An On-Chip Robust Real-Time Automated Non-Invasive Cardiac Remote Health Monitoring Methodology

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Abstract

This paper introduces a novel Real-time Automated Non-invasive Cardiac Remote Health Monitoring Methodology for the detection of human condition by analyzing the ECG signal under the real-time environment. We proposed a novel System-on-Chip (SoC) architecture which has four folded modeling. After the data sensing, firstly, the classification module uses Hurst exponent as a metric in classifying the condition of the ECG signal. Secondly, if there is an abnormal detection by classifier, the Feature Extraction (FE) extracts QRS complex, P wave and T wave from ECG frames. As there is demand of ECG frames, a robust Boundary Detection (BD) mechanism is introduced to identify such frames. The fragmented-QRS (f-QRS) feature is also introduced as our third contribution to detect the fragmentation in the QRS complex and identify its morphology. The fourth step is compressing the ECG data using Hybrid compression technique for low area implementation and communicating this data to the nearest health care center by incorporating the concept of an Adaptive Rule Engine (ARE) based classifier. The proposed SoC architecture is prototyped on Xilinx Virtex 7 FPGA and it is tested on 100 patient's data from PTBDB (MIT-BIH), CSE and in house IITH DB, the percentage of accuracy obtained is 91% and it is under process for Tape-out.

1. Introduction

Recent surveys on Cardiovascular Diseases (CVD) risk management, fortified the upsurge of CVDs especially in under-developed and developing nations causing 17 million people deaths accounting to 25 million CVD deaths worldwide by 2020.

To confront these issues there is a need to develop a health monitoring device which is affordable such that it can reach to huge masses and also it should be reliable enough to substitute the bedside bulky ECG machines. Considering this, we propose a novel System-on-Chip (SoC) architecture here (Fig.1), Scrutinizing the technical challenges like low-power, low-area and high speed processing we proposed low-complexity, low-power Hybrid Feature Extraction Algorithm (HFEA) [1], f-QRS Detection and Morphology Identification (FDMI) methodology [2], ARE [3], Token based compression technique [4]. In this paper, our aim is to take this idea further to the system level from the concept and propose a low-complexity but medically reliable architecture. To the best of our knowledge, this is the first attempt to have highly accurate system used for remote healthcare system-on-chip. The added step here is the patient data can be sent to doctor by continuous monitoring using Internet of Things (IoT).

The paper is organized as follows. Section 2 describes the proposed SoC architecture and detailed explanation of all the blocks. Section 3 shows the result and concludes the discussion.

2. Proposed SoC architecture

Figure. 1(a) and Figure.1 (b) show the proposed chip level and overall block diagram of the entire SoC architecture respectively.

The SoC architecture becomes functional by taking the digital ECG samples from Data Acquisition block and processing ends with transmitting the abnormal condition of the patient along with the compressed ECG data using communication module.

2.1. Proposed classifier block

ECG classifier block provides binary classification (NORMAL / ABNORMAL) of ECG signals. In this SoC chip the early classification of ECG signal helps to reduce the redundant processing of normal signal by feature extraction and transmission blocks which helps in reduction of power as only the signals which are classified as Abnormal are sent to feature extraction and then to transmission block.

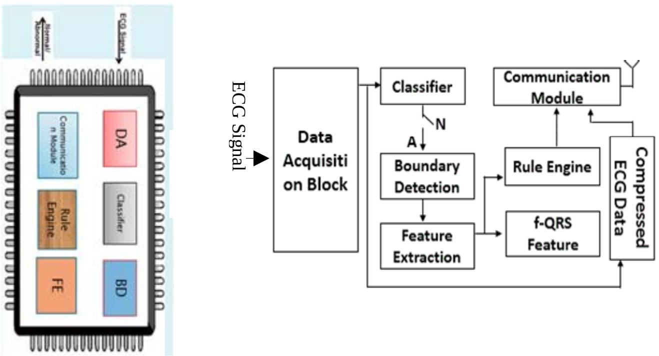

Figure 1. (a) Chip view of the proposed method. (b) Overall block diagram of SoC architecture

This proposed classification block uses the standard Hurst exponent method which has been fine tuned to improve its classification quality which outperforms the standard methods in terms of number of diseases which can be classified and the classification efficiency as well. The effect of scaling property on ECG signals have been analyzed and then proper energy levels are chosen which fits the scaling property [5]. This classifier takes 4096 samples to calculate the Hurst exponent as shown in Fig.2. While choosing the energy levels to fit straight line, we have used only 6 levels instead of standard 12 levels since only 6 levels fits the scaling property. This modification helped us get more contrast in Hurst values of Normal and Abnormal ECG signals.

The architecture has been divided into five main parts as 1. Wavelet transformation 2. Energy calculation 3. Log calculation 4. Straight line curve fitting 5. Decision making block as shown in Fig.2.

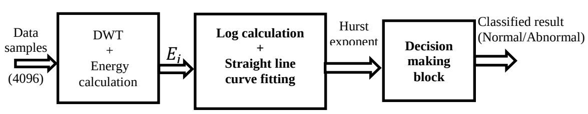

Figure 2. Classification block diagram.

The proposed classifier has been synthesized using UMC 130nm technology. The design occupies $0.14mm^2$ on silicon. Power consumption of design is 52µW at 2 MHz. This helps the classier to work for longer time as the power consumed by it is very low. The sensitivity of the classifier is 94.61% while the specificity is 99.66%. The overall accuracy of the classifier on PTBDB (MITBIH), CSE and in house IITH DB is 97.75%.

2.2. Proposed boundary detection and feature extraction

The proposed Boundary Detection and Feature Extraction block automate the process of identifying the perfect boundaries in a chunk of ECG samples (4096 samples) this is followed by the feature extraction to identify the features (QRS complex, P wave and T wave) within the starting and ending boundaries.

The BD algorithm has been implemented in three stages. The first stage gives the DWT coefficients, the second stage is R-peak estimation and the third stage is estimating the exact starting and ending boundaries containing P, Q, R, S, T fiducial points.

Pseudo Code for Stage 2 and Stage 3:

1: Initialize
2: Divide 512 detailed coefficients of level 3 into 4 chunks each of 128 samples
3: Find the max in each chunk (let x_1,x_2 ,x_3, x_4)
4: Take the minimum value among the x_1,x_2 , x_3, x_4 values (say “Min”).
5: Find the threshold $\tau = 0.6 * \text{Min}$;
6: Compare all DL3 coefficients with the threshold (τ)
7: Fill the new memory of depth 512 samples. If DL3 coefficients>= τ memory will be loaded with ‘1’else memory will be loaded with ‘0’.
8: Start Adaptive counting, if there are 50 zeros between two successive ones in the memory then the starting index which is holding one is stored in a register.
9: 8th step is repeated until 512 memory locations is over.
10: This will get 4 to 7 indexes stored in the registers.
11: The index values is multiplied by ‘8’ (since the decomposition is done till level 3), ‘index_mul8’
12: Add and subtract this ‘index_mul8’ with value ‘20’, ‘add_20’ and ‘sub_20’ respectively.
13: Find min between the range ‘add_20’ and ‘sub_20’, ‘min_20’
14: Finally R-peak is obtained by taking the maximum In the range of ‘index_mul8’ and ‘min_20’.
15: Repeat the process ’11 to 14’ for all the indexes to get all R-peaks in 4096 samples.
16: Take the average of successive R-Peaks to get all the boundaries.

The feature extraction operates once the starting and ending boundaries and R-peaks are given as inputs, which contains PQRST-complex. Our recently proposed FE technique [1], the combination of modulus-maxima analysis (MMA) and Time-Domain Morphology (TDM) is used for the extraction of QRS complex, P wave and T wave and there indices. We have skipped the detailed discussion FE algorithm. Interested readers may refer [1] for the details.

The proposed BD+FE methodology has been synthesized using UMC 130nm technology. The design occupies $0.21mm^2$ on silicon. Power consumption of design is 92µW and also tested on 100 patients from PTBDB (MITBIH), CSE and in house IITH DB and we got the overall percentage of 98% accuracy.

2.3. Proposed FDMI

Proposed Fragmentation detection module [2] is used to detect all the kind of discontinuities which may be present in the QRS complex. The overview of proposed FDMI architecture is shown in Fig. 3.

It provides the information regarding the number of notches, maxima(s) and minima(s) and their positions as the output. The patterns for the detection of notches are categorized as A1, A2, A3, A4, B1 and B2, whereas the patterns C1 to C6 are classified as extremas, for details please refer [2]. In the Fig.3 The decision branch use the rules for detection of discontinuities to make all the decisions are connected only with the sign bit line and not to entire data lines of the DWT storage unit (except for the branches A2, A3, B1 and B2, which require magnitude of the DWT coefficient as well [2]) thereby it results in reducing the hardware complexity.

The morphology identification process starts after all the relevant information about the notches, maxima(s) and minima(s), i.e. their number, position on the horizontal

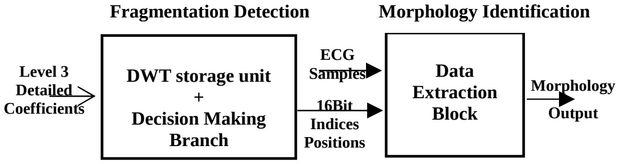

Figure 3. Fragmentation Detection and Morphology Identification Block

axis and relative position on the vertical axis, is obtained from the fragmentation detection module and the data extraction block. Based on the criteria of the number of notches and extremas and their relative position at vertical and horizontal axis, we get the output of the morphology identification module.

FDMI architecture is tested on 100 patient's data from PTBDB (MITBIH), CSE and in house IITH DB and we got the overall percentage of 95% accuracy with consuming 32μW power and occupying 0.19mm^2 area when it is synthesized using 130nm technology.

2.4. Proposed rule engine

The rule engine proposed in this section aids for the low power consumption and the low network traffic generation. The decision making section as shown in Fig.4 makes use of the features extracted and decides whether the data is normal or abnormal based on the concept of our proposed adaptive rule engine [3]. The continuous transmission of the data is better optimized using this adaptive rule engine in not transmitting data in all the times. Table I explains the working of ARE.

H.T/ S.T = Hard Threshold / Soft Threshold.
O.P = Output Parameters from FE Block.
A/N = Abnormal / Normal, Txn = Transmission.
A_count = Abnormal count.
'<=' represents assigning values.

Table I. Pseudo code describing ARE

1st iteration	2nd or any other iteration
1. S.T <= H.T 2. If any O.P ≥ H.T Enter -> o/p =A, txn, & S.T<=O.P 3. Else o/p=N	1. If O.P ≥ H.T Enter -> begin If O.P ≥ S.T enter o/p =A, Txn and T=0 Else A_count= A_count +1, o/p = N end 2. Else o/p = N 3. ARE will be rest after 20 min

The performance analysis of the proposed rule engine [3] is done on 100 patients. Energy consumption is used as metric in evaluating the performance. We got an overall energy consumption of 0.01 J for PTBDB (MITBIH), CSE and 0.05 J for IITH DB. The high value of energy consumption for IITH DB is because of the larger number of abnormal patients in ITTH DB compared to PTBDB, CSE.

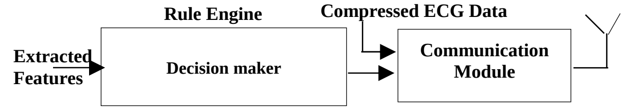

Figure.4 Proposed Rule Engine Block Diagram

2.5. Communication module

In this paper ARE makes use of IEEE 802.15.4 standard for transferring data to the gateway. ZigBee devices, which uses IEEE 802.15.4 PHY and MAC standard for wireless transmission to the central node [6]. ZigBee uses DSSS which maps four bit message symbols to 32 bit chip sequences and gives In-phase and Quadrature-phase samples as outputs which are later used for the RF transmission.

2.6. Proposed compression technique

The proposed low complexity on-chip ECG data compression [4] methodology targeting remote health-care applications gives high compression ratio. In this compression technique we perform selective thresholding on the DWT coefficients of the ECG signal [4]. We used 5 levels of DWT coefficients. The level 1 detailed coefficients were neglected completely. From level 2 to 5 we used threshold factors of 0.64, 0.32, 0.16 and 0.08 for the detailed coefficients [4]. The level 5 approximate coefficients were not thresholded. We store only the non-zero data points and completely ignoring the zeroes among the thresholded coefficients. In order to ensure proper reconstruction of the signal the position of each of the stored non-zero coefficients are also stored. While reconstructing the signal, zeroes are added to the positions that are not stored in the memory. Once all the thresholded coefficients are obtained, the ECG data can be reconstructed by finding the inverse DWT of the reconstructed coefficients.

The proposed architecture is given in Fig.5. The comparator checks if the thresholded values is zero or not and generates the output signal ctr_out. The output signal ctrl_out, given by the comparator is used to indicate whether the data and its position need to be stored or not. The counter counts the position of the sample thresholded values. The proposed architecture has been implemented using VHDL and synthesized using UMC 130nm technology at 2 MHz for a word length of 16 bit. Power consumption of the compression architecture was found to be 97µW and the area was 286µm^2.

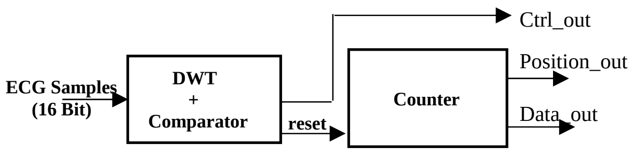

Figure.5 Proposed Compression Block Diagram

The proposed compression technique has been tested for 6300 frames (4096 samples) of data of different patients. Since the error imparted to the signal is only due the selective thresholding, the reconstructed signal is found to have a very high correlation to the original signal. The proposed method gives an average Cross Correlation (CC) of 99.43%. The compression method give an average percentage compression of 94%.

3. Results

The proposed SoC architecture methodology is implemented and tested on Xilinx Virtex 7 by taking 100 patient's data from PTBDB (MITBIH), CSE and in house IITH DB, the accuracy obtained is 92%. The performance and results of individual blocks in terms of accuracy are shown in Table 2.

Table 2. Individual results of SoC blocks

DB	Accuracy				Energy Calculation
	Classifier	BD+FE	F-QRS	Comp	ARE
PTBDB & CSE	98.2	98.5	95.5	98	0.01Joules
IITHDB	97.3	97.5	96.4	90	0.05Joules
Total	97.75	98	95.95	94	0.03Joules

5. Conclusion

In this paper we have come up with a Non-invasive SoC architecture to automate the detection of human condition by analyzing the ECG signal under the real-time environment targeting remote health care applications. As all the individual blocks consume very low power and less area this will enable us to develop a compact portable ECG monitoring system which will consume less power.

Acknowledgements

This work is partly supported by the Department of Electronics and Information and Technology (DeitY), India under the "Internet of Things (IoT) for Smarter Healthcare" under Grant No: 13(7)/2012-CC&BT, Dated 25th Feb, 2013.

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