Implementation of A Low Power Architecture Using Truncation Multiplier for the Detection of Audio Biological Signals

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Abstract-- In digital audio recording the audio signals are picked by a microphone or other transducer and converted into a stream of discrete numbers, representing the changes over time in air pressure for audio, then recorded to a storage device. Hence these audio recordings are analysed to detect the audio biological symptoms, such as cough, sneeze, vomiting, wheezing, belching and so on, which are spectrally analyzed using a discrete wavelet transform (DWT). The DWT will help to find out the signal level of variation and also use simple mathematical metrics, such as energy, quasi-average, and coastline parameters. These parameters are used to find out type of symptoms patterns to be detected. Furthermore a Mel-frequency cepstrum-based analysis is applied to distinguish between signals, such as cough and sneeze, which have similar frequency response and hence occur in common wavelet coefficients. The proposed approach is to detect the symptomatic patterns using acoustic non speech human signals which increases the efficiency of mathematical metrics and in particular reduces the area occupied by the architecture. Thus the aim of the proposed work is to design a low power and area efficient mathematical architecture for the calculation of energy parameter, coastline parameter, quasi-average and Mel Cepstrum based analysis for the detection of different symptomatic patterns in audio biological signals.

Existing method uses Multiple Constant Multiplication technique in the design of multiplier which is used in the architecture of DWT and energy parameter calculation. The proposed work employs truncation multiplier technique in the design of DWT and energy parameter calculation. The power consumption performance of the truncation multiplier design is almost the same as like the design based on Multiple Constant Multiplication technique. However as LSB part is not required in the realization of FIR filter if truncation multiplier is employed in the realization of DWT architecture it reduces the number of FIR filters required and hence it reduces the power and area consumption thereby makes the design a power and area efficient.

I. INTRODUCTION

Digital recording is the audio signals picked up by a microphone or other transducer or video signals picked up by a camera or similar device which are converted into a stream of discrete numbers, representing the changes over time in air pressure for audio, chroma and luminance values for video, then recorded to a storage device. Audio signal processing or audio processing is the intentional alteration of audio signals often through an audio effect or effects unit. As audio signals may be electronically represented in either digital or analog format, signal processing may occur in either domain.

Health monitoring is the continued oversight of the progression of a clinical trial. This is to ensure that it is conducted according to protocol as well as good clinical practice, regulatory requirements and standard operating procedures. The purpose of monitoring is to see whether a particular intended result or set of results has actually happened after a clinical process or substance has been applied and to provide ongoing oversight to the quality of care given to meet a person's need. In Literature [1] proposed a generic system based on wavelet transform, mathematical metrics, and mel cepstrum based analysis, which can be used to detect symptomatic patterns in audio biological signals. Modifications in the algorithm and the use of low-power methodologies to implement the algorithm into circuit enable the design of a low-power system. The system can be scaled to include other health markers and can also be made user-specific.but the drawback was that it Consumes more number of hardware resources.[2] proposed architecture which employs floating-point arithmetic operations to minimize the operation bit-width and the total size of LUTs. Furthermore, a floating-point MAC unit and memories are shared with many processes to reduce hardware complexity and energy consumption remarkably but at the cost of operating Speed.[3] have presented a new method for non-intrusive quality assessment of noise-suppressed speech, by using mel-filter bank energies as features to capture signal variations, and SVR for feature mapping. We showed that noise injection and suppression affects the FBEs and such changes (represented by the mean and variances) are also effective and parameterizable to assess quality. But this leads to a complex and time consuming task. [4] presented a wireless health monitoring system for monitoring children health in day-care facilities. The device consists of a combination of sensors to collect information about meaningful events such as extent of coughing, sneezing, activity level and amount of sleep, which can be used to predict health issues, diagnose symptoms, and monitor healthy habits and also presents the sensing mechanism and the necessary signal processing algorithm to identify relevant events. Higher computational load hence leads to higher power consumption.[5] proposed a work which attempts to comprehensively review the current research and development on wearable biosensor systems for health monitoring to evaluate the maturity level of the top current achievements in wearable health monitoring systems. A set of significant features, that best describe the functionality and the characteristics of the system has been selected to derive a thorough study. This system can detect only a single acoustic symptom.[6] proposed a system which nuses audio recordings from a miniature microphone and the detection algorithm is based on statistical models of the time-spectral characteristics of cough sounds. By applying advanced pattern recognition techniques, usually used in the field of speech recognition, it is possible to exploit the time-varying characteristics of these signals to detect and distinguish them from other occurring sounds.[7] proposed an efficient constant multiplier architecture based on vertical-horizontal binary common sub-expression elimination (VHBCSE) algorithm for designing a reconfigurable finite impulse response (FIR) filter whose coefficients can dynamically change in real time. To design an efficient reconfigurable FIR filter, according to the proposed VHBCSE algorithm, 2-bit binary common sub-expression elimination (BCSE) algorithm has been applied vertically across adjacent coefficients on the 2-D space of the coefficient matrix initially, followed by applying variable-bit BCSE algorithm horizontally within each coefficient. This technique is capable of reducing the average probability of use or the switching activity of the multiplier block adders.[8] proposed an architecture that includes transforms modules, a RAM and bus interfaces. This architecture works in non separable fashion using a serial-parallel filter with distributed control to compute all the DWT (1D-DWT and 2D-DWT) resolution levels. The so-called lifting scheme represents the fastest implementation of the DWT. VHDL language was used to describe the functionality and synthesize the design.[9] proposed the use of hidden Markov models (HMMs) to automatically detect cough sounds from continuous ambulatory recordings. The algorithm can be used to extract candidate events from long recordings, for further manual analysis by a trained observer. The algorithm's output makes this analysis faster and easier for the operator. Further work is under way to reduce the number of false-alarms returned by the algorithm and eliminate the necessity of a manual analysis stage.[10] proposed a better analysis, namely the auto-regressive analysis, on the frame energy, which outperforms its 1st and/or 2nd order differential derivatives. Experiments across the 863 Speech Database shows that compared with the traditional MFCC with its corresponding auto-regressive analysis coefficients, the FBE MFCC and the frame energy with their corresponding auto-regressive analysis coefficients form the best combination, reduces the Chinese syllable error rate (CSER) and FBE-MFCC with the corresponding auto-regressive analysis coefficients reduces CSER.

Session II gives a detailed description about each block available in the audio biological system. **Session III** elaborates on the existing work and the proposed work of the thesis.**session IV** describes the results and explanation of the obtained results. And also the simulation tools used to simulate the designed audio biological system. **Session V** concludes the project and also highlights the scope for the future work.

II. AUDIO BIOLOGICAL SYSTEM

Technology scaling has resulted in the development of novel applications in a wide array of fields. The field of medical systems is no exception to this and has benefitted immensely. Numerous wearable health monitoring systems have been proposed in order to deliver early warning of an impending health condition. These systems monitor various internal as well as external parameters related to the human health, such as temperature, heart rate, and so on. Apart from these parameters, it is well known that acoustic symptoms, such as cough, sneeze, belching, and so on, are early markers of serious health issues, such as influenza, diarrhea, and whooping cough, especially among children. If repetitive occurrence of these symptoms is detected in advance, it is possible for the patient or the healthcare personnel to commence remedial action prior to aggravation of the problem.

An algorithm has to be derived and its corresponding circuit to detect symptomatic patterns in human acoustic non-speech signals. These include audio recordings of cough, sneeze, belch, wheeze, and vomit patterns. These five human non-speech audio tracks are selected, because they are the most commonly observed signals. They are also known to be symptoms for diseases ranging from influenza, ear infection to serious conditions, such as asthma, bronchitis, stomach flu, and so on. It should be noted that apart from the identified five acoustic symptoms, the proposed system is scalable to other human non-speech audio as well. In order to correctly classify the type of symptom, the acoustic signal needs to be processed efficiently to cause detection. Complexity of this processing is directly translated into equivalent power consumption of corresponding hardware implemented. In order to design an effective and long lasting wearable system for symptomatic pattern detection, it is necessary to reduce its power consumption without degrading the efficacy of detection.

Architecture of audio biological system

A successful design can be achieved by optimizing algorithmic efficacy and hardware power efficiency during the design process. Previously, such approach has been used in the development of implantable systems as well. Using intelligent approximations at the algorithm level and low power circuit techniques, it was shown that a high efficacy of pattern detection can be achieved while maintaining power efficiency. The primary contribution is to address two important issues. First, using a single input (human audio recording), multiple symptomatic patterns have been identified with a high efficacy. Second, the implemented hardware has been made scalable over variety of signals and power efficient. Methodology can be extended to efficaciously detect other symptomatic patterns using power-efficient circuits. Using the wavelet transform as a mathematical tool to resolve the acoustic signals into their spectral components. Each component can be subsequently identified for specific pattern. In order to reduce the effect of sporadic spikes and noise in the signal, we have utilized the statistical nature of mathematical metrics, such as average, coastline (CL), and so on. Using such methods, the dominant patterns can be detected and classified efficaciously. Furthermore, we have used processing based on mel cestrum computation to detect signals, which have indistinguishable frequency spectrum.

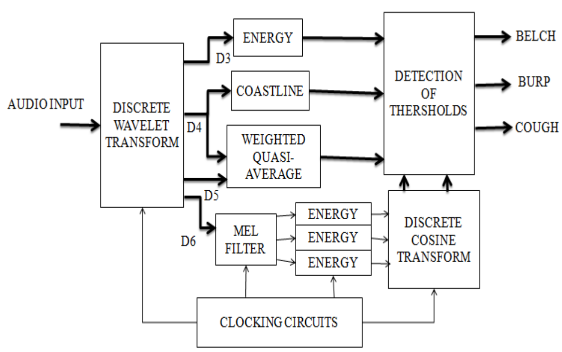

Fig.1: Basic Architecture for the Detection of Audio Biological Signals.

Using low-power design methodologies, such as multiplierless filters, the power constraints on the design are met. The Basic Architecture for the Detection of Audio Biological Signals as shown in figure 1.This enhances the feasibility of integrating the system into a wearable product. Design parameter choices have been made at algorithm and circuit levels of abstraction in order to achieve power efficiency in the implementation. For instance, ideally, a wavelet transform would be sufficient to decompose a signal into its component frequencies. However, to do that at a lower hardware cost, we make modification to filter coefficients (algorithm modification) and filter circuit topology (circuit modification) to achieve similar functionality without any degradation in quality at a much lower hardware cost and power.

Mathematical Metric Blocks

The block diagrams for the mathematical metric blocks are shown in Figure 5 which induces for the detection of audio biological signals by detecting the threshold values for each biological signals. The block diagram for computation of energy is shown in Figure 2(a). It consists of a multiply and accumulate operation, which adds the squared value of the input. The input window size is chosen in the training phase and corresponds to 1024 samples of the digitized input data.

$$E_{AVG}[n] = \frac{1}{N}\sum_{i=1}^{N} E\,(i+(n-1)*N) \qquad (3)$$

The average energy value is then compared against the threshold to detect acoustics pertaining to belching sound. Energy parameter captures the continuous increase in the amplitude of the low-frequency component in human auditory signal to correctly detect this symptom.

The CL parameter block diagram is shown in Figure 2(b). The CL parameter is calculated based on (4).

$$CL(k) = \sum_{i=1}^{N} x[i+(k-1)*N] - x[i-(k-1)*N] \quad (4)$$

where x is the input data and N is the window size for kth window.The input is delayed by a clock cycle in order to calculate the difference between two adjacent samples. The magnitude of the difference is accumulated over a prefixed window in order to calculate the trace length of the signal.

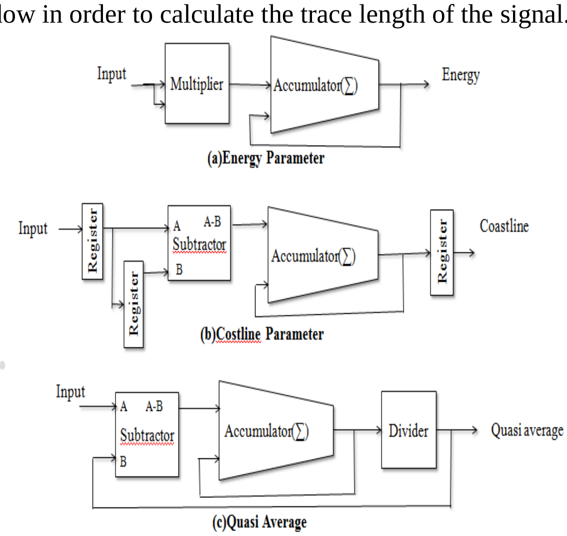

Fig.2: Block Diagrams of the Mathematical Metric Blocks

This accumulated value is then compared with the threshold for detecting coughing. Since coughing signal is periodic signal for time duration without any significant increase in amplitude, the CL parameter captures this pattern accurately.

The block diagram for the quasi-averaging circuit is shown in Figure 2(c). In order to enable a memoryless implementation and a continuously moving average, the average calculated in the previous window is subtracted from the sum of the running window instead of the individual data sample. Since the window size is a power of two, the divider is implemented by discarding the appropriate least significant bits. The weights are used to normalize the magnitudes of the two coefficients. The weighted sum is compared with a prefixed threshold to detect occurrence of belching or burping pattern.

$$\langle W_{k+1}\rangle = \frac{1}{w}\left(S_{i:i+w} - \langle W_k\rangle + x_{i+w+1}\right) \qquad (5)$$

where W is QA of kth window, S is the accumulated sum of the k^{th} window, and w is the window size.

Processing of the Audio Biological System

In this section, the circuit level techniques that are used to implement the proposed algorithm into a power efficient hardware. Our approach is to detect the symptomatic patterns using acoustic non speech human signals with an increase in the efficiency of mathematical metrics, especially the Mel-frequency cepstral coefficients (MFCC) as shown in figure 8.

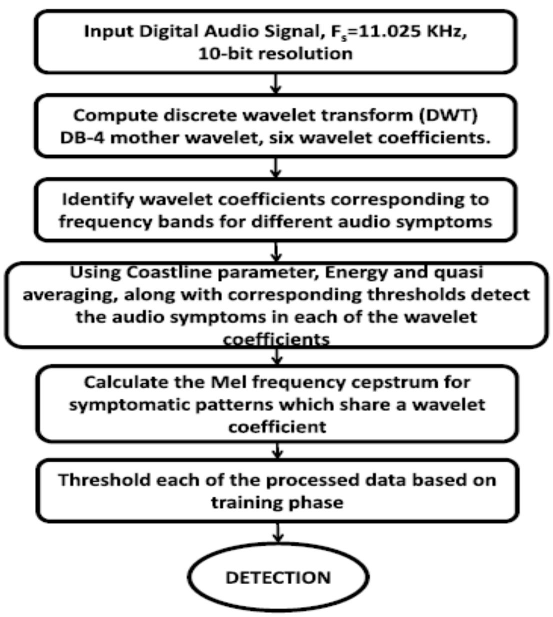

Fig.3: Proposed Methodology

Obtaining Discrete Wavelet Coefficients

The input data is the human audio recording of various symptomatic patterns, such as cough, sneeze, belch, wheeze and vomit. In this paper the input signal will be generated from audio file, such as MP3, wave, avi and so on. Using MATLAB to Convert the audio file to Hex Conversion, and Transfer the data to UART Communication at the baud rate of 115200, then stored the data to Memory as per signal with sampled digital format, the MATLAB GUI is as shown in Figure 9. This digitized sampled signal is streamed at the input of the algorithm at its sampling frequency (11.025 KHz).

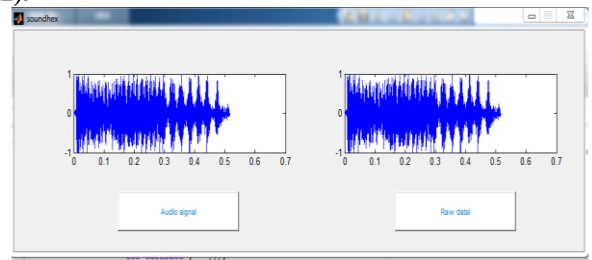

Fig.4: Streaming of Input Signal

The input has to be spectrally resolved using the DWT. Its multi-resolution ability to retain both temporal and spectral information justifies it to be the ideal choice for spectral resolution as compared with FFT or STFT. The DWT resolves the symptomatic patterns into narrow frequency bands or wavelet coefficients (Di) as shown in below Table 1.

Table 1:Mapping Of Dwt Coefficients To Frequency

DWT COEFFICIENT	RESOLVED FREQUENCY
D1	2.75-5.5kHz
D2	1375 Hz-2.75 kHz
D3	687 Hz-1375 Hz
D4	343 Hz-687Hz
D5	172.5 Hz-343 Hz
D6	86.25 Hz-172.5 Hz

The Daubechies fourth-order wavelet is used as the wavelet function for computation of the wavelet transform due to its optimal coarseness and smoothness to truly represent the signals of interest. The order of the selected mother wavelet is an algorithmic design decision, which has a direct impact on the complexity of its FPGA implementation. The various values of Di are classified as the coefficients of interest for specific symptomatic patterns. For instance, the acoustic patterns corresponding to wheezing and vomiting are resolved in the D5 and D6 wavelet coefficients, respectively. The pattern consistent with burp/belching is found in multiple coefficients (D4 and D5). The cough and sneeze signals have a common frequency spectrum and are resolved into a signal coefficients (D3). Another algorithm level design decision is the approximation of the filter coefficients used in computation of DWT. This has a negligible change in their frequency response.

Subsequent to the signal decomposition, the spectral as well as the temporal information of the signal is available for further processing. Although the symptomatic patterns are frequency resolved into separate wavelet coefficients, there are several sporadic spikes in the wavelet processed data, which might trigger false detection. Some of the coefficients are consisting of multiple symptoms too, while other patterns are resolved into multiple coefficients. In order to separate out these patterns further and reduce the noisy spikes to avoid false detection, these coefficients are subjected to various mathematical metric-based computation and MFCC base computation depending on the type of pattern to be detected.

Computing the Mathematical Metrics--The energy parameter is computed according to (3). The block diagram for computation of energy in shown in Figure 2(a). It consists of a multiply and accumulate operation, which adds the squared value of the input viz., D6 coefficient. The D6 window size is chosen in the training phase and corresponds to 1024 samples of the digitized input data. The average energy value is then compared against the threshold to detect acoustics pertaining to coughing sound. Energy parameter captures the continuous increase in the amplitude of the low-frequency component in human auditory signal to correctly detect this symptom.

The CL parameter block diagram is shown in Figure 2(b). The CL parameter is calculated based on (4). The D5 coefficient is the input to the CL block. The input is delayed by a clock cycle in order to calculate the difference between two adjacent samples. The magnitude of the difference is accumulated over a prefixed window in order to calculate the trace length of the signal. This accumulated value is then compared with the threshold for detecting belching. Since wheezing signal is periodic signal for time duration without any significant increases in amplitude, the CL parameter captures this pattern accurately.

The block diagram for the quasi-averaging circuit is shown in Figure 2(c). In order to enable a memory less implementation and a continuously moving average, the average calculated in the previous window is subtracted from the sum of the running window instead of the individual data sample. Since the window size is a power of two, the divider is implemente by discarding the appropriate least significant bits. The QA is calculated over two coefficients viz., D4 and D5. The weights are used to normalize the magnitudes of the two coefficients. The weighted sum is compared with a prefixed threshold to detect occurrence of belching or burping pattern.

Detection of Threshold

The threshold block consists of registers that are loaded with the prefixed threshold values corresponding to each individual acoustic pattern to be detected. These threshold values are fixed in training phase. Comparators in the threshold blocks are used to compare and raise the detection flag for each of the symptomatic pattern detected. The clock circuitry is used to synchronize all the operations in the system. The input data are streamed in at 11.025KHz. Each successive coefficients of the wavelet transform is computed at half the frequency as that of the previous coefficient. In this chapter the existing binary common sub-expression multiplier technique is discussed in detail and compared with the multiple constant multiplier technique. The merits of multiple constant multiplier technique is utilized in the realization of the proposed audio biological system with processing of each block in the detection of the audio biological signals. Thus the signal patterns can be detected accurately by utilizing the process stated in this section.

III. RESULT AND DISCUSSION

Simulation Results

Audio Signal to Hex Conversion --Initially, the input signal is generated from MATLAB, to convert the audio signal file such as mp3, wave, Avi, etc., to convert hex conversion, and we can also convert hex to audio file in this GUI, Figure 5. shows the MATLAB GUI.

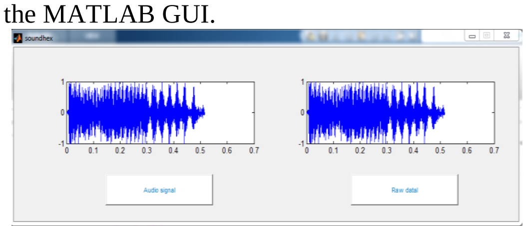

Fig.5: MATLAB GUI for Input / Output

Figure 6 shows the hexa-decimal value for the processed input signal in MATLAB GUI which is used as input for DWT.

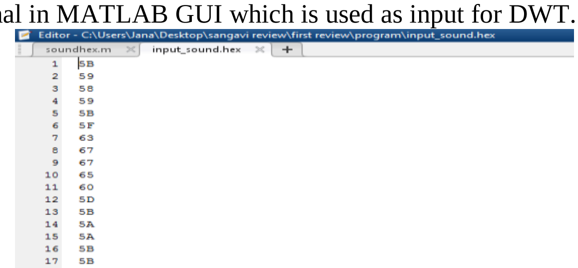

Fig.6: Hexa-Decimal Values of the processed audio input signal

DWT Output

The converted hexadecimal values of the audio signal is fed to the DWT block as input which has processed the input data by using the FIR filters and provide the low frequency signals in oder to reduce the complexity of the architecture. Thus the processed data provides the needed signal as data D3, D4, D5 and D6 as shown in figure 7.

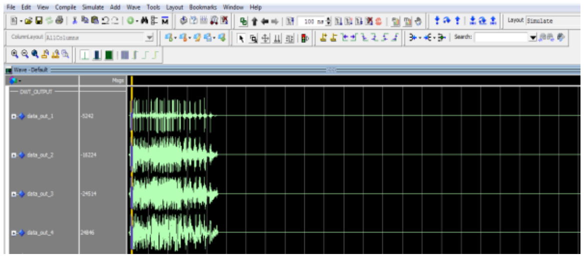

Fig.7: Processed DWT Output

Mathematical Metrics Output

The processed data D3 from the DWT is given as input to the energy block which is one of the important metrics involved in the detection of the audio biological signal. The output of the energy is as shown in figure 8(a). The other data D4 is fed into the coastline parameter block in order to detect the biological signal. The output of the coastline parameter is as shown in figure 8(b). D5 and D6 are the other two more data which are given as input to the quasi-average in which the two data are subtracted and then accumulated using the blocks in the detection of the quasi-average as shown in figure 8(c).

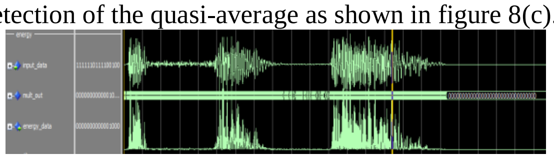

Fig.8(a) Output of Energy Parameter

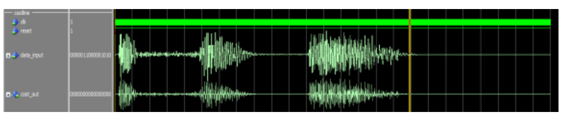

Fig.8(b) Output of the Coastline Parameter

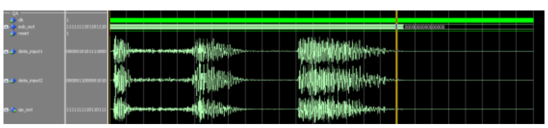

Fig.8(c) Output of the Quasi-average

Fig.8: Output of the Mathematical Metrics

Mel-Filter output

The mel-filter performs the operation of adding alone since the filtering is already done in the DWT block. The processed audio signal gets filtered and then added thus the energy of the signal gets reduced so that the output is fed into the energy block to energize the signal. The output of the Mel-Filter is as shown in figure 9.

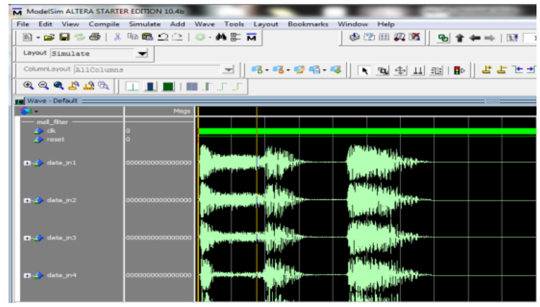

Fig.9: Output of the Mel-Filter

Detection of the Audio Biological Signal

Threshold Detection

When the overall processing of the input audio signal is done the type of the biological signal can be identified by using the threshold block in which there will be a mounting point so that each signal can be detected. The detection of threshold is done as shown in figure 10.

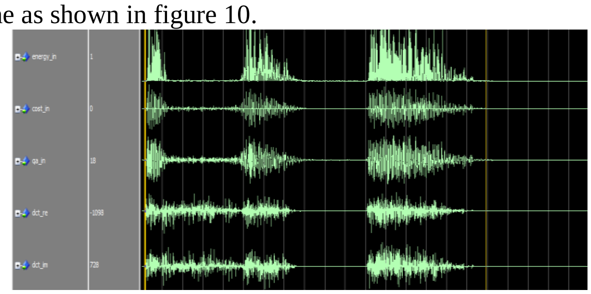

Fig.10: Threshold Detection

Detected Biological Signals

When the input signal is cough, the biological signal detected is as shown in figure 11(a)

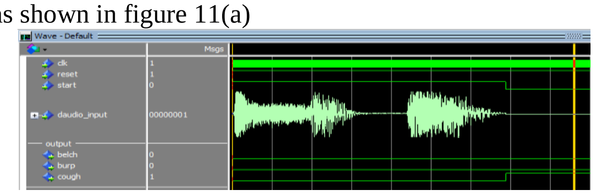

Fig.11(a) Detection of Cough Signal.

When the input signal is belch, the biological signal detected is as shown in figure 11(b)

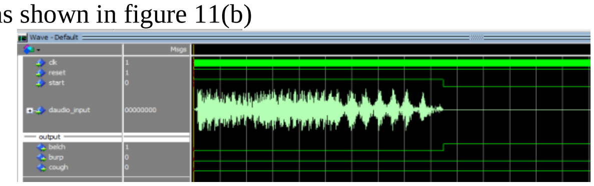

Fig.11(b) Detection of belch Signal

When the input signal is burp, the biological signal detected is as shown in figure 11(c)

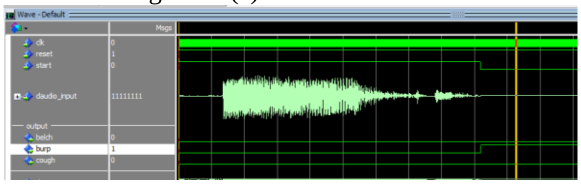

Fig.11(c) Detection of burp Signal

Fig.11: Detected Biological Signals

VLSI Implemntation

Synthesis Report

The synthesis report for audio biological system as shown in figure 12 infers the number of logic used, number of slice registers and slice LUTs which are involved in determining the area utilized.

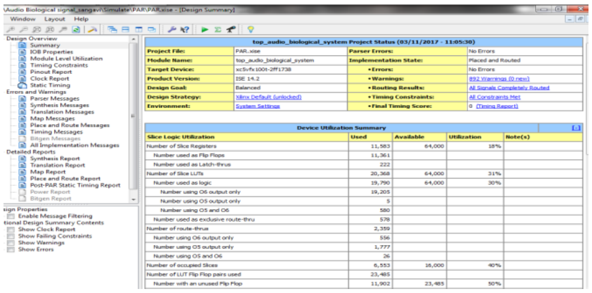

Fig.12: Synthesis Report for Audio Biological System

Power Report

Figure 13 shows the power report the audio biological system which utilizes 2066mW.

Fig.13: Power Report for Audio Biological System

Table 2. Comparison Table for Existing and Proposed Technique

Table 2 Comparison Table for Existing and Proposed Technique					
Audio Biological System	LUT	SREG	Occupied Slice	Delay(ns)	Power(W)
Using Truncation Multiplier	4095	2856	1312	19.186	0.053
Using Multiple Constant Multiplier	20368	11583	6553	16.781	2.066
Efficiency (%)	79	75	79	12.5	97

In this section the comparison for the existing and proposed technique is shown in figure 12. this provides the efficient utilization of the truncation multiplier technique compared with the BSCE technique.

In this session simulation is performed for binary common sub-expression multiplier technique and the multiple constant multiplier technique. From the results it is inferred that the multiple constant multiplier using Radix-2r outperforms the binary common sub-expression multiplier in terms of hardware resources and power consumption. Finally the proposed multiplier technique outperforms the existing work in terms of area and power by 41% and 87% respectively. However this merit has been achieved at the cost of speed.

IV. CONCLUSION

The proposed truncation multiplier algorithm is efficient in terms of area and power compared to the existing binary common sub-expression elimination technique. Experimental results demonstrate that by using multiple constant multiplier technique for detecting the audio biological signals the proposed architecture is able to interpolate the available area and power more efficiently compared to the existing binary common sub-expression elimination technique. In addition, a hardware sharing technique was used to reduce the hardware cost of the biological system.

The experiments are performed on the recorded audio signals observed from the patients by using MATLAB tool to determine the hexa-decimal value for each audio signal and the performance of the multiple constant multiplier by using Xilinx ISE tool. Experimental results revealed that the proposed multiple constant multiplier technique is superior to the existing binary common sub-expression elimination technique in terms of area and power.

Compared to the existing, the proposed system has improved performance with the area reduced along with the power of 2066mw. Hence the proposed system is power and area efficient.

Future Work

The future work would involve the improvement of the proposed algorithm for the signal processing and also to decrease the power and area consumption of the proposed multiplier architecture. The proposed system is tested with only few recorded audio signals. It may be extended to more audio signals. Algorithms that perform well but computationally complex can be implemented in VLSI so that they can be used in off-line application where processing speed never matters. The main research problem is area and low power architecture for the signal processing applications. Multiplier is frequently required in signal processing. Multipliers provide a high speed method for multiplication, but require large area for VLSI Implementations. So efficient multiplier architecture can be used to minimize the area and power in VLSI design.

V. REFERENCES

[1]. Himanshu S. Markandeya and Kaushik Roy, *Fellow, IEEE*, "Low-Power System for Detection of Symptomatic Patterns in Audio Biological Signals", *IEEE transactions on very large scale integration (VLSI) systems*, vol. 24, no. 8, August 2016.

[2]. Jihyuck Jo, Hoyoung Yoo, and In-Cheol Park, "Energy-Efficient Floating-Point MFCC Extraction Architecture for Speech Recognition Systems", *IEEE transactions on very large scale integration (VLSI) systems*, vol. 24, no. 2, pp. 754 – 758, 2016.

[3]. Manish Narwaria, Weisi Lin, Senior Member, IEEE, Ian Vince McLoughlin, Senior Member, IEEE, Sabu Emmanuel, Member, IEEE, and Liang-Tien Chia, Member, IEEE, "Nonintrusive Quality Assessment of Noise Suppressed Speech With Mel-Filtered Energies and Support Vector Regression", *IEEE transactions on audio, speech, and language processing*, vol. 20, no. 4, May 2012.

[4]. A.Basak, S. Narasimhan, and S. Bhunia, "KiMS: Kids' health monitoring system at day- care centers using wearable sensors and vocabulary based acoustic signal processing", in *Proc. 13th IEEE Int. Conf. e-Health Netw. Appl. Services (Healthcom)*, pp. 1–8, Jun. 2011.

[5]. Alexandros Pantelopoulos and Nikolaos G. Bourbakis, Fellow, IEEE, "A Survey on Wearable Sensor-Based Systems for Health Monitoring and Prognosis", *IEEE transactions on systems, man, and cybernetics—part c: applications and reviews*, vol. 40, no. 1, January 2010.

[6]. Sergio Matos*, *Member, IEEE*, Surinder S. Birring, Ian D. Pavord, and David H. Evans, *Senior Member, IEEE*, "An Automated System for 24-h Monitoring of Cough Frequency: The Leicester Cough Monitor", *IEEE transactions on biomedical engineering*, vol. 54, no. 8, August 2007.

[7]. Indranil Hatai, Indrajit Chakrabarti, *Member, IEEE*, and Swapna Banerjee, *Senior Member, IEEE*, "An Efficient Constant Multiplier Architecture Based on Vertical-Horizontal Binary Common Sub-expression Elimination Algorithm for Reconfigurable FIR Filter Synthesis", *IEEE transactions on circuits and systems—i: regular papers*, vol. 62, no. 4, April 2015.

[8]. Dhaha Dia, Medien Zeghid, Taoufik Saidani, Mohamed Atri, Belgacem Bouallegue, Mohsen Machhout and Rached Tourki, "Multi-level Discrete Wavelet Transform Architecture", *Design Proceedings of the World Congress on Engineering 2009*, vol I, pp. 1 - 3, July 2009.

[9]. Sergio Matos, *Student Member, IEEE*, Surinder S. Birring, Ian D. Pavord, and David H. Evans*, *Senior Member, IEEE, "* Detection of Cough Signals in Continuous Audio Recordings Using Hidden Markov Models" *IEEE transactions on biomedical engineering*, vol. 53, no. 6, June 2006.

[10]. Hannu Pulakka and Paavo Alku, "Bandwidth Extension of Telephone Speech Using a Neural Network and a Filter Bank Implementation for Highband Mel Spectrum", *IEEE transactions on audio, speech, and language processing*, vol. 19, no. 7, September 2011.

[11]. S. Umesh, *Member, IEEE*, and Rohit Sinha, *Member, IEEE, "*A Study of Filter Bank Smoothing in MFCC Features for Recognition of Children's Speech", *IEEE transactions on audio, speech, and language processing*, vol. 15, no. 8, November 2007.