Investigation on MLP Artificial Neural Network Using FPGA for Autonomous Cart Follower System

By

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List of Abbreviations

| Abbreviation | Meaning | | | |
|--------------|--|--|--|--|
| ADC | Analogue Digital Converter | | | |
| ALVINN | Autonomous Land Vehicle in a Neural Network | | | |
| ANN | Artificial Neural Network | | | |
| ASIC | Application-Specific Integrated Circuit | | | |
| BPDLR | Backpropagation with Declining Learning-rate Factor | | | |
| BPLRF | Backpropagation with Plummeting Learning-rate Factor | | | |
| BR | Bayesian regularization | | | |
| СМ | Committee Machine | | | |
| CPU | Central Processing Unit | | | |
| DEA | Differential Evolution Algorithm | | | |
| DSP | Digital Signal Processor | | | |
| FIFO | First-In-First-Out Buffer | | | |
| FPGA | Field Programmable Gates Array | | | |
| FLP | Floating-Point Arithmetic | | | |
| FPS | Frames per Second | | | |
| FPU | Floating-Point Processing Unit | | | |
| FSM | Finite State Machine | | | |
| FXP | Fixed-Point Arithmetic | | | |
| GA | Genetic Algorithm | | | |
| GAMLP | Genetic Algorithm trained Multilayer Perceptron | | | |

| GNA | Gaussian Newton algorithm | | | |
|---------------------------------------|---|--|--|--|
| GPIO | General Purpose Input / Output | | | |
| GUI | Graphical User Interface | | | |
| HDL | Hardware Description Language | | | |
| ISP | In-System-Programming | | | |
| LE | Logic Element | | | |
| LM | Levenberg-Marquardt | | | |
| MIPS | Million Instructions per Second | | | |
| MLP | Multilayer Perceptron | | | |
| MSE | Mean Square Error | | | |
| | Phase-Lock Loop | | | |
| PLL | Phase-Lock Loop | | | |
| PLL PWL | Phase-Lock Loop Piece-Wise Linear Approximation | | | |
| | - | | | |
| PWL | Piece-Wise Linear Approximation | | | |
| PWL PWM | Piece-Wise Linear Approximation Pulse Width Modulation | | | |
| PWL PWM R | Piece-Wise Linear Approximation Pulse Width Modulation Correlation Value | | | |
| PWL PWM R RAM | Piece-Wise Linear Approximation Pulse Width Modulation Correlation Value Random Access Memory | | | |
| PWL PWM R RAM RMSE | Piece-Wise Linear Approximation Pulse Width Modulation Correlation Value Random Access Memory Root Mean Square Error | | | |
| PWL PWM R RAM RMSE RTL | Piece-Wise Linear Approximation Pulse Width Modulation Correlation Value Random Access Memory Root Mean Square Error Register-Transfer Level | | | |

PENYELIDIKAN RANGKAIAN NEURAL BUATAN MLP DALAM FPGA MENGGUNAKAN SISTEM PEDATI PENGIKUT AUTONOMI

Abstrak

Dengan kos alat pengesan yang semakin rendah, masa depan sistem pedati pengikut autonomi akan dilengkapi dengan lebih banyak alat pengesan. Ini menjadi cabaran rekabentuk dalam mengendalikan data besar dan kerumitan perkukuhan. Kebanyakan sistem yang sedia ada menggunakan papan mikropengawal yang mempunyai prestasi yang terhad dan pengembangan tidak mungkin tanpa penggantian yang lebih baru. Projek ini mencadangkan perlaksanaan alternatif sistem pedati pengikut autonomi dengan model rangkaian neural MLP menggunakan FPGA. Sistem pedati pengikut autonomi yang mengguakan papan mikropengawal telah diubah suai untuk menggunakan papan FPGA dan dilaksanakan melalui Sistem pada Chip (SOC). System rangkaian neural dilatih dalam simulasi dengan vektor latihan yang dikumpul daripada sistem pedati pengikut autonomi yang sedia ada. System rangkaian neural kemudian dilaksanakan sebagai perkukuhan dalam SOC itu. Dalam pemerhatian, jejak perkukuhan model rangkaian neural kekal saiz kecil tanpa mengira saiz rangkaian neural. Hasil kajian menunjukkan bahawa dengan penggunaan sumber tambahan sebanyak 40%, penambahbaikan sistem secara keseluruhan sebanyak 27 kali dicapai dengan penggunaan blok pecutan perkakasan di SOC, berbanding dengan SOC tanpa penggunaan blok pecutan perkakasan.

INVESTIGATION ON MLP ARTIFICIAL NEURAL NETWORK USING FPGA FOR AUTONOMOUS CART FOLLOWER SYSTEM

Abstract

The future of the autonomous cart follower system will equipped with lots of sensory data, due to the ever lower cost of sensory device. This provides design challenge on handling large data and firmware complexity. Most of the existing systems are implemented via usage of microcontroller board, which has limited performance and expansion is not possible without replacement of newer board. The project proposes an alternative approach of running the autonomous cart follower systems on neural network model using Field Programmable Gates Array (FPGA). A microcontroller based autonomous cart follower systems is modified to use the FPGA board and implemented via the System on Chip (SOC) approach. The neural network is trained offline in simulation tools with training vector collected from running the existing autonomous cart follower systems. The trained neural network model then implemented as software code in the SOC. By observation the firmware footprint of the neural network model remains small size regardless of the neural network size. The result shows that with 40% more additional resource utilization, the overall system improvement of 27 times is achieved with the usage of hardware acceleration block in SOC compared to SOC without hardware acceleration.

CHAPTER 1 : INTRODUCTION

1.1 Overview

Autonomous cart following system is not a new concept as automated guided carts are being introduced since 1950s. Those systems are designed to following different type of navigation. Some systems implement the line-follower methodology, where the cart will follow the underground wire, or guided tape. Other system use vision based navigation, which use the camera to capture and process the designated destination path. While most of the autonomous carts following systems are commonly used in industry, the interest of the usage of such system is just started to attract focus in our daily life recently.

One of the beneficial usages of such system is to develop an autonomous cart follower for wheelchair user. The cart could be design to follow the user when moving around with loaded items. However, extra caution has to be given on such implementation as these involve human activity and safety is of high priority here. A cart system with better precision and responsiveness is greatly needed.

Multilayer perceptron (MLP) is one of the simple feedforward neural networks implemented, where the information flows from the input layer through the hidden layer

to the output layer, without any loop or cycle. The MLP network could be used to learn the generalization, classification or pattern recognition based on the supervised training vectors. To train the MLP network, there are many learning techniques could be used; backpropagation is one of the chosen techniques in this paper.

In MLP network, each node in the layer has different weight as the input of the activation function of the downstream nodes. To train the MLP network, a set of sampled data is needed to feed through the network. This weight of the node will then be tuned till the error computed from the comparison between the output value and the sampled output is acceptably small. Thus, large numbers of training cycles need to be performed to archive the desired outcome.

1.2 Problem Statement

Current developments of autonomous cart following system rely on the microcontroller to process the input data, and to determine the control output. Such implementation would require developer to hand coding write firmware program to run on the microcontroller board, to process the control tasks above mentioned. The complexity of the firmware code usually proportional to the number of the sensor input and the control output, and most importantly the level of processing rules applied in the system. If the developer wishes to deliver a sophisticated system for better precision and responsiveness, then there is possibility that the firmware structure will become complicated for hand coding and maintenance. The resulted firmware code might as well too complicate to be processed by the microcontroller in the system, as most microcontrollers are not designed for performance. Besides, the ever increasing firmware footprint will become a challenge for fitting in the limited memory size in the microcontroller system.

The project is investigating the implementation of the artificial neural network in the autonomous cart following system, which implemented via Field Programmable Gates Array (FPGA). Multiple sensor inputs will be feed through the MLP network and the output result is compared to train the neural network. Training cycles will be repeated till the artificial neural network is learned to produce control output with minimal error rate relatively the sampled control data. Such approach offers an alternative cart following implementation, where the artificial neural network is used as the control system. In this scenario, developer emphasize on the training MLP network rather than optimizing the firmware code.

1.3 Objective

The aim of the project is to investigating the implementation of autonomous cart follower system running on MLP artificial neural network using FPGA.

1. To implement the MLP neural network in the FGPA system for autonomous cart follower.

2. To compare the performance between SOC system with/without hardware acceleration.

1.4 Scope of Work

In order to achieve the aim of the project, the artificial neural network system will be used for the autonomous cart following system on FPGA. The artificial neural network system will be developed and with cart sensor input and output as the input node and output node of the network.

An existing microcontroller based autonomous cart following system will be used to gather the sensor input and control output data. The artificial neural network will be trained with the sampled data and repeated till the result is achieved with minimum error rate. MLP neural network is the chosen model for the project. The microcontroller board of the system will then be replaced with FPGA board for neural network realization of the system.

1.5 Thesis Organization

This project is organized into five organized into five chapters. Chapter 2 review the existing works have been done on the autonomous cart following system, with some improvement of the system via the assistance of the artificial neural network. It also includes an introduction of the multilayer perceptron (MLP) neural network and how

the artificial neural network is developed and trained. Lastly the implementations of neural network on FPGA will be presented.

Chapter 3 discuss on the methodology to develop the MLP artificial neural network system, and the work to setup the architecture for the cart following system. Some work will be evaluating the technique used to train and optimize the system, in order to produce the desired control output. The software coding guidance for efficient result is discussed here.

Chapter 4 will discuss the result produced from implementing the artificial neural network system. Beside, some limitation of the project will be discussed here.

Chapter 5 will conclude the result of the paper. The project will discuss on how the MLP network is implemented in System-on-Chip (SOC) design approach and executed in a cart following system. The evaluation of the system performance will be discussed here.

CHAPTER 2 : LITERATURE REVIEW

Chapter 2 review the existing works have been done on the autonomous cart following system, with some improvement of the system via the assistance of the artificial neural network. It also includes an introduction of the multilayer perceptron (MLP) neural network and how the artificial neural network is developed and trained. Lastly the study of the neural network implementations on Field Programmable Gate Array (FPGA) will be presented.

2.1 Autonomous navigation system

2.1.1 Laser target navigation system

One of the autonomous navigation systems is to use laser transmitter and receiver for detecting the following target. For pulse laser radar system, the angle of the target is based on the reflected pulse to the turret position. With the conventional approach, the time of flight method is used here to calculate the distance of the target, based on the time interval between the reference pulse value and reflected pulse value. Joodaki, Kompa et al. (2001) suggest that using the neural network in such system could improve the resolution and speed of measurement, which the trained neural network could produce the distance information just by feeding in the reflected laser value (Table 2-1). The result also shows that the neural network has 86% best case improvement on standard deviation on distance measurement, compared to the standard

method. And such resolution only can be outmatched by standard method if the input averaging on 32 sampling data, which increase latency.

Table 2-1 Comparison of result resolution between standard method and neural network model (Joodaki, Kompa et al. 2001)

| Number of average | Standard method | | Neural method | |
|-------------------|--------------------|----------------------|--------------------|----------------------|
| | Standard deviation | Maximum deviation | Standard deviation | Maximum deviation |
| | [um] | [um] | [um] | [um] |
| 1 | 1200 | 4560 | 168 | 410 |
| 4 | 470 | 1570 | 110 | 241 |
| 16 | 230 | 720 | 67 | 174 |
| 32 | 150 | 420 | 53 | 149 |

2.1.2 Vision guided autonomous system

There have been researches done on the implementation of neural network on the automated guided vehicle. Dean (1993) with project Autonomous Land Vehicle in a Neural Network (ALVINN) demonstrates the utilization of the multilayer perceptron network (MLP) in learning to control the steering wheel of the vehicle. To train the system, a human driver is required to drive the vehicle while the cameras in front of the vehicle capture image and feed the input nodes of the network. The output nodes of the network are produced to determine the angle of the steering direction. The vehicle is able to run up to 70 mph on the 90 miles autonomous drive on public highway.

Such implementation does not require predefined line of path nor distance measurement, as the images captured during training cycles will used to learn steer as the human driver do down the roads. However, the effectiveness of the network relies on the environment of the training as it is limiting to the variation of the road types that have been seen by the cameras. There is no emergency handling during the autonomous drive, as the network only recognizes the recorded human driver's response during the training cycles. While the junction, traffic light, and ramp are not part of the training inputs, these would provide as obstacle for the project from implementing in daily life.

2.1.3 Microcontroller based autonomous cart follower system

Sani, bin Syed et al. (2012) present a wireless cart follower system using PIC18F4550 microcontroller board, which running at 48MHz frequency with performance benchmark of 12 MIPS. The PIC microcontroller only has 32KB flash program memory and 2KB data memory (PIC18F2455/2550/4455/4550 Data Sheet). The chip has an Analogue Digital Converter (ADC) which supports up to 13 channels of 10 bit resolution output. To program the PIC chip, a special PICkit2 Programmer device is needed. The In-System-Programming (ISP) method is used here to program the flash memory of the PIC chip after placed on the microcontroller board.

The autonomous cart follower system consists of other controller board and sensory parts to form the framework design (Figure 2-1). The input sensory devices built with

the CMUCAM3 camera and GP2D120 infrared distance sensor. The CMUCAM3 camera is used for the visual object detection and provides the horizontal location offset of the target. In this system, red colour object is chosen as the choice for detection. The infrared distance sensor is to provide collision avoidance and distance measurement of the target within line of sight.

The motor controller board used is the MD30B Enhanced 30A Motor Driver board, which capable to supply driving current up to 30A peak. In this system, a windscreen wiper motor is used as the cart forward and reverse motor and the motor driver board output is sufficient to drive the motor in various speed. For the steering of the cart moving direction, a hexTronik HX12K standard metal gear servo motor is used to control the angle of the front moving wheels. The servo motor is capable with one side operation angle of 45 degree.

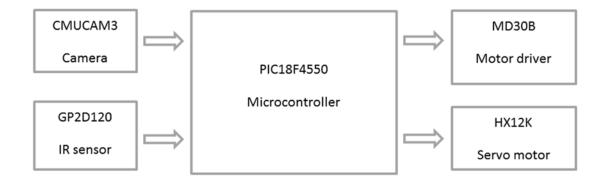


Figure 2-1 PIC microcontroller based autonomous cart follower system diagram

The purpose of the autonomous cart follower system project is to provide load carrying support for wheelchair users to move heavy and sizable object like luggage.

2.1.4 Neural network in motor control system

Feedforward neural network usage in motor control is now a popular topic on how to improve the non-linear handling and reduce the noise of the input value. Secco and Magenes (2002) have suggested that the neural network could be used as the control system for dynamic motor system to achieve a more natural movement. The generalization of the trained neural network could be used to control the dynamic motor system for any newly input movement command and retained the human-like natural movement.

Kaminski, Orlowska-Kowalska et al. (2014) present a neural network based speed controller for elastically connected motor system, where the speed control error due to transient of the motor state variables could be reduced. In this system, the motor speed and shaft torque are both feed into the neural network for higher precision output. This selection of inputs achieves better reduction of torsional vibration than neural system with just motor speed as the single input variable. Tatikonda and Agarwal (2008) present a neural network control system for induction motor drive system which implemented on a Field Programmable Gate Array chip (FPGA). Such implementation has advantages on the flexibility, cost and the speed of parallel processing of the network logic in the FPGA. This neural network system improve the fault tolerance of the motor control system as drive topology could be configured for continuous operation during the event of single leg breakdown.

2.2 Multilayer Perceptron neural network

2.2.1 Feedforward neural network

Multilayer perceptron (MLP) neural network is a feed forward neural network, which the flow of the network information is unidirectional from the input nodes to the output nodes. The MLP neural network consists of basic layers of input nodes, output nodes and hidden nodes (Figure 2-2). Each layer of nodes is connected to the downstream nodes with the connection carried different weight on the input to the receiving nodes. The nodes are described as neuron and the connections are synapses in the neural network terminology. The neuron output consists of the product of all weighted input with the activation function. The activation function is the transfer function which mostly are hyperbolic tangent or logistic sigmoid.

The purpose of MLP neural network could be used for approximation, generalization, classification. To achieve this purpose, the weight on the MLP nodes connections have to be tuned and this process is called the training of the neural network. One of the commonly used techniques for neural network training is backpropagation algorithm, which the gradient descent method is used for weight calibration. A set of training vector of sampled input and output will feed through the neural network during training phase, till the acceptable error rate is achieved. The total training cycles are the epochs of the training phase, for complicated topology, the number of epochs might need to be larger to achieve the convergence.

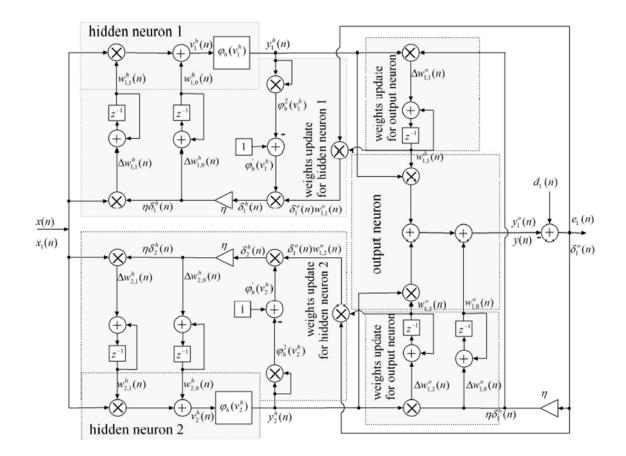


Figure 2-2 one-two-one multilayer perceptron architecture (Bahoura and Park 2011)

2.2.2 Optimization on the training methodology

The convergence of the training phase could be accelerated with the some modification over the gradient descent method. Alizadeh, Frounchi et al. (2008) use the backpropagation with plummeting learning rate factor (BPLRF) and backpropagation with declining learning-rate (BPDLR) to train the network, able to achieve reasonable total sum square error within 300 epochs. Such approaches purposely choose the last ending epochs to have smaller learning rate and step size to prevent network being destabilized and achieve smaller recognition error.

Several researches have been done on improving the MLP neural network training phase performance, and some modified backpropagation technique has been present. Bahoura and Park (2011) have presented a pipelined adaptive MLP neural network on FPGA. This architecture takes the advantage of parallelism from FPGA chip, and implements a modified pipelined backpropagation algorithm with delayed weight updating rules. The result has shown that such implementation is able to achieve performance improvement up to 4 times over the unmodified backpropagation algorithm implementation.

One of the limitations of the backpropagation algorithm is that the convergence might happen at the local minimum. Amudha, Venkataramani et al. (2008) develop a neural network digital recognition system with modified backpropagation algorithm to overcome this training problem, by using logarithmic error function as the targeted error reduction threshold. The observed convergence result is 2.62 times faster than the original backpropagation algorithm.

Yilmaz, Erkmen et al. (2014) propose to use the differential evolution algorithm (DEA) to train the MLP neural network for the simplicity of the algorithm. However, such implementation utilizes higher area usage and slightly lower accuracy compared to software simulation. To achieve higher network performance, more epochs and