Context Predictor Based Sparse Sensing Technique and Smart Transmission Architecture for IoT Enabled Remote Health Monitoring Applications

M. P. R. Sai Kiran, P. Rajalakshmi, Amit Acharyya

Abstract— **In hyperconnectivity scenario, managing the amount of data acquired from sensors in the Body Area Networks (BANs) is one of the major issues. In this paper we propose an on-chip context predictor based sparse sensing technology with smart transmission architecture which makes use of confidence interval calculation from the features that present in the data, thereby achieving statistical guarantee. The proposed architecture uses intelligent sparse sensing, which eradicates the collection of redundant data, thereby reducing the amount of data generated. For the performance analysis, we considered ECG data acquisition and transmission system. The proposed architecture when applied on the data collected from 10 patients reduces the duty cycle of the sensing unit to 27.99%, by achieving an energy saving of 72% and the mean deviation of sampled data from the original data is 2%.**

I. INTRODUCTION

Trending development in the Internet of Things (IoT) enabled applications realizes the hyperconnectivity scenario much sooner than the predictions. In such cases one of the primary concern relates to the data management. Due to continuous monitoring of the physiological parameters, the amount of data generated is very huge. This huge collection of data results into improper data management in hyper connectivity scenario [1], [2]. In this paper we address this issue by proposing an on-chip by which we mean an on-sensor node context predictor based intelligent sparse sensing mechanism along with smart transmission based which can greatly reduce the duty cycle of the system thereby reducing the amount of data generated. The proposed architecture reduces the sensing of unnecessary data without losing statistical guarantee in the data collected.

Computation capabilities in wireless sensors associated embedded systems impose a big challenge in wireless sensor networks. The trade-offs between limited computation and battery power, precision and accuracy of data and delay in discovery of events would need to be balanced and adjusted depending on the applications. Battery may be conserved in different stages of information processing within the systems, from adaptive sampling, processing, to networking and delivery of the data. We have to make sure that the developed processing techniques on the node are low complex and low power for enabling ubiquitous operation of the device.

*This work is partly supported by the DEITY, India under the "IOT for Smarter Healthcare" under Grant No: 13(7)/2012-CC&BT, Dated 25th Feb, 2013.

M.P.R.S.K., P.R. and A.A. are with Dept. of Electrical Engineering, Indian Institute of Technology Hyderabad, 502205, India, with email {ee12m1021,raji,amit_acharyya}@iith.ac.in respectively.

Most adaptive sampling algorithms developed mainly aim for conserving power for a particular type of application. For example, an adaptive sampling algorithm for rare-event detection has the characteristics of sampling more often when an event is likely to happen [3]. This cannot be directly applied to the health monitoring applications as we wish to obtain sensible statistics of the data in the experiments. Moreover, an useful sampling strategy should incorporate data characteristics in the design of the algorithm in order to preserve the features present in the data collected. Therefore, in this paper, we aim for preserving features that have to be present in the health care data collected. These characteristics will affect the decisions on the choice of adaptive parameters including sampling intervals, frequency of adaptation, and so on.

For the performance analysis of the proposed architecture we have considered ECG data acquisition and transmission system which can communicate using ZigBee. The performance metrics used are the mean deviation, data rate generated and energy consumption. The rest of the paper is organized as follows. Section II discusses the functional units of the proposed architecture. In section III, the performance of the proposed architecture is analyzed. Section IV concludes the paper by briefly summarizing the proposed methodology.

II. PROPOSED ON-CHIP CONTEXT PREDICTOR BASED INTELLIGENT SPARSE SENSING AND SMART TRANSMISSION ARCHITECTURE

The proposed architecture of on-chip context predictor based intelligent sampling and transmission for remote health monitoring applications is shown in Fig. 1. The main idea behind the sparse sampling is to reconstruct the original signal from fewer samples. What is most remarkable about these sampling protocols is that they allow a sensor to very efficiently capture the important information required that is present in a sparse signal [4]. ECG data in general consists of important features such as PR, QRS and QT intervals. The proposed architecture mainly aims to capture these features by collecting minimum amount of samples. Rest of the sections briefly describe the functional units of the proposed on-chip context predictor based intelligent sparse sensing mechanism along with smart transmission.

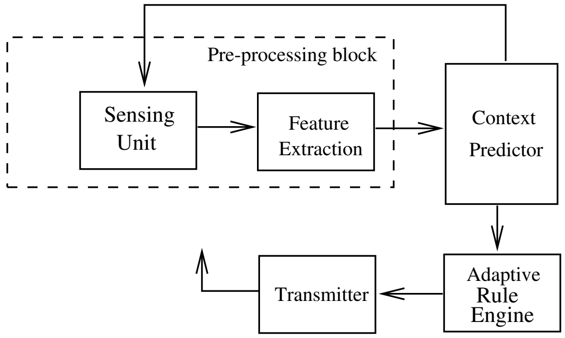

Fig. 1: Proposed on-chip context predictor based intelligent sparse sensing and smart transmission Architecture

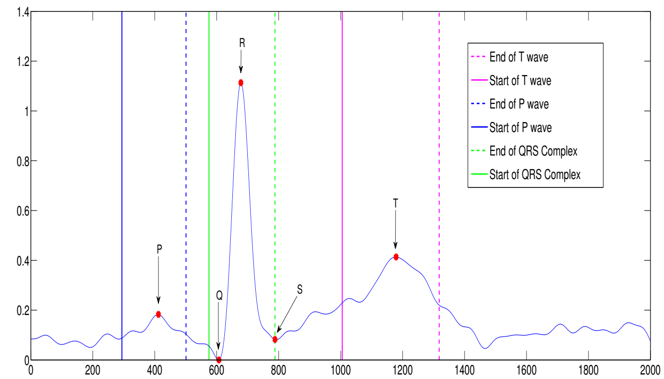

Fig. 2: PQRST complex from the collected Lead I Digital ECG data

A. *Pre-processing blocks*

The pre-processing block includes the sensing unit which acquires the medical data from sensors using noise removal signal processing techniques and feature extraction which extracts the important features from the collected data. Many architectures for the data acquisition system have been developed in the past [5], [6] & [7]. In this paper for the analysis of performance, Lead I ECG data is considered. The sensing unit which is developed in IIT Hyderabad, has a lower cutoff frequency of 0.5 Hz and an upper cutoff frequency of 120 Hz with a sampling rate of 1000 Hz. Better proactive diagnosis can be given only if the data collected from the patient is classified properly. This intelligent classification can be achieved by extracting important features from the collected data, from which we can discover the abnormalities in the patient. This process of collecting features from the patients physiological data is termed as feature extraction. Feature extraction plays an important role in automating the remote health monitoring. Features like P, Q, R, S and T points shown in Fig. 2 from the Lead I ECG signal plays a prominent role in classifying the data collected from the patient. For a detailed description of several feature extraction algorithms available, kindly refer to [8], [9] & [10]. Using these extracted features the intervals shown in parameters column of TABLE I are calculated and fed to the on-chip context predictor. TABLE I shows the important features that are present in ECG signal and their normal threshold values for a healthy patient.

Case	Parameter	Normal Threshold
1	PR interval	0.12 - 0.20 Sec
2	QRS interval	$\leq$ 0.12 Sec
3	QT interval	$\leq$ 0.42 Sec

TABLE I: Threshold values of the features present in ECG signal

B. *On-chip context predictor*

The on-chip context predictor aids for controlling the sampling rate of sensing unit by predicting the context of the patient. It makes use of the confidence interval calculated over the features extracted from the collected data. If the confidence interval meets the expected threshold it stops sampling, thereby reducing the duty cycle of the system. In [11], Parkin et al. have investigated five methods of calculating confidence intervals (CI) for the mean of a log-normally distributed variable and concluded that the method developed by Land [12] was the best at estimating the lower (LCL) and upper confidence limits (UCL) for small number of samples and are given by

$$LCL = exp\left\{\bar{\mu} + \frac{\hat{\sigma}^2}{2} + \frac{\hat{\sigma}C_L}{\sqrt{n-1}}\right\} \quad (1)$$

$$UCL = exp\left\{\bar{\mu} + \frac{\hat{\sigma}^2}{2} + \frac{\hat{\sigma}C_U}{\sqrt{n-1}}\right\} \quad (2)$$

Where C_L and C_U are H-statistic parameters calculated from a function that depends on the number of observations (n), the standard deviation of the log-transformed values ($\hat{\sigma}$) and the significance level α selected. The values of C_L and C_U used in this paper are based on 98 percentile values of the methods and tables in [11], [12]. Equation (1) and (2) are used in the calculation of CI of data in context predictor which is given by

$$CI = UCL - LCL \quad (3)$$

From the analysis made on ECG data collected from different patients, the features tend to follow log-normal distribution which is the case in most of the physiological signals. Every time the pre-processing block switches on, it collects the data for 8 seconds and the features corresponding to the data collected are fed to the context predictor. The context predictor calculates the confidence interval for mean of the features and compares it with threshold. If the threshold is not exceeded, it forces the pre-processing block into sleep state for some fixed duration. The sampling duration has to be chosen based on the wake up time of the sensors. The ECG sensors in general have a very less wake up time, which makes the 8 seconds sampling interval a reasonable selection. If in the first phase, the confidence interval has exceeded the threshold, the pre-processing block again samples for 4

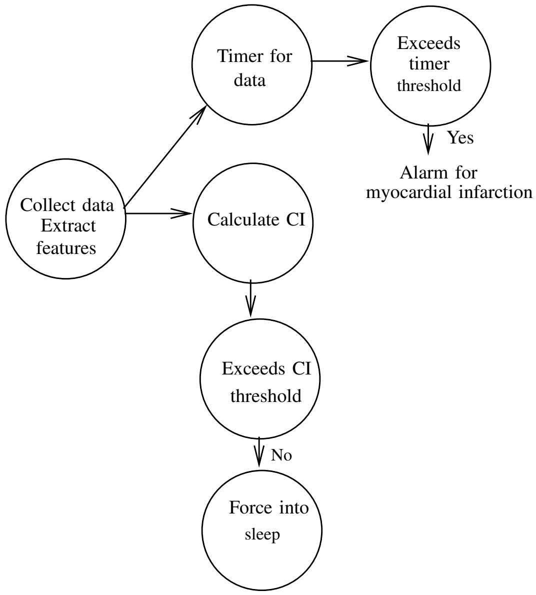

Fig. 3: Flow of on-chip context predictor in different scenarios

seconds. Now the context predictor calculates the CI on the features extracted from the complete 12 seconds interval and based on the value of CI, it re-decides on the sampling.

Possible reasons behind the calculated CI exceeding beyond the threshold are improper electrode contacts, which generate incorrect features or the person might be suffering from myocardial infarction (heart attack), whose PR, QRS and QT intervals fluctuate rapidly for about 30 min. In such cases, if the convergence of the CI below the threshold is happening at a very long period, it can be considered as a myocardial infarction and the system triggers an alarm indicating for a proactive diagnosis. The complete flow of the context predictor is depicted in Fig. 3.

C. Adaptive Rule Engine

The on-chip adaptive rule engine based smart transmission mechanism classifies the data collected and decides whether the data is worth transmitting or not. Using this mechanism the transmission can be made smart which reduces the amount of data to be transmitted thereby reducing the energy consumption. Performance analysis of the adaptive rule engine based smart transmission system has been analyzed in [5]. In [5], the authors have considered remote ECG monitoring system with ZigBee communication facility. The inputs to the adaptive rule engine are the features extracted from the collected medical data. In ECG, these features primarily include PR interval, QRS interval and QT interval. Adaptive rule engine consists of *"decision making"* section and *"transmitter control"* section, decision making section analyzes the features extracted from the collected data and decides whether to transmit or not. The transmitter control section triggers the transmitter and starts transmission, if the data is to be transmitted. For further details on the adaptive rule engine based smart transmission mechanism, one can refer to [5].

III. Performance analysis

For the performance analysis of the proposed architecture ECG data collected from 10 patients using the in house developed ECG data acquisition unit is used and the metrics used for the analysis are duty cycle, mean deviation, data rate generated and energy savings. The analysis makes use of 30 seconds of ECG data collected from every patient due to the reason that in all the cases the CI has converged within 30 seconds. Fig. 4 shows the original ECG signal collected from the patient and the sampled signal obtained by using the proposed architecture. From the Fig. 4, one can observe the sleep time achieved by using the on-chip context predictor based intelligent sampling. On an average of 30 seconds over 10 patients, the duty cycle of the system is observed to be 27.99%. Fig. 5 shows the mean of PR interval extracted from the original signal of 30 seconds duration and sampled signal obtained by the proposed architecture from the original signal. The average deviation of features extracted from the sampled signal compared to the features extracted from the original signal, taken over all the 10 patients is observed to be 0.0032 seconds which is a negligible deviation. Hence the proposed architecture also provides the statistical guarantee.

The proposed architecture also aids for the reduction in the network traffic by reducing the amount of data generated. Fig. 6, shows the amount of data generated for all the 10 patients for period of 30 seconds when using the on-chip context predictor based intelligent sampling. On an average, there is a 72% of reduction in the amount of data generated, which is a significant reduction in IoT scenario.

Fig. 7, shows the energy saving obtained for each patient. The energy saving obtained for patient 2 is lesser when compared with other patients, due to the slower convergence of the confidence interval. An average of 72% energy saving over 10 patients for the sensing unit has been obtained by using the proposed intelligent sparse sensing architecture, which is a significant amount of saving.

IV. Conclusions

In this paper we proposed an on-chip context predictor based intelligent sparse sampling and smart transmission architecture for IoT enabled remote health monitoring applications. The proposed architecture greatly aids for achieving a significant reduction in the duty cycle of the system thereby reducing energy consumption and the amount of data rate generated while maintaining the statistical guarantee of the data collected. This architecture when analyzed on the ECG data collected using the in house developed ECG data acquisition system at IIT Hyderabad from 10 patients, achieved a duty cycle of 27.99% and 72% of reduction in data generated on an average taken over a 30 seconds interval. On an average over 10 patients, the proposed architecture achieved an energy saving of 72%, which is a significant amount of saving in remote health monitoring applications.

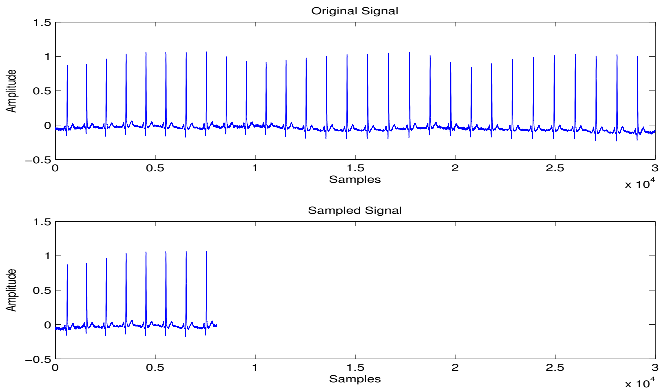

Fig. 4: Original and sampled signals

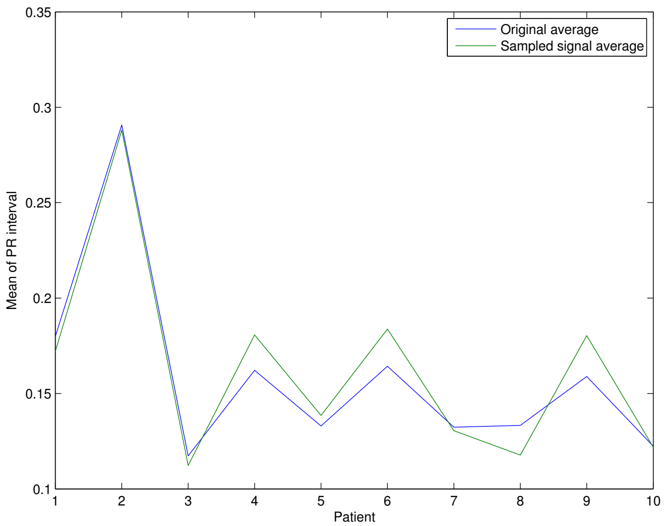

Fig. 5: Mean of PR interval over 30 sec interval for original and sampled signals

The analysis shown above is also performed using the ECG data from "The PTB Diagnostic ECG Database" [13], [14], which also yielded the similar performance.

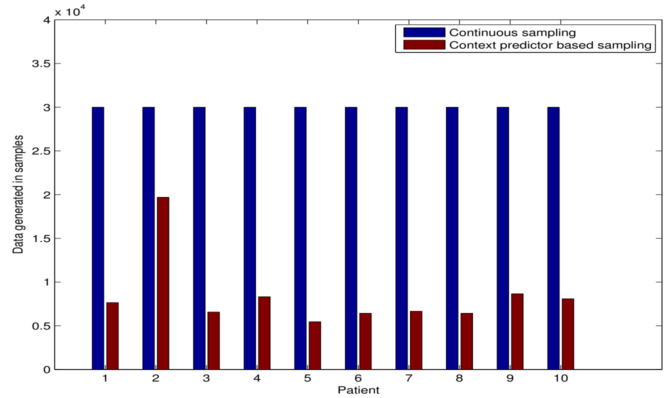

Fig. 6: Amount of data generated

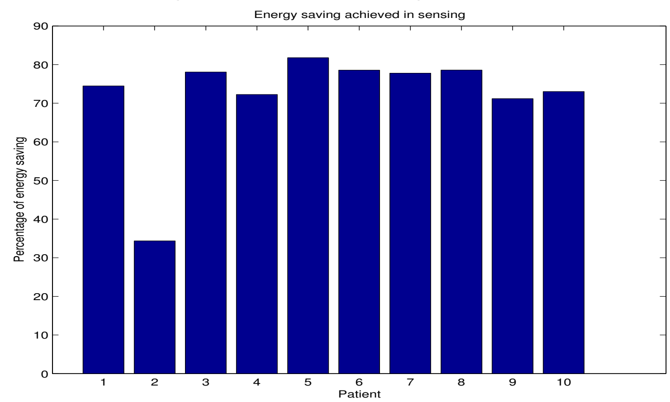

Fig. 7: Energy saving obtained for each patient

REFERENCES

[1] http://gigaom.com/2011/10/13/internet-of-things-will-have-24-billion-devices-by-2020/

[2] The Mobile Economy, GSMA, 2013.

[3] Yu Meng; Dunham, M.H.; Marchetti, F.M.; Jie Huang, "Rare Event Detection in a Spatiotemporal Environment," *Granular Computing, 2006 IEEE International Conference on* , vol., no., pp.629,634, 10-12 May 2006

[4] Candes, E.J.; Wakin, M.B., "An Introduction To Compressive Sampling," *Signal Processing Magazine, IEEE* , vol.25, no.2, pp.21,30, March 2008

[5] Kiran, M.P.R.S.; Rajalakshmi, P.; Bharadwaj, K.; Acharyya, A., "Adaptive rule engine based IoT enabled remote health care data acquisition and smart transmission system," *Internet of Things (WF-IoT), 2014 IEEE World Forum on* , vol., no., pp.253,258, 6-8 March 2014

[6] S. Maheshwari, A. Acharyya, P. Rajalakshmi, P. E. Puddu and M. Schiariti (2013), "Accurate and Reliable 3-Lead to 12-Lead ECG Reconstruction Methodology for Remote Health Monitoring Applications," *IEEE International Conference on e-Health Networking, Applications and Services (Healthcom, 2013)*, 9-12 October, 2013, Portugal, 2013.

[7] Abdul Qayoon Bhat, Vineet kumar, Sunil Kumar, "Design of ECG Data Acquisition System," *International Journal of Advanced Research in Computer Science and Software Engineering*, vol. 3, issue 4, April 2013.

[8] L. Y. Di Marco, Lorenzo Chiari, "A wavelet-based ECG delineation algorithm for 32-bit integer online processing," *Biomedical Engineering online,* vol. 10, no. 2, article 23, 2011.

[9] Mazomenos, E.B.; Biswas, D.; Acharyya, A.; Chen, T.; Maharatna, K.; Rosengarten, J.; Morgan, J.; Curzen, N., "A Low-Complexity ECG Feature Extraction Algorithm for Mobile Healthcare Applications," *Biomedical and Health Informatics, IEEE Journal of* , vol.17, no.2, pp.459,469, March 2013.

[10] Cuiwei Li; Chongxun Zheng; Changfeng Tai, "Detection of ECG characteristic points using wavelet transforms," *Biomedical Engineering, IEEE Transactions on* , vol.42, no.1, pp.21,28, Jan. 1995.

[11] T.B. Parkin, S.T. Chester and J.A. Robinson, "Calculating Confidence Intervals for the Mean of a Lognormlaly Distributed Variable," vol. 54, no. 321?326, 1990.

[12] C. E. Land, "Confidence Intervals for Linear Functions of the Normal Mean and Variance," *Annals of mathematical Statistics*, vol. 42, no. 4, pp. 1187-1205, 1971.

[13] Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, Mietus JE, Moody GB, Peng C-K, Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. Circulation 101(23):e215-e220 [Circulation Electronic Pages; http://circ.ahajournals.org/cgi/content/full/101/23/e215]; 2000 (June 13).

[14] Bousseljot R, Kreiseler D, Schnabel, A. Nutzung der EKG-Signaldatenbank CARDIODAT der PTB ber das Internet. Biomedizinische Technik, Band 40, Ergnzungsband 1 (1995) S 317