An Area and Power Efficient VLSI Architecture to Detect Obstructive Sleep Apnea for Wearable Devices

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***Abstract*—Sleep disorders are a common detrimental health condition that reduces quality of life. Among different sleep disorders, Obstructive Sleep Apnea (OSA) is one of the most common sleep disorders. OSA is characterized by a reduction or cessation of airflow during sleep. However, due to expensive and cumbersome detection process, only 10% of the OSA cases are actually diagnosed in the real world. To overcome this challenge, an area and power efficient VLSI Architecture for non-invasive detection of OSA, using features of ECG signal and support vector machines (SVM), is proposed in this manuscript. The proposed classifier achieves an accuracy of 84.60% and sensitivity and specificity of 83.85% and 85.58% respectively. The design is further synthesised using 180 nm Bulk CMOS technology consuming 0.46μW power at 1 kHz and occupies an area of 0.429 mm^2. The low−power implementation of the proposed design makes it suitable for preventive health wearable devices.**

***Index Terms*—ECG signal, QRS Complex, Wavelet Transform, Support Vector Machine.**

I. Introduction

Sleep Apnea is a sleep−related breathing disorder which causes recurring pauses in breathing, or very shallow breathing during sleep. These sleep episodes can range in frequency and duration. Nearly 2% middle−aged women and 4% middle−aged men suffer from sleep apnea [1]. Obstructive Sleep Apnea (OSA) is the most common form of sleep apnea. Depending on lifestyle, OSA prevalance varies from 3% to 24% [2], with an estimation of 5% worldwide [3], [4]. Although OSA is treatable, about 90% of patients remain unidentified and hence, untreated [5]. Untreated OSA can be an aggravating factor for multiple health disorders including ischemic heart disease, stroke and cardiovascular disfunction [6], [7], high blood pressure [8], clinical depression [9] and decreased cognitive skills [10]. This results in people with OSA having a higher risk of fatality [11]. OSA is diagnosed by using a Polysomnography or PSG in a hospital setup. This method is gold-standard for apnea detection but is expensive and complex. Further, it requires the patient to be present at a sleep center where he is extensively monitored by a trained expert for consecutive nights. The tedious setup involves 22 electrodes and a respiration mask which leads to huge discomfort for the patient. The PSG data is then analyzed manually by a specialist. This method involves manual screening of the PSG which cannot be scaled to handle a large number of patients and data. Moreover, the wearisome process makes patient reluctant to undergo PSG [5]. Despite the progress in the healthcare sector, the existing solutions are bulky, intrusive, compute−intensive and expensive. Thus, there is a dire need of an inexpensive, easily accessible and non−intrusive automatic OSA monitoring system.

In the past decade, several methods have been proposed as an alternative to PSG. However, most of the proposed methods focus on recording signals and then processing them off−line over a more powerful platform including general purpose micro−controllers and smart devices. Authors in [12] use a similar approach and a set of non-invasive physiological signals. These signals are transmitted to a cellphone via bluetooth for further processing. However, the method consumes more power and requires overhead resources due to continuous transmission of data. This makes it less efficient for a wearable application. Several researchers focus on an alternative non-invasive approach for OSA detection. Among different approaches, ECG is the most reliable method to detect the episodes of sleep apnea. In some recent studies, authors have explored the use of multiple features extracted from a single-lead ECG. Classification is performed either directly using extracted features of ECG or by feeding them to an advanced machine learning algorithm. Authors in [13] achieved a classification accuracy of 92.5% using multiple frequency-domain and morphological features extracted from a single-lead ECG. However, this method required manual classification which makes it time-consuming. According to De Chazal et al. accuracy of manual classification is 93% [14]. Authors in [15] propose an automatic classification approach reaching an accuracy of 90.6%. Further, [16] uses time-domain features and non-linear statistics to reach an accuracy of 85.6%. Finally, authors in [17] use Neural Network to achieve a classification accuracy of 82.1% with sensitivity and specificity of 88.4% and 72.3% respectively. Authors in [18] proposed use of LSTM-RNN and reported an accuracy of 100% but considered only a limited set of data. These previously reported methods mentioned high accuracy in detection of sleep apnea. These algorithms employ complex feature extraction and deep learning algorithms which are suitable only for software implementation. However, if the reported

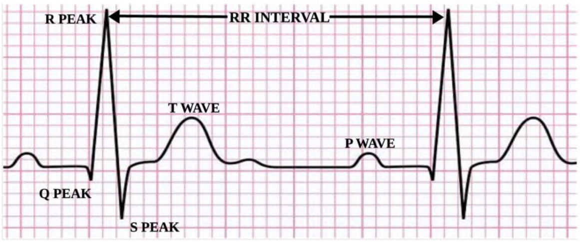

Fig. 1. Normal ECG [20]

methods are implemented on hardware, these would cost high power and hardware resources.

Therefore, in this paper, we propose a low power and area efficient algorithm with its VLSI architecture for non-intrusive detection of OSA using ECG signals. The proposed design will be suitable for wearable healthcare devices that enables in-home monitoring of patients. The paper is organized as follows. Section II depicts implementation details of feature extraction and Support Vector Machine. Section III discusses about experimentation and results. Section IV concludes the manuscript.

II. Proposed Work

A typical bio-medical classification system broadly includes two blocks: an analog front end for acquiring and digitizing signals and a co-processor to analyse the acquired data and perform classification. The primary aim of the manuscript is to develop VLSI architecture for the co-processor to Classify Apneic Events. Further, the co-processor consists of two blocks. First is the ECG feature extraction block responsible for delineating ECG features. Second is the classifier block which utilises a machine learning model to classify the ECG excerpts as apneic and non-apneic. These two sub-blocks are explained below.

A. *ECG Feature Extraction Algorithm*

Fig.1 represents a typical ECG signal excerpt. As shown in Fig.1, an ECG beat has three main features, P wave, QRS Complex, and T wave. P and T waves represent atrial depolarisation and ventricular repolarisation, respectively. The QRS Complex characterises rapid depolarisation of the ventricles and RR interval depicts the time duration between two consecutive R−peaks. It is observed that episodes of sleep-apnea causes variations in the QRS complex and RR intervals [19], [13]. Therefore, in this manuscript, we have employed handcrafted features from the QRS Complex for OSA detection.

Several algorithms have been proposed in the literature to extract QRS complexes from ECG Signal across the past decades. However, due to optimal hardware implementation and high feature delineation accuracy, we have employed the technique discussed in our previous reported work [20] to extract the QRS features. In [20], we have proposed a discrete wavelet transform based ECG delineation algorithm which has optimal requirement of hardware resources.

Wavelet transform is a linear transformation which enables the performance of overall frequency analysis of non-stationary signals [21] by extracting local spectral and temporal information with desired resolution. Typically, wavelet transform is implemented using Mallat's algorithm [22] in which the ECG signals are passed through a series of low pass filters and high pass filters as shown in Fig.3. At each stage, the output of the low pass filter is the approximate coefficient (CA) and the output of high-pass filter is the detailed coefficients (CD) of the ECG signal. The detailed (CD) and approximate coefficients (CA) of the discrete Wavelet Transform of any signal $x[n]$ can be calculated by using a set of Low pass and High pass filters with g and h impulse responses respectively, as represented by (1), (2).

$$CA_i = \sum_{k=-\infty}^{\infty} x[k]g[n-k] \tag{1}$$

$$CD_i = \sum_{k=-\infty}^{\infty} x[k]h[n-k] \tag{2}$$

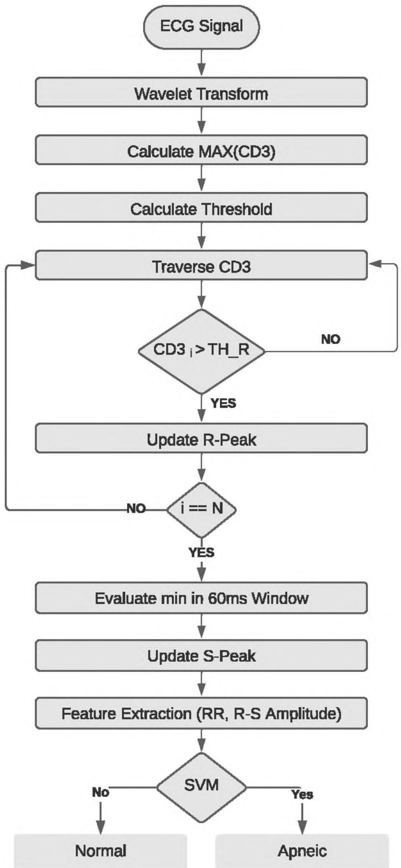

Fig. 2. Proposed Algorithm

Impulse response of high pass and low pass filters depends on choice of the mother wavelet. The integer Haar wavelet is the simplest wavelet. The coefficients of LPF and HPF for Integer−Haar wavelet are represented by (3), (4). Further, at each level, the output of the filters are downsampled by a factor of two to remove redundancy as depicted in Fig.3.

$$CA[n] = \left\lfloor \frac{1}{2}x[2n] + \frac{1}{2}x[2n+1] \right\rfloor \tag{3}$$

$$CD[n] = x[2n] - x[2n+1] \tag{4}$$

As evident from the equations, the complete wavelet transform is implemented using a simple shift and add operations, where division by two can be implemented as $(>> 1)$.

In the proposed work, we use a 10 sec ECG segment to extract wavelet coefficients up to the third dyadic (2^3) scale (CD3) according to Mallat's Decomposition criteria [22]. The complete algorithm is represented by the Flowchart in Fig.2. Using a simple comparator, the absolute max of the third scale wavelet coefficient is calculated, as represented by (5). The absolute max is then used to calculate the threshold value for R−peak detection, as depicted by (6). The value of threshold is updated after every 10 second duration to make the algorithm adaptive.

$$abs\_max = max(CD3) \tag{5}$$

$$Th\_R = abs\_max >> 2 \tag{6}$$

After calculating threshold, we traverse through third scale coefficients to mark points with magnitude greater than the threshold. This point is marked as a temporary R−peak position. Later, the next seven samples are skipped to avoid multiple R−peak detection in same QRS complex. The temporary R−peak position is now multiplied by 2^3 to get an exact R−peak position in the ECG signal. Further, to find the S−peak, we find the minimum in $60ms$ window after R−peak which is later marked as S peak. RR intervals are also calculated in parallel from the detected R−peaks. The R−S amplitude is calculated which is the difference between R and S peak. Finally, the average of the R−S amplitude and RR interval is fed as an input feature vector into the SVM for classification.

B. Implementation of Support Vector Machine

The Support Vector Machine or SVM is a supervised machine learning algorithm originally developed for binary classification [23]. SVM is very effective for classification on hardware, as it uses a subset from training data as a support vector making it memory efficient. The SVM algorithm estimates a hyper−plane based upon the feature vector. The best suitable hyperplane is the one which represents the largest separation between two classes. Using the hyperplane, SVM is able to capture the complex relationship between the data points, without using difficult transformations. As it is known, the complexity and hardware resource utilisation of SVM depends on the number of features and support vectors.

TABLE I
KERNEL FUNCTIONS

Kernel	Function
Linear	$F(x, x_j) = sum(xx_j)$
Polynomial	$F(x, x_j) = (xx_j + 1)^d$
Gaussian Radial Basis Function	$F(x, x_j) = e^{-\gamma \|\|x - x_j\|\|^2}$

Here, we use a set of two features, RR interval and R−S amplitude. In the case of two features, the hyperplane simplifies to a line. Classification using SVM is made more efficient by using a kernel transformation. The kernel transformation converts a low-dimension space to a high−dimension space to make classification more accurate. Table I represents different kernels used for SVM.

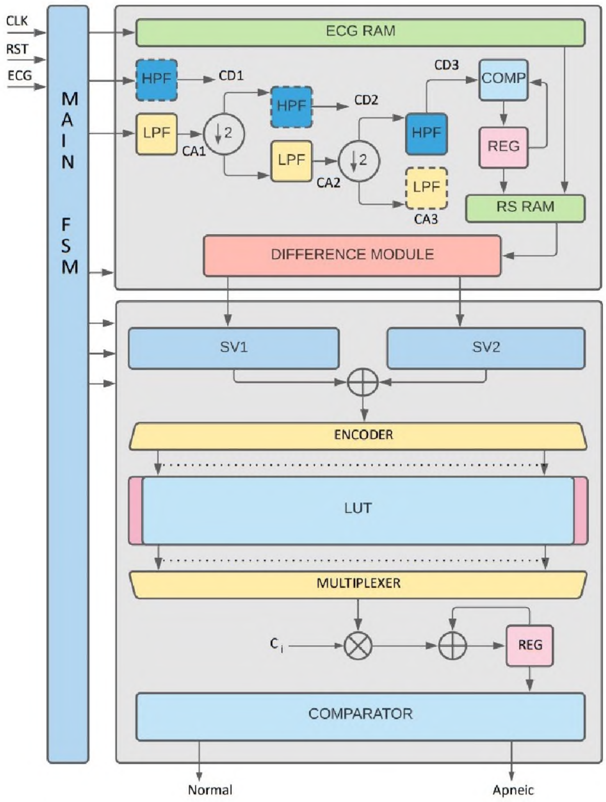

Fig. 3. Proposed Architecture

Among all other kernels, Gaussian RBF is the most versatile and hence, is widely used for classification problems. It is similar to the K-Nearest Neighbour algorithm (KNN) but overcomes the problem of memory. The SVM needs to store only support vector unlike KNN which stores the entire dataset for classification. In the proposed work, the SVM classifier is first trained and tested on python using ECG excerpts from open source Physionet database [24]. It is necessary to mention, that the Gaussian Radial Basis Kernel is used

TABLE II
VIRTEX−7 FPGA RESOURCE UTILISATION

Resource	Feature Extraction	SVM	Total Utilisation	Total Available	Percentage Utilisation
LUT	838	1518	2356	53200	4.42
REG	192	452	644	106400	0.6
MUX	–	3	3	26600	0.01
BRAM	15	15	30	140	21.42
IOB	66	35	101	200	50.5
BUFGCTRL	-	1	1	32	3.13

to extract values of support vectors, the coefficients C_j, and the kernel parameter γ. Finally, these parameters are used to implement the decision function as shown in (7).

$$F(x) = \sum_{j=0}^{N} C_j e^{-\gamma||x-x_j||^2} \tag{7}$$

The trained SVM is implemented on hardware using Verilog HDL and synthesised over Xilinx Virtex−7 FPGA. The complete implementation is depicted by Fig.3. The ECG signal is first preprocessed to extract features (R−S (F1) amplitude and RR interval (F2)) in the feature extraction block. As it is known that floating point operation demands more resources than fixed point operation, the proposed classifier uses fixed point notation where each feature is presented in 16 bits. Next, features F1 and F2 are respectively fed into their Support Vector blocks SV1 and SV2. A support vector block is a simple block that calculates the difference between feature and support vectors obtained post model training on python. The outputs of the support vector blocks is added and fed into the exponential block. The exponential block is a LUT block that implements the function e^{-x}. The output of the Exponential block is added up for all support vectors and is finally fed into the decision block. The decision Block is a Comparator that detects OSA based on magnitude.

III. RESULTS AND DISCUSSION

In this section, a detailed discussion is presented on evaluation of the proposed design. In this work, the ECG signals with apneic and normal episodes are acquired from the open source physionet database [24]. The dataset contains ECG data of several patients sampled at $100Hz$. The acquired data was split into a $80-20$ ratio which were used as training and testing sets. Post training, the classifier model with an ECG feature extraction block is implemented on hardware using Verilog HDL to verify its performance with multiple testcases. The proposed classifier achieves an overall accuracy of 84.60% and sensitivity and specificity of 83.85% and 85.58% respectively on test data. The proposed classifier is further synthesised on Virtex−7 FPGA and its resource utilisation is shown in Table II. It is observed that the proposed classifier utilises only 3.13% of the total available hardware making it resource efficient. Finally, the proposed architecture is also synthesised using SCL $180nm$ Bulk CMOS PDKs to obtain an area and power estimate of the design. Further, the comparison of proposed architecture with state of the art methods is described in Table III. It can be observed from table III that our proposed classifier yields an accuracy of 84.60% with sensitivity and specificity of 83.85% and 85.58% respectively which is higher than methods reported in [17] and comparable to [16]. Our proposed classifier has 3% less accuracy as compared to work reported in [25]. However, it is to be noted that authors in [25] use a spectogram of an ECG which is highly complex to be implemented in hardware. Whereas in the proposed work, we have utilised simple feature vectors that require estimation of only RR and R-S amplitude. Therefore, our proposed design is less complex than [25] for hardware implementation. Further, it is to be noted that authors in [13] report an accuracy of 92.5%, but their methodology requires manual interpretation of extracted features by a medical expert. Moreover, [18] reports an accuracy of 100%, but considers only a limited set of recordings, and uses a complex RNN-LSTM model which makes the classifier complex and demanding in terms of power and area. Therefore, it is summarised that such classifiers with complex computations are not suitable for hardware implementation and further utilisation in power and resource constrained wearable healthcare devices. Thus, our proposed classifier has better or comparable performance as compared to other state-of-the-art methods.

IV. CONCLUSION

In this paper, an area and power efficient OSA classifier is proposed for preventive wearable healthcare applications. The proposed classifier is the first VLSI architecture that can detect OSA with an accuracy of 84.6%. Integer haar wavelet is employed in the proposed methodology to delineate ECG features for efficient classification of OSA. The proposed design requires an area of 0.429mm^2 and has minimal power requirements of 0.46μW. As we know, the primary application of a wearable device is to forewarn an individual against any abnormality and not to provide any clinical suggestions, our proposed design with its area and power efficient implementation is a suitable candidate for preventive healthcare applications.

V. ACKNOWLEDGEMENT

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TABLE III
COMPARISION OF PROPOSED WORK WITH STATE OF THE ART METHODS

Work / Parameter	[13]	[16]	[17]	[18]	[25]	Proposed Work
Platform	Mannual	Software	Software	Software	Software	ASIC
Features	ECG Spectogram, HR, S-Amplitude	Time-domain and statistical features, including SDNN, SD, RMSSD, SDANN, NME, EBF, pNN50, NN50count	14 Time domain features of the Heart Rate Variability (HRV) and the ECG-derived respiration (EDR)	Instataneous Heart Rate (IHR)	ECG Spectogram	RR Interval, R-S Amplitude
Classifier	Mannual Classification	Polynomial Classifier	ANN	LSTM-RNN	K-Nearest Neighbour	SVM
Sample Window	-	-	60 sec	60 Beat Window	-	10 sec
Sensitivity	-	72.12	88.4	-	-	83.85
Specificity	-	91.23	72.37	-	-	85.58
Accuracy	92.5	85.55	82.17	100	88	84.60
Area	NA	NA	NA	NA	NA	0.429mm^2
Frequency	NA	NA	NA	NA	NA	1 kHz
Power	NA	NA	NA	NA	NA	0.46μW

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