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| An Evaluation of Fast Multi-Layer Perceptron Training Techniques for Games  David Robertson  Computer Games Applications Development, 2017 |

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# Abstract

# Abbreviations, Symbols and Notation

Multi-layer perceptron - MLP

Error Back Propagation - EBP

Random-Minimum Bit Distance Gram-Schmidt - RMGS

Artificial Neural Network - ANN

Resilient propagation - RPROP

Artificial Intelligence - AI

# Introduction

TAKEN FROM PROPOSAL AND REMOVED EARLY HISTORY SECTION.

Artificial intelligence has been at the absolute core of video games since the beginning, as Alex Champandard (2004) states “since the days of Pong and Pac-man artificial Intelligence has played an undeniable role in computer games.” AI has been fundamental to keeping computer games engaging and enjoyable. Because of this, game AI has continued to develop and evolve over the years, slowly introducing more academic techniques into the field and adapting them to suit what will make the game the most fun. Although this trend has been going on for the last 40 years, games have never really found the place for artificial neural networks.

There have been a number of attempts to implement Artificial Neural Networks into video games, but nonetheless they have all done just what a far less complicated game AI technique could easily take care of. There are a number of drawbacks to using a neural network for controlling the game AI; including that if offline training is used, then once the network has been trained, it has been trained for good and can no longer learn on the fly. Online learning allows this kind of on the fly learning, but the majority of learning algorithms for neural networks are unsuitable for this and must be adapted for real-time dynamic processes (Charles and McGlinchey 2004).

The key problem with implementing an artificial neural network in a game is the training time. It takes hundreds of iterations to train the network, so if any adaptations have to be made or the training data was incorrect the entire process will have to be stopped and restarted with the updated training data. Thus there have been attempts at different methods of training a neural network in particular, the multi-layer perceptron neural network, has had many different training methods proposed to speed up learning time. Methods such as Quick Propagation and Resilient Propagation reduce some of the issues with Error Back Propagation and are "batch" methods (Champandard 2004) which inevitably speed up the process. However, they do not reduce the time significantly.

The algorithm that this project will mainly compare to error back propagation is the "Random-Minimum Bit Distance Gram-Schmidt (RMGS)" method (Verma 1997). The training time for this particular method is negligible as it trains the entire neural network in one iteration instead of hundreds. It is noted that this method is not as accurate as other methods. However, in a game scenario, it is not necessary and in some cases important, to make the AI not 100% accurate, otherwise the player would never be able to beat them. Since this method only takes one iteration to train the network, there is potential for MLPs to be able to be used and trained on the fly during a game, and if it is feasible and accurate enough, it may finally start the rise in use of this mature technique in games. This project aims to prove that feasibility.

The relevance of this project is that it aims to discover if using a faster method of training a MLP neural network will still be as accurate as using the standard error back propagation method. If this were to be successful then it would show that not only can MLP networks be trained more quickly, but also in particular, using the RMGS method, MLP networks have the potential to be retrained in real time rather than taking incredible amounts of time to be retrained.

## Research Question

Can alternative training methods for multi-layer perceptron neural networks be as effective as error back propagation in order to promote their use in games?

## Aim

This project aims to evaluate the effectiveness of different multi-layer perceptron training methods by comparing the training times, accuracy and viability of each.

# Literature Review

ALSO TAKEN FROM PROPOSAL, NEEDS FLESHED OUT

It has been proven that MLP neural networks can control a car in a racing game, for example Colin McRae Dirt 2 utilises this for its game AI, however training multi-layer perceptrons takes a lot of time and thus they are rarely used in games. This project aims to prove that alternative training methods for MLP networks can not only reduce the training time, but be as effective as the most commonly used "Error Back Propagation".

Racing games are especially good for testing MLP networks as there are many potential inputs to think about for driving a racing car around a track. For this kind of neural network, as the number of inputs increases, the harder the network has to work. This will test the Random Minimum Bit Distance Gram-Schmidt (RMGS) and resilient training methods thoroughly. These training methods will be discussed in the following sections.

## Spiking vs Multi-Layer Perceptron Neural Networks

In the paper "Spiking Neural Network vs multi-layer perceptron: who is the winner in the racing car computer game" the authors Urszulla Markowska-Kaczmar and Mateusz Koldowski created a top down racing game in which the competing networks would race against one another to aim for the best time around the track. Both of the networks are trained via genetic algorithms and given points based on their performance for further evolutions.

Spiking Neural Networks are the third generation of neural network (Markowska-Kaczmar and Koldowski 2015). They are modeled to most accurately represent a brain. Each neuron in a Spiking Neural network is given an activation voltage and the current voltage that the neuron has will be calculated by the input of the network. Once the activation voltage has been reached, a pulse will fire and the neuron will revert to the resting voltage. This means that the input of the network will not affect the size and shape of the "pulse" from the neuron; instead, it will determine when it fires. They are regarded as a "computationally powerful and biologically more plausible model of distributed computation"(Yee and Teo 2011).

This project is similar to this particular paper as it is comparing the performance of two types of neural networks in a racing game; the difference is that the comparison in this project is between two training methods for multi-layer perceptron networks instead. The paper states that the car uses ray casted sensors to follow a racing line around the track. In this project the car will also use sensors to find its position, however it will be searching for waypoints that will be placed on the track. A similar evaluation technique will also be used in this project; as the time it takes for the car to get around the track is the best measure of the performance of the training methods in a racing game scenario.

## Colin McRae Dirt 2

Colin McRae Dirt 2 is one of the only games that has been documented to use an Artificial Neural Network for controlling the AI in game. In an interview with the website "AI-Junkie" the programmer responsible for the neural network, Jeff Hannan, evaluated his work and how the process worked. The Neural network that he implemented was not extremely complex stating that "The outputs from the neural net were simply on/off flags for pressing buttons on the controller"(Buckland 2004), and that the neural net was only programmed to follow the racing line as "The AI in these other situations was simply rule based when it came to crashes and overtaking. The training method that was implemented in this neural network was resilient back propagation (RPROP).

This project could be compared to Hannan’s work and is somewhat a spiritual continuation on the AI that was implemented. For example, the output of the neural network in this project will be flags for the buttons on the "controller" and the neural network will be a multi-layer perceptron network. However, this project also has some differences including; using ray casts and waypoints around the track to steer correctly instead of following a racing line, and although resilient propagation will be implemented, the RMGS training method (which will be discussed in the next section) will be the focus of this project.

## Training Methods

### Error Back Propagation

The error back-propagation method is the most common training method for multi-layer perceptron neural networks. It works by firstly setting all of the neurons to a random weight and sending the training data through the network. Then it calculates the error of the network's output compared to the desired training data output. Following this, the error is then used to adjust the weights of the output layer's neurons; this sequence is then repeated for the hidden layers working backwards from the output layer until the entire network has been corrected. This entire process is then repeated multiple times until the calculated error reaches a minimum. (Bourg and Seemann 2004)

### Resilient Propagation

Resilient Propagation works somewhat similarly to Error Back Propagation in the sense that all the weights are updated depending on a calculated error. However, Resilient propagation does not update the weights until all of the training data has been seen. Since it is a batch algorithm a gradient must be calculated for each neuron, this is done by passing all of the training data through the network and calculating a gradient for the error on the neuron. Once this has been completed, the weights are then adjusted accordingly in relation to the gradient of error that has been calculated. (Champandard 2004)

### The Random-Minimum Bit Distance Gram-Schmidt Method

Many methods to speed up the training time of multi-layer perceptron neural networks have been proposed over the years. The training method that is going to be the main comparison to error back propagation is the RMGS method. The interesting thing about this method is that it uses different techniques to train different layers of the network. However, it only needs one iteration to be trained. Hypothesized by Brijesh Verma (1997) the method makes use of supervised and unsupervised learning for training the output layer and the hidden layers respectively. As stated by Verma(1997) "The proposed solutions are much faster and without local minima because they use direct solution methods". This makes the implementation of the method far more complicated but, once completed, the training time is negligible compared to error back propagation.

# Methodology

In this section, an overview of the how practical work was completed and discusses how each of the training techniques was implemented and tested in the game Application.

## The Game

Game Application

The game application that was created for this project was a 2D top down racing game.

The tools used to create this game were Microsoft Visual Studio 2015, Box2D and the Games Education Framework, the entire application was written in C++.

## Training

To implement the training techniques, firstly a base neural network class was created in order to keep the application more structurally sound.

Training techniques

* Error Back Propagation
* Resilient Propagation
* RMGS
  + MBD
  + Gram Schmidt
  + Linear Equations

### RMGS

The RMGS method is by far the most complex of the training techniques used in this project, however this pays off with the low training times.

There are a number of equations used to train the network using this method, to make the explanation of the technique clearer, the individual equations will be explained and then referenced in the overall explanation of the RMGS method. The first of which is Minimum Bit Distance(MBD) as seen below (Verma 1997):

This is very simply a measurement in vector similarity. X is the input vector and w is the weight vector for the neuron, n is the number of neurons in the layer and i is the current neuron. This equation simply takes the magnitude of the vector created after the weight vector is taken away from the input vector. To make sure that similar vectors do not give the same output the value of the equation before taking the square root it multiplied by the current neuron divided by the total number of neurons in the layer.

This is important as described in the paper by Verma, some vectors with similar values in different positions may give the same output without this extra multiplication.

The next equation we need to cover is the Modified Gram-Schmidt method. This is used to get the QR decomposition of Matrix X, as the Q and R matrices can then be used to solve linear equations such as:

The pseudo code to calculate the QR decomposition from (<http://www.math.iit.edu/~fass/477577_Chapter_4.pdf> ) is as follows:

for i = 1 : n

vi = ai

end

for i = 1 : n

rii = ||vi||2

qi = vi/rii

for j = (i + 1) : n

rij = qi ∗ vj

vj = vj – rij\*qi

end

end

This firstly copies the X matrix.

Next for each column in the matrix: firstly the position ii in the R matrix is set to the magnitude of vector Vi and the vector I in the Q matrix is set to Vi divided by Rii(the magnitude of Vi).

Then for each remaining column in the matrix: the position ij in matrix R is set to Qi \* Vj and then the value of Rij \* Qi is taken away from Vj.

Once this has been completed the output is the Q(orthonormal) matrix and the R(upper triangular) matrix are produced and can be used to solve linear equations.

In this project they are used to solve the over-determined system of equations:

The following must be done using the Q and R matrices from the gram Schmidt method to solve this.

Firstly y must be calculated by multiplying the transpose of Q by net:

Then since the upper triangular matrix R has already been calculated, it can be used to find the weight vector in back substitution:

And the weight matrix has been solved.

The RMGS method makes use of both of these equations in the training of the network. It trains the network as follows:

1. The weights of the first hidden layer are set to small random values between -0.5 and 0.5.
2. All of the input training sets are passed through this layer and a matrix of the ouputs is created.
3. The weights of the second hidden layer are set to input vectors from the training data.
4. Using the MBD method the matrix is then passed through the second hidden layer and another matrix is created with the outputs of the layer.
5. A linear system of equations is then created for the output layer using the desired outputs and the second hidden layer output matrix
6. using the modified gram-schmidt method to get the QR decomposition of the second layer output matrix
7. For each neuron in the output layer
   1. Using the previously discussed method of solving the linear equations, the weight vector for the neuron is calculated
8. Steps 6 and 7 are then repeated on the second hidden layer to get the actual weights of the second hidden layer using the output from the first hidden layer as X and the second hidden layer as net.

## Data Collection

Training Times

Computational Performance

Time trials

Survey collection method

# Results

Training Times

Time trial results

Human Participant Survey Results

Computational Performance

# Discussion

Discussion of Time Trial Results

Discussion of Human Racing Results

Discussion of Computational Performance Results

Final Comparison of Training Techniques

Critical Evaluation of the Solution and Application

# Conclusion

Possible Future Research

# Appendices

# List of References

# Bibliography

If required