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ARRHYTHMIA DETECTION BASED ON HERMITE POLYNOMIAL EXPANSION AND MULTILAYER PERCEPTRON ON SYSTEM-ON-CHIP IMPLEMENTATION

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ABSTRACT

As the number of health issues caused by heart problems is on the rise worldwide, the need for an efficient and portable device for detecting heart arrhythmia is needed. This work proposes a Premature Ventricular Contraction detection system, which is one of the most common arrhythmia, based on Hermite Polynomial Expansion and Artificial Neural Network Algorithm. The algorithm is implemented as a System-On-Chip on Altera DE2-115 FPGA board to form a portable, lightweight and cost effective biomedical embedded system to serve for arrhythmia screening and monitoring purposes. The complete Premature Ventricular Contraction classification computation includes pre-processing, segmentation, morphological information extraction based on Hermite Polynomial Expansion and classification based on artificial Neural Network algorithm. The MIT-BIH Database containing 48 patients' ECG records was used for training and testing purposes and Multilayer Perceptron training is performed using back propagation algorithm. Results show that the algorithm can detect the PVC arrhythmia for 48 different patients with 92.1% accuracy.

Keywords: artificial neural network, electrocardiography, FPGA, hermite polynomial expansion, multilayer perceptron.

INTRODUCTION

The heart is the most important organ in the human body and it beats non-stop throughout the human lifespan. Its main function is to supply oxygen and nutrients throughout the body. Cardiovascular diseases (CVD) are heart related diseases and they are the leading cause of death worldwide. According to World Health Organization estimate, in the year 2012, 17.5 million people died from CVD, representing 31% of all global deaths (Dinc, 2013). Electrocardiography is the process of monitoring the electrical activity that is primarily used to diagnose heart disease. A study done in (De Backquer, 1998) shows that the CVDs that caused mortality have high correlation with arrhythmia found in the patient's electrocardiogram (ECG) record. Therefore, a highly accurate screening device is important to detect arrhythmia for early treatment, thus reducing the risk of death due to CVD.

Premature Ventricular (PVC) heartbeat is the most common arrhythmia. Framingham Heart Study reported that risk of mortality, cardiac death and myocardial infarction is double when associated with PVC (Ng, 2006), (Bikkina, 1992). PVC can be recognized by its irregular rhythm, absence of P wave and wide QRS complex shape. If PVC happens more than three times, it is named as Ventricular Tachycardia that later might evolve to Ventricular Fibrillation that is a fatal rhythm (Reid, 1924). Thus it is important to monitor and detect PVC at early stage.

The electrocardiogram is a widely accepted tool used to detect abnormal heart rhythms and as the first indicator to investigate cardiac disorder, such as the cause of chest pain. It records the electrical activity of heart by attaching electrodes to the patient limbs.

However, the ECG signals are irregular in nature and occur randomly at different time intervals during the day. Thus the need of continuous monitoring of the ECG signal is desired, which by nature is complex to comprehend. Moreover, there is a possibility of the analyst missing vital information through manual analysis which can be crucial in determining the nature of the disease. To reduce the medical practitioner's workload, a highly accurate algorithm for computerized arrhythmia detection proposed by researchers.

To design a portable, lightweight heart monitoring device that can detect arrhythmia accurately, the most suitable implementation is as a System-On-Chip (SOC). The prototype of SOC can be designed on Field Programmable Gate Array (FPGA) where the more compute intensive computation modules can be designed in hardware while other process blocks are implemented on software. This would greatly reduce the computational clock cycle needed to perform the task, thus it might reduce the computational time tremendously compared to general purpose embedded processor (Nambiar, 2012).

RELATED WORK

There are many general computations involved in detecting the arrhythmia in ECG. The first is preprocessing stage to remove noise, normalize the signal and prepare the data so that it contains only useful information. The second stage is feature extraction, which is to extract the ECG feature so that it can be classified accordingly. Feature extraction algorithm such as Hermite Polynomial Expansion (Lagerholm, 2000), Wavelet transform (Pachauri, 2009), Peak Valley Detection (Al-Aloui, 1986), Statistical analysis based on heart rate variability (Mohammadzadeh, 2006) and many more can

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be used**.** Lastly, these extracted features will be classified using a classifier to determine whether the beat is arrhythmia. There are many possible classifiers proven to be used to classify ECG arrhythmia such as example Multilayer Perceptron(MLP) (Inan, 2006), Support Vector Machine (SVM) (Zadeh, 2010), Probabilistic Neural network (PNN) (Zadeh, 2010), Linear Discriminant (LD) (de Chazal, 2003), Genetic Programming (Inan, 2006), Block Based Neural Network (Nambiar, 2012), Artificial neural network (Sahar, 2013) and other classifiers.

Despite many algorithms that have been proposed to detect ECG arrhythmia, there is still a lack of implementation on portable, resource constrained devices such as a system-on-chip FPGA. In (Nambiar, 2012), ECG classification implementation was done on FPGA. But it was focusing on the classification part only while the preprocessing and feature extraction processes were done on computer (PC) rather than on-board for a fully stand-alone arrhythmia detection device. But in this work, raw ECG data is used as input for the SoC. Furthermore the feature extraction is the block that consumes the most computation time thus it is the most critical part to be designed as hardware accelerator on FPGA.

In one research work, (Chang, 2004) the preprocessing stage which can be used to detect heart beat for Holter device was successfully implemented, but the beat is still not classified on the system. In another work (Jian, 2007), have implemented the classification algorithm on FPGA. Their work used Block Based Neural Network to classify arrhythmia. The drawback of their methodology is that it still needs 5 minutes to train for each new patient. As the classifier is supervised and needs annotations, this part is contradicts with the purpose of generating a generic weight for the classifier that can be used to classify the ECG signal of new patient.

Preprocessing

Before we classify the ECG beat, the ECG data needs to be preprocessed to prepare for feature extraction. This preprocessing includes noise removal, segmentation, remove offset and normalization. Firstly, the ECG data is processed by a Butterworth Band pass filter which consist of 48Hz low pass filter and 1Hz high pass filter (Nambiar, 2012). This is to attenuate noise due to electromyography interference, power line interference, baseline drift caused by respiration, abrupt baseline shift, and any other noise (Friesen, 1990).

Then the ECG signal is segmented to 300 ms per beat, where 100 ms is before the QRS complex and 200 ms is after the QRS complex. This window is enough to differentiate and cluster many types of arrhythmia (Lagerholm, 2000)**.** Then the offset is removed to ensure the baseline of the ECG signal is as near to zero as possible.

After that, the signal is further processed, normalized where maximum positive is 1 and maximum negative is -1 with respect to zero as a baseline. This is because we want to standardize every patient as different patients carry a different amplitude so that the trained artificial neural network later can be used for general population. The process still maintains the ECG beat shape to allow for useful feature extraction for arrhythmia detection later on. The preprocessing stage flow is described as shown in Figure-1 below.

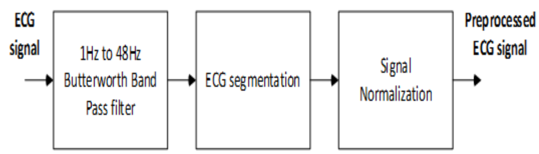

Figure-1. ECG preprocessing stage.

Hermitian polynomial expansion feature extraction

Hermite Polynomial Expansion is a method to extract useful morphological features from the ECG and it is efficient to classify ECG cluster (Lagerholm, 2000). The Hermite Polynomial is given by equation (1),

$$H_n(x) = (-1)^n \left[e^{x^2}\right] \frac{d^n}{d_x n} e^{-x^2} \tag{1}$$

The first derivative of this equation results in equation (2).

$$\frac{d}{d_x} H_n(x) = \left[\frac{d^n}{d_x n} e^{-x^2}\right] . \left[(-1)^n e^{x^2} 2x\right] + \left[(-1)^n e^{x^2}\right] . \left[\frac{d^{n+1}}{d_x n+1} e^{-x^2}\right] \tag{2}$$

Equation (1) is substituted into equation (2) and can be rearranged to get equation (3)

$$H_{n+1}(x) = 2xH_n(x) - \frac{d}{d_x} H_n(x) \tag{3}$$

From the recursive equation (3), we can expand this equation order from n = 0 up to infinitive order. Then the ECG is evaluated with the Hermite Polynomial. A higher order Polynomial used can define the beat more accurately, but there is a tradeoff between accuracy and computation time. However, it was found that a small order of the equation is enough to classify the arrhythmia fairly (Nambiar, 2012). Here is the 3rd to 7th order Hermite Polynomial used in this work.

$$H_3(x) = x^3 – 3x \tag{4}$$

$$H_4(x) = x^4 – 6x^2 + 3 \tag{5}$$

$$H_5(x) = x^5 – 10x^3 + 15x \tag{6}$$

$$H_6(x) = x^6 – 15x^4 + 45x^2 - 15 \tag{7}$$

$$H_7(x) = x^7 – 21x^5 + 105x^3 – 105x \tag{8}$$

Where H is Hermite Evaluated ECG data and X is Preprocessed ECG data. Another feature that been used is the ratio of previous beat to current beat and next beat to

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current beat as an additional feature vector. This feature is correlated with premature heartbeats.

Multilayer perceptron classification

Artificial neural network (ANN) are statistical learning algorithm that try to emulate a biological neural network, the part of brain that is making decisions. Multilayer Perceptron (MLP) network is one type of fully connected feed forward artificial neural network. MLP has been used previously as ECG signal classifier (Shar, 2013). In another work (Martis, 2013), ANN was proven to give higher accuracy compared to SVM and RBF machine learning for ECG arrhythmia detection.

ANN consists of nodes which are divided into 3 main layers, where the first layer contains input node, one or more layers in the middle contain hidden nodes and the last layer contained output nodes. Each layer is interconnected to each other. In an example of ANN in Figure-2, there are 2 input nodes, 3 hidden layer nodes and 2 output nodes.

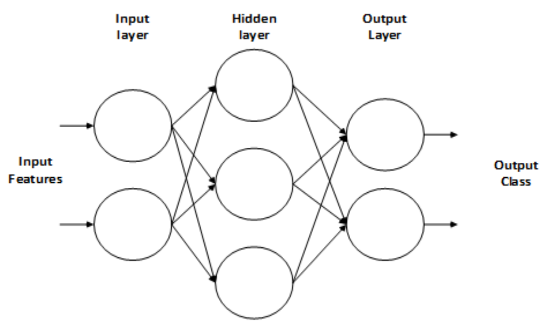

Figure-2. ANN nodes.

Each hidden and output node contains weights that can be trained to recognize our input feature and give the correct output class. This falls under supervised artificial intelligence which means that in order to classify a certain class, it needs to be trained with dataset that have known output class first.

The weight training algorithm is called back propagation algorithm. In this algorithm, the weights initially have a random number, and in every iteration, the algorithm tries to correct or update the weights to suit the pattern from the last layer first, then the second-last layer until the first layer, thus the name back propagation. From the feature vector set obtained, a dataset using 12 patients is stored. This dataset is then used for training of the MLP.

$$e_j(t) = d_j(t) - y_j(t) \tag{9}$$

Where e_j (t) is difference between correct output, d_j (t) and system output y_j (t). Next, mean square error is calculated after pass through the MLP network using equation (10).

$$MSE_j(t) = \frac{1}{N} \sum_{j=0}^{N} (e_j(t))^2 \tag{10}$$

Then Equation (11) is use to update the weights in the output layer of our MLP. The aim of every iteration is to get the minimum MSE thus the best weight to recognize PVC arrhythmia.

$$\begin{aligned} w_{j+1}(t) = \frac{L}{S} * [Y_i * (Y(t)_i * (1 - Y(t)) \\ * e_j(t)] * S_j(t)) + w_j(t) \\ + M * w_{j-1}(t) \end{aligned} \tag{11}$$

M = Momentum of training
L = Learning Rate of the training
w = weight of Multilayer perceptron
S = Output of Hidden layer
Y = Output of Output layer

Momentum, which is a parameter used to control the partial part of previous weight iteration as a factor of the weight update. This helps the system to converge to a local minimum error. w_{j-1} is the previous weight value, w_j is current weight value and w_{j+1} is latest or updated weight value. S_j is layer output. Whereas learning rate and it is a parameter that controls the changes in every iteration. Small learning rate number will increase the training 'resolution' but it will also increase the number of iterations needed to reach minimum error. The same algorithm is applied to each layer. In this work we use Learning rate of 0.0001 with momentum 0.75 and 12 patients' ECG signals with the correctly identified output are used as training data set.

This weights are used as generalized weights that can later be used to classify all 48 patients' records available in the MIT-BIH database record.

After the weights are trained until the minimum error is achieved, the MLP can be used to classify PVC arrhythmia pattern. In the testing phase, the input is convolved with the trained weights and the total sum is fed as an input to the activation function to get the final output.

In this work we are using Logistic Sigmoid Activation Function, shown in equation (12)

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{12}$$

After the input is computed with this network and all the beats are classified, we then profile the computation time and perform accuracy analysis. The output will be compared with the correct annotation provided by MIT-BIH. If the output is correctly classified as PVC arrhythmia it will be recorded as True Positive (TP) or True Negative (TN). Any misclassification will be recorded either as False Positive (FP) or False Negative (FN). Then equation (13), (14) and (15) are used to calculate the sensitivity, specificity and accuracy of the MLP.

Sensitivity=TP/(TP+FN) * 100% (13)

Specificity=TN/(TN+FP) * 100% (14)

Accuracy=(TP+TN)/(TP+TN+FP+FN) *100% (15)

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Proposed system-on-chip architecture

The MLP back propagation training algorithm is executed in MATLAB to generate the trained weights. These weights are stored on the SD-Card to be used for MLP testing phase which is executed on the FPGA board.

Figure-2 shows the proposed system-on-chip architecture for PVC arrhythmia detection. The Nios II soft-processor is the main processor to execute the algorithm. JTAG is added to the system-on-chip as interface to the PC USB connection.

Phase Locked Loop is added to increase the crystal generated clock obtained from the DE-115 board from 50 MHz to 120 MHz, This will reduce the overall processing computational time. The timer is hardware clock counter module to measure the computational clock cycle.

ECG data needs to use a large amount of intermediate memory usage. In this system, a lot of memory, totaling 204800 bytes is required. Using inferred register or MK64 memory provided on FPGA chip will not be efficient. Thus SD-RAM controller is added in order to utilize the on board 64 MB SD-RAM. SD-Card controller is also added to allow offline ECG data to be used as input data. The SD-Card also contains the trained weights of the MLP. SD-Card is also used to store the output results for recording and analysis purposes.

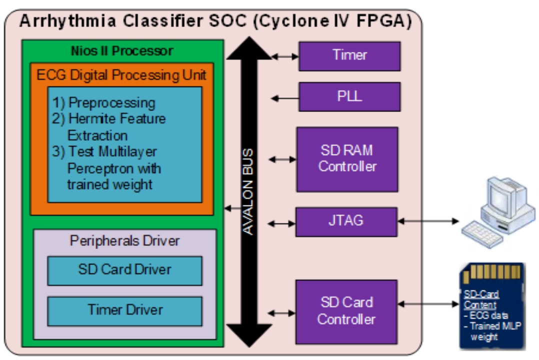

Figure-3. Hardware design architecture on altera FPGA.

The system-on-chip design for the arrhythmia detection system was realized on the Altera-Terasic Cyclone IV DE2-115 board as shown in Figure-3. This FPGA board was chosen as the prototyping platform for our system application, because it provides many features and hardware peripherals such as SD-RAM and SD-Card that suit our application. It also provides LCD to show the number of arrhythmia beats detected by the algorithm from the ECG record.

RESULT ANALYSIS

Hermite Polynomial Expansion can cluster the ECG beat efficiently. Figure-4 and Figure-5 show the plot for two different beat classes on patient #191 with a total of 1987 heart beats. The two classes which are Normal beat and PVC arrhythmia beat were evaluated with Hermite Polynomial expansion. PVC's heart beats evaluated with Hermite Polynomial Expansion is original ECG signal after preprocessing, while a,b,c,d,e,f are 3^{rd},4^{th},5^{th},6^{th},7^{th} order Hermite Polynomial beats expansion respectively. Figure-5 is PVC beats where the QRS complex is wider compared to the normal beats on Figure-4. From both figures, we can see that Hermite Polynomial can differentiate the PVC beats more distinctively as the order is increased.

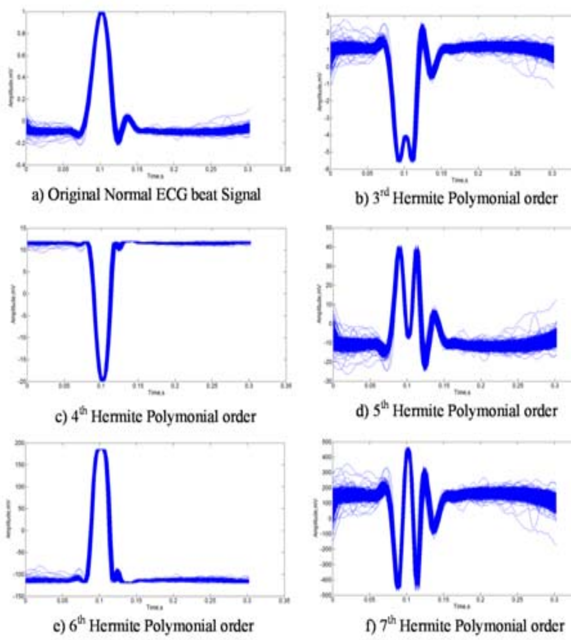

Figure-4. Preprocessed of normal ECG beats signal and its result of hermite polynomial expansion.

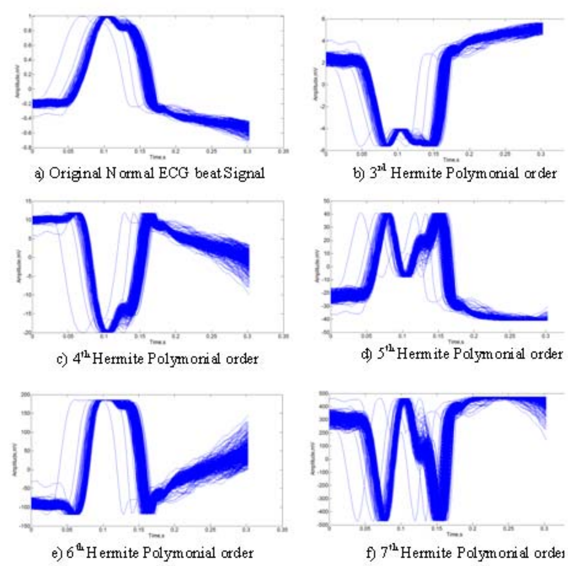

Figure-5. Preprocessed of PVC ECG beats signal and its result of hermite polynomial expansion.

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We tested the PVC arrhythmia detection algorithm to all 48 available patient's records in ECG MIT-BIH Arrhythmia database with a total of 111500 heart beats. The algorithm was executed on Altera FPGA board. After the detection was completed for each patient, we did the analysis based on the accuracy of detection and the algorithm computation time.

Table-1. Arrhythmia detection accuracy analysis.

Database Number	Sensitivity (%)	Specificity (%)	Accuracy (%)	Computation Time (minutes)
#100	100.00	99.86	99.86	20.36
#101	100.00	99.46	99.46	17.48
#102	75.00	99.63	99.58	19.77
#103	100.00	99.66	99.66	19.05
#104	50.00	91.24	91.20	20.63
#105	97.56	90.97	91.07	23.37
#106	80.34	96.07	92.17	19.10
#107	100.00	80.08	80.62	19.40
#108	41.17	80.87	80.50	17.12
#109	94.73	79.27	79.50	22.25
#111	100.00	81.44	81.45	19.35
#112	100.00	99.21	99.21	22.36
#113	100.00	99.60	99.6	16.92
#114	88.37	98.15	97.93	17.60
#115	100.00	99.33	99.33	18.11
#116	98.16	99.04	99.00	21.43
#117	100.00	99.73	99.73	15.07
#118	75.00	94.21	94.08	20.56
#119	99.77	93.86	95.12	19.07
#121	100.00	98.07	98.07	17.49
#122	100.00	99.87	99.87	21.84
#123	66.66	99.86	99.8	14.92
#124	87.23	96.65	96.38	15.75
#200	84.01	87.36	86.37	24.1
#201	81.31	84.6	84.28	18.67
#202	94.73	91.71	91.74	19.44
#203	75.90	54.41	57.49	26.38
#205	60.56	99.57	98.53	23.23
#207	93.33	73.91	74.76	21.16
#208	82.05	93.39	89.69	25.89
#209	100.00	98.12	98.13	25.97
#210	86.08	96.22	95.48	23.33
#212	100.00	99.23	99.23	23.89
#213	82.72	95.01	94.19	27.72
#214	94.92	97.84	97.51	20.53
#215	88.41	98.54	98.05	28.48
#217	90.12	88.65	88.75	20.41
#219	96.87	89.93	90.12	20.64
#220	100.00	98.15	98.15	18.88
#221	98.98	96.65	97.03	21.72
#222	100.00	90.04	90.04	22.96
#223	68.49	94.23	89.62	23.02
#228	96.95	95.44	95.69	19.4
#230	100.00	90.25	90.21	21.75
#231	100.00	78.96	78.98	18.47
#232	100.00	81.24	81.24	17.06
#233	84.71	97.49	94.12	26.70
#234	100.00	99.52	99.52	23.90
Average	**87.80%**	**92.64%**	**92.10%**	**20.89**

From the results in Table-1, the average accuracy achieved is 92.10%. Some of the records show a lower accuracy than others due to higher noise levels.

The average time required to compute the whole algorithm is 20.89 minutes per record. Some record takes longer time to compute because they have different number of beats.

The higher the number of beats in a record means more cycles are needed to extract features from these beats and classify the beats. The timing for computation is further analyzed to a single operation where we measure the timing of each operation to find the operations that consume the most operating time. Figure-6 shows the average computation time and percentage for each operation compared to the total algorithm computation.

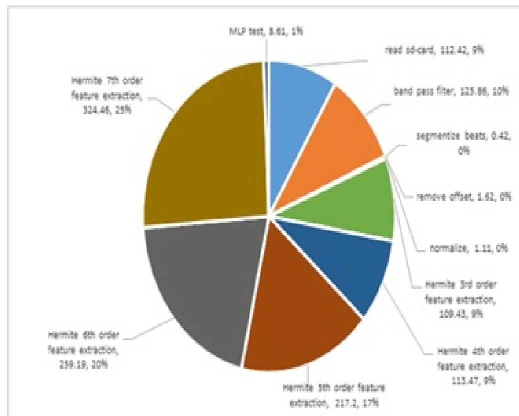

Figure-6. Average timing computation for each operation.

From the timing analysis, it can be observed that feature extraction takes the most computation time. Hermite Polynomial 7th order takes the longest time which is 324.46 seconds. The complete feature extraction process takes about 80% percent of the whole computation time. Whereas the MLP testing just requires 8.61 second or 1 percent of the whole computation time.

In a previous work (Karimifard, 2011) Hermitian basis and 1-ANN was used to classify arrhythmia beats from ECG record. The overall algorithm was executed on PC with a 2.2 GHz AMD 2200+ processor and 512 Mb RAM. It required 0.6 seconds to process an ECG beat with classification accuracy of 99.67%, and 23.23 minutes on average to compute one MIT-BIH arrhythmia patient's record. The comparison between our proposed arrhythmia detection system and previous related works can be seen in Table-2.

Table-2. Comparison with other works.

Author	Platform	Average Accuracy	Average time to process 30 minutes ECG record
Karimifard, 2011 [18]	PC with 2.2 GHz AMD Processor 512 MB Ram	99.67%	23.23 minutes
Gil, 2014 [19]	PC with Intel i-7 1.6 GHz Processor and 4 GB Ram	No Classifi-cation	4922 ms
Gil, 2014 [19]	PC with Intel i-7 1.6 GHz Processor and 4 GB Ram with NVDIA TESLA GPU as co-processor	No Classifi-cation	198 ms
The proposed work	DE2-115 FPGA board with 120 MHz Nios 2 Processor 128 MB Ram	92.10 %	20.89 minutes

In (Karimfard,2011) used longer computation time even though it was executed on higher performance PC system because it used more sophisticated algorithms with additional complex algorithms to increase the detection accuracy and extracted features with higher Hermite basis coefficient for up to 26th order compared to direct Hermite evaluation 7th order used in this work. The feature set generated is able to differentiate between 4 types of arrhythmia. Meanwhile Gil *et al.* studied the performance boost when using Nvdia Graphic Processing Unit (GPU) to execute the Hermite Polynomial Expansion (Gil, 2014). They used high-end PC and execute up to 9th order Hermite Polynomial Expansion and managed to get fast execution timing though no classification was implemented.

CONCLUSIONS

This work has presented a system-on-chip architecture prototyped on Altera FPGA DE2-115 board for PVC arrhythmia detection. This provides a standalone, low cost, lightweight and efficient platform for arrhythmia detection. A training set of 12 patients' ECG records were used to train the MLP which was then used to classify all the ECG records in the MIT-BIH arrhythmia database with a total of 48 patients with 111500 beats. Based on the timing analysis, the Hermite Polynomial feature extraction takes the highest computation time. Compared to the overall algorithm, MLP as a classifier takes an insignificant amount of computation time. Therefore for future work, taking advantage of FPGA as a hardware acceleration platform, feature extraction which uses Hermite Polynomial Expansion is going to be designed in hardware and will be integrated with the current proposed system-on-chip to reduce the computation time.

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