System Architecture for Smart Ubiquitous Health Monitoring System With Area Optimization in Multiple On-chip Radios Scenario

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***Abstract*—Realization of ubiquitous connectivity in remote health monitoring is a primary issue yet to be addressed. In this paper we propose a system architecture for IoT enabled remote health monitoring with smart transmission which can also aid in ubiquitous connectivity by targeting multiple on-chip radios (IEEE 802.15.4 & IEEE 802.11b in this case). We also optimize the area overhead by using modified IEEE 802.15.4-PHY architecture which uses Raised Cosine pulse shaping and the BER performance is also analyzed for same. The modified IEEE 802.15.4-PHY when used in multiple radio architecture along with IEEE 802.11b can result in significant area savings by multiplexing the commonly available functional units. The proposed architecture also aids for significant energy savings due to the presence of smart transmisison technique. Performance of the proposed architecture is analyzed using energy consumption and BER as key performance metrics. The BER performance shows that the usage of raised cosine pulse shaping for IEEE 802.15.4-PHY achieves significant amount of area savings without losing any performance in BER.**

***Keywords*-Remote health monitoring, IEEE 802.15.4, Pulse shaping, BER.**

I. Introduction

In the last few years the way remote diagnosis being offered has gained a lot of attention. Plethora of developments have been made in various aspects of the remote health monitoring such as low power architectures, small form factor, non-invasive technologies and intelligent on-chip diagnosis [1], [2]. In the above mentioned technologies, the patient condition is monitored using a biological sensing units with widely communication facility. In [2], authors have developed an electronic patch for wearable health monitoring incorporating biomedical sensors, microelectronics, radio frequency (RF) communication, and a battery. The architecture uses IEEE 802.15.4 standard for wireless communication, which supports low range and low data rate communications. IEEE 802.15.4 is one of the widely used standard in Wireless Sensor Networks (WSNs) and Body Area Networks (BANs) due to it's low power consumption. In [3], a demonstration of the capability of Personal Digital Assistants (PDAs) to provide mobile, low-cost, and efficient remote health monitoring through a mobile web services-based approach is provided. Indeed battery puts a primary constraint in using mobile web services based remote health monitoring. In all the above architectures discussed, the connectivity is limited by range or the inefficient energy management leading to the realization of ubiquitous connectivity a challenging issue. Ubiquitous connectivity is an important aspect of IoT enabled remote health monitoring. In this paper we propose a system architecture for smart remote health monitoring which can aid for ubiquitous connectivity by targeting multiple on-chip radios. We consider remote Electrocardiography (ECG) monitoring system with two different radios IEEE 802.15.4 and IEEE 802.11b as a case scenario to investigate the performance of the proposed architecture. We introduced a multiplexing methodology between the two radio PHY architectures which can reduce the area overhead and can result in a small form factor. The proposed architecture uses an adaptive rule engine based smart transmission mechanism proposed in [4] which aids in significant reduction of energy consumption and data rate generated. For the performance evaluation of the proposed architecture, data rate generated and Bit Error Rate (BER) are used as key performance metrics.

In the IoT enabled remote health care monitoring applications, the data collected from the sensors should be made accessible from anywhere which requires ubiquitous network connectivity. If the remote health care monitoring application, transmits the data continuously, the amount of data generated will be huge which leads to the hyper connectivity scenario. In hyper connectivity each device which has an ability to connect to the network will be connected to the network. According to the predictions made by GSMA, the total number of devices connected will be 15 billion by around 2015 and 24 billion by the year 2020 [5], [6]. In remote health care monitoring applications we cannot make use of the available bandwidth effectively, if we use the traditional mode of transmitting the data continuously. It even leads to loss of data due to delay and buffer overloading, which is not acceptable particularly in the health care applications. In order to address the above mentioned issues a smart transmission architecture with multiple radios such as using IEEE 802.15.4 which supports low data rate and low power along with IEEE 802.11b which supports high data rate and long range communication with intelligent controlling is an efficient solution.

1905.1-2013 - IEEE Standard [7] defines an abstraction layer hiding the diversity of media access control technologies for multiple home networking technologies. It provides a common interface to widely deployed home networking technologies, but do not multiplex the architectures at physical and MAC layer levels. This paper explores the performance evaluation of ZigBee and discuses the possibilities of multiplexing the IEEE 802.11b and IEEE 802.15.4 architectures without any degradation in performance. Both IEEE 802.11b and IEEE 802.15.4 operate at the 2.4 GHz ISM band. Typically, WLAN devices operate within 100 meters of distance range depending on the surrounding environment. The IEEE 802.11b spreads the message signal by Direct Sequence Spread Spectrum (DSSS) mechanism using Complementary Code Keying (CCK) modulation [8]. Raised cosine (RC) pulse shaping in IEEE 802.11b constrains the signal bandwidth and prevents the Inter Symbol Interference (ISI) at the receiver.

Rest of the paper is organized as follows. Section II discusses the IEEE 802.15.4-PHY architecture and explores the architecture multiplexing between IEEE 802.11b-PHY and IEEE 802.15.4-PHY. Section III discusses the adaptive rule engine based smart transmission mechanism for remote health monitoring. In section IV, we discuss the proposed system architecture for IoT enabled remote health monitoring with smart transmission for achieving ubiquitous connectivity. Section V analyzes the performance of the proposed system architecture. Finally, section VI concludes the paper.

II. Architecture Multiplexing Between IEEE 802.15.4-PHY and IEEE 802.11*b*-PHY

In this section we propose a novel architecture multiplexing methodology between IEEE 802.15.4-PHY and IEEE 802.11b-PHY for reducing the area overhead when targeting on-chip multiple radio architectures for remote health monitoring. Fig. 1 shows the transmitter architecture of IEEE 802.15.4-PHY. It uses DSSS for spreading the information signal and makes use of Half-Sine (HS) pulse shaping with Offset QPSK resulting to Minimum Shift Keying (MSK) for modulation. DSSS in IEEE 802.15.4-PHY maps four bit message symbols to 32 bit chip sequences. The predefined chip sequences are shown in TABLE I. Upon mapping, the information signal is spread over a large bandwidth. Selection of chip sequences uses the minimum similarity criteria which is measured using the cross correlation. The chip sequences used here are quasi orthogonal (not perfectly orthogonal). In this paper we propose a modified IEEE 802.15.4-PHY architecture which uses Raised Cosine (RC) pulse shaping instead of HS pulse shaping. The modified IEEE 802.15.4-PHY is shown in Fig. 2.

IEEE 802.11b uses the Raised Cosine pulse shaping technique along with CCK spreading. For targeting multiple radios in remote deployment applications especially in remote health monitoring applications, the form factor is a major constrain. Hence reusing the design is one of the primary approaches in reducing the area consumption. In order to exploit the design reuse the commonly available functional units in different architectures have to be multiplexed. The advantage in using the modified IEEE 802.15.4-PHY is the reduced area overhead when targeting multiple radio architecture with IEEE 802.11b. The same pulse shaping functional unit can be used for both architectures with a minimal adjustment and control in the clock frequency.

Symbol	**Chip sequence**
0000	11011001110000110101001000101110
1000	11101101100111000011010100100010
0100	00101110110110011100001101010010
1100	00100010111011011001110000110101
0010	01010010001011101101100111000011
1010	00110101001000101110110110011100
0110	11000011010100100010111011011001
1110	10011100001101010010001011101101
0001	10001100100101100000011101111011
1001	10111000110010010110000001110111
0101	01111011100011001001011000000111
1101	01110111101110001100100101100000
0011	00000111011110111000110010010110
1011	01100000011101111011100011001001
0111	10010110000001110111101110001100
1111	11001001011000000111011110111000

Table I: Symbol to chip mapping

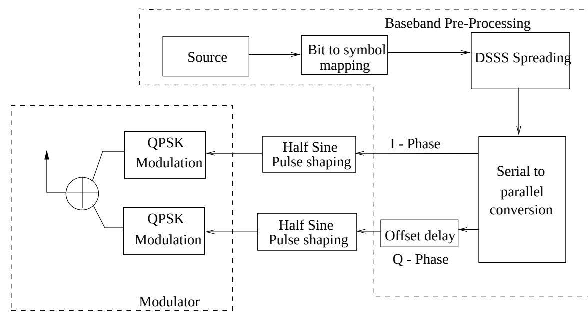

Figure 1: Architecture of IEEE 802.15.4-PHY transmitter

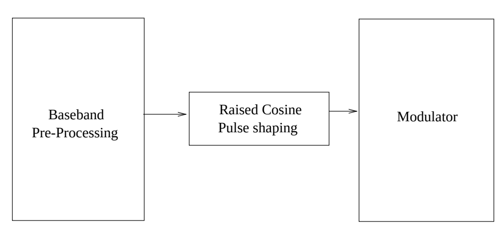

Figure 2: Architecture of modified IEEE 802.15.4-PHY transmitter

III. Adaptive Rule Engine Based Smart Transmission System

The rule engine plays a prominent role for achieving energy saving by reducing the data traffic in the network.

Clinicians in general use an ECG data collected over a fixed duration for classifying the patient health condition and diagnosing. The main problems with the traditional burst transmission of data are increase in network traffic, power consumption and storage. Transferring this huge amount of data leads to a very high power consumption. Keeping in mind the hyper connectivity scenario, limiting the network traffic generated should be given a significant priority. By the use of adaptive rule engine, transmission can be made smart by transferring the data only when required which limits the network traffic and reduces energy consumption. Performance analysis of the adaptive rule engine based smart transmission system has been analyzed in [4]. In [4], 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 ECG data by the feature extraction unit. Adaptive rule engine consists of *"decision making"* section and *"transmitter control"* section, decision making section analyzes the features provided by the feature extraction unit and decides whether to transmit or not. The transmitter control section triggers the transmitter and starts transmission, if the data is to be transmitted. The working principle of the adaptive rule engine is shown in Algorithm 1

In adaptive rule engine we use two thresholds *soft threshold* and *hard threshold* to classify the data. The key features that doctors use to classify the data are listed in the TABLE II which are normal ranges of the ECG data for a healthy patient [11] and are used as the *hard threshold*. If the values of the parameters are in the range listed in the table, the data is then classified as a normal data else it is classified as an abnormal data. The *soft threshold* is an internal variable, which is initialized to *hard threshold* and whenever the sensed value exceeds the current *soft threshold*, the sensed value is assigned to the *soft threshold*. In ALGORITHM 1, initially the $SoftThresold$ value is same as the $HardThreshold$. Later the values of the $SoftThreshold$ parameters are changed based on the observed parameters of the data. In the first iteration, the parameters observed from the data are compared with the $HardThreshold$ values. If any of the parameter exceeds, it is classified as an abnormal data and it is again compared with the $SoftThreshold$. In the first iteration the values of the parameters in $SoftThreshold$ and $HardThreshold$ are same. Hence the parameters also exceed $SoftThreshold$, if they exceed $HardThreshold$. Then the parameter values in which the data exceeded $HardThreshold$ are assigned to the $SoftThreshold$ parameters i.e. if in a case the data of a patient has a QRS interval of 0.14 seconds, it will be classified as an abnormal data by the static rule engine. The same will be the case in the first iteration of the adaptive rule engine. Now in the adaptive rule engine, the parameter QRS interval value is changed to 0.14 seconds. In the second iteration, if the same case is repeated, the

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Algorithm 1 Adaptive Rule Engine

Initial: Set $HardThreshold$ values
Set $SoftThreshold$ = $HardThreshold$
Set $abnormal\_count$=0 and start timer T;

procedure DECISION MAKER($ExtractedFeatures$)
    Comment: Calculate PR, QRS, QT intervals.
    Calculate $Data.PR\_interval$;
    Calculate $Data.QRS\_interval$;
    Calculate $Data.QT\_interval$;
    if T expires **then**
        Reset $SoftThreshold$; Restart timer T;
    end if
    Decide the data is abnormal;
    if $Data > HardThreshold$ **then**
        Decide the data is abnormal;
        Store the data in local storage;
        if $Data > SoftThreshold$ **then**
            CONTROL SECTION(on);
            Transmit the data;
            if abnormal $Data.PR\_interval$ **then**
                $SoftThreshold.PR\_interval$= $Data.PR\_interval$;
            else if abnormal $Data.QRS\_interval$ **then**
                $SoftThreshold.QRS\_interval$= $Data.QRS\_interval$;
            else if abnormal $Data.QT_interval$ **then**
                $SoftThreshold.QT\_interval$= $Data.QT\_interval$;
            end if
            Set $abnormal\_count$=0;
        else
            Do not change $SoftThreshold$ parameters;
            $abnormal\_count$ = $abnormal\_count$+1;
        end if
    else
        Decide the patient is normal;
        Do not transmit the data;
    end if
end procedure
procedure CONTROL SECTION($ControlSignal$)
    if $ControlSignal$ == on **then**
        Switch on the transmitter;
        Wait for the data to be transmitted;
        Switch off the transmitter;
    else
        Maintain transmitter in off state;
    end if
end procedure

data will be classified as the abnormal data and the value of the $abnormal\_count$ value is incremented but the data will not be transmitted. The value $abnormal\_count$ is used to determine the number of times the patient has crossed the $HardThreshold$ but is within the particular $SoftThreshold$. If in the third iteration the data exceeds the QT interval threshold, again the parameter QT interval in the $SoftThreshold$ values are adjusted accordingly. The parameter *T* indicates the time to reset the *SoftThreshold*, which can be defined by the doctor. After every *T* duration the *SoftThreshold* is reset to the *HardThreshold* value.

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 II: Threshold values of the intervals

IV. Holistic View of the System Architecture for Smart Remote Health Monitoring targetting ubiquitous connectivity

Fig. 3, shows the holistic view of the proposed system architecture with smart transmission. For the analysis of the performance, ECG monitoring system is considered. The pre-processing block includes the data acquisition system which acquires the medical data from sensors using various signal processing techniques and feature extraction unit which extracts the important features from the collected data. Many architectures for the data acquisition system have been developed in the past [4], [12] & [13]. For the analysis of performance Lead I ECG data is considered. The data acquisition system used has an upper cutoff frequency of 0.5 Hz and a lower 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 classied properly. This intelligent classication 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 known as feature extraction. Feature extraction plays an important role in automating the remote health monitoring. Features like P, Q, R, S and T points as shown in Fig. 4 from the Lead I ECG signal plays prominent role in classifying the patient. For a detailed description of several feature extraction algorithms available, kindly refer to [14], [15] & [16]. Using these extracted features the intervals shown in Table II are calculated and fed to the on-chip adaptive rule engine. The adaptive rule engine using the extracted features decides the amount of data to be transmitted and triggers the transmitter section.

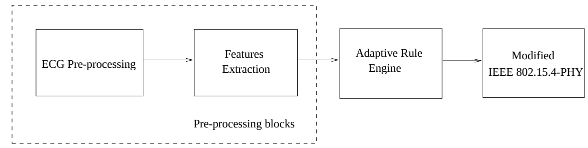

Figure 3: System architecture for smart remote health monitoring targetting ubiquitous connectivity

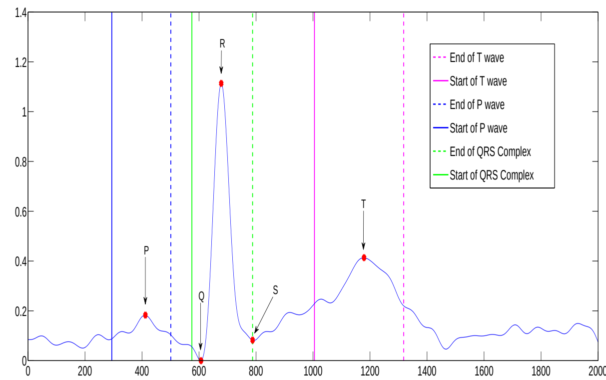

Figure 4: Extracted features from Lead-I ECG Data

V. Performance analysis of proposed architecture

In this section we analyze the performance of the proposed system architecture. The performance analysis is analyzed in two stages. First the performance of modified IEEE 802.15.4-PHY is analyzed and later the performance of adaptive rule engine based smart transmission is discussed.

A. *Performance of modified IEEE 802.15.4-PHY*

The BER performances of the proposed modified IEEE 802.15.4-PHY and IEEE 802.15.4-PHY are analyzed and shown in Fig. 5. It is observed that, the performance of raised cosine and half sine pulse shaping along with DSSS is similar at low values of SNR, but gradually half sine pulse shaping dominates the performance of raised cosine at high values of SNR. The advantages of using Raised Cosine pulse shaping is the ease of digital FIR implementation and architecture multiplex when using multiple radios. IEEE 802.11b uses raised cosine pulse shaping technique, which is a well established standard and is more suitable for long range Personal Area Networks (PANs). The other advantages of using modified IEEE 802.15.4-PHY architecture is the ease of adaptability since the IEEE 802.11b standard is widely established and easily available. Upon using the modified IEEE 802.15.4-PHY, the area reduction achieved in the multiplexed architecture of IEEE 802.15.4 and IEEE 802.11b is significant.

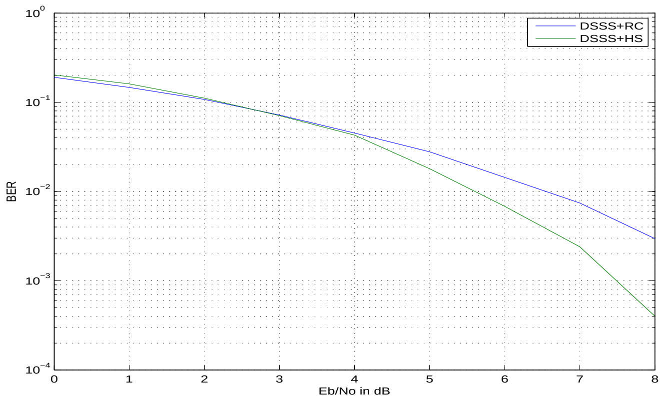

Figure 5: Comparison of BER performances for proposed modified IEEE 802.15.4-PHY and traditional IEEE 802.15.4-PHY

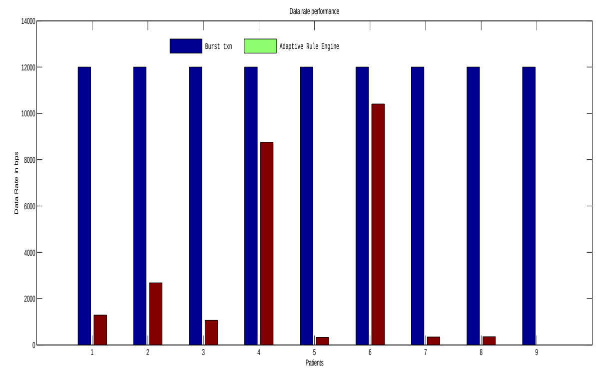

Figure 6: Comparison of data rate generated with traditional transmission and transmission using adaptive rule engine

B. Performance of adaptive rule engine based smart transmission system

The usage of adaptive rule engine leads to a drastic reduction in the data rate generated. Fig. 6 compares the data rate generated in traditional transmission mechanism to data rat generated using adaptive rule engine based smart transmission mechanism. For the performance analysis ECG data has been collected from ten different patients of different age groups. The data rate generated depends on the number of abnormal samples, that have to be transmitted. Each sample is encoded using 12 bits symbol. From Fig. 6, it is observed that the continuous transmission transmission for patient 1, leads to a data rate of 12 Kbps and remains constant for all the patients, whereas the adaptive rule engine generates a data rate of 1.6 Kbps. On an average over 10 patients, upon using the adaptive rule engine based smart transmission the data rate generated is 2.5195 Kbps. The expected delay and losses in the burst transmission scenario will be high compared to the adaptive rule engine scenario. Thus by using the adaptive rule engine based transmission, the network traffic can be significantly reduced compared to the continuous transmission scenario.

VI. CONCLUSION

In this paper we have proposed a system architecture for smart remote health monitoring which can also aid for ubiquitous connectivity by targeting multiple on-chip radios. We have also proposed a modified IEEE 802.15.4-PHY architecture which uses Raised Cosine pulse shaping for achieving significant area reduction in multiple radio architecture along with IEEE 802.11b. The performance analysis shows that the modified IEEE 802.15.4-PHY delivers similar performance compared to traditional IEEE 802.15.4-PHY. The proposed system architecture adaptive rule engine based smart transmission mechanism aiding for low data rate generation thereby reducing the energy consumption significantly and data rate generated significantly. The multiplexing of architectures among the multiple radios can result in low form factor and provide ubiquitous connectivity which are important challenges in remote health monitoring applications.

Our future scope of the work is to develop the multiplexed system architecture among multiple radios and analyze the performance tradeoffs.

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REFERENCES

[1] Paradiso, R.; Alonso, A.; Cianflone, D.; Milsis, A.; Vavouras, T.; Malliopoulos, C., ”Remote health monitoring with wearable non-invasive mobile system: The Healthwear project,” *Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE* , vol., no., pp.1699,1702, 20-25 Aug. 2008.

[2] Haahr, R.G.; Duun, S.B.; Toft, M.H.; Belhage, B.; Larsen, J.; Birkelund, K.; Thomsen, E.V., ”An Electronic Patch for Wearable Health Monitoring by Reflectance Pulse Oximetry,” Biomedical Circuits and Systems, IEEE Transactions on , vol.6, no.1, pp.45,53, Feb. 2012.

[3] Khalid Elgazzar, Muhammad Aboelfotoh, Patrick Martin, Hossam S. Hassanein, Ubiquitous Health Monitoring Using Mobile Web Services, Procedia Computer Science, Volume 10, 2012, Pages 332-339, ISSN 1877-0509, http://dx.doi.org/10.1016/j.procs.2012.06.044.

[4] Kiran, M.P.R.Sai; Rajalakshmi, P.; Bharadwaj, Krishna; Acharyya, Amit, ”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.

[5] Standard[online]. Available: http://gigaom.com/2011/10/13/internet-of-things-will-have-24-billiondevices-by-2020/

[6] ”The Mobile Economy”, GSMA, 2013.

[7] 1905.1-2013 - IEEE Standard for a Convergent Digital Home Network for Heterogeneous Technologies.

[8] Peizhong Yi; Iwayemi, A.; Chi Zhou, Developing ZigBee Deployment Guideline Under WiFi Interference for Smart Grid Applications, textitSmart Grid, IEEE Transactions on , vol.2, no.1, pp.110,120, March 2011.

[9] Fei Shang; Ben-qing Gao; Ge Liu; Xuan Xiao, ”Bit error performance analysis of FH/MSK system in different multi-tone noise jamming,” *Microwave, Antenna, Propagation and EMC Technologies for Wireless Communications, 2005. MAPE 2005. IEEE International Symposium on* , vol.2, no., pp.1398,1401 Vol. 2, 8-12 Aug. 2005

[10] Da Gang Xie; Nan Wu; Chun Wang; Qi Feng Liu, ”Performance analysis and simulation of DSSS in tactical data link communication system,” *Environmental Electromagnetics (CEEM), 2012 6th Asia-Pacific Conference on* , vol., no., pp.194,197, 6-9 Nov. 2012.

[11] Standard[online]. Available: www.meds.queensu.ca/central/modules/E CG/normal_ecg.html

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

[13] 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.

[14] 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.

[15] 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.

[16] 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.