/data networks to WBANs. The benefit of our architecture is that it can be directly useful in mitigating inter and intra-WBAN interference issues, by adding to the solutions proposed by Jamthe et al. [17]. None of the previous works proposes such a solution for dealing with WBAN interference.

III. ANALYTICAL MODEL AND PROBLEM FORMULATION

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 as 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.

A. Sample reduction and encoding error

In order to encode the data from Arterial Pressure (ART), Central Venous Pressure (CVP), Electrocardiogram lead II (ECG/EKG) and Pulmonary Artery Pressure (PAP) signals 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 ART, CVP, 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 requirement 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 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. Data aggregation schemes could further cut down on the sensors' transmission load.

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. The results for all four signals are summarized in Table I.

TABLE I: SIGNAL SPECIFICATIONS FOR THE FOUR VITAL SIGN WBAN PARAMETERS

	Parameters			
Characteristics	ART	CVP	PAP	ECG-II
Signal Span	40.0 mV	25.0 mV	25 mV	1.75 mV
Encoding Error	0.078 mV	48.8 µV	48.8 µV	3.41 µV
Step Size	0.156 mV	97.6 µV	48.8 µV	6.83 µV

IV. PROPOSED ARCHITECTURE AND FRAMEWORK

The enhancement proposed by us is intended to send the physiological data via a GSM network using two different means. However, 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. When it comes to deciding if the level of approximation is fine or not, the end users need to be consulted. In this case, the end users are the cardiac physicians and surgeons. In no case can the approximation be allowed to affect or alter their diagnosis. We followed this practice and consulted the cardiac physicians at each stage while running these approximations. Dual prediction techniques as proposed by Mishra et al. [18] 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.

Our proposed architecture, shown in Fig. 2, involves enhancement of body sensor nodes discussed in [19], with a coprocessor which is an additional microcontroller which 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.

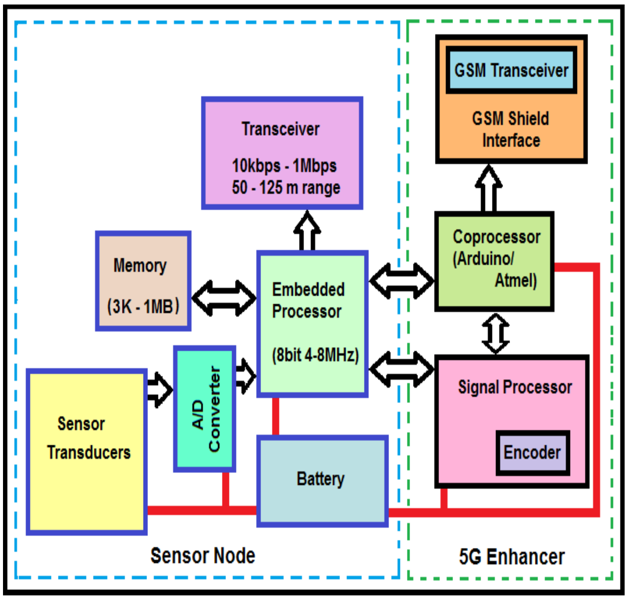

Fig. 2. 5-G enhancement for a typical WBAN BSN

However, even if such provisions are not envisaged in the 5G or future extensions, the proposed architecture can be designed so as to exploit the current analog or digital cellular design. We use a smartphone as the CSS in our architecture as smartphones have become very common these days. They come with a variety of applications available today. Such applications could also be custom made to cater to the user’s healthcare needs. This also means that, if needed, the WBAN would then have the capability to send the user’s 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 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 a 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 digital modulation, and then transmitting the data as a voice call. The coprocessor sends 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 from the digital modulation used. 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 would allow 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.

V. RESULTS

For our proposed system, we focused on the real life ART, CVP, PAP and ECG signals corresponding to healthy subjects and actual patients obtained from Physionet [20].

A. *Sample reduction and signal reconstruction*

The range specifications for the four signals have been shown in Table 2. From Table II, it can be observed that the ART signal has the widest span of about 50.0 mV while that of the ECG Lead – II signal is the least span at approximately 1.75 mV.

We converted the sample data from these signal data sets into four different subsets of each of the original sets by progressively reducing on the number of samples in the signal.

TABLE II: SIGNAL RANGES FOR THE FOUR VITAL SIGN WBAN PARAMETERS

	Parameters			
Characteristics	ART	CVP	PAP	ECG-II
Signal Minimum	50.0 mV	-15.0 mV	20 mV	-0.5 mV
Signal Maximum	90.0 mV	7.0 mV	45 mV	1 mV
Signal Span	40.0 mV	22.0 mV	25 mV	1. 5 mV

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 were then transmitted and received at the other end. At the receiving end, the original and complete set of samples was recreated from these four sets by numerical interpolation. The recreated samples were then compared with original unreduced set of samples for finding out the error between the two sets. The results of the reconstruction after sample reduction are shown in subsequent figures for the ECG-Lead II signal and the CVP signal. Similar analysis has been performed on the other two signals as well.

The recreated signals were compared with the original sets and an error analysis has been presented in Table 3. From Table III, it can be seen that the error is less for the other three signals as compared to the ECG signal. This is because compared to the other three signals, the signal span range and wave nature of the ECG signal that has more and subtle variations that get encoded due to smaller step size.

TABLE III: MAXIMUM ERROR WITH SAMPLE REDUCTION FOR ART, CVP, PAP AND ECG LEAD-II SIGNALS

	Sample Reduction			
Signals	Halved	1/3rd	1/4th	1/5th
ART	0.27 mV	0.32 mV	0.39 mV	0.63 mV
%Error	0.72	0.85	1.05	1.69
CVP	0.13 mV	0.25 mV	0.21 mV	0.25 mV
%Error	1.72	3.17	2.71	3.18
PAP	0.18 mV	0.26 mV	0.44 mV	0.48 mV
%Error	0.84	1.20	2.02	2.19
ECG	0.05 mV	0.08 mV	0.13 mV	0.20 mV
%Error	3.77	6.15	9.67	15.00

The reduced physiological signals were then compressed, encoded as text messages and transmitted over GSM network. Our set up comprised of an Arduino microcontroller board with a GSM shield extension. Arduino is a commonly available open-source electronics prototyping platform that can be used for developing small embedded applications. The Arduino GSM shield is basically a GSM modem. From the perspective of the mobile operator, the Arduino GSM shield works like a mobile phone while from the perspective of the Arduino board, the shield works like a modem. The Arduino GSM shield lets an Arduino prototyping board to make voice calls, send and receive SMS, and connect to the Internet using a dedicated library. 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 ECG Lead – II parameter in Table 4 as an example.

TABLE IV: PERCENTAGE ERROR VALUES FOR ECG LEAD-II FROM THE FIVE NUMERICAL INTERPOLATION TECHNIQUES

	Sample Reduction				
Reduction to	Linear	Near	Spline	Pchip	Cubic
1/2	3.77	14.49	3.69	3.67	3.70
1/3	6.15	16.44	6.39	5.45	5.45
1/4	9.67	25.02	9.08	9.32	9.35
1/5	15.00	32.97	9.31	10.20	11.73

From the Table IV, it is obvious that apart from the nearest neighbor interpolation algorithm, the other four are comparable, and yield lower 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 ART, CVP, PAP and ECG Lead-II signals from healthy individuals and multiple patients for evaluating the performance of prediction algorithms. The four 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 Fig. 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.

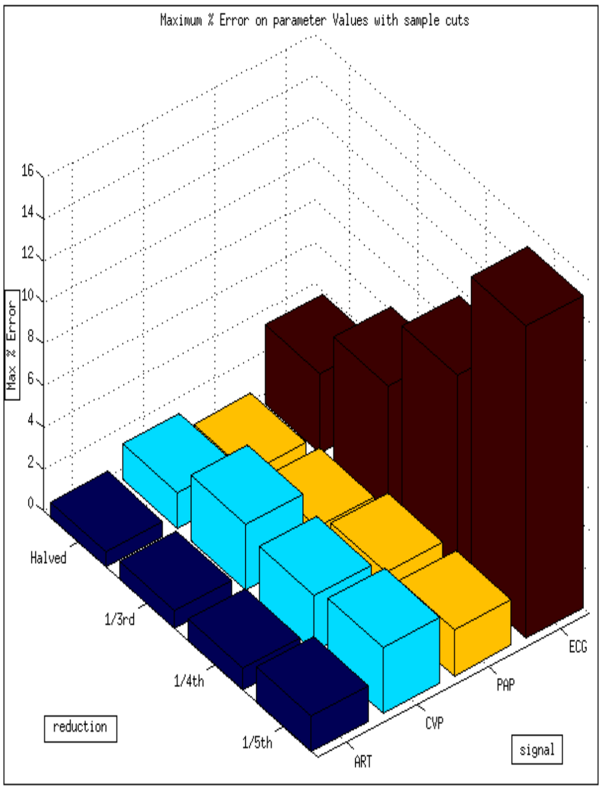

Fig. 3. Plot of maximum error in the prediction of the four signals with variations in sample cuts.

The performance comparison of the five interpolation algorithms in the reconstruction of missing algorithms is laid out as a graphical representation in Fig. 4. The figure shows a plot of the mean square error values resulting from the approximation using the interpolation algorithms.

The axis marked ‘Reduction’ in Fig. 4 shows the signal sets with stepped reduction in the number of samples. The axis marked ‘Technique’ indicates the five interpolation techniques as the prediction algorithm that we used in rebuilding of missing samples at the receiving end for the corresponding row. For the sample analysis and its graphical evaluation, we wrote the programs in MATLAB r2012 [21] and in Java 1.7 [22].

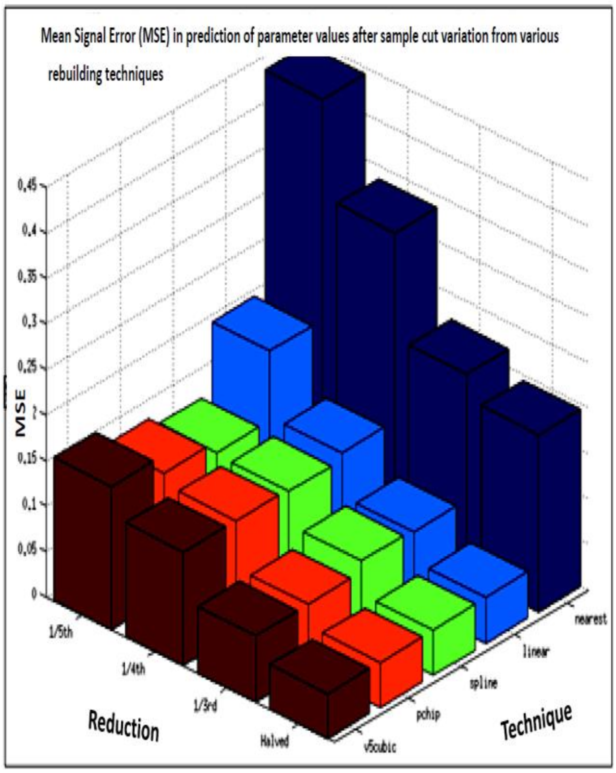

Fig. 4. Plot of maximum error in the prediction of the ECG signals with the five interpolation algorithms.

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.

Fig. 5 shows the reconstructed versions for different amounts of sample cuts in the ECG signal and their error plots as compared with the original signal waveform are shown in Fig. 6. Similar results can be obtained for CVP signal and are shown in Fig. 7 and Fig. 8. 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 were of the opinion that their diagnosis would not have changed for the signals obtained after the sample cuts up to the sample set with 1/3rd of the original samples. This implies that the error observed up to this stage of sample reduction is tolerable to them.

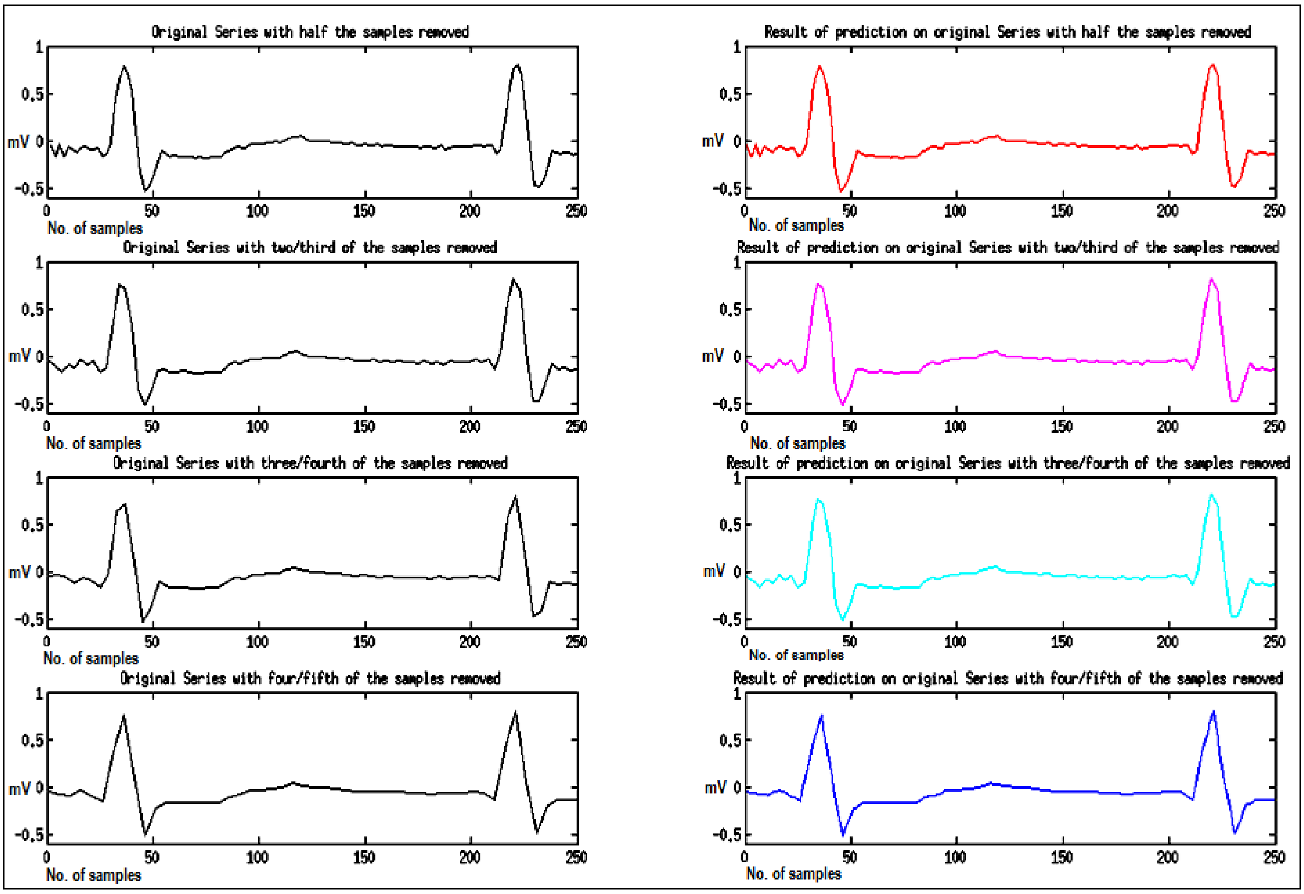

Fig. 5: Plots for predictive rebuild of the ECG Lead-II signal

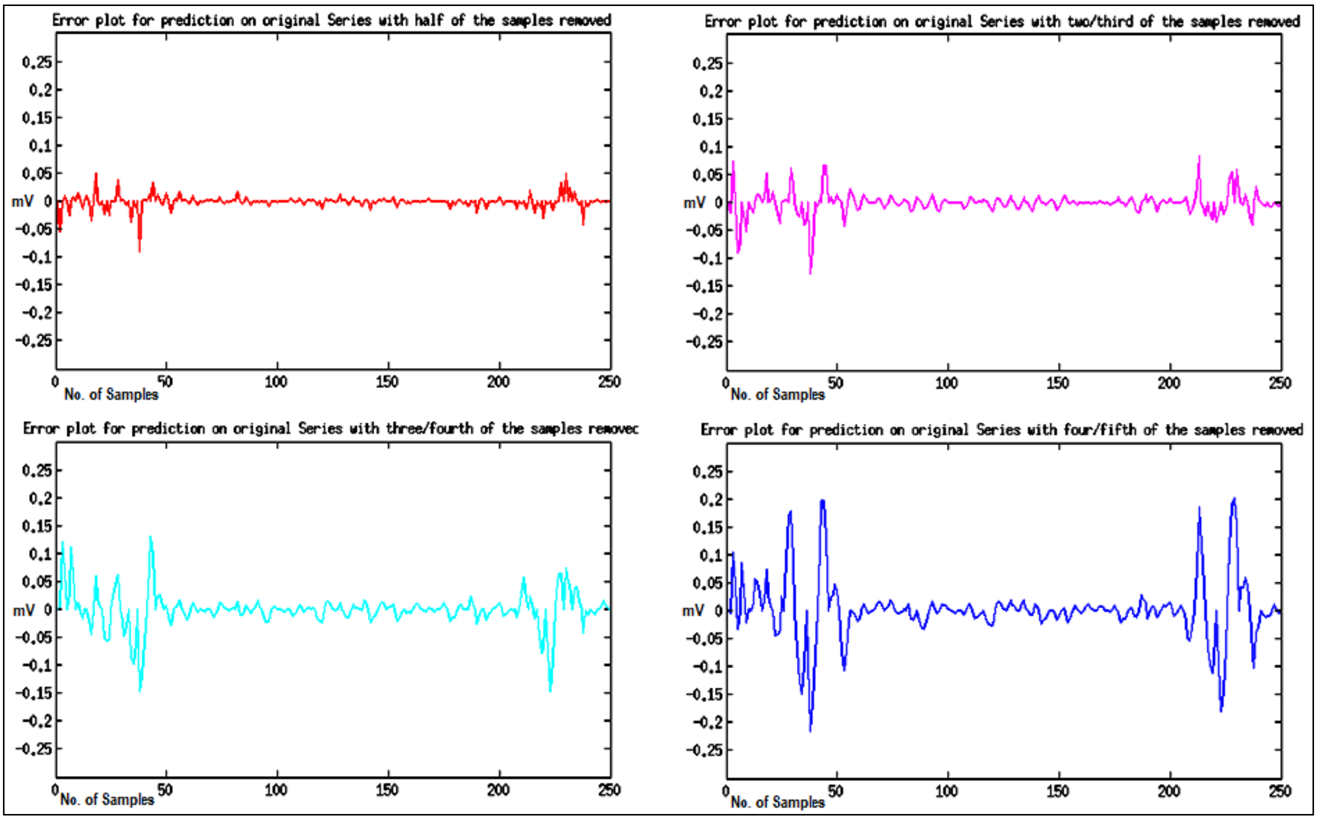

Fig. 6: Plots for error for the predictive rebuild of the ECG Lead-II signal for the four reduced sample sets

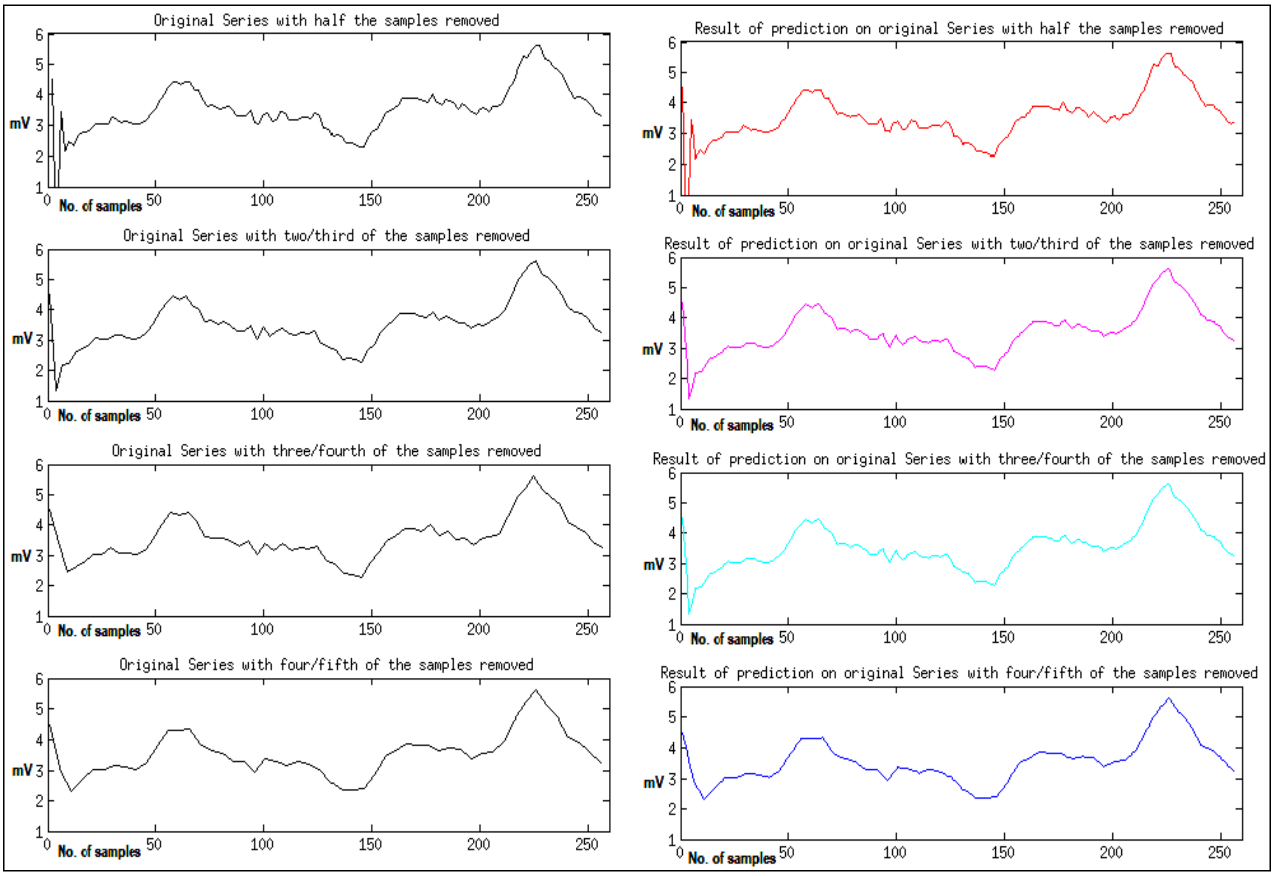

Fig. 7: Plots for predictive rebuild of the CVP signal

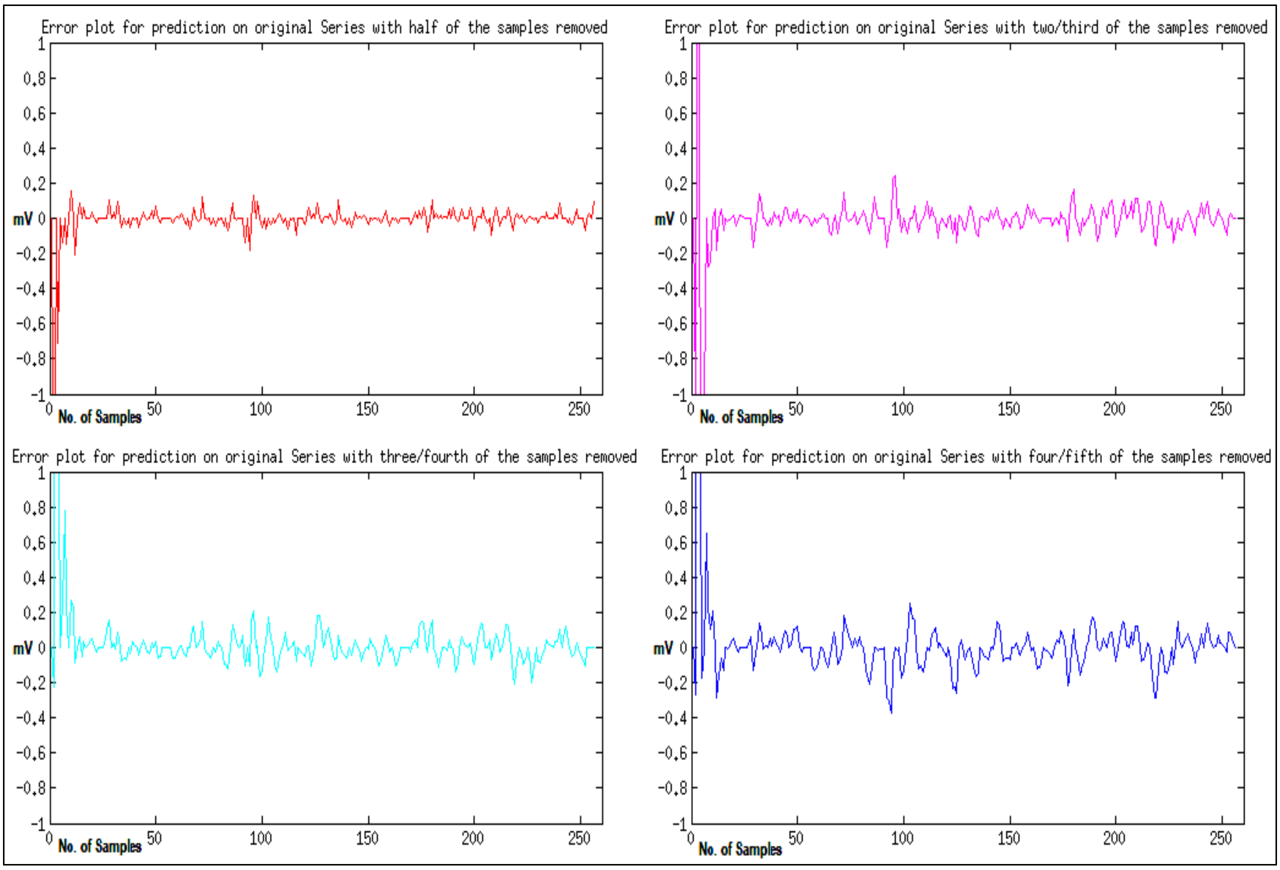

Fig. 8: Plots for error for the predictive rebuild of the CVP signal for the four reduced sample sets

B. *Network lifetime*

One of the major challenges faced by WBAN designers is the management of energy consumption, for resourceful operation of the network. In several WBAN applications, it is practically impossible to change or recharge the batteries when implanted sensors are being considered. Such scenarios make it significant for a WBAN to implement mechanisms to efficiently manage energy with the purpose of maximizing the working time of the system. In turn, this would increase the lifetime for the supported monitoring applications. The sensor nodes consume energy in their transducer and A/D converter unit, communications unit for transmission and reception, and in the computing unit for the processing of data. As the communications unit demands the most power of the three and exceeds the power requirement of the other units by several orders in magnitude, the design schemes involve a sleep-awake cycle for conservation of energy. We have also tried to evaluate the lifetime of the WBAN system in the proposed framework when some common sensors are used in WBAN nodes. We have focused on the duration that the sensors would stay powered on with the help of commonly available batteries.

The signals considered by us in this evaluation are sampled at the rate of 360 samples per second. We have considered two possibilities of encoding the samples using 8-bits and the more common 12-bits. The overall energy required by a WBAN sensor node depends on several factors like inter-sensor distances, node sleep-awake cycle, the time durations that the node stays in a particular mode, and a constant.

On the basis of Heinzelman's sensor node transceiver model [23], the transmission energy required to transmit a *k*-bit message to a distance of d can be computed as:

$$E_{Tx}(k,d) = E_{Tx\text{-}elec}(k) + E_{Tx\text{-}Ampl}(k, d) = E_{Elec} * k + \varepsilon\, k\, d^{2},$$

where,

$E_{Tx\text{-}elec}$ is the energy consumption in transmission electronics,

$E_{Tx\text{-}Ampl}$ is the energy consumption in the transmission amplifier,

ε is a factor involved in amplification

and, d is the inter-sensor communication distance.

Their model assumes

$$E_{Tx\text{-}elec} = E_{Rx\text{-}elec} = E_{Elec}, \text{ and } \varepsilon = 100 \text{ pJ/bit/m2}$$

In the receiver, to receive a k bit message, the energy consumed is

$$E_{Rx}(k) = E_{Rx\text{-}elec}(k) = E_{Elec} * k$$

For most sensor nodes, the energy consumed for powering up the transceiver electronics is the same for transmission and reception circuits and is of the order of tens of nJ/bit.

For continuous operation, the energy required for transmitting all the samples in a minute comes out to be 8.65 mJ for an 8-bits/sample encoding while it is 12.97 mJ for samples encode in 12-bits.

We tried evaluating the lifetimes of networks involving two of the low-power sensor nodes available commercially. The Eco [24] is a low-power ultra-compact sensor that needs 16 mA of current while transmitting, 22 mA while receiving and just 2 µA during sleep. The duty cycle involves 10 seconds each of transmission and reception followed by 40 seconds of sleep to complete the minute-long cycle.

The TI CC3100 [25] fares comparatively in its 1DSSS mode while performs much better when operated in the 54OFDM mode. Based on the transmission power requirements of these two sensor modes in the mentioned modes, the following table emerges for three of the commonly used batteries – CR2032, CR123A and iXTRA, all the three capable of supplying 3.0 volts, 0.5A. The following table sums up the performance of the battery model results without any power management applied.

TABLE V: LIFE IN DAYS FOR DIFFERENT BATTERY MODELS AS PER THEIR CAPACITIES AND NODE POWER REQUIREMENTS

Battery →	CR2032	CR123A	iXTRA
Sensor Node ↓	225 mAH	1550 mAH	1700 mAH
ECO (16 mA)	1.76	2.11	13.28
TI-DSSS (21 mA)	1.34	).23	10.12
TI-OFDM (9.39 mA)	2.99	).63	22.63

From the table, it can be inferred that the advances in battery technology and low-power sensor design actively improve the lifetime of the network.

C. *Spectral Translation*

The sample sets corresponding to the four physiological parameters were analyzed for their frequency spectral components. This information was required in order to assist with the design of a framework for their possible transmission over the voice channels in the next generation technologies. After obtaining the baseband in the signals corresponding to the four physiological parameters, the sample sets for the four signals were translated in frequency domain. The translation was affected such that the signals would occupy exactly the same spectral range as the human voice (200 cycles/sec to 3200 cycles/sec) by employing a product-bias algorithm. The algorithm works by mapping individual spectral components derived from the signal samples to the new range as specified above. The idea is to shift the low frequency data information to the human speech window so as to utilize the voice communication provisions in the smartphone for its transmission. The translation would also provide a bigger spread while retaining the power information of the baseband, and the resulting signal could then be transmitted using OFDM over the regular voice channels, as envisage in the framework. Figures 9 and 10 show the baseband of the frequency spread for the ECG lead II signal and Figures 11 and 12 show the spectrums for the CVP signal.

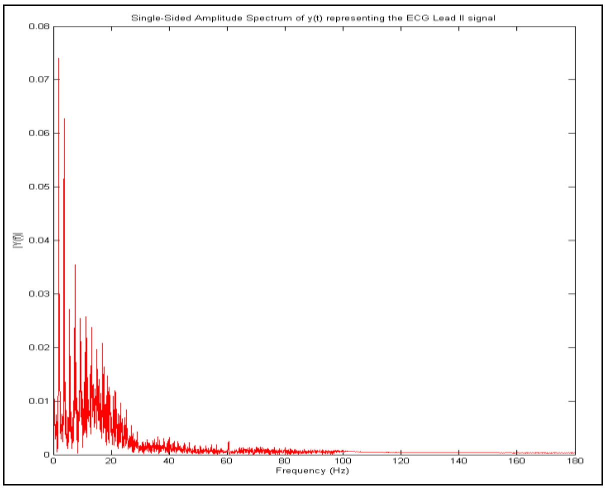

Fig. 9. Frequency spectrum of the baseband signal for the ECG Lead II signal.

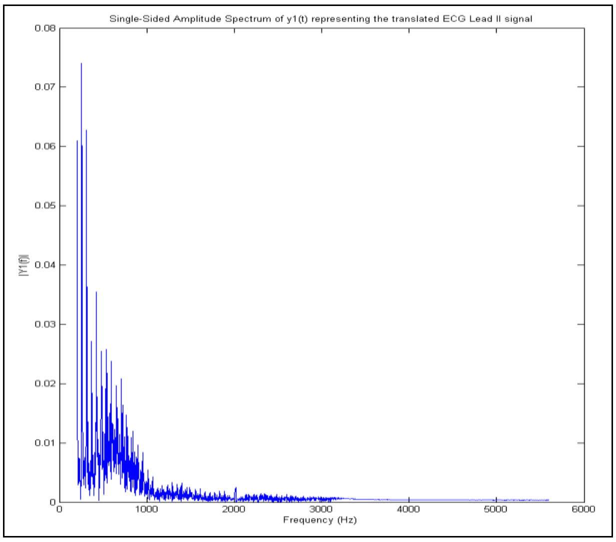

Fig. 10: Spectral translation of the ECG Lead II signal to the human voice range

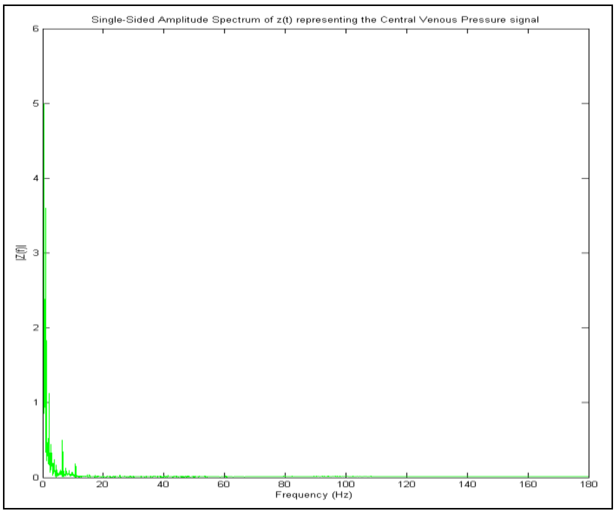

Fig. 11: Frequency spectrum of the baseband signal for the CVP signal

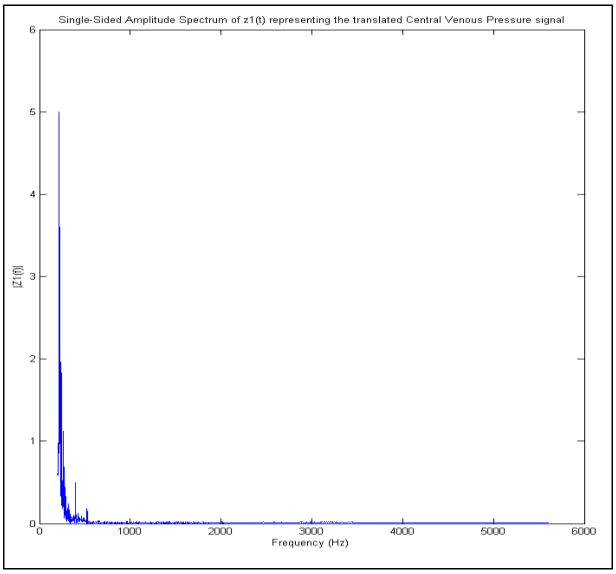

Fig. 12: Spectral translation of the CVP signal to the human voice range

VI. 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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REFERENCES

[1] G. V. Crosby, T. Ghosh, R. Murimi, and C. A. Chin, “Wireless Body Area Networks for Healthcare: A Survey,” International Journal of Ad Hoc, Sensor & Ubiquitous Computing, vol. 3, no. 3, 2012.

[2] L. Atzori, A. Iera, G. Morabito, "The Internet of Things: A survey”, The International Journal of Computer and Telecommunications Networking archive, vol. 54 no. 15, pp. 2787-2805, October, 2010.

[3] C. Y. Lin, M. Wu, J. A. Bloom, I. J. Cox, and M. Miller, “Rotation, scale, and translation resilient public watermarking for images,” *IEEE Trans. Image Process.*, vol. 10, no. 5, pp. 767-782, May 2001.

[4] D. Giusto, A. Iera, G. Morabito, and L. Atzori, "The Internet of Things", Springer, 2010. ISBN: 978-1-4419-1673-0.

[5] K. Kwak, S. Ullah, and N. Ullah, “An overview of IEEE 802.15. 6 standard.” In 3rd IEEE International Symposium on Applied Sciences in Biomedical and Communication Technologies (ISABEL), pp. 1-6, 2010.

[6] http://www.who.int/mediacentre/news/releases/2003/pr27/en.

[7] S. Ullah, H. Higgin, M. A. Siddiqui, and K. S. Kwak, “A study of implanted and wearable body sensor networks,” In 2nd KES International Conference on Agent and Multi-Agent Systems: Technologies and Applications, pp. 464-473, Springer-Verlag, Berlin Heidelberg, 2008.

[8] E. Dishman, “Inventing wellness systems for aging in place,” Computer, vol. 37, no. 5, pp. 34-41, May 2004.

[9] N. Jain and D. P. Agrawal, “Current Trends in Wireless Sensor Network Design,” International Journal of Distributed Sensor Networks, vol. 1, pp. 101–122, 2005.

[10] J. Yick, B. Mukherjee, and D. Ghosal, “Wireless Sensor Network Survey,” in Computer Networks, vol. 52, issue 12, pp. 2292-2330, 22 August, 2008.

[11] M. A. Hanson, H. C. Powell, A. T. Barth, K. Ringgenberg, B. H. Calhoun, J. H. Aylor, and J. Lach, “Body area sensor networks: Challenges and opportunities,” in Computer, vol. 42, no. 1, pp. 58-65, 2009.

[12] M. Wagner, B. Kuch, C. Cabrera, P. Enoksson, A. Sieber, “Android based Body Area Network for the evaluation of medical parameters,” Proceedings of the Tenth Workshop on Intelligent Solutions in Embedded Systems (WISES), Klagenfurt, pp. 33 – 38, 5-6 July, 2012.

[13] O. O. Ogunduyile, O. O. Oludayo, and M. Lall, “Healthcare Monitoring System Using a Collection of Sensor Nodes,” International Journal of Emerging Technology and Advanced Engineering, ISSN 2250-2459, vol. 3, no. 2, pp. 632-639, February 2013.

[14] N. R. Baviskar, and A. Shinde, “Android Smartphone Based Body Area Network for the Evaluation of Medical Parameters in Real Time,” International Journal of Electrical, Electronics and Data Communication, ISSN: 2320-2084, vol. 2, no. 4, pp. 66-69, April 2014.

[15] A. Bourouis, M. Feham, and A. Bouchachia, “Ubiquitous Mobile Health Monitoring System for Elderly (UMHMSE),” International Journal of Computer Science & Information Technology (IJCSIT, vol. 3, no. 3, pp. 74-82), June 2011.

[16] D. P. Agrawal and Q. A. Zeng, Introduction to Wireless and Mobile Systems, 3rd ed., Ed.: Stamford, CT: Cengage Learning, ch.14, pp. 399.

[17] A. Jamthe, A. Mishra, and D. P. Agrawal, “Scheduling schemes for Interference Suppression in Healthcare Sensor Networks,” ICC-2014, Sydney, Australia, 10-14 June, 2014.

[18] A. Mishra, S. Chakraborty, H. Li, and D. P. Agrawal, “Error Minimization and Energy Conservation by predicting data in Wireless Body Sensor Networks using Artificial Neural Network and Analysis of Error,” CCNC-2014, Las Vegas, NV, USA, Jan. 10-13, 2014

[19] D. P. Agrawal and A. Mishra, “Designing Wireless Sensor Networks: from Theory to Applications,” WCSN 2011, Seventh IEEE Conference on Wireless Communication and Sensor Networks, Panna, India, Dec 5-9, 2011.

[20] http://www.physionet.org.

[21] MATLAB, version (R2012). Natick, Massachusetts: The MathWorks Inc., 2012.

[22] J. Gosling, The Java Programming Language, http://docs.oracle.com/javase/specs/#23760.

[23] W. Heinzelman, “Application specific Protocol Architectures for Wireless Networks”, Ph.D. dissertation, Massachusetts Institute of Technology, 2010.

[24] C. Park, J. Liu, and P. H. Chou, "ECO: an ultra-compact low-power wireless sensor node for real-time motion monitoring", Conference on Information Processing in Sensor Networks, 2005. IPSN 2005. Fourth International Symposium on, pp. 398-403, April 2005.

[25] http://www.ti.com/product/CC3100/datasheet.

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