Constructing an Associative Memory System Using Spiking Neural Network

A Seminar Report

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CERTIFICATE

This is to certify that the report entitled **Constructing an Associative Memory System Using Spiking Neural Network** submitted by **SANKAR VINAYAK E P** (PKD19CS046), to the APJ Abdul Kalam Technological University in partial fulfillment of the B.Tech. degree in Computer Science and Engineering is a bonafide record of the seminar work carried out by him under our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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DECLARATION

I SANKAR VINAYAK E P hereby declare that the seminar report **Constructing an Associative Memory System Using Spiking Neural Network**, submitted for partial fulfillment of the requirements for the award of degree of Bachelor of Technology of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by me under supervision of Liji L Dominic

This submission represents my ideas in my own words and where ideas or words of others have been included, I have adequately and accurately cited and referenced the original sources.

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Sreekrishnapuram

15-12-2022

SANKAR VINAYAK E P

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Abstract

An associative memory system is a type of artificial neural network that can learn and store associations between input and output patterns. Spiking neural networks, on the other hand, are a type of neural network that models the behaviour of neurons in the brain by using discrete time steps to simulate the firing of individual neurons. Combining these two concepts can result in an effective memory representation technique in which the contents can be accessed with speed and efficiency. The report provides an overview of the principles of associative memory and spiking neural networks, and then describe the architecture and training procedure for the system. The results show that spiking neural networks can be effective for implementing associative memory systems, and have potential applications in a range of computational neuroscience and machine learning problems.

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Abbreviation

Abbreviation	Description
ANN	Artificial Neural Network
NN	Neural Network
SNN	Spiking Neural Network
STDP	Spiking-time-dipendent plasticity

Notations

Chapter 1

Introduction

The ability to store and retrieve associations between different stimuli is a fundamental component of many cognitive processes, including perception, learning, and memory. Associative memory is a type of memory system that allows for the storage and retrieval of relationships between different items in memory. It is a key component of many artificial intelligence and machine learning systems and has been extensively studied in both neuroscience and computer science.

Spiking neural networks (SNNs) are a type of neural network that can simulate the dynamics of individual neurons and synapses in the brain. They are effective for modelling a range of cognitive and sensory processing tasks and have potential applications in a variety of fields, including computational neuroscience and machine learning.

This work presents a study on the construction of an associative memory system using a spiking neural network. We describe the architecture and training procedure for our system and evaluate its performance on a variety of associative memory tasks. We discuss the implications of our results for the use of SNNs in implementing associative memory systems and highlight their potential applications in computational neuroscience and machine learning.

Chapter 2

Literature Review

2.1 Associative Memory

Associative memory also known as content addressable memory is a type of memory which is specially optimized for access to memory locations without using the memory address of the location that needs to be accessed. Its electronic circuit will have extra connections which enable it to parallelly search through the contents in a single clock pulse. It is widely used in applications like database management systems which require searching through the data as fast as possible figure 2.1 shows one such circuit.

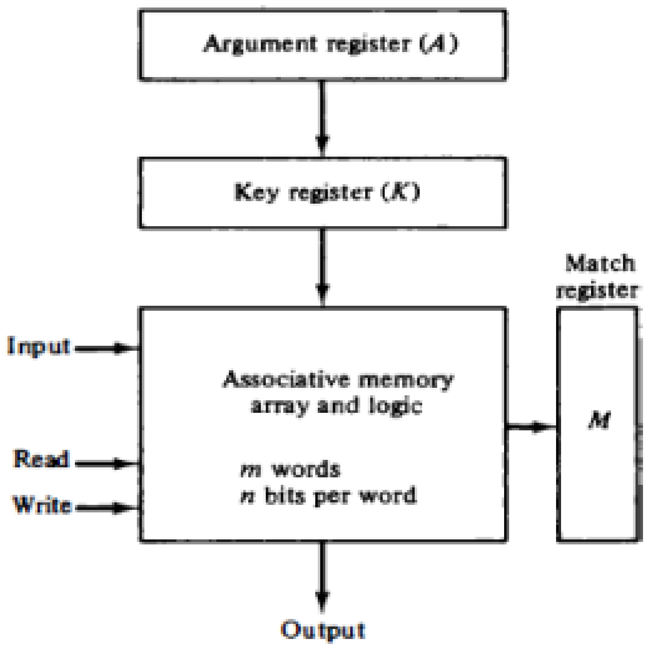

Figure 2.1: Associative memory circuit

2.2 Neural associative memory

Neural associative memory is also known as the associative network, which works based on pattern association. It can store different patterns and produce the output which closely matches the already given patterns. They are implemented using the artificial neural network, which tries to mimic the working of the brain. They are commonly used in applications like pattern recognition, data storage and information retrieval. There are two types of associative networks

Auto associative memory A single layer neural networkin which the number of training vectors and the number of output vectors are the same. The weights are determined by the stored patterns

Hetero associative memory A single layer neural networkin which the number of input training vectors and output are different. Weights are determined by the pattern stored in the network. It is static in nature and hence there would be no linear or delay operations

2.2.1 Hopfield model

The Hopfield model [2] is a type of recurrent neural network. The model is designed to mimic the behaviour of neurons in the brain. It is a type of associative memory system and hence it can store and recall information based on the relationship between the data stored. It has application including pattern recognition, optimization, and error correction.

It is a fully connected neural networkand weights between connections determine the strength of the connections. When the network is supplied with an input these weights are updated sequentially until the network reaches a stable state, at which the output is determined. By adjusting the weights in a specific way, the the network is able to recall the information as a set of stable states

The main drawbacks of the model are that it may not converge to correct output state when it is supplied with a pattern which is only partially similar to the stored patterns or when it is not trained on sufficiently distinct data.

2.3 Spiking neural network

Spiking neural networks are a type of neural network that models the behaviour of biological neurons by using spikes or pulses to encode and transmit information. They are a relatively new type of neural network that has the potential to improve the performance and efficiency of artificial intelligence systems. The use of spiking neural networks for building associative memory systems is a relatively new area of research that has only recently started to gain attention.

2.3.1 Spike time dependent plasticity

Spike-timing-dependent plasticity (STDP) [6] is an unsupervised learning rule based on the functioning of neurons in the brain for neuromorphic computing, which is the study inspired by the structure and functioning of the brain. In the process strength of the connection between neurons change based on the relative timing of spikes or impulses

The basic idea behind STDP is that if two N_{pre} and N_{suc} neurons are connected and their spike time are t_1 and t_2 respectively according to STDP

Weight of connection from N_{pre} to N_{suc} should increase, if $\boldsymbol{t_1 > t_2}$

Weight of connection from N_{pre} to N_{suc} should decrease, if $\boldsymbol{t_1 < t_2}$

Weight of connection from N_{pre} to N_{suc} should remain same, if $\boldsymbol{t_1 = t_2}$

This process allows the neurons to adjust connection in a way which reflects the relationship between input and output spikes signals.

2.3.2 SpikeProp

SpikeProp is an unsupervised learning algorithm used in the field of neuromorphic computing used to train Spiking neural networkbased on the principle of STDP. It is similar to the gradient descent algorithm used in conventional deep neural networks. It is computationally efficient and well-suited for real-time applications. The issue with this algorithm is the need for a large amount of data to achieve good results and only applicable to Spiking neural network.

Chapter 3

Methodology

Construction of associative memory using Spiking neural network [1] in this method consist of four phases

1. Initialization :Initialization of Spiking neural networkand the input spiking signals
2. Structure formation :
3. Parameter training :
4. Pruning :

3.1 Initialization

3.1.1 Initialization input spiking signals

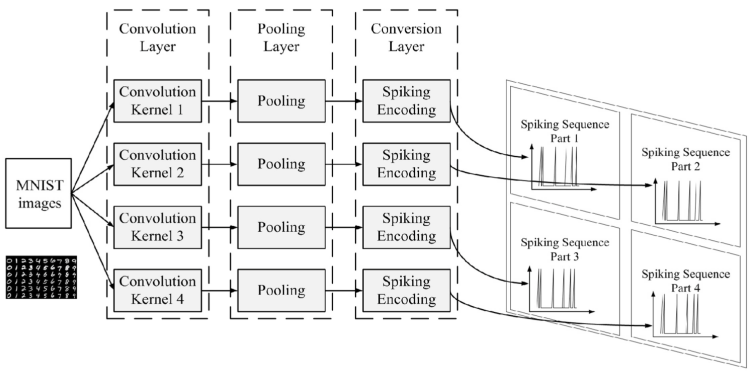

Figure 3.1: Data preprocessing

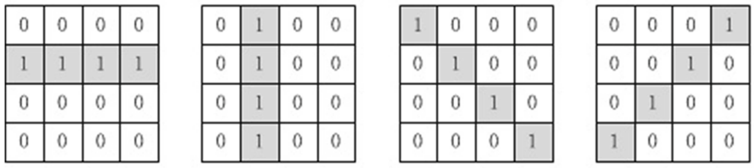

Figure 3.2: Kernels used

3.1.2 Initialization of Spiking neural network

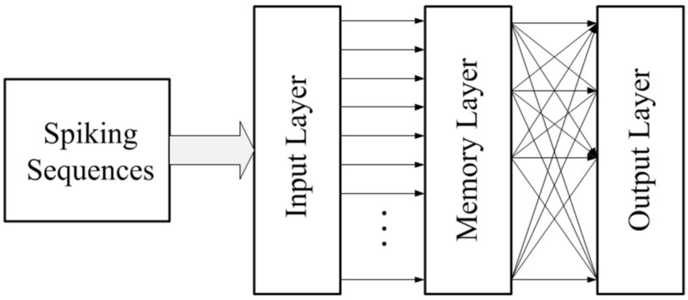

Figure 3.3: Structure of network

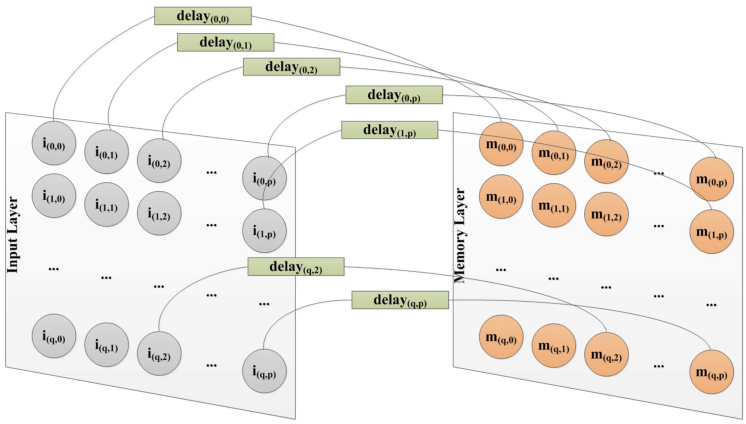

Figure 3.4: Delay for neuron

3.2 Structure formation

3.3 Parameter training

3.4 Pruning

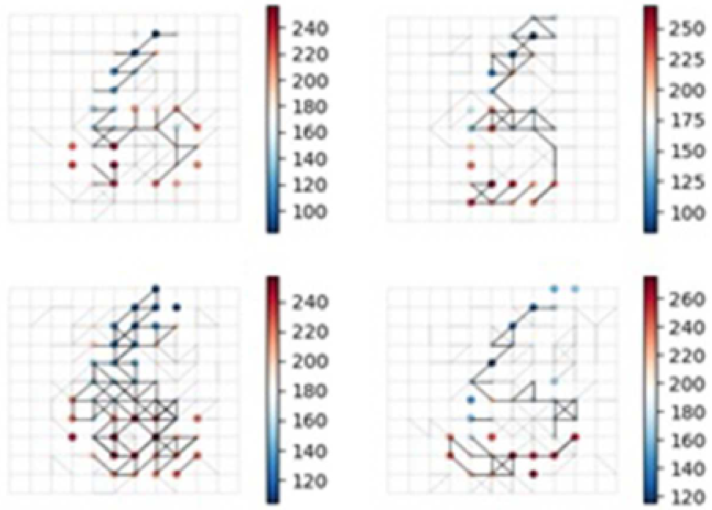

Figure 3.5: Recall response for number 6

Chapter 4

Results and Discussion

This section presents the findings of the research, including any statistical analyses or other data that support the conclusions.

This section interprets the results and places them in the context of the existing literature, highlighting the implications and contributions of the research.

4.1 Growing process of memory layer

4.2 Memory process

4.3 Recall process

4.4 Verification of association ability

Chapter 5

Conclusion

In conclusion, the study demonstrates the feasibility of using spiking neural networks for implementing associative memory systems. The SNN-based associative memory system is able to perform robust and efficient associative memory retrieval, and discuss the potential applications of this approach in computational neuroscience and machine learning. Our findings indicate that SNNs are a promising tool for modeling and implementing associative memory systems, and highlight the need for further research in this area.

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Appendices

Hebb's learning rule: When an axon of a cell A is sufficiently close to excite a cell B, and repeatedly and or persistently takes part in firing it some growth related process or metabolic changes takes place in one or both of the cell such that A's efficiency, as one of the cells firing B is increased.