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# VHDL Modeling of EMG Signal Classification using Artificial Neural Network

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**Abstract:** Electromyography (EMG) signal based research is ongoing for the development of simple, robust, user friendly, efficient interfacing devices/systems. An EMG signal based reliable and efficient hand gesture identification system has been developed for human computer interaction which in turn will increase the quality of life of the disabled or aged people. The acquired and processed EMG signal requires classification before utilizing it in the development of interfacing which is the most difficult part of the development process. A back-propagation neural network with Levenberg-Marquardt training algorithm has been used for the classification of EMG signals. This study presents the neural network based classifier modeling using Hardware Description Language (HDL) for hardware realization. VHDL (Very High Speed Integrated Circuit Hardware Description Language) has been used to model the algorithm implemented into the target device FPGA (Field Programmable Gate Array). The designed model has been synthesized and fitted into Altera's Stratix III, chipset EP3SE50F780I4L using the Quartus II version 9.1 Web Edition.

**Key words:** Electromyography, EMG signal classification, neural network, VHDL modeling, FPGA, quartus and stratix

## INTRODUCTION

EMG signal is the electrical muscle activity that reflects the physiological behavior of the neuromuscular system upon certain excitation. There are various applications in the field of EMG signals. The signal can be used in detecting neuromuscular disorders (Moghtaderi *et al*., 2006), operating prosthetic or orthotic limbs; controlling human-computer interfaces and virtual-reality games, developing excise equipment; rehabilitation engineering etc. (Ahsan *et al*., 2009). In the past couple of decades, development of EMG based control has got the focus in the sense that it will increase the social acceptance of the disabled and aged people by improving their quality of life. However, for developing myoelectric control based interfaces, the most challenging part is the classification of EMG signals according to the requirement of application field. It is due to large variations in EMG signal's characteristics in terms of age, motor unit patterns, muscles activity, muscle movement styles, skin-fat layer etc. Like other biomedical signals, EMG signals also easily affected by different types of noise that are caused by inherent equipment and environment noise, electromagnetic radiation, motion artifacts and the interaction of different tissues (Reaz *et al*., 2006). Additionally, sometimes it becomes difficult to extract most significant features from EMG signals which are recorded from residual muscles of an amputee or disabled person. Even more difficulties may be added while resolving a multiclass classification problem (Ahsan *et al*., 2011a).

Due to the lack of computer facilities and successful classifiers, EMG based device controlling did not see much improvement. In early 90's, the pattern classification and recognition approach was improved with the help of applying Artificial Neural Network (ANN) classifiers. Extensive research work has been done afterwards keeping ANN as the core processing technique for the analysis. It can be used as classifier in diagnosis system (El-Ramsisi and Khalil, 2007), automatic heart disease detection system (Khorasani *et al*., 2011), classifying heart beats (Hendel *et al*., 2010), predicting cardiovascular disease (Fidele *et al*., 2009; Sekar *et al*., 2011), predicting neoplasm (Alsaade, 2011) etc. Some other biosignal based applications of ANN can be mentioned here as ECG based cardiac arrhythmia classification (Jadhav *et al*., 2010), EEG based classification for epilepsy diagnosis (EL-Gohary *et al*., 2008), EEG based classification to

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diagnosis subnormal eyes (Guven and Kara, 2006) and mixed signal analysis to find sleep stages (Tagluk *et al*., 2010). There are many pattern classification techniques available and applicable for EMG signal classification by using the extracted features from signal. Through extensive review, it has already been found that most of the researchers claimed successful utilization of ANN for the processing of biosignals especially in the context of classification (Ahsan *et al*., 2010). ANNs are particularly useful for complex pattern recognition and classification tasks by simulating the low-level functions of biological neurons. ANNs are capable of learning from examples, able to reproduce random non-linear functions from unknown inputs and have highly paralleled structure which make them especially fit for classifying patterns (Subasi *et al*., 2006). Considering these properties, many researchers have successfully employed ANN to classify EMG signals using numerous types of extracted features. As for example (Hiraiwa *et al*., 1989) applied ANN based on Integral Absolute Value (IAV) feature (Naik *et al*., 2006) applied ANN with Independent Component Analysis (ICA) feature set, different Multi-Layer Perceptron (MLP) based neural network used by (Englehart *et al*., 1995; Kelly *et al*., 1990; Ito *et al*., 1992; Karlik *et al*., 1994), prominent researcher (Hudgins *et al*., 1993) have used Hopfield and ART and later FIRNN. Most of the ANN based research works have performed with MLP that consist of one hidden layer and back-propagation learning algorithm. Many of the research work which have been carried out with multichannel EMG signals except the recent work of (Kim *et al*., 2008). The EMG signals from increased numbers of channels obviously will increase the classification efficiency. Some of the previous studies by Englehart and Hudgins (2003) and Lyman *et al*. (1977) present that it is advantageous to use multiple channels. It has also found that though the average classification accuracy will increase with increased numbers of channels but a diminishing return may observed after the numbers of channels more than four (Tsenov *et al*., 2006). Many researchers had chosen multichannel i.e., multi electrode scheme for a specific muscle to perform some specific function. Whereas, some of the researchers interested to consider best and effective features other than using multiple channel EMG signals or array of electrodes or a combination of these strategies (Kim *et al*., 2008). Placing the electrodes in different muscle sites may facilitate the classification process depending on whether or not additional signal features are utilized for the classification. For the case of EMG amplitude feature based multifunctional controlling, the electrodes are targeted to specific muscles for the elimination of crosstalk and maximizing channel independence (Bu *et al*., 2003; Fukuda *et al*., 1999; Tsuji *et al*., 2000). Another important thing is that the classification accuracy decreases with the increased number of classes. It is very much normal to the decreasing nature of accuracy because the increasing number of output classes will further subdivide the feature space. Therefore, this will certainly reduce the feature space associated with each class. The previous studies show that the classification efficiency decrease with increase in class and vice versa (Naik *et al*., 2007; Englehart *et al*., 1995). It has found that different types of ANN structure have been used by many researchers because of its ability to adapt and learn from various arbitrary data to classify EMG signals. Different types of ANN models are composed of many interconnected network elements which can develop internal pattern classification strategies based on a set of training data. The ANN models in work in parallel thus providing higher computational performance than traditional classifiers which function sequentially. The presence of inconsistency in accuracy in most of the above mentioned classification methods is possibly due to the fidelity of collected signals, signal conditioning along with physiological characteristics of the subject etc.

This research work is a continuation of previous work which involved in designing of a back-propagation neural network to classify the pre-processed EMG signals which are obtained for different hand motion (Ahsan *et al*., 2011b). Seven statistical time and time-frequency based features are extracted from EMG signals which are used as inputs to the neural network. The features includes Moving Average (MAV), RMS (Root Mean Square), VAR (Variance), SD (Standard Deviation), ZC (Zero-crossing), SSC (Slope Sign Change) and WL (Waveform Length). There are a very few contribution of VHDL development can be observed in the area of EMG signal processing and ANN modeling (Bu *et al*., 2004; Reaz *et al*., 2011). This study describes the processes of developing a VHDL model of neural network classifier to classify EMG signal. Later on, the VHDL model could be loaded into the physical FPGA chip for intermediate hardware realization.

## MATERIALS AND METHOD

**Neural network architecture for EMG classification:** Back-propagation neural network is based on the generalized form of Widrow-Hoff learning rule to multiple-layer network and nonlinear differentiable transfer function. Here, the input vectors and corresponding target vectors are used to train the neural network until it can approximate a function or associate input vectors with specific output vectors or classify input vectors in an

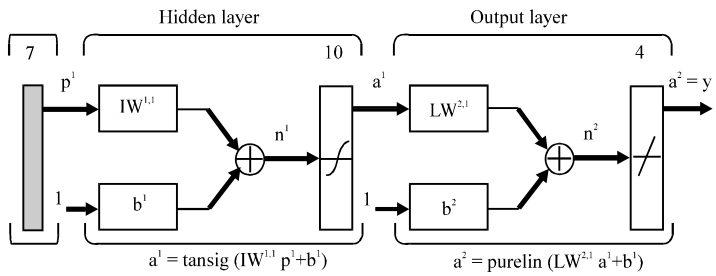


Fig. 1: Architecture of artificial neural network

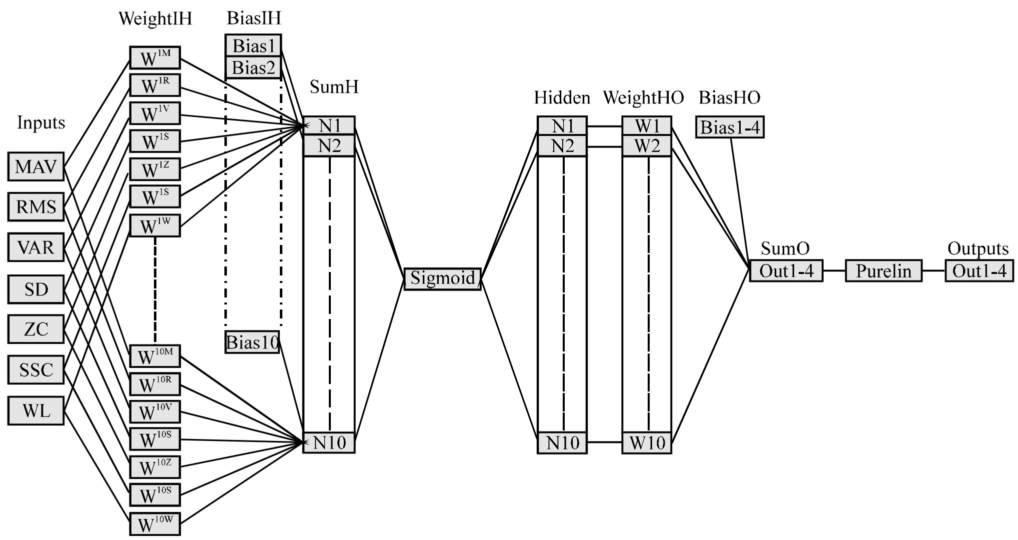


Fig. 2: Neural network input to output architecture

appropriate way based on certain criteria. The designed network consists of three-layers: input layer, tan-sigmoid hidden layer and linear output layer. Each layer except input layer has a weight matrix W, a bias vector b and an output vector a. The weight matrices connected to inputs called Input Weights (IW) and weight matrices coming from hidden layer outputs called Layer Weights (LW). Additionally, superscripts are used to denote the source (second index) and the destination (first index) for the various weights and other elements of the network.

The feedforward back-progpagation network architecture has shown in Fig. 1 with seven neurons in input layer, 10 tan-sigmoid neurons in hidden layer and four linear neurons in output layer. Since, there is no specific way to find out the number of hidden neurons, so it has been determined from best classification result by selecting different numbers of neurons. The predefined features were extracted for four types of hand movements from five different EMG signals. Two hunedred and four sets of input feature vectors from four EMG signals and their corresponding target vectors were fed to the network for training purpose. The feature vectors from remaining EMG signal used for testing the performance of network. The input feature vectors were normalized before feeding for the purpose of efficient training of neural network.

**Design entry for neural network classifier scheme:** The VHDL model for Neural Network classifier has been designed with the guidelines from John Bullinaria's Step by Step Guide to Implementing a Neural Network in C (http://www.cs.bham.ac.uk/~jxb/NN/nn.html). Figure 2 and 3 are presented the complete structure of ANN and backpropagation, respectively. It is mentioned before that the ANN has 7 (seven) inputs which are MAV, RMS, VAR, SD, ZC, SSC and WL.

According to Fig. 2, the inputs are first multiplied by corresponding weight, bias added with it and finally pass through sigmoid function. As for example, to calculate the neuron value N1 in hidden layer, inputs are first multiplied by WeightIH ($W^1$). After that the BiasIH (Bias1) is added and stored in SumH (N1). Then the value in SumH (N1) is passes to the Hidden through sigmoid function. For

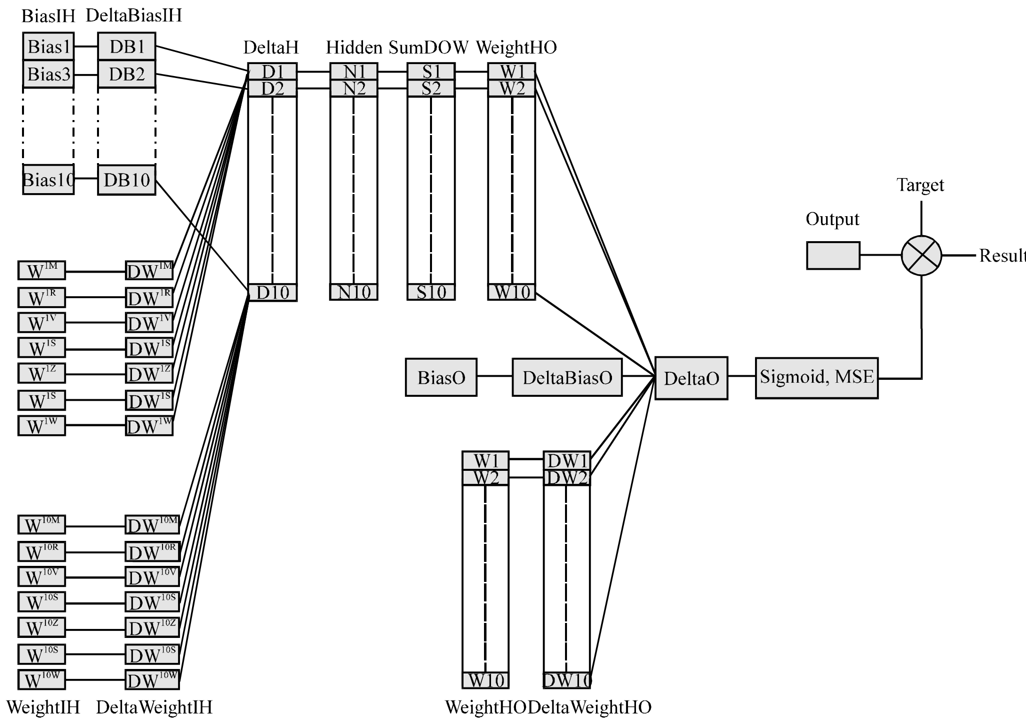


Fig. 3: Neural network architecture for back-propagation

calculating the output, the Hidden neurons are multiplied by WeightHO (W1) and BiasHO is added with it before storing in SumO. At the end, SumO is send to output terminal through pureling function.

When output is generated, the error is being calculated from the difference between target and output vector as shown in Fig. 3. If the error meets the criteria (MSE<=0.001), then the actual output is produced. However, if the error doesn't meet the criteria then the error is passed through sigmoid function and MSE function the finally stored into DeltaO. After that DeltaWeightHO has been calculated from DeltaO. This DeltaWeightHO is then summed up with current WeightHO to get updated WeightHO. Similarly, BiasO is being updated from the calculated DeltaBiasO and current BiasO. For updating the weights and biases in between input and hidden layer, DeltaH is calculated with the help of SumDOW where sumDOW is the multiplication of corresponding WeightHO and DeltaO. From DeltaH, the DeltaWeightIH and DeltaBiasIH is estimated and then WeightIH and BiasIH is updated accordingly.

The final VHDL model for ANN has been developed with 3 (three) module and one package. The top entity NeuralNet as shown in Fig. 4 is the main module to manage and control other components of it. The components as a module are Data_buff, net_Train and net_Run (Fig. 5). The first module to read and store data, second module to train the network and last one to classify the data by utilizing the trained network. A modified version of floating point number system is used. In this case each number inside the VHDL code is converted and calculated by splitting two parts (Mantissa and Exponential). A user defined package is also added namely utilitypack which defines the different data structure, saves some constants values of the network architecture and maintains 3 (three) functions namely power, Conv_Exp and tanSigmoid.

**Compilation and functional simulation:** After designing every VHDL module, it requires to compile separately for getting the better result and for debugging and testing perfection. If any fault found in the designed model, then it requires to modify the architecture and configuration to map the desired function of the module. However, modifying the architecture that contains the component instantiation statements requires recompilation of module which contains the architecture. All the modules for the designed model are compiled for the purpose of testing the Analysis and Synthesis check, Place and Route (Fitter) check Assembler check and Classic Timer Analyzer check by using the Quartus II software. Simulation is the most important part for VHDL based hardware modeling flow. It is also one of the most difficult part, not for the mechanism of the processes but because

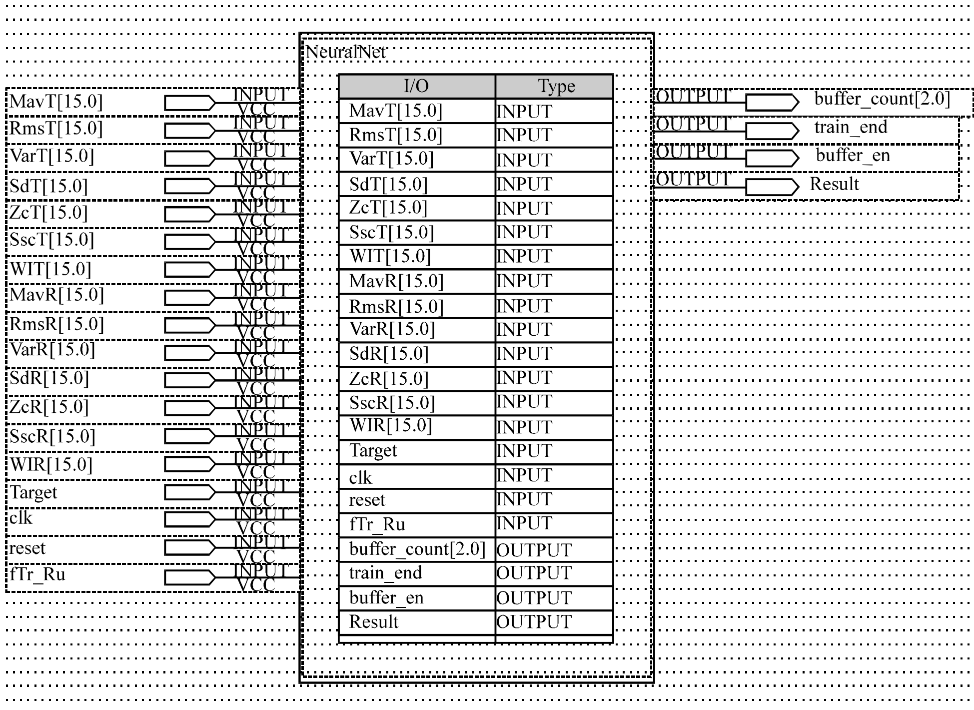


Fig. 4: Top entity for VHDL model of ANN classifier

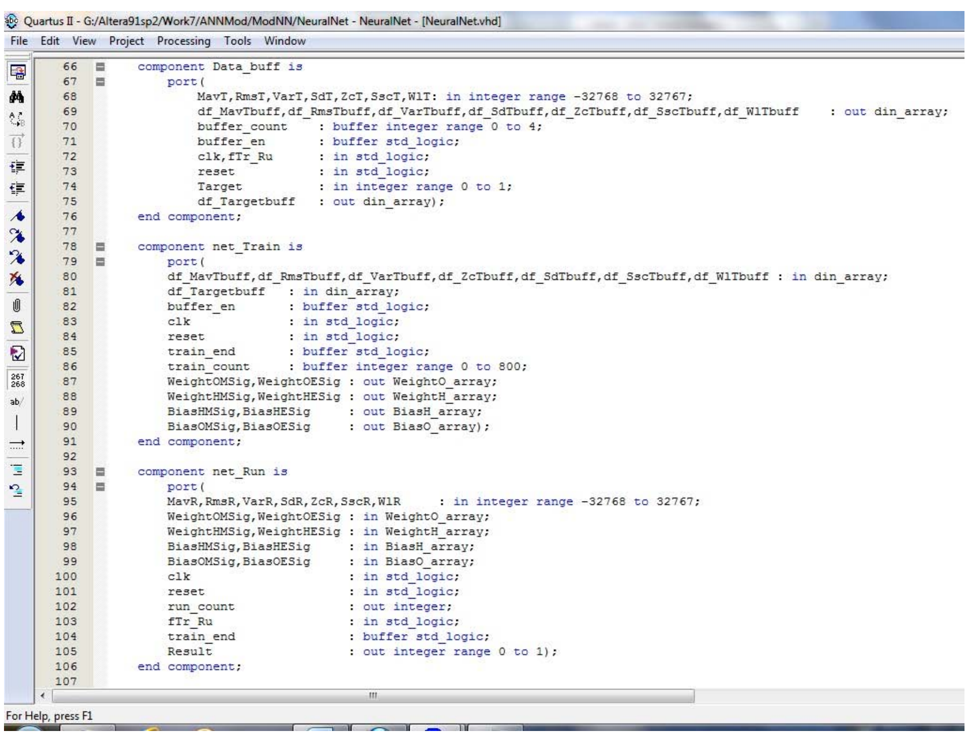


Fig. 5: Components of NeuralNet entity

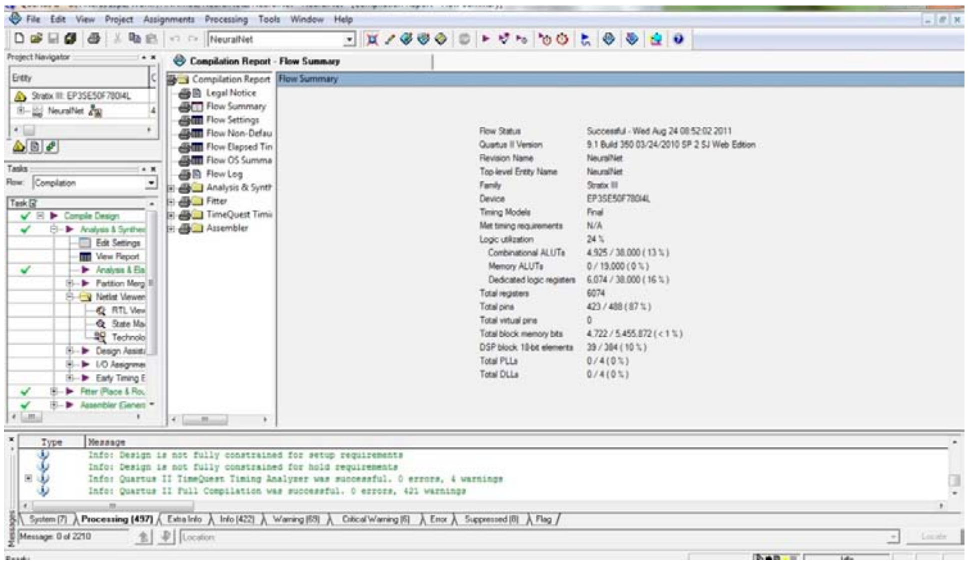


Fig. 6: Compilation summary of ANN based classifier

it needs to evaluate all possible processes and failure modes and also requires to test them carefully. These may include understanding the required operations of the design, creating set of conditions for testing correct operation and possible modes of failure and finally testing all possibilities. The most systematic and thorough way to test the designed model is to apply all possible inputs or combination of inputs in an ascending binary sequence. The EDA software Quartus II has the facility to create Vector Waveform File (vwf) in the form of graphical waveforms that represents simulation inputs and outputs. To perform functional simulation, in this study, the inputs are given by using .vwf format through designing proper waveform for corresponding process modeling. A simulation summary report is generated after performing the compilation and functional simulation. As an empirical method of design verification, the simulation report presents that whether for a given set of inputs, the simulation model gives the desired output response or not and if there is any design error in the model. In other way, simulation can be considered as a verification tool can only be considered as a fist order approximation before designing physical hardware model. If the outputs from the simulation run satisfy the desired requirements then the designed model is considered as ok. Otherwise, it may require re-designed the design entry part again and perform continuous debugging process until the simulation run gives satisfactory output.

## RESULTS AND DISCUSSION

After designing the VHDL model of the ANN based EMG signal classifier, the feature sets and corresponding targets are fed as input. Before feeding the feature sets, all the data are multiplied first by 1000 to treat as integer. Since, the internal calculations of VHDL model are of floating point based but there is no other way to input the data as floating point. Quartus II software is not also able to show any data as floating point through vector waveform. Hence, the input-output data deals by VHDL model of ANN as integer. The same device (StratixIII, chipset EP3SE50F780I4L) is used for VHDL model of ANN synthesizing and simulation. The compilation summary is shown in Fig. 6 and also in tabular form in Table 1. The RTL diagrams are shown in Fig. 7 and 8.

The neural network itself is a complex structure with various kinds of variables in input layer, hidden layer and output layer. Additionally, the back-propagation based training and learning added much more complexity with some more variables. The VHDL model of ANN classifier is first train with 15 feature sets and corresponding targets. Furthermore, the number of epochs was set to 10 to avoid huge amount of time consumption. The reasons behind the time consumption are: large numbers of variables are used inside the VHDL model of ANN, every calculation involves with both mantissa and exponential part and most of the processes has multiple iterations. Still it takes 6 to 7 h on average to complete the training through analysis and synthesis in Quartus II software.

Table 1: Compilation summary for ANN based classifier

| Family | Stratix III | | |
|---|---|---|---|
| Device | EP3SE50F780I4L | | |
| Logic utilization | 24% | Combinational ALUTs | 4925/38000 (13%) |
| | | Memory ALUTs | 0/19000 (0%) |
| | | Dedicated logic registers | 6074/38000 (16%) |
| Total registers | 6074 | | |
| Total pins | 423/488 (87%) | | |
| Total block memory bits | 4722/5455872 (<1%) | | |
| DSP block 18 bit elements | 39/384 (1%) | | |

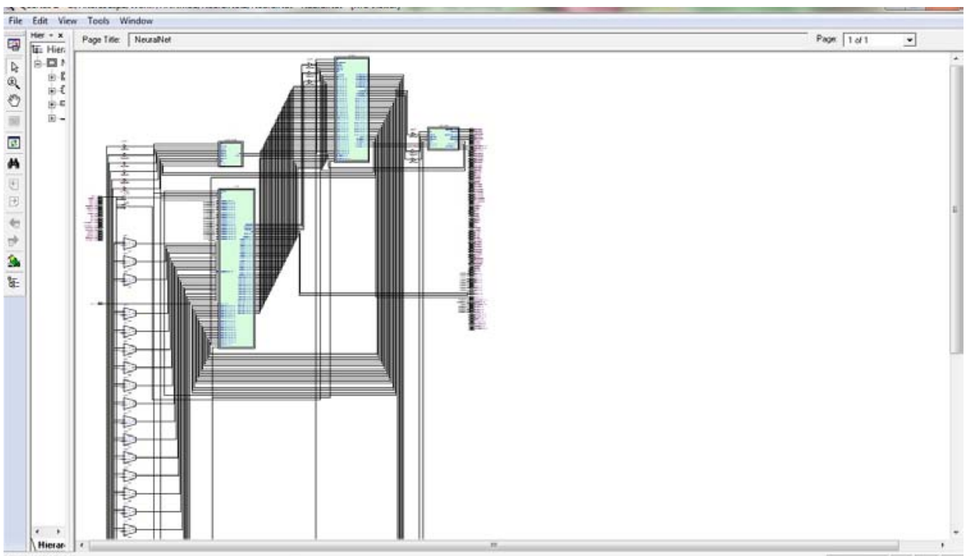


Fig. 7: Part of RTL view of the designed ANN classifier (a)

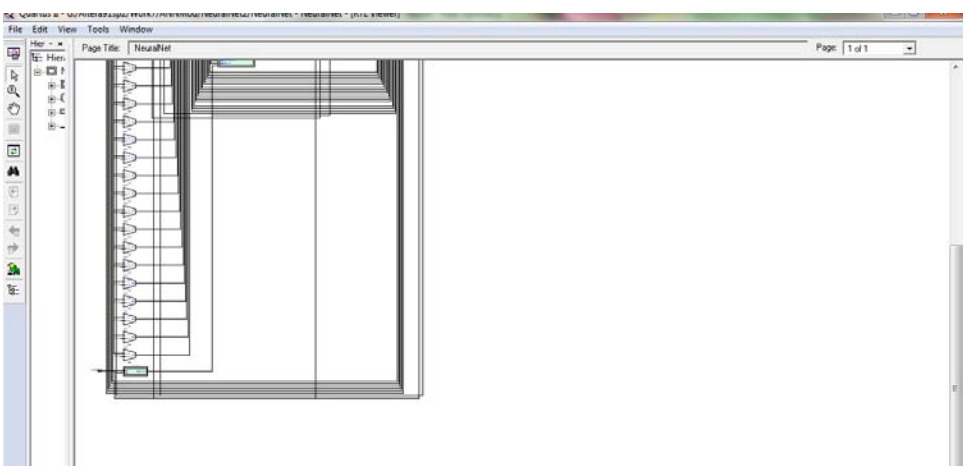


Fig. 8: Part of RTL view of the designed ANN classifier (b)

However, after a single successful training, the designed VHDL based ANN classifier can be used to classify EMG signal that will take less time. For this purpose a control flag is introduced namely fTr_Ru (flag for Training and

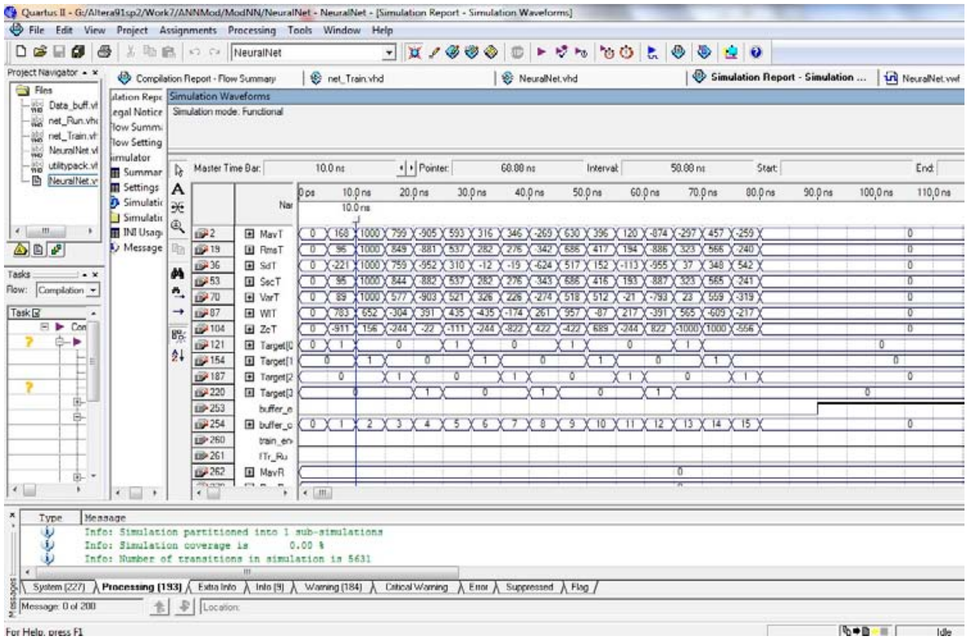


Fig. 9: Simulation output for ANN classifier (with input feature sets and targets)

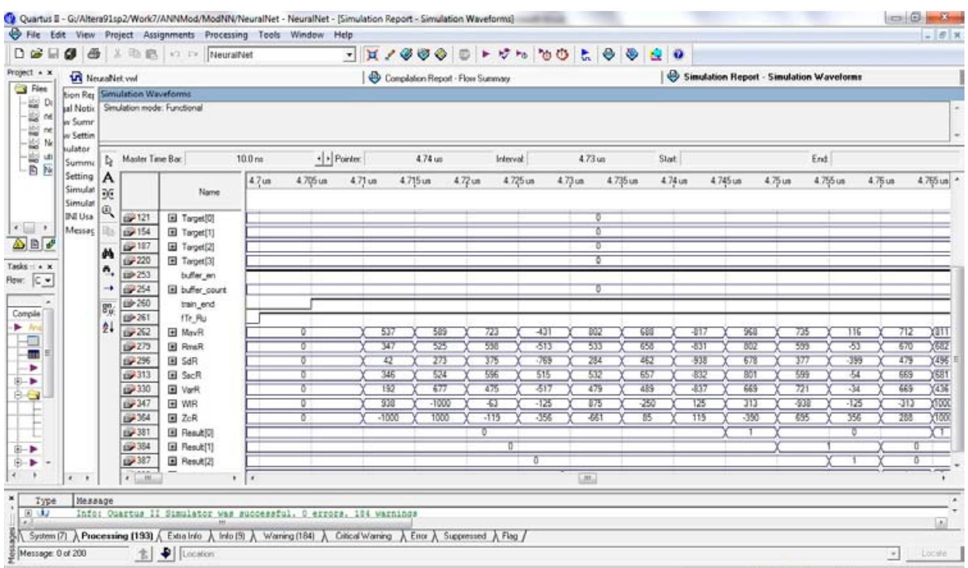


Fig. 10: Simulation output for ANN classifier (with run data and corresponding classification result)

Running), if it is set to high then the neural network will simulate to give classification result by using previously trained weights and biases. The result becomes '1' for the corresponding hand movement if the mantissa part of the output from neural network is greater than or equal to '1'. The sample simulation outputs are given in Fig. 9 and 10.

The network was tested 3 (three) times to obtain its classification performance with 12 and 11 different feature sets each time. Table 2 summarizes the classification performance of the designed VHDL model for ANN. It has been found that the average classification rate for this testing is 71.46%.

Table 2: Classification output from VHDL model of ANN

| Data set | Total movements | Classified | Misclassified | Efficiency (%) |
|---|---|---|---|---|
| dt1 | 12 | 9 | 3 | 75 |
| dt2 | 11 | 8 | 3 | 72.72 |
| dt3 | 12 | 8 | 4 | 66.67 |
| | | | Average >> | 71.46 |

## CONCLUSION

The VHDL model of ANN based EMG signal classifier has been successfully developed and its average classification performance is 71.46% in accuracy. The classification performance is not same as achieved in MATLAB, due to several reasons. Hardware model of the network is designed for 800 epochs to complete training but only 10 epochs are set for optimum structure of the network. This structure consumes 6 to 7 h to complete the training of the network. Till date, the design of neural network requires utilization of trial-error method to find out optimum structure by highly experienced person. The VHDL model of ANN has been developed directly from C++ programming based ANN structure. There are lots of variables regarding input, output and hidden layers which are related to weights and biases. In VHDL modeling, all the variables are considered. This is because, still now there is no way to find out which weights and biases are significant to obtain best classification output. Besides that, there are various iterations for every kind of calculations in each layer. As it was mentioned before that the internal calculations of VHDL model was based on modified floating point where each number is split into two parts: mantissa and exponential. All these above criteria make the network structure complex and hence huge amount of time is required during training. However, implementation of whole VHDL model in IEEE format floating point number system may reduce the time consumption but that will require expert knowledge in utilizing float type mathematical calculation.

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