

**A Real Time Visual Monitoring Module for Traffic Conditions  
Based on a Modified Auto-Associative Memory**

BY

EMAD ISSA ABDUL KAREEM

Thesis submitted in fulfillment of the requirements for the degree of  
Doctor of Philosophy

April, 2012

**Modul Pemantauan Tampak Masa Sebenar bagi Keadaan Lalu  
Lintas berdasarkan Ingatan Autosekutu Terubah Suai**

**OLEH**

**EMAD ISSA ABDUL KAREEM**

**Tesis ini diserahkan sebagai memenuhi keperluan pengijazahan  
Doktor Falsafah**

**April, 2012**

## **Acknowledgements**

I am heartily thankful to my supervisor, Dr. Wafaa A.H Ali Alsalihi, whose encouragement, guidance and support me to develop a better understanding of this research. Additionally, I wish to thank my family for supporting me. I am grateful to my parents who has brought me up and taught me many things. I would also like to express my gratitude to my wife for her patience and love.

I would like to express my appreciation to USM for awarding the postgraduate research grant and fellowship. Finally, I offer my regards and blessings to all of those in the school of computer science who have supported me in any respect during the completion of the project, including Dr. Rosalina and Dr. Munir.

## Tables of Contents

Acknowledgement .....	II
Table of Contents .....	III
List of Table .....	VII
List of Figures .....	VIII
List of Abbreviations .....	XI
List of Symbols .....	XII
Abstrak .....	XIII
Abstract .....	XV

### CHAPTER ONE: INTRODUCTION

1.1 Introduction .....	1
1.2 Problem Statement.....	4
1.3 Research Objectives .....	6
1.4 Scope of Research.....	6
1.5 Proposed Solution.....	7
1.6 Research Methodology.....	9
1.7 Organization of Thesis.....	10

### CHAPTER TWO: LITERATURE REVIEW

2.1 Traffic Light System.....	11
2.1.1 Traffic Light System without Visual Monitoring Module.....	11
2.1.1.1 Knowledge Based Traffic Light Systems.....	12
2.1.1.2 Fuzzy logic-Based traffic light system.....	13
2.1.1.3 Petri Net-Based Traffic Light Systems.....	16
2.1.1.4 Extension Neural Network (ENN)-Based Traffic Light Systems.....	17
2.1.1.5 Reinforcement Learning-Based Traffic Light Systems.....	18
2.1.1.6 Genetic Algorithm-Based Traffic Light Systems.....	18
2.1.1.7 Summary of Literature Review.....	19
2.1.2 Traffic Light Systems with a Visual Monitoring Module.....	20
2.1.2.1 Traffic Light Systems Using a Background Subtraction Monitoring Module.....	21
2.2 Associative Memory.....	24
2.3 Hopfield Neural Network.....	26
2.3.1 Hopfield Neural Network Architecture.....	26

2.3.2 Hopfield Neural Network Algorithm.....	27
2.3.3 Hopfield Neural Network Applications.....	28
2.3.4 Energy Function (Lyapunov Function).....	30
2.3.5 Hopfield Neural Network Limitations.....	31
2.3.6 Modified Hopfield Neural Network.....	33
2.3.6.1 Hopfield Neural Network Modifications to Improve its Efficiency.....	33
2.4 Summary.....	36

**CHAPTER THREE: A REAL TIME VISUAL TRAFFIC MONITORING MODULE**

3.1 Introduction.....	38
3.2 Design of Real Time Visual Traffic Monitoring Module.....	39
3.2.1 Video to Image Convert Phase.....	40
3.2.2 Edge Detection Filter.....	41
3.2.3 Bipolar Conversion phase.....	41
3.2.4 The MCA Associative Memory.....	41
3.2.4.1 Architecture of the MCA.....	42
3.2.4.2 The MCA Algorithm.....	43
3.2.4.3 MCA complexity.....	53
3.2.4.4 MCA Examples.....	55
3.2.5 Training Phase.....	64
3.2.6 Analyzing Phase.....	64
3.3 Summary.....	64

**CHAPTER FOURE: EXPERIMENTAL RESULTS AND DISCUSSION**

4.1 Introduction.....	66
4.2 The Required Components.....	66
4.2.1 Hardware Components.....	67
4.2.2 Software Components.....	67
4.3 MCA Evaluation.....	67
4.3.1 Experiment 1.....	68
4.3.2 Comparison between the MCA and the Hopfield Neural Network.....	70
4.3.2.1 Network Architecture.....	70

4.3.2.2 Learning Phase.....	71
4.3.2.3 Convergence Phase.....	75
4.3.3 Summary of Comparison.....	79
4.4 RTVTM Module Evaluation.....	80
4.4.1 Camera Setup.....	80
4.5 Real World Evaluation of the RTVTM Module.....	86
4.5.1 Daytime Tests.....	89
4.5.1.1 Sunny Weather Condition .....	89
4.5.1.2 Cloudy Weather Condition .....	90
4.5.1.3 Rainy Weather Condition.....	92
4.5.2 Night time Tests.....	94
4.5.2.1 Normal Weather Condition.....	94
4.5.2.2 Rainy Weather Condition.....	96
4.5.3 Analysis and Discussion .....	97
4.6 Comparison with Other Works.....	97
4.6.1 The Procedure .....	98
4.6.2 Day Time Evaluation.....	100
4.6.2.1 Sunny Weather Condition.....	100
4.6.2.2 Cloudy Weather Condition.....	102
4.6.2.3 Rainy Weather Condition.....	105
4.6.3 Night Time Evaluation.....	107
4.6.3.1 Normal Weather Condition.....	107
4.6.3.2 Rainy Weather Condition.....	110
4.6.3 Quantitative Comparison.....	112
4.6.4 Summary of Comparisons.....	113
4.7 Summary.....	115
<b>CHAPTER FIVE: CONCLUSION AND FUTURE WORK</b>	
5.1 Conclusions.....	116
5.2 Research Contribution.....	119
5.3 Future work.....	120
<b>List of Publication</b>	
List of Publication .....	121

**References**

References..... 123

**APPENDIXES**

Appendix A..... 140  
Appendix B..... 148  
Appendix C..... 164  
Appendix D..... 168

## LIST OF TABLES

		<b>Page</b>
Table 2.1	Summary of the techniques used with the traffic light systems in terms of ability and efficiency	22
Table 3.1	All the possible vector states	45
Table 3.2	The bipolar representation for all possible vectors with their decimal code and corresponding <i>svw</i> array in the lookup table	47
Table 3.3	The vectors versus there corresponding majority description ( <i>MD</i> )	48
Table 3.4	The energy function values corresponding to each vector	52
Table 3.5	Lookup table of the MCA network which is used to store (P1 and P2)	59
Table 3.6	The summation of the energy functions for both patterns (P1 and P2)	61
Table 4.1	Training phase of RTVTM	83
Table 4.2	Results of the sunny weather condition	90
Table 4.3	Results of the cloudy weather condition	91
Table 4.4	Results of the Rainy weather condition	93
Table 4.5	Results of the normal weather condition	95
Table 4.6	Results of the rainy weather condition	96



## LIST OF FIGURES

		Page
Figure 1.1	A general framework for the proposed RTVTM module	8
Figure 1.2	Research methodology flow	10
Figure 2.1	Block diagram of an associative memory	24
Figure 2.2	Hetero-association response	25
Figure 2.3	Auto-association response	26
Figure 2.4	Single-layer $n$ -neurons Hopfield network architecture	27
Figure 2.5	Hopfield neural network algorithm	28
Figure 2.6	An example of the behavior of a Hopfield network when it is content-addressable memory	29
Figure 2.7	Local and global minima	32
Figure 3.1	Traffic light system	38
Figure 3.2	The RTVTM module using an MCA associative memory	40
Figure 3.3	The Multi-Connect Architecture (MCA) associative memory	43
Figure 3.4	The MCA learning algorithm	44
Figure 3.5	A training pattern is divided into $k$ vectors, each with three elements	45
Figure 3.6	All the possible vectors with their weight matrices	46
Figure 3.7	MCA associative memory weight matrices	47
Figure 3.8	Lookup table for all $n$ stored patterns	49
Figure 3.9	Training pattern with its corresponding array in the lookup table	49
Figure 3.10	The convergence algorithm for the MCA	51
Figure 3.11	MCA convergence of the unknown pattern towards one of the stored patterns	54
Figure 3.12	Two patterns (P1 and P2)	57
Figure 3.13	Pattern P is presented in this example	59
Figure 3.14	The converged pattern $CP$	63
Figure 3.15	The convergence phase for example 3.3	63
Figure 4.1	MCA architecture with 4 weights corresponding to each connection.	69
Figure 4.2	Average of convergence rates for MCA	70
Figure 4.3	The Hopfield network architecture deals with patterns of	71

	64×64 pixel size	
Figure 4.4	A comparison between the MCA and the Hopfield networks with respect to different patterns size	71
Figure 4.5	The learned vehicle patterns of the Hopfield network and the MCA associative memory with their convergence patterns	72
Figure 4.6	A comparison between the capacity network of MCA and the Hopfield network when storing and retrieving vehicle patterns of the size 64×64 pixels	73
Figure 4.7	A Comparison between MCA and the Hopfield networks with respect to the weight sizes of different patterns size	75
Figure 4.8	Average of convergence rates for Hopfield neural network	76
Figure 4.9	A comparison between the Hopfield neural network and MCA for 100 tests	77
Figure 4.10	The standard deviation for the 100 tests results for both the Hopfield neural network and the MCA	77
Figure 4.11	A comparison between MCA and the Hopfield network with respect to the convergence of inverse values of different patterns	78
Figure 4.12	A comparison between MCA and the Hopfield network with respect to the local minimum convergence of different patterns	79
Figure 4.13	(a) A view from the top of the street. (b) A side view of the street	80
Figure 4.14	Camera setup positions	81
Figure 4.15	The number of ground truth images for both normal and crowded traffic condition	82
Figure 4.16	RTVTM comparison with the ground truth with a recall value equals 0.360	84
Figure 4.17	A comparison of RTVTM with ground truth when the recall value is 0.692	84
Figure 4.18	A comparison between RTVTM and ground truth when the recall value is 0.538	85
Figure 4.19	A comparison between RTVTM and the ground truth when the recall value is 0.692	85
Figure 4.20	A comparison between RTVTM and the ground truth when the recall value is 0.891	86
Figure 4.21	A comparison between RTVTM and the ground truth when the recall value is 0.999	86

Figure 4.22	List of the edge detection filters used in the evaluation	88
Figure 4.23	Recall values with their ground truth	100
Figure 4.24	The processing step with image sample 1	101
Figure 4.25	The processing step with image sample 2	102
Figure 4.26	The processing step with image sample 3	103
Figure 4.27	Recall values for the images compared with the ground truth	103
Figure 4.28	The processing step with image sample 4	104
Figure 4.29	The processing step with image sample 5	105
Figure 4.30	Recall values for the images compared with their ground truth	106
Figure 4.31	The processing step with image sample 6	106
Figure 4.32	The processing step with image sample 7	107
Figure 4.33	Recall values for the images compared to their ground truth	108
Figure 4.34	The processing step with image sample 8	109
Figure 4.35	The processing step with image sample 9	110
Figure 4.36	Recall values for the images compared to their ground truth	110
Figure 4.37	The processing step with image sample 10	111
Figure 4.38	The processing step with image sample 11	112
Figure 4.39	Quantitative comparisons between the proposed real time visual monitoring module and the Deng and Lee (2006) work	113
Figure 4.40	A view that covers two sides of a street	114

## **List of Abbreviations**

ENN	Extension Neural Network
TOD	Time Of Day
VHDL	Very High Description
VHSIC	Very High Speed Integrated Circuit
NMR	Nuclear Magnetic Resonance
MRS	Magnetic Resonance Spectroscopy
PC	Paging Cells Scheme
BDT	Boll Dropping Technique
HNN	Hopfield Neural Network
MHNN	Modified Hopfield Neural Network
MCA	Multi-Connect Architecture
RTVTM	Real Time Visual Traffic Monitoring

## List of Symbols

<i>md</i>	Majority description
<i>smd</i>	Stored vector majority description
<i>svw</i>	Stored vector weight
<i>tvw</i>	Test vector weight
<i>minp</i>	Stored pattern number with minimum energy function
<i>tempcv</i>	Temporary converge vector
<i>rmd</i>	Result vector majority description

# **Modul Pemantauan Tampak Masa Sebenar bagi Keadaan Lalu Lintas berdasarkan Ingatan Autosekutu Terubah Suai**

## **Abstrak**

Suatu trend baru bagi modul pemantauan lampu isyarat adalah modul yang menggunakan data visual masa sebenar dan pendekatan visi komputer bagi menggambarkan keadaan lalu lintas semasa (sibuk, normal dan lengang). Pendekatan ini menentukan keadaan lalu lintas dengan cara mengira kenderaan di jalan raya menggunakan teknik yang kompleks. Walau bagaimanapun, teknik ini mempunyai batasannya. Namun, batasan ini boleh ditangani apabila suatu jumlah besar kenderaan di jalan raya dikesan sebagai suatu kumpulan dan bukannya sebagai individu. Teknik ini boleh dicapai dengan menggunakan ingatan bersekutu automatik.

Tesis ini mencadangkan suatu modul pemantauan baru yang menggunakan ingatan bersekutu Hopfield, yang diubah suai dan dibangunkan untuk disesuaikan dengan data visi masa sebenar. Rangkaian Hopfield baru yang disuai dikenali sebagai Seni Bina Multihubung (Multi-Connect Architecture, MCA).

Penilaian yang dilakukan bertumpu pada tiga arah. Dalam ketiga-tiga penilaian tersebut, penilaian MCA terbukti lebih cekap daripada rangkaian Hopfield. Kecekapan ini diukur dari segi saiz rangkaian yang kecil, saiz yang kecil dan kapasiti rangkaian yang besar. Tambahan pula, masalah umum seperti permasalahan minimum global, permasalahan korelasi, peratusan hingar yang dibenarkan, capaian nilai pola songsang dalam rangkaian Hopfield dapat diatasi. Di samping itu, analisis

*Big-O* bagi MCA menunjukkan derajat kekompleksan yang lebih rendah daripada pendekatan Hopfield dan juga kebolehnya untuk digunakan dalam masa sebenar. Penilaian kedua dijalankan untuk menilai modul dari segi kejituan dan bilangan imej latihan yang diperlukan. Sementara itu, penilaian ketiga menilai modul pemantauan dalam persekitaran yang sebenar. Penilaian menunjukkan bahawa adalah mungkin untuk menentukan keadaan lalu lintas yang berbeza dengan jitu. Nilai kejituan berjulat di antara 90.8% hingga 100% meskipun berbeza jalan, masa dan keadaan cuaca, yang membuktikan kestabilannya

# **A Real Time Visual Monitoring Module for Traffic Conditions Based on a Modified Auto-Associative Memory**

## **Abstract**

A new trend of traffic light monitoring module is the module that uses real time visual data and a computer vision approach to reflect the traffic conditions (crowded, normal and empty). This approach determines the traffic conditions by counting the number of vehicles individually on the street with the use of complex techniques. However this gives rise to some limitations. These limitations can be tackled when a multitude of vehicles in the street is detected as a group rather than individually. Such a technique can be achieved by using the auto-associative memory.

This research proposes a new monitoring module using the Hopfield associative memory, which is further modified and developed to be able to work with the real time visual data. The newly modified Hopfield network is called the Multi-Connect Architecture (MCA).

The evaluations have been directed into three directions: among these three directions, the MCA evaluation has proved to be more efficient than the Hopfield networks. This efficiency is measured in terms of its small network size, small weight size and its large network capacity. Furthermore, common problems, such as global minimum problem, correlation problem, allowable percentage noise and inverse pattern's value convergence problem in the Hopfield network have been prevented. In addition, the Big-O analysis for MCA showed a lower degree of complexity as compared to the Hopfield approach and hence its ability to work in



real time. A second evaluation is conducted to evaluate the module in term of its accuracy and the number of training images needed. Meanwhile, the third evaluation evaluates the monitoring module in real environment. The evaluations have shown that it is possible to determine all the different traffic conditions accurately. The value of accuracy ranged approximately between the average of 90.8% to 100% despite the differences in streets, daytime and weather conditions; thus proving its stability.

# CHAPTER ONE

## INTRODUCTION

### 1.1 Introduction

The number of vehicles on the roads, according to Wen (2009), has increased constantly although the current resources provided for infrastructures are quite limited. In many cases, bridges or tunnels are used to assist in the smooth movements of vehicles from having to stop at intersections (hence reducing the number of intersections) (Wen, 2009). Geographical conditions on the other hand, such as hills or valleys sometimes prevent the building of new roads. These conditions require high cost or budget to modify them for building roads.

Jae-Bong et al. (2008) and (Papageorgiou et al.,2007) mentioned that the public transportation management system is a technology that ensures a smooth and fast movement of vehicles and pedestrians on the roads. Intelligent Transportation System (ITS) technologies are a collection of technologies that increases the efficiency and safety of public transportation management systems and offers users greater access to the information on system operations (Jae-Bong et al., 2008; Qi, 2008; Marell and Westin, 1999). Nowadays, ITS technologies are gradually becoming popular as congestion; traffic accidents, air pollution, etc. are becoming critical issues. Furthermore, the use of ITS technologies has helped to provide users with information about traffic status in a reliable, accurate, and in a timely manner.

ITS benefits can be summarized into five categories (Birnerová E., 2006), viz., decreasing the rate of transport accidents, the probability of congestion occurrence, environment protection and by increasing travel comfort. The most popular ITS

applications are (Xiangjian et al., 2008; Padmadas et al., 2010): traffic light systems, highway planning, vehicle theft detection, automatic toll collection system, security management systems, and parking lot management.

Deng and Lee (2006) stated that a traffic light system is used mostly to control the traffic at intersections in urban areas. The traffic light cycle normally depends on fixed cycle protocols that use a fixed-time timer. These existing traffic light systems control the intersection regardless of the traffic conditions. However, Deng and Lee (2006) noticed that despite the drastic improvement of traffic light system by making it dependent on the time-based dominant flows, i.e. the Time of Day (TOD) traffic light system, it still has serious drawbacks. The traffic light setting with a fixed cycle protocol is based on survey data. These data are obtained through a manual survey on the traffic conditions of an intersection, and the green durations, which are needed for each street to allow most vehicles to pass through the intersection, are usually determined during this survey, and it requires several days before initializing a traffic light system Deng and Lee, (2006).

Inefficient traffic light system may lead to unnecessarily long waiting times for vehicles (Gupte et al., 2002; Andrea et al., 2005; Ruta et al., 2009; Mayukh and Theresa, 2009). In this respect, Kurt et al. (2008) pointed out that the annual traffic waiting time in 85 cities in the U.S. increased from 16 hours to 46 hours per capita since 1982. In the same period, the annual financial cost of traffic congestion soared from USD14 billion to more than USD 63 billion (Kurt et al., 2008). So, it is estimated that Americans burn approximately 5.6 billion gallons of fuel in unnecessary waiting times at the traffic lights.

Depending on the type of data used, traffic light systems can be classified into two categories. The first category contains systems that do not use real-time data while the second category contains systems that use real time data. The first category is the most commonly used at intersections. This kind of traffic light system suffers from several drawbacks (Lee, 2006) as follows:

1. Vehicle demand at intersections are inconsistent throughout different times of the day;
2. Vehicle demands at intersections vary according to days and special events;
3. Vehicle demands at changeable intersections in the long term might lead to invalid optimized settings.

The second category (i.e. the system that uses real time data) consists of two sub-categories which are traffic light systems without a visual monitoring module and traffic light systems with a visual monitoring module.

Shapiro (2001) claimed that, basically, the system without a visual monitoring module consists of a data recorder and a sensor placed over or in the road. This type of traffic light system has been employed for many years, using several types of sensors, e.g., pneumatic road tubes, magnetic loops, passive and active infra-red and passive magnetic (Shapiro, 2001). Pneumatic road tubes are placed across the road lanes to detect vehicles according to pressure changes produced when vehicles pass over the tube. The pulse of air created is recorded and processed by a counter located on the side of the road. Magnetic loops are the most conventional technology used to collect traffic data. The loops are embedded in roadways in a square formation that generates a magnetic field. The information is then transmitted to a counting device placed at the side of the road. Passive and active infrared is based on an infrared energy radiating

from the detection area to detect the number of vehicles. Finally, the passive magnetic, which is a magnetic sensor, is fixed under or on top of the roadbed.

As for the drawbacks of this technology, Wolfbeis (2000) highlighted the following:

1. Limited lane coverage and its efficiency is subject to weather, temperature and traffic conditions;
2. It is inefficient in measuring low speed flows;
3. It has a short life expectancy for it can be damaged by heavy vehicles;
4. The implementation and maintenance cost can be expensive; and
5. It has difficulty to differentiate between closely spaced vehicles.

The second sub-category involves the traffic light system that uses a visual monitoring module to mitigate the above drawbacks. Deng and Lee, (2006), Deng et al., (2005a), Deng et al., (2005b) investigated a real time vision-based transportation monitoring module. This module can be used to analyze and detect the objects and to determine the number of cars after extrapolating the transportation information of the main urban road. This visual monitoring module is more economical, and more precise in comparison with the previous approaches (Bertozzi et al. 2007). However, the problem is that the visual traffic light modules cannot determine traffic conditions accurately as it suffers from some limitations, as explained in the next section include vehicles' obstructed limitations due to vehicles' overlapping problems.

## **1.2 Problem Statement**

An in-depth analysis of the current vision-based traffic light modules approach reveals the following problems:

1. The vehicle overlapping problem, which has obscured many vehicles in the streets. Therefore, vehicles should move at least with a speed of 10 k/h for the visual module to count the vehicles. Slow motion or motionless vehicles increase the effect of the overlapping problem. Evidently, Deng and Lee (2006), Deng et al., (2005a), and Deng et al., (2005b) expressed this as the ‘occlusion problem’.
2. The inability of the visual module to work at night (Deng and Lee, 2006, Deng et al., 2005a and Deng et al. 2005b).
3. The noisy objects problem (e.g. pedestrians and trees) decreases the efficiency of the approach owing to incorrect counting of light reflections, the noisy objects and/or overlapping with the adjacent vehicles (Noriega and Bernier, 2006).
4. The need for extra-processing, such as object segmentation (the noise and connection between the fragments of an object, using the median filter and morphological operations), object classification and vehicles tracking (Deng and Lee, 2006, Deng et al., 2005a and Deng et al. 2005b).

The above mentioned problems can be tackled when a multitude of vehicles in the street is detected as a group, rather than detecting each vehicle individually. Such a technique can be achieved by using the auto-associative memory. The latter is actually a generic term that refers to all memories that enable the process of retrieving a piece of data from the sample itself. The Hopfield neural network (Hopfield, 1982) (Coppin, 2004) has the ability to act as an auto-associative memory because of its capability to remember data through observation. Hopfield (1982) introduced an energy function to demonstrate the behavior of the Hopfield neural network.

Since the monitoring process of the traffic must be accomplished visually and in real time, the modified Hopfield neural network is proposed to achieve such a task i.e. developing a real time visual monitoring module.

### **1.3 Research Objectives**

The main goal of this study is to develop a real time visual monitoring module for monitoring traffic conditions at intersections. To achieve this goal, the specific objectives are set forth, as follows:

1. To design and develop a new associative memory by modifying the Hopfield neural network. An associative memory, named the Multi-Connect Architecture (MCA) is introduced, and the learning and convergence processes of the MCA are developed.
2. To develop a Real Time Visual Traffic Monitoring (RTVTM) module using the MCA.
3. To evaluate the developed RTVTM module using data samples collected from real traffic conditions.

### **1.4 Scope of Research**

This research focuses on one of the ITS technologies, i.e. visual based traffic light systems. A real time visual monitoring module is developed to determine different traffic conditions (i.e., crowded, normal and empty) at intersections. The results from this monitoring module are useful for the controller of the traffic light system to adjust the green period dynamically. However, connecting such a monitoring module with the controller of the traffic light system is out of the scope of this research.

## 1.5 Proposed Solution

The research proposes a Real Time Visual Traffic Monitoring (RTVTM) module that detects traffic conditions by recognizing a multitude of vehicles in the street without detecting or tracking an individual vehicle or object. It can be used for various scenarios e.g. when the condition is crowded, normal or empty, even when the vehicles are from different viewpoints, moved, rotated or partially obstructed.

Figure 1.1 shows a general framework of the proposed RTVTM module. In this figure the module consists of three main components: training phase, analyzing phase and MCA as a modified auto-associative memory. The input to the proposed module is a video streaming of vehicle at a monitored intersection. A camera monitors a multitude of vehicles in a street and then passes the video streaming to the monitoring module. The video streaming is converted into a sequence of images. During training phase, these images are used as training images, which reflect the different types of traffic conditions, in different times and weather conditions. These images are initially chosen during the training process, which is conducted only once during the system installations stage.

Classification of the training images depends on the definitions by the domain expert, as attached in Appendix C.1. For the crowded traffic conditions, the images show that when the street is filled with vehicles; that is, when there is no empty space on the street. For the normal traffic conditions, the street has some empty spaces for the incoming vehicles to fill up the spaces. Finally, for the empty traffic condition, the images chosen are those when the vehicles pass through the intersection during the green period time without having to stop. After the training phase the module will be able to monitor and identify traffic conditions during the analyzing phase, depending on what has been learn previously.



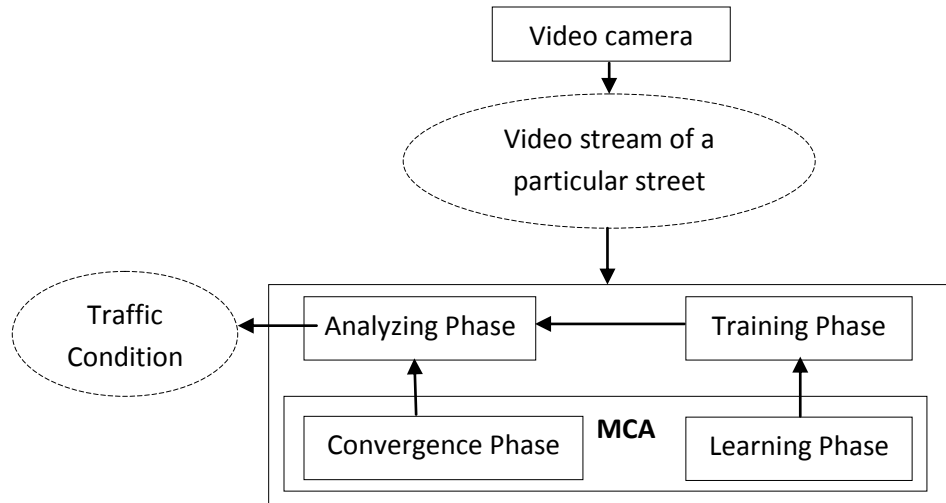


Figure 1.1: A general framework for the proposed RTVTM module

As shown in the Figure 1.1, the process of both phases depends on the MCA, which has been modified to get the possibility of working in real time. Therefore, the MCA modification is based on two principles:

1. Using the smallest network size by applying the MCA with a small number of neurons.
2. Limiting the performance aspect of the learning process to avoid learning similar parts several times.

In accordance with the first principle, the size of the network is small and fixed (i.e., three neurons). Therefore, the network deals with parts of the image, instead of the entire image as one vector. This leads to the advantage of working with a small network size regardless of the image size, and with multiple connections among the three neurons. The new architecture permits the possibility of avoiding to learn similar vectors (which represents a certain part of the image) several times. This arrangement satisfies the second principle.

The modified MCA paves the way to achieve an efficient real time visual traffic monitoring module that can be used to analyze any stream of images emerging from the video. The output of the analysis is based on the input of the training phase.

## **1.6 Research Methodology**

The flow of research methodology is illustrated in Figure 1.2. In this figure, data collection will be done through video streaming of the selected streets during day and night times and under different weather conditions. The selected streets are based on the expert's reports in the main traffic police office, as attached in Appendix C.2. The development of RTVTM module has been achieved using Delphi programming language. The latter is trained by using the selected videos, which reflect the different traffic conditions in accordance with the expert's reports in the main traffic police office (Consider Appendix C.1). Then a quantitative comparison between the MCA and the Hopfield neural network and between the RTVTM module and the other work will be conducted by using ground truth. At the end, the results of both comparisons (i.e., MCA and RTVTM) will be analyzed, discussed and summarized.

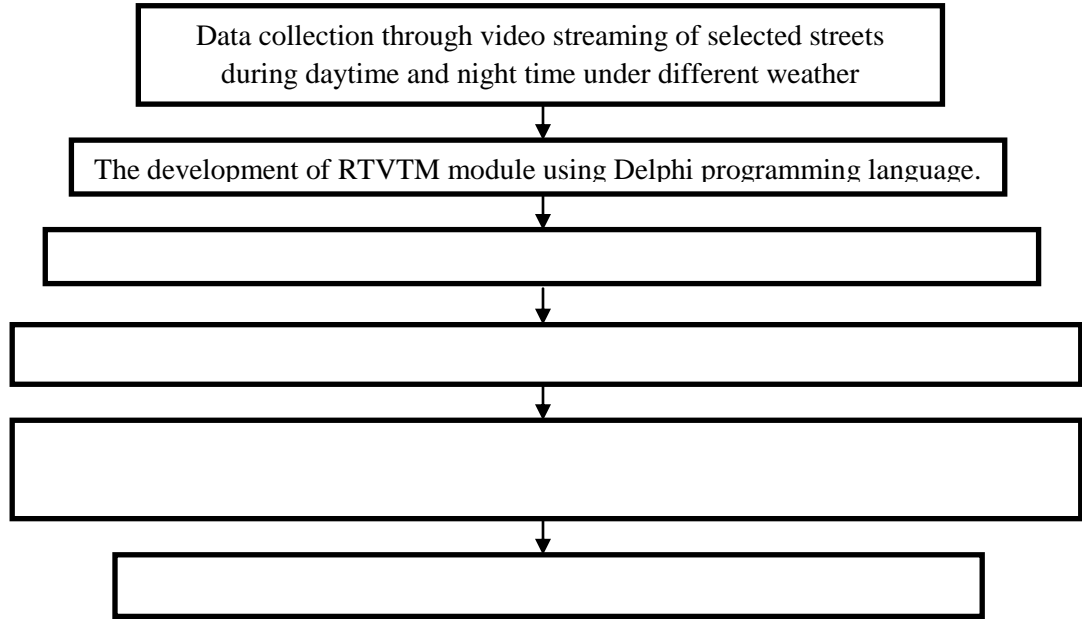


Figure 1.2: Research methodology flow

## 1.7 Organization of Thesis

The structure of the thesis is as follows:

Chapter 2 focuses on the literature review. It presents supportive background information of this research. Chapter 3 presents the methodology that has been used to achieve the objectives of this research. Chapter 4 presents the discussion and analysis of the results of a series of experiments. Chapter 5 presents the conclusion and future work related to this thesis.

## **CHAPTER TWO**

### **LITERATURE REVIEW**

This chapter presents a review on traffic light systems and related traffic condition monitoring modules. In addition, the architectures, algorithms, limitations of the Hopfield neural network and its variants are also explained in this chapter.

#### **2.1 Traffic Light Systems**

Methods to reduce traffic congestion at intersections have been proposed in several disciplines, such as traffic engineering physics and artificial intelligence (Munakata and Pawlak, 1996; Mayukh and Theresa, 2009). A classical consideration is the coordination or synchronization of traffic lights so that vehicles can traverse on the roads within a specific speed without having to stop.

The next subsections provide a literature survey related to traffic light systems. This survey highlights different traffic light systems that have been developed using different techniques to improve traffic efficiency. These include traffic light systems without and with a visual monitoring module. The details are as follows.

##### **2.1.1 Traffic Light System without a Visual Monitoring Module**

This type of traffic light system consists of a data recorder and a sensor that are placed on the road. This type of traffic light systems have been developed using various artificial intelligence-based techniques, as reviewed in the following sub-sections.

### **2.1.1.1 Knowledge Based Traffic Light Systems**

Knowledge based systems use artificial intelligent techniques in problem solving process (Leondes, 2000; Akerkar and Sajja, 2009). Knowledge is acquired and is represented using various knowledge representation rules, frames, and scripts. Many researchers have used knowledge-based systems to develop traffic light systems.

Findler et al. (1997) described a distributed knowledge-based system for real-time and adaptive control of traffic signals. The first of a two-stage learning process optimizes the control of steady-state traffic at a single intersection and over a network of streets. The second stage of learning deals with the predictive/reactive control in responding to sudden changes in traffic patterns.

Wen (2008) proposed a framework for a dynamic and automatic traffic light control expert system. The system adopts an inter-arrival time and an inter-departure time to simulate the number of arrival and departure of cars on roads. This system uses a knowledge-based system and rules. Depending on the traffic light data, which are collected by an RFID reader, this system makes decisions that are needed to control the intersections.

Akerkar and Sajja (2009), Chen and Cheng (2010) and Niazi and Hussain (2011) stated that a number of researchers turned to developing agent-based traffic light systems, which are a class of computer systems for simulating the actions and interactions of both individual and group agents. The stimulation is to evaluate their effects on the whole system. According to Preece (1999), page (2008) and Akerkar and Sajja (2009) the basic advantages offered by such a system are the documentation of knowledge, an intelligent decision support, self-learning, reasoning and explanation module. In addition, they used an inference engine technique, which requires the use of a

knowledge base in the system. However, the use of a knowledge base affects the efficiency of the traffic light system in term of the size of the knowledge base; in addition to the quality of rules that plays a role in decision-making.

An agent-based approach for traffic light control was adopted by Hiranmitti and Krohkaew (2007). The system consists of agents and their “world”. In the traffic context, the world consists of cars, road networks, and traffic lights. Each agent controls all traffic lights at road junctions by an observe-think-act cycle. This means that the agent continuously observes the current traffic conditions by collecting traffic data, and then uses them for the traffic-light-control rules by means of the inference engine to determine how a signal changes each traffic light near each junction.

#### **2.1.1.2 Fuzzy logic-Based traffic light system**

Researchers have used fuzzy systems that consist of three components. First, for traffic control, fuzzy elements have degrees of membership. Second, a membership function is created, which is a curve that defines how each point in the input space is mapped into a membership value (or degree of membership) between 0 and 1. Third, if-then rules are applied to formulate the conditional statements that comprise the fuzzy logic.

A number of papers on how to control traffic systems using fuzzy statements have been published. For example, Kaur and Konga (1994) and GiYoung et al. (2001) described the design of a fuzzy traffic light controller at the intersection of two streets. Such a system works by changing the cycle time by taking into consideration the densities of cars behind green and red lights and the current cycle time. A fuzzy system has been designed to improve the performance and to offer flexibility to the traffic flow

through an intersection. The design has been implemented by using eight incremental sensors (increments the count with any vehicle passes over it). The first sensor behind each traffic light counts the cars that come to the intersection area whereas the other counts the cars that pass the traffic lights. So every time a car passes the incremental sensor, the sensor increases its value by one. The number of cars behind the traffic lights between the two sensors is the difference in the two readings.

Khalid et al. (2004) proposed a fuzzy traffic light controller to be used at a complex traffic junction. The proposed fuzzy traffic light controller communicates with the neighbouring junctions and manages phase sequences and phase lengths adaptively. The average flow density, average delay time and the overflow link of the intersections are used as performance indices for comparison purposes.

A traffic light system based on fuzzy logic was proposed by Kulkarni and Waingankar (2007) to be used for fluctuating traffic volumes, such as over saturated or unusual road conditions. The rules of a fuzzy logic controller are formulated to control the time intervals of the traffic light. The length of the current green phase is extended or terminated depending on the time of arrival, the number of vehicles approaching the green phase, and the 'queue' that corresponds to the number of queued vehicles in red phases.

Pedraza et. al. (2008) detailed the design of a traffic system for vehicles that examines the traffic during traveling through a series of traffic lights on a main road. The adaptive network-based fuzzy inference system was used to synchronize the duration and phase angle of the traffic lights.

A Complex Adaptive System (CAS) is a network of intelligent agents (Ahmed et al., 2005) where each agent adapts its behaviour to collaborate with other agents to

achieve the overall system goals. The overall system often exhibits an emergent behaviour that cannot be achieved by any proper subset of agents on its own. This system uses one network of traffic light controller agent at each intersection. Each traffic light agent uses a fuzzy classifier block to make decisions about traffic light timing to minimize the local time of waiting for vehicles.

Hong et al. (2001) presented the concepts that described main and minor urgent phases. Traffic data are acquired from the detectors in the intersections and lanes. Based on the concepts of the main and minor urgent phases, a set of fuzzy control rules are developed to control the phases and the delay of traffic lights according to the dynamic characters of some correlative traffic intersections.

An application of the diffuse systems in traffic lights for the road control of urban transits was proposed by Alejandro et al. (2007). With reference to the vehicular problems for a certain city, it was intended to look for options to make vehicular traffic more agile. With this in mind, three proposals for the diffuse control design were formulated. The first proposal was to control two traffic lights for cars placed in the crossing of a few streets. The functioning of the traffic light was typical (green-amber-red). The system included sensors entrusted to indicate the arrival pace of cars and the length of the trail of cars at a certain point in time. The principal street had one sensor and the lateral street had another sensor. Second, the proposal had, as a basic principle, the modification of the traffic light timing around a predetermined nominal value. Such a nominal value was calculated based on normal traffic conditions in a designated crossroad, using a standard traffic theory and criteria. The objective of the fuzzy controller was to dynamically adjust the timing of each light stage to support variations in the vehicular load, such as during rush hours. Finally, the third proposal was to



optimize the flow of vehicles on the street. This was carried out by defining the times that each light of the traffic light remains lit. This proposal has a fuzzy inference system control where the input variables for the control are car density and the waiting times.

### **2.1.1.3 Petri Net-Based Traffic Light Systems**

Petri net (PN) systems consist of places (graphically represented as circles) and transitions (graphically represented as bars) connected via a set of directed arcs (Ciardo et al. 1999; Petri and Reisig, 2008). Furthermore, places may contain tokens (represented by dots inside the circle) that move through the network (i.e., from place to place), according to certain rules. Such systems have been used as a tool for various kinds of discrete event systems, simulation and logic control. However, these models, according to Reisig and Rozenberg (1996) and Ciardo et al. (1999), have several disadvantages. The main disadvantage is that PN constructs are quite primitive; i.e., they are not only a burden placed on the analyst in order to specify complex models, but also the fact that their graphical representations are too complex to be useful. The state-space of the Petri net grows exponentially to the extent that it becomes too difficult to manage both graphically and analytically. In addition, it fails to model similar processes using one graphical representation (Ciardo et al. 1999; Desel and Juhás, 2001). This means, in the case of traffic light, each intersection should have its own PN graph representation. Another disadvantage is that the representation of priorities or orderings is difficult to manage although priority queues are important in formability modelling. Therefore, the control logic is hard-wired, i.e. inflexible to cope with any system changes.

Di Febbraro et al. (2002) applied a PN system to traffic light. They provided a modular representation of urban traffic systems regulated by signalized intersections.

Such systems comprise elementary structural components, namely, intersections and road stretches. The movement of vehicles in the traffic networks is described with a microscopic representation and is realized via timed PNs. An interesting feature of the system is its possibility to represent the offsets among different traffic light cycles as embedded in the structure of the system itself.

#### **2.1.1.4 Extension Neural Network (ENN)-Beased Traffic Light Systems**

In this respect, de la Escalera et al. (2003) stated that an ENN consists of an extension theory and a neural network that uses a modified extension distance (ED) to measure the similarity between data and a cluster centre. They further added that this type of system represents another traffic light control system developed to deal with object recognition in outdoor environments.

Kuei-Hsiang et al. (2008) and Chao et al. (2008) presented an intelligent traffic light control method based on the extension theory. First, the number of passing vehicles has been counted using an infrared counter. The maximum passing time of one vehicle within the green light period is measured in the main-line and sub-line of selected crossroads. Then, the measured data are adopted to construct the extended matter-element system. Accordingly, the correlation degrees are calculated to recognize the traffic flow of a standard crossroad.

Although the ENN has advantages (i.e. less learning time and less memory consumption), the learning and convergence processes are iterative in nature (Wang and Hung, 2003; Wang, 2005; Lovrek et al., 2008). On the other hand, the number of passing vehicles is counted using an infrared counter, which suffers from drawbacks, e.g. being

inefficient in measuring low speed flows and having difficulties to differentiate between closely spaced vehicles.

#### **2.1.1.5 Reinforcement Learning-Based Traffic Light Systems**

Nijhuis et al. (2005) used a reinforcement learning technique to improve traffic light configurations. Such a technique is a sub-area of machine learning, that is concerned with how an agent should take actions in an environment to maximize some notions of long-term rewards. They also described the existing approach of the reinforcement learning that is applied to the optimization of traffic light configurations. This approach uses an implicit cooperation between traffic lights taking into account the traffic situation of the road ahead.

Due to the necessary exploration (i.e. exploring the environment), the performance was found to be less stable. In addition, it is often impossible to fully determine the current state due to a limited perception (Sutton and Barto, 1998; Alpaydin, 2004; Bishop, 2006; Vrancx et al., 2012).

#### **2.1.1.6 Genetic Algorithm-Based Traffic Light Systems**

A Genetic Algorithm (GA) is an evolutionary algorithm. Fraser and Burnell (1970) and Crosby (1973) described the rules of nature, such as an evolution occurs through a selection among the fittest individuals; accordingly, individuals can present solutions to a mathematical problem. Some researchers have used GAs to improve traffic light configurations.

Sanchez et al. (2004) presented a new architecture for the optimization of traffic light cycles in a traffic network. The system was based on three basic design items: the use of the GA as an optimization technique, the use of cellular automata simulators

within the evaluation function, and the use of a cluster as a parallel execution environment for the architecture.

Winter and Periaux (1995) stated that GAs have a number of advantages. It can solve optimization problem, which can be described with the chromosome encoding, and it solves problems with multiple solutions. Another advantage is that structural GA gives the possibility to solve solution structures and solution parameter problems at the same time by means of a GA.

As for the disadvantages of this system, Winter and Periaux (1995) and Akbari and Ziarati (2011) further stated that certain optimization problems (variant problems) cannot be solved through the use of GAs. Usually such problems occur owing to poorly known fitness functions, which lead to the generation of bad chromosome blocks in spite of the fact that only good chromosome blocks can cross-over. Besides, there is no absolute assurance that GAs will find a global optimum. Such assurance happens very often when the populations involve a lot of subjects. Like other artificial intelligence techniques, the GA cannot ensure constant optimization response times (Winter and Periaux 1995; Mitchell, 1996; Banzhaf et al., 1998). In addition, the difference between the shortest and the longest optimization response time is much larger than that encountered in conventional gradient methods. So, GA property limits its usefulness in real time applications. This is because of the random solutions and convergence. That is, the entire population is improving, but one cannot generalize such an improvement for every individual within this population. Therefore, it is recommended not to use genetic algorithms in real systems without testing them first by means of a simulation model.

### **2.1.1.7 Summary of literature review**

The above literature review showed that the current traffic light systems suffered from many limitations. Therefore, a new research direction has been followed to avoid most of these limitations. This direction involves the use of visual traffic light model that uses a video sensor. Video sensors have become particularly important in traffic applications, mainly owing to their fast response and ease of installation, operation, and maintenance.

### **2.1.2 Traffic Light Systems with a Visual Monitoring Module**

Kastrinaki et al. (2003) and Padmadas et al. (2010) stated that video-based vehicle detection is a promising solution for traffic surveillance. Recently, it has played an important role in real-time traffic management systems. They added that video-based traffic monitoring systems offer a number of advantages. In addition to vehicle counting, more traffic information can be obtained by video images, including vehicle classifications and lane changes. Furthermore, the researchers stated that video cameras can be easily installed and used in mobile environments.

A computer vision approach has been used widely in classifying vehicles on motorway, measuring vehicles speed and for automatic accident monitoring and intelligent vehicle environment such as, the works by Houben et al. (2009), Kiratiratanapruk and Siddhichai (2009) and Surgailis et al. (2011) respectively. Recently the computer vision approach is used to determine traffic conditions. The next section focuses on previous works related to the goal of this research.

### **2.1.2.1 Traffic Light Systems Using a Background Subtraction Monitoring Module**

Deng et al. (2005) introduced a visual monitoring module for traffic light systems. They used the background subtraction technique to detect vehicles in the street scene. Deng and Lee (2006), Deng et al. (2005a), and Deng et al. (2005b) compared three variants for the same work, which presented the use of vision-based surveillance to keep sight of unpredictable and complex measurable disturbances that perturb the traffic flow. They integrated and performed vision based techniques that embed object segmentation, classification and tracking to compute real time measurements of traffic conditions in urban road. According to the real time traffic measurement, they derived an adaptive traffic signal control algorithm to settle the red–green switching period of traffic lights.

Although the background subtraction method can be used in busy street situations, it has a disadvantage. The background subtraction method needs extra processing time to minimize the effect of non-static background objects, such as that of the moving leaves of the trees, and to reduce the effect of the general camera noise that blurs the image before the background subtraction stage (Coifman et al., 1998; Cheung and Kamath, 2004; Milla et al., 2010; Barrero et al., 2010). Therefore, many challenges in developing a good background subtraction algorithm have been elaborated by Chalidabhongse et al. (2003), Piccardi (2004) and Mandellos et al. (2011) as follows:

1. The background subtraction algorithm must be robust against changes in illumination;
2. The background subtraction algorithm should avoid detecting non-stationary background objects, such as moving leaves of the trees, rain, snow, and shadows casted by moving objects;

3. The internal background model of the background subtraction algorithm should react quickly to background changes, such starting and stopping of vehicles.

The above reviews have been summarized in Table 2.1 in terms of the techniques used.

Table 2.1: Summary of the techniques used with traffic light systems in terms of ability and efficiency.

Technique	Advantages	Disadvantages
TOD	-Simple control technique.	- It is a fixed cycle protocol; and - It uses manual survey data. - Vehicles demands of an intersection are: 1. To be inconsistent, even within different times of a day; 2. To be susceptible to variation in different days due to unexpected events; and 3. To avoid changes since the latter leads to invalid optimized settings.
Knowledge-based system and Fuzzy logic	-The basic advantages offered by such a system are the documentation of knowledge, intelligent decision support, self-learning, reasoning and explanation.	- It requires a big knowledge base; in addition to the quality of rules that will be a part of the decision-making process; and - It uses non-visual sensors, which suffer from many drawbacks.
Petri-net	- it is simple and straightforward to model features like precedence relation, concurrency, conflict and a mutual exclusion of real-time system; - the formal graphical representation provides a medium to visualize the complex system; -It has a well-developed mathematical foundation; Its analysis can be carried out to detect deadlock, overflow and irreversible situations, etc; and -Performance evaluation is	- It is not straightforward when modeling the notion of time; -As the system evolves in its size and complexity, the state-space of the Petri net grows exponentially; a matter which makes it too difficult to be managed both graphically and analytically; -Its control logic is hard-wired; and - It uses non-visual sensors, which suffer from many drawbacks.

	possible through the mathematical analysis of the system model.	
ENN	-less learning time. -less memory consumption.	-Its learning and converges process are iterative; and - It uses infrared sensors, which suffer from drawbacks.
Reinforcement learning	-it automatically learns to recognize complex patterns; and - It makes intelligent decisions based on the data.	- It is less stable due to the necessary explorations of the environment; - It is often impossible to fully determine the current state; and - It uses non-visual sensors, which suffer from many drawbacks.
GA	- It can solve the optimization problem; - It solves problems with multiple solutions; -it can solve multi-dimensional, non-differential, non-continuous, and even non-parametrical problems; -The structural genetic algorithm gives the possibility to solve the solution structures and solution parameter problems at the same time; -Genetic algorithm is a method, which is very easy to understand. Practically, it does not demand mathematical knowledge; and -It is easily transferred to the existing simulations and models.	-Certain optimization problems cannot be solved by means of genetic algorithms; -There is no absolute assurance that a genetic algorithm will find a global optimum; - It cannot ensure constant optimization response times; -Genetic algorithm applications, which are performed in real time are limited; and - It uses non-visual sensors, which suffer from many drawbacks.
Computer vision	-It is more economical, tireless, and more precise compared to the previous approaches; and - The technique manages to determine the number of vehicles via using the existing computer vision approaches, such as vehicle detection/classification or the segmentation approach.	- It suffers from vehicles' overlapping problem, which obstructs many vehicles in the streets; - Stopping or slow-moving vehicles will increase the effect of the vehicles overlapping problem; - It is unable to work in the nighttime; - The noisy objects problem (e.g. trees and pedestrians) will decrease the efficiency of the work because of the inaccuracy; and - It needs extra-processing, such as: object segmentation, object classification and vehicles tracking.



## 2.2 Associative Memory

Mehrotra et al.,(1996) and Ponce et al., (2010) mentioned that it is believed that human memory is stored in the form of complex interconnections among various neurons. Similarly, the artificial neural network simulating associative memory collects the stored pattern in the form of a memory or weight matrix, which helps generate an output that corresponds to a given input. Gurney (1997) and Mehrotra et al.,(1996) further stated that such a process is referred to as learning or storing the desired patterns while the retrieval or recall process is referred to as the generation of an output pattern. Figure 2.1 shows a general block diagram of an associative memory performing an associative mapping between an input vector  $x$  and an output vector  $v$  (see Equation 2.1).

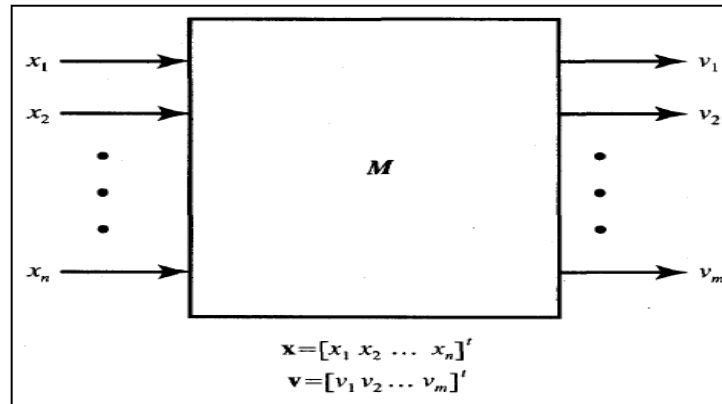


Figure 2.1: Block diagram of an associative memory.

(Kishan Mehrotra, et al., 1996).

$$\mathbf{v} = M[\mathbf{x}] \quad (2.1)$$

As shown in Figure 2.1 shows a map of vector  $x$  to vector  $v$ , in the pattern space  $R^m$  and the output space  $R^n$ , respectively, is formed by means of a transformation. Operator  $M$  denotes a general nonlinear matrix-type operator, which has different meanings for different memory systems. The form of the operator, in fact, defines a specific system that needs to be carefully outlined for each type of memory whereas its structure reflects a specific neural memory paradigm. For dynamic memories,  $M$  also

involves a time variable. Thus,  $v$  will be available at the memory output at a later time when the input is applied (Zurada, 1992).

An associative memory can be applied to either auto-associative or hetero-associative applications. Mathematically, it is a mapping from an input space to an output space. In other words, when the network is presented with a pattern similar to the member of the stored set, it may associate the input with the closest stored pattern (Faustt, 1994).

Generally, in hetero-associative applications, the dimensions of the input space and the output space are different, as illustrated in Figure 2.2. It shows how a pair of patterns has been associated in a hetero-associative memory to make it able to respond to the input pattern. Nevertheless, the training input and the target output of an auto-associative memory are identical, as shown in Figure 2.3 (Faustt, 1994, Zurada, 1992). Figure 2.3 also shows how the auto-associative memory stores the patterns and how the target output stores patterns similar to the input patterns. The Hopfield neural network is an auto-associative memory neural network, which is further explained in the next section.

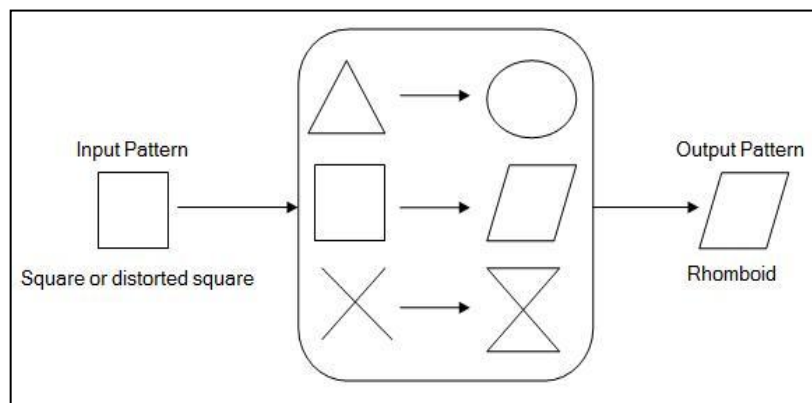


Figure 2.2: Hetero-association response  
(Zurada, 1992)