FAULT TOLERANCE SIMULATION AND EVALUATION TOOL FOR ARTIFICIAL NEURAL NETWORKS

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Abstract: This paper presents the FTSET tool for fault tolerance evaluation and improvement of Artificial Neural Networks. Fault tolerance is a characteristic of parallel distributed systems such as neural networks. Although there is a built-in fault tolerance in neural networks, it is possible to improve this characteristic, but changing the structure of an artificial neural network to improve its fault tolerance is a complex task because of the non-linear activation functions that can be used in the network. The software proposed in this work performs both the evaluation of fault tolerance capabilities and the improvement of this parameter. The solution implemented here for improving the fault tolerance was proposed by the authors and is partially discussed here.

Keywords: Neural Networks, Fault tolerance, Simulator, Hardware.

1. INTRODUCTION

This paper presents a software tool for teaching, evaluating and improving the fault tolerance of an Artificial Neural Network.

Fault tolerance is a characteristic of parallel distributed systems such as neural networks. This property, though usually pointed out as one of the main advantages of the Neural Networks, is difficult to evaluate and can be a residual property allowing to maintain only a small part of the Neural Network characteristics.

The fault tolerance of the Artificial Neural Networks (ANN) can be very important in critic applications where a graceful degradation (GD) of a system is preferable to a complete failure.

In the presence of faults, a system can exhibit complete failure or its performance can degrade in a graceful way, loosing only part of its properties, depending on the extension of the faults suffered.

This property can be of extreme importance. Suppose that an artificial heart is applied to a patient. If this heart is to suffer a fault it is critic that the failure resulting from this fault is not complete, but that this heart exhibits graceful degradation because it will allow the replacement of the heart without further risk to the patient.

To evaluate and teach the concepts of fault tolerance associated with neural networks (NNs) a software tool was developed. The tool is called Fault Tolerance Simulation and Evaluation Tool for Artificial Neural Networks (FTSET) and is composed of three main sub-tools: the Insertion tool,

to receive the ANNs that were previously trained and prepared, the Evaluator, for evaluation of the tolerance and the Improver, for improving the built-in tolerance.

The FTSET is able to evaluate the fault tolerance in feedforward ANN of arbitrary size, though the bigger the network, the longer it takes to evaluate its characteristics.

The tool can be used to evaluate fault tolerance from the set of weights of the network and the ranges of the inputs. The expression fault tolerance is in fact incorrect for most of the situations, since for real valued outputs what can be achieved is GD. Each fault does in fact affect the output, but for most of the situations the effect is not catastrophic and a concept of GD applies.

The graceful degradation evaluation follows an exhaustive approach, testing all possible faults in the network (the faults mentioned here are physical faults that may happen in the hardware). It supplies a numerical analysis of the results obtained to the user and this information is then used by the Improver to build an ANN with a higher GD degree.

Changing the structure of an ANN to improve GD is a complex task since it may involve dealing with nonlinear functions such as the common activation functions hardlimit, hyperbolic tangent or other sigmoidal functions. Dias and Antunes (2007) proposed a solution that involves duplicating part of the network (inputs, neurons, bias) to improve this characteristic, after the evaluation of the critical connections in terms of output impact. The Improver implements the ideas proposed in this paper.

The proposed tool is very useful to teach the concepts of fault tolerance and GD and to illustrate these concepts associated with neural networks.

The software tool presented here is the result of the final project of the Engineering degree (5 years) in Electronics and Computers and was implemented by a group of 2 students during a full year.

2. ARTIFICIAL NEURAL NETWORKS

This section describes the types of ANNs that can be used with the FTSET tool. The tool deals with feedforward ANNs. In this type of networks, shown in figure 1, the signal flows in a single direction: from input to output. There are no lateral or feedback connections.

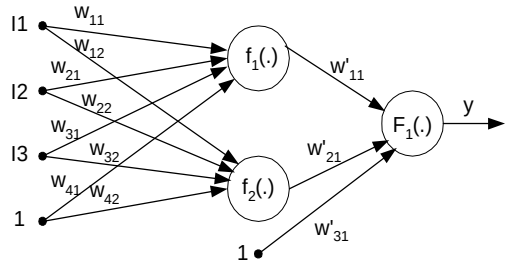

Fig. 1. Feedforward Neural Network structure.

The network of figure 1 is referred to as having an input layer, a hidden layer and an output layer. The intermediate layer is referred this way because its inputs and outputs are not directly accessible.

The activation functions can be chosen to be: Heaviside, Symmetrical Heaviside, Linear, Linear with saturation, Linear Symmetrical with saturation, Hyperbolic Tangent and Log-sigmoidal.

The FTSET does not impose a limit in the size of the network either in terms of inputs, outputs, hidden layers or number of weights. Nevertheless, the user should be aware that the larger the network is, the longer the calculations will take.

3. FAULT TOLERANCE IN ARTIFICIAL NEURAL NETWORKS

Fault tolerance has been an important topic among the Neural Network community. Although it has been mostly assumed that ANNs are inherently fault tolerant, there are several reports that study this subject: Chiu et. al (1993), Phatak (1995), Piuri et. al (1991) and Tchernev and Phatak (2005) deal with models to evaluate and represent fault tolerance; Arad and El-Amawy (1997) and Cavalieri and Mirabella (1999) consider different solutions for improving fault tolerance and Bolt (1991), Eickhoff et. al (2005), Elsimary et. al (1995) and Protzel et. al (1993) analyze ANNs in the fault tolerance perspective.

The model for representing fault tolerance in the present work was discussed in Dias and Antunes (2007) and the solution that motivated the construction of the simulator was presented in Dias and Antunes (2007b).

This solution improves the fault tolerance of a fully trained network through architecture change. The details will not be discussed here but the principle is that, independently of the activation functions, it is possible to modify an ANN while maintaining the outputs if the sum at each neuron remains the same. Based in this axiom the ANN can be analyzed for the points where a failure can have a highest impact in the output and this impact can be reduced while maintaining the outputs unchanged. This results in some of the connections being split and their weights set to half of their value.

4. THE FTSET SIMULATOR

The FTSET simulator is composed of three main sub-tools. The first one is responsible for receiving the parameters of an ANN, the second does the evaluation of the fault tolerance capabilities and the last one improves the fault tolerance capability of the ANN.

Figure 2 shows a block diagram of the FTSET simulator where the interaction of the sub-tools can be seen.

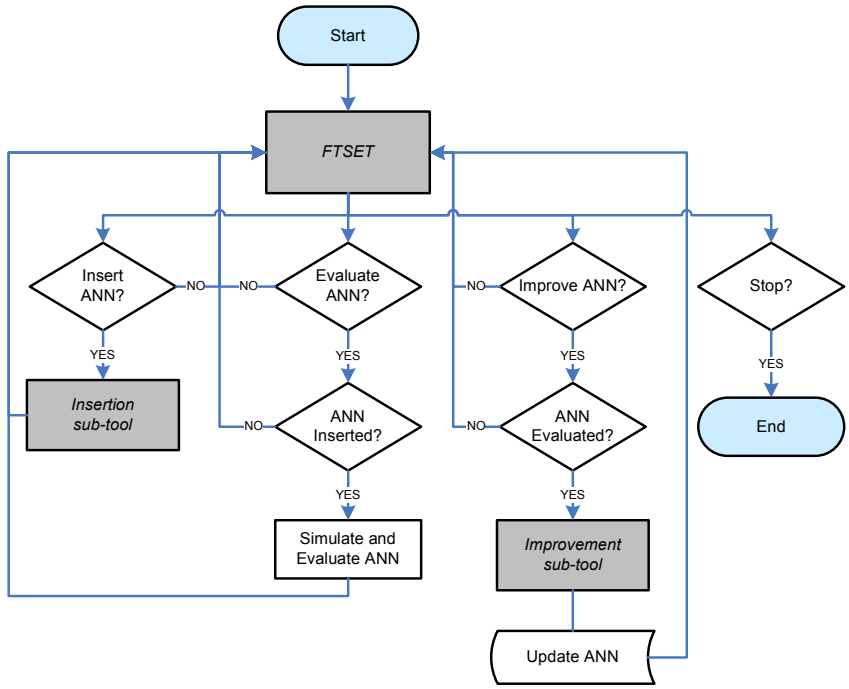

Fig. 2. Block diagram of the FTSET simulator.

4.1 The Insertion sub-tool

The Insertion sub-tool is responsible for receiving the parameters of the ANNs that will be evaluated and improved with respect to their fault tolerance. The simulator can receive networks in three different formats: an Excell format (defined in the user's manual), a Matlab file and it can also be inserted manually in the main window (see figure 3) by selecting the appropriate parameters.

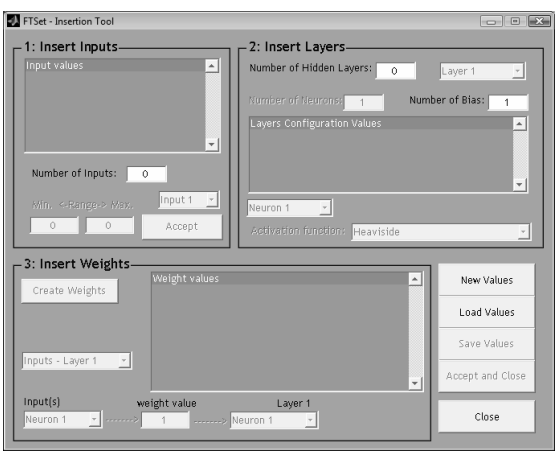

Fig. 3. Main window of the Insertion sub-tool.

4.2 The Evaluator sub-tool

The Evaluator sub-tool allows the simulation of the output of the network. The main window of this tool is shown in figure 4.

The faults are considered according to the models proposed in (Dias and Antunes 2007b).

The evaluation of the GD is done in percentage, according to the following expression:

$$GD = \frac{output\_with\_fault - output\_without\_fault}{output\_without\_fault} \qquad \text{Eq. 1}$$

To evaluate the GD, the output of the network must be calculated in several different situations. Since the input can take several values and it is not possible to consider a single value of the inputs to measure the effects of each fault, the limits in the range of values for each input will be used as a worst case value.

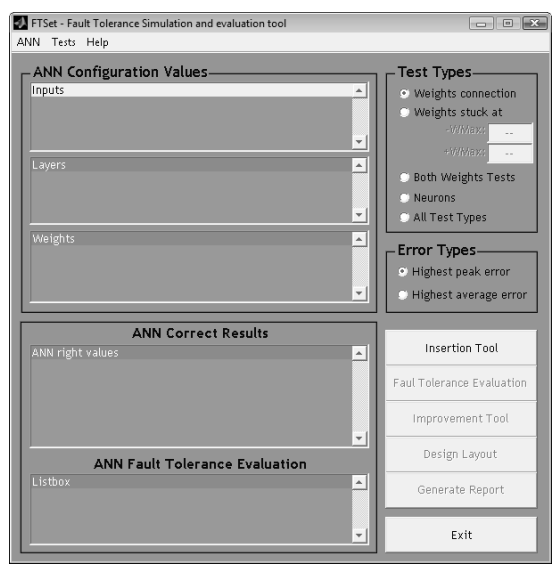

Fig. 4. Main window of the Evaluator sub-tool.

After calculating the outputs for every possible combination of the inputs ranges, a matrix of possible values for the output is obtained. For each

possible single fault, the network must be evaluated in the very same situations taken before simulating the fault, resulting for each fault in a new matrix that must be compared with the one obtained in the absence of faults.
As can be easily observed, this procedure has a rapid growth of calculations with the size of the network.
In fact the number of calculations needed can be evaluated from the size of the network through the following expressions:
The number of outputs to be calculated initially is:

$$n\_out\_calc = X^{I} \qquad \text{Eq. 2}$$

Where X is the number of possible values that the input can assume and I is the number of inputs.
The total number of weights for a network of k layers is given by:

$$n\_weights = (I+1)*K_1 + (K_1+1)*K_2 + ... + (K_{n-1}+1)*K_n + (K_n+1)*O \qquad \text{Eq. 3}$$

Where K_j is the number of neurons in the layer j and O is the number of outputs.
Equation 3 can be written as:

$$n\_weights = (I+1)*K_1 + \sum_{j=1}^{n-1}(K_j+1)*K_{j+1} + (K_n+1)*O \qquad \text{Eq. 4}$$

The number of calculations that has to be performed is then:

$$n\_calculations = (n\_weights+1)*n\_out\_calc \qquad \text{Eq. 5}$$

Or

$$n\_calculations = ((I+1)*K_1 + \sum_{j=1}^{n-1}(K_j+1)*K_{j+1} + (K_n+1)*O+1)*X^{I} \qquad \text{Eq. 6}$$

From this equation, with the size of the network to be evaluated, an estimate of the complexity of the calculations that need to be performed can be obtained.
Apart from estimating the complexity, the Evaluator has to calculate every output in the presence and absence of a fault and determine the effect of each fault according to equation1. This can be done in two different ways: searching the highest peak error and largest average error, according to the options chosen by the user in the Improver sub-tool.

4.3 The Improver sub-tool

The GD improvement tool, the Improver (whose main window is shown in figure 5), is based on the algorithm proposed in [12].
This algorithm proposes the augmentation of the GD capabilities through a two step methodology: detection of the most sensible connections or neurons to a fault and replacement of these connections or neurons by two connections or neurons which are less sensible to a fault. This results in an iterative procedure that can be applied in several different ways.
Because of this, the Improver is implemented here with several options:
At the implementation level:

- Reduce the importance of the connection that has the highest peak error introduced by a single fault.
- Replace the importance of the connection that shows the highest average error.

At the stopping condition level:

- Stopping when the limits (in terms of number of neurons and inputs) of the hardware are reached.
- Stopping after a certain number of iterations
- Stopping when the fault tolerance/GD exhibited reaches a predefined level

The options can be chosen by the user at the very beginning, resulting in different sets of weights being supplied to the user at the end.

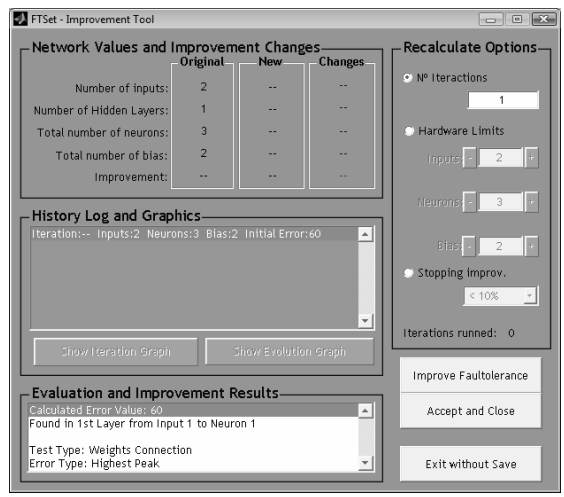

Fig. 5. Main window of the Improver sub-tool.

The FTSET shows the improvements obtained at each step and supplies the user with the configuration and the weights of the network after the GD has been improved.

5. RESULTS

This section presents an example of the simulator improving the GD of an ANN.
The network for the example is a feedforward ANN with 2 inputs, 1 hidden layer with 2 neurons and 1 output neuron. The hidden layer's activation functions are hyperbolic tangents while the output neuron has a linear function.
For the evaluation of the fault tolerance, the range of the inputs is needed. The range of both inputs can be seen in the matrix 1.

$$\begin{bmatrix} -5 & 5 \end{bmatrix} ; \begin{bmatrix} -3 & 7 \end{bmatrix} \qquad \text{mat. 1}$$

This range has to be supplied by the user. It can be determined by the knowledge of the inputs nature or by the hardware characteristics.
The weights associated with each layer of the ANN can be seen in the matrix 2.

$$\begin{bmatrix} 0.5 & -0.9 \\ -0.1 & 0.3 \\ 0.9 & -0.4 \end{bmatrix} \begin{bmatrix} 0.5 & -0.7 & 0.8 \end{bmatrix} \qquad \text{mat. 2}$$

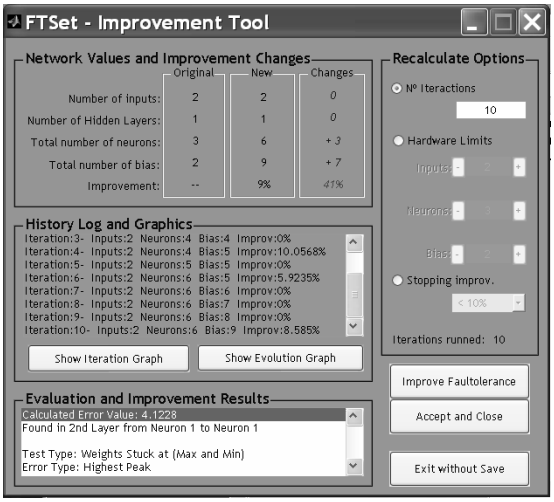

Fig. 6. Final result of the Improver.

Selecting the "weights stuck at" in the test type with the highest peak error option, the initial evaluation of the fault tolerance produces a value of 6.97. This option allows using the range of the weights as obtained from the amount of values available or selecting a different range if that is convenient for the type of implementation (for instance selecting the limits that result from a certain hardware implementation or analog to digital converter).
This value obtained by the Evaluator is the base value that the FTSET will try to improve.
For this example the Improver will work with a request of 10 iterations.
After these iterations, as can be seen in figure 6, 3 additional neurons were introduced, 7 new bias inputs were added and the fault tolerance has improved 41%. This means that the worst failure evaluated in the highest peak error mode was of 6.97 and is now of only of 4.1228.
Naturally the improvement of tolerance came at the cost of using more hardware than it was used at the initial implementation.
In Figure 7 the evolution of the relative error is shown. Here it is possible to see that some iterations do not contribute at all to improving the fault tolerance level. This can be explained quite easily. If one connection is split, because of its high impact on the output, two new connections are created with half of the weight. If afterwards these connections are evaluated as having the highest importance then two iterations are needed to solve the problem. In this situation the first of such iterations does not result in any improvement since the second iteration finds a similar fault tolerance level due to the existence of two similar weights.

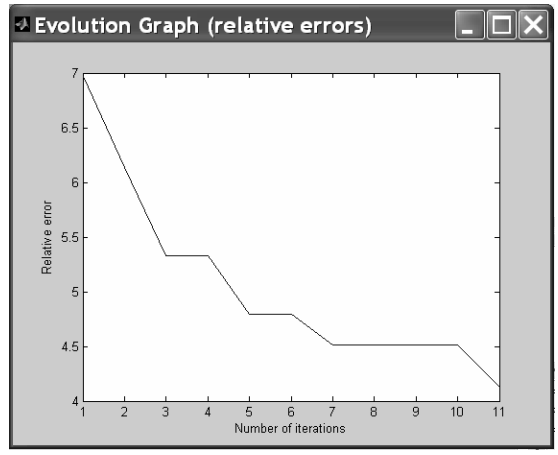

Fig. 7. Evolution of the fault tolerance level during the 10 iterations of the example.

The weights modified by the Improver sub-tool can now be saved and exported for the user to apply them where necessary.

6. CONCLUSION

The FTSET tool implements a software tool to evaluate fault tolerance/graceful degradation in NN.
The tests made show that the methodologies implemented allow assessing the GD accurately and allow improving this characteristic without the need to recalculate the weights of the network.
The utility of the FTSET is also shown here through an example where, with only 10 iterations, it was possible to enlarge the fault tolerance capability by 41% at the expense of adding 3 additional neurons and 7 additional bias inputs.
The FTSET is also very versatile when choosing how to improve the NN's graceful degradation, allowing the stopping condition to be determined by the number of iterations, the GD level or the limits of the hardware that can be physically implemented.
The use of the simulator is improving the way students learn about both ANNs and the fault tolerance subject, allowing them to explore the subject on their own and see the immediate impact that a fault produces in the output.

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