



**Faculty of Electronics & Computer Technology and
Engineering**



**DESIGN OF AN EFFICIENT SPIKING NEURAL NETWORK FOR
HUMAN ACTIVITY RECOGNITION**

Tan Yee Leong

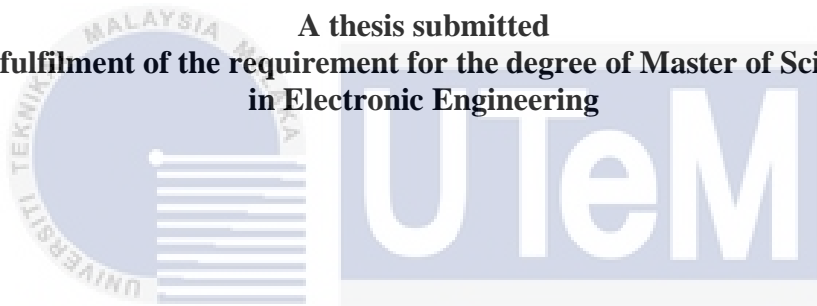
Master of Science in Electronic Engineering

2024

**DESIGN OF AN EFFICIENT SPIKING NEURAL NETWORK FOR HUMAN
ACTIVITY RECOGNITION**

TAN YEE LEONG

**A thesis submitted
in fulfilment of the requirement for the degree of Master of Science
in Electronic Engineering**



اونيورسيتي تيكنيكل مليسيا ملاك

Faculty of Electronics & Computer Technology and Engineering

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2024

DECLARATION

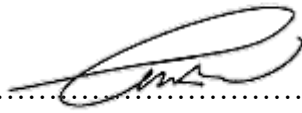
I declare that this thesis entitled “Design Of An Efficient Spiking Neural Network For Human Activity Recognition” is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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APPROVAL

I hereby declare that I have read this thesis and in my opinion, this thesis is sufficient in terms of scope and quality for the award of Master of Science in Electronic Engineering.

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Date : 22 NOVEMBER 2023



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DEDICATION

To my beloved mother and father, Ting Chiew Hiong and Tan Tze Ming, and also my supervisor, Associate Professor Wong Yan Chiew, your kindness and advice should never be forgotten.



ABSTRACT

Human activity recognition (HAR) using Wi-Fi Channel State Information (CSI) has attracted significant interest as an alternative to conventional methods due to its potential to address human privacy concerns. While Long Short-Term Memory (LSTM) models have shown promising results in HAR, their resource-intensive nature and time-consuming computations limit their suitability for edge computing. The development of Spiking Neural Networks (SNNs) as a more power-efficient computational model presents a compelling alternative. However, a critical research gap exists as no prior study has explored the application of SNNs for time series data, particularly for Wi-Fi CSI analysis, within the context of the Industrial Revolution 4.0. This work addresses the research gap by proposing an SNNs model that involves preprocessing the CSI signals and encoding them into spike trains. The spike trains modulate the membrane potential at the postsynaptic neurons based on their respective weight values, enabled by the Spike-Timing-Dependent Plasticity (STDP) learning rule during the training process. The combination of these techniques enables accurate class prediction. Additionally, with different preprocessing methods and different values on the model's parameters, SNNs models can achieve varying accuracy results. The application of the majority vote method to the outputs of divided signal segments ensures a robust final class prediction. Experimental results demonstrate that the proposed SNNs model achieves accuracy levels comparable to those of the LSTM model while significantly reducing computational memory usage by up to 70%. Remarkably, the SNNs model exhibits consistent performance even with smaller datasets and varying train-test ratios, showcasing its robustness in the face of limited training data. This memory-efficient and resilient nature positions SNNs as a viable solution for edge computing within the scope of the Industrial Revolution 4.0. In conclusion, this study introduces a pioneering application of SNNs for HAR using Wi-Fi CSI, highlighting the efficacy of spike trains and the STDP learning rule in enabling efficient computation and precise predictions. The demonstrated memory savings and robustness of the SNNs model underscore its potential to address the challenges associated with HAR while upholding privacy concerns and optimising resource utilisation in the era of the Industrial Revolution 4.0.

REKABENTUK RANGKAIAN NEURAL PANCANG YANG CEKAP UNTUK PENGECAMAN AKTIVITI MANUSIA

ABSTRAK

Pengecaman kegiatan manusia (HAR) menggunakan Maklumat Keadaan Saluran Wi-Fi (CSI) telah menarik minat yang ketara sebagai alternatif kepada kaedah konvensional kerana potensinya untuk mengelakkan kebimbangan privasi manusia. Walaupun model Long Short-Term Memory (LSTM) telah menunjukkan hasil yang menjanjikan dalam HAR, sifat intensif sumber dan pengiraan yang memakan masa mengehadkan kesesuaiannya untuk perkomputeran pinggir. Pembangunan saraf rangkaian pancang (SNNs) sebagai model pengiraan yang lebih cekap kuasa memberikan alternatif yang menarik. Walau bagaimanapun, jurang penyelidikan kritikal wujud kerana tiada kajian terdahulu telah meneroka aplikasi SNNs untuk data siri masa, terutamanya untuk analisis CSI Wi-Fi, dalam konteks Revolusi Perindustrian 4.0. Kerja ini menangani jurang penyelidikan dengan mencadangkan model SNNs yang melibatkan prapemprosesan isyarat CSI dan pengkodannya ke dalam spike train. Spike train memodulasi potensi membran pada neuron pascasinaptik berdasarkan nilai berat masing-masing, didayakan oleh peraturan pembelajaran Spike-Timing-Dependent Plasticity (STDP) semasa proses latihan. Gabungan teknik ini membolehkan ramalan kelas yang tepat. Selain itu, dengan kaedah prapemprosesan yang berbeza dan nilai yang berbeza pada parameter model, model SNNs boleh mencapai hasil ketepatan yang berbeza-beza. Penggunaan kaedah undi majoriti pada pengeluaran segmen isyarat yang dibahagikan memastikan ramalan kelas akhir yang mantap. Keputusan eksperimen menunjukkan bahawa model SNNs yang dicadangkan mencapai tahap ketepatan yang setanding dengan model LSTM sambil mengurangkan penggunaan memori pengiraan dengan ketara sehingga 70%. Hebatnya, model SNNs mempamerkan prestasi yang konsisten walaupun dengan set data yang lebih kecil dan nisbah ujian train-test yang berbeza-beza, menunjukkan kekukuhannya dalam menghadapi data latihan yang terhad. Sifat cekap ingatan dan berdaya tahan ini meletakkan SNNs sebagai penyelesaian yang berdaya maju untuk pengkomputeran tepi dalam skop Revolusi Perindustrian 4.0. Kesimpulannya, kajian ini memperkenalkan aplikasi perintis SNNs untuk HAR menggunakan Wi-Fi CSI, menonjolkan keberkesanan spike train dan peraturan pembelajaran STDP dalam membolehkan pengiraan yang cekap dan ramalan yang tepat. Penjimatan memori dan keteguhan model SNNs yang ditunjukkan menunjukkan potensinya untuk menangani cabaran yang berkaitan dengan HAR sambil mengekalkan kebimbangan privasi dan mengoptimumkan penggunaan sumber dalam era Revolusi Perindustrian 4.0.

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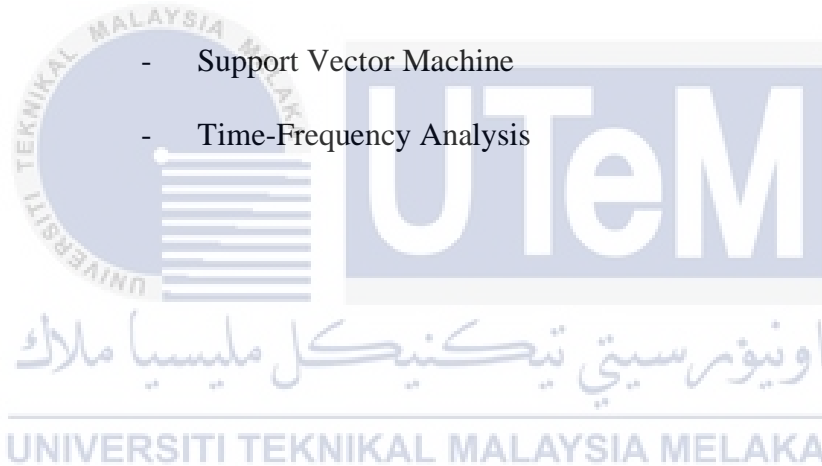
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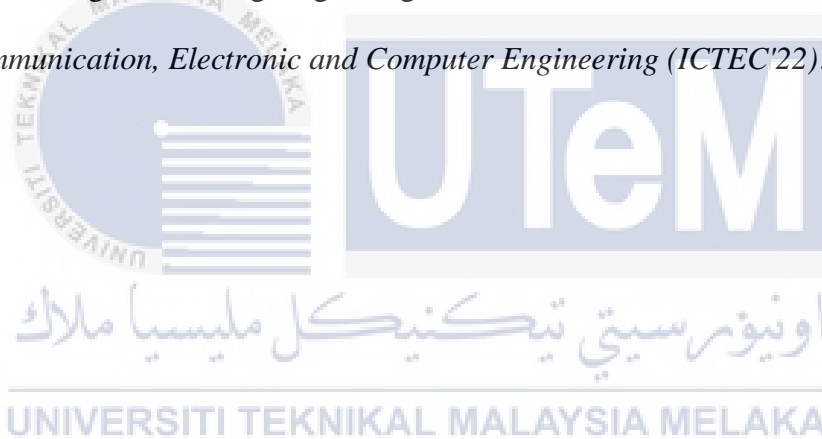
AGC	-	Automatic Gain Control
ANNs	-	Artificial Neural Networks
BCM	-	Bienenstock-Cooper-Munro
Bi-LSTM / BLSTM	-	Bidirectional Long Short-Term Memory
CFO	-	Carrier Frequency Offset
CNN / CNNs	-	Convolutional Neural Networks
CPV	-	Channel Power Variation
CSI	-	Channel State Information
DFB	-	Device-free Biometric
DWT	-	Discrete Wavelet Transform
EPSP	-	Excitatory Postsynaptic Potential
GRU	-	Gated Recurrent Units
HAR	-	Human Activity Recognition
HMM	-	Hidden Markov Model
IF	-	Integrate-and-Fire
IPSP	-	Inhibitory Postsynaptic Potential
LIF	-	Leaky Integrate-and-Fire
LSTM	-	Long Short-Term Memory
NIC	-	Network Interface Card
NN	-	Neural Network
PCA	-	Principal Component Analysis
PSD	-	Power Spectral Density

RF	-	Receptive Field
RNNs	-	Recurrent Neural Networks
RSS	-	Received Signal Strength
SAC	-	Sparse Approximation based Classification
SAE	-	Sparse autoencoder
SFO	-	Sampling Frequency Offset
SNNs	-	Spiking Neural Networks
SRM	-	Spike Response Model
STDP	-	Spike-Timing-Dependent Plasticity
STFT	-	Short-Time Fourier Transform
SVM	-	Support Vector Machine
TFA	-	Time-Frequency Analysis



LIST OF PUBLICATIONS AND PAPERS PRESENTED

1. Tan, Y. L., Wong, Y. C. and Radzi, S. A., (2021). Brain-Inspired Spiking Neural Networks For Wi-Fi Based Human Activity Recognition. *Jordanian Journal of Computers and Information Technology* (JJCIT), 07(04), 363–372. doi:10.5455/jjcit.71-1629096728.
2. Tan, Y.L. and Wong, Y.C., 2022. Wireless sensing for human activity using lightweight spiking neural networks., *The 7th International Conference and Exhibition on Sustainable Energy and Advanced Materials (ICE-SEAM '21)*, pp.32–34.
3. Tan, Y. L., Wong, Y. C., Radzi, S. A. and Chuah, J. H., (2022). Wi-Fi Based Human Activity Recognition using Lightweight LSTM. *4th International Conference on Telecommunication, Electronic and Computer Engineering (ICTEC'22)*.



CHAPTER 1

INTRODUCTION

1.1 Background of Thesis

In this research, a spiking neural networks (SNNs) model is designed and applied to Wi-Fi channel state information (CSI)-based human activity recognition (HAR). Wi-Fi CSI is a complex time series data that performs well on recurrent neural networks (RNNs) such as the long short-term memory (LSTM) model (Wang et al., 2019; Zhang et al., 2021). However, the high hardware resource and time consumption by LSTM is a critical issue (Chen et al., 2019). SNNs are the third generation of neural networks when classified based on their computational units, which are McCulloch-Pitts neurons, activation function, and spiking neurons (Maass, 1997). SNNs can be a more power-efficient computational model with their spiking characteristic, but so far, none of the research on using SNNs for time series data such as Wi-Fi CSI data has been done. Therefore, this project will focus on designing an SNNs model which will be used to classify human activities from the Wi-Fi CSI data. The performance of the developed SNNs algorithm based on the neuron model, accuracy, and hardware resources for the application of HAR will be evaluated and optimized.

1.2 Problem Statements

LSTM is a well-known method for classifying temporal datasets in HAR due to its ability to automatically select features. However, high hardware resource requirements are

a significant issue for LSTM. To address this, Spiking Neural Networks (SNNs) have been developed as a more power-efficient computational model that can perform similar tasks as LSTM with lower hardware requirements. Further research is needed to optimize SNN algorithms based on neuron model, accuracy, and hardware resources on the application of HAR.

1.3 Research Objectives

The objectives of this research project are summarized as follows:

- i. To investigate the architecture of SNNs for CSI-based human activity recognition applications.
- ii. To design an efficient spiking neural network model for time series data processing and classification.
- iii. To evaluate the performance measure in terms of accuracy and hardware resources on the application of human activity recognition.

1.4 Research Scopes

This research aims to design a SNNs model that can do HAR on Wi-Fi CSI data and achieve good performance on both accuracy and hardware resource consumption. The details of the research scope and the limitations of this work are as follows:

- i. The HAR dataset utilised in this research focuses on Wi-Fi Channel State Information (CSI). This choice is motivated by the absence of human privacy concerns associated with Wi-Fi CSI and its user-friendly nature, as it eliminates the need for worn sensors or line-of-sight considerations. Consequently, CSI emerges as an effective method for collecting data on human activities.

- ii. The datasets employed in this study are not self-collected. Two established CSI datasets, featuring human activity data from diverse individuals and various room environments, have been utilised. The distinct originators of these datasets ensure differences in both individuals and room environments.
- iii. The selection of these two datasets aims to enhance the robustness of the Spiking Neural Networks (SNNs) model. The first dataset comprises both pre- and post-activity data, while the second dataset exclusively covers activity periods. Furthermore, the datasets vary in size, with one having a limited number and the other a substantial number. Importantly, these datasets are sourced from different individuals.
- iv. In this research, the Spike-Timing-Dependent Plasticity (STDP) learning rule is employed to train the weight layer between the presynaptic and postsynaptic spikes of the output neuron. This approach is adopted due to the SNNs model being trained with reference output spiking time.
- v. All the models in this study are executed using MATLAB on a lab desktop lacking a graphics card. This configuration extends the running time of the SNNs models, which have the potential for parallel execution.

1.5 Hypothesis / Research Questions

1. How to model SNN in object detection and classification.
2. Which neuron models have better energy efficiency?
3. What is the learning method for SNN?
4. What is the input and output of an SNN?

1.6 Organization of Thesis

The thesis comprises five chapters. Chapter 1 presents the introduction of this project, which includes the background, problem statement, research objectives, scope or limitations of the research, research questions, and the organization of the thesis.

Chapter 2 describes the literature review on human activity recognition (HAR) technology and existing machine learning models applied to the HAR dataset. Additionally, this chapter reviews the differences between three generations of neural networks, encoding methods, learning rules, and related works on SNNs.

Chapter 3 depicts the methodology for the proposed SNNs model. This chapter explains the research flow and provides details about the SNNs model.

Chapter 4 presents the impact of several important model parameters that can affect the performance of the proposed SNNs model. Furthermore, it includes the results of the SNNs model and its performance compared to the existing machine learning LSTM model. Two different Wi-Fi CSI datasets are used to evaluate the performance of the proposed SNNs model.

Chapter 5 discusses the conclusion of this research, including the research outcomes, the contribution of this study, and recommendations for future research based on the study.