



**A NEW LORA BASED POSITIONING
ALGORITHM UTILIZING SEQUENCE BASED
DEEP LEARNING TECHNIQUE**

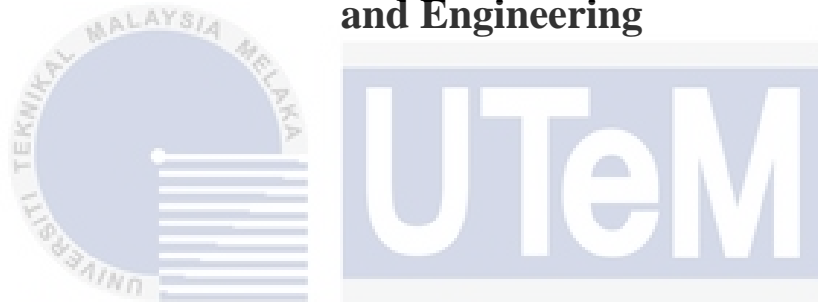
KAVETHA A/P SUSEENTHIRAN

**MASTER OF SCIENCE
IN ELECTRONIC ENGINEERING**

2023



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



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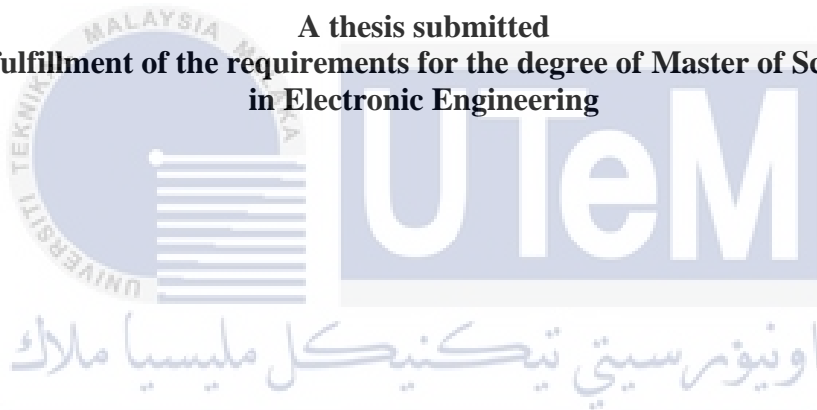
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BASED DEEP LEARNING TECHNIQUE**

KAVETHA A/P SUSEENTHIRAN

**A thesis submitted
in fulfillment of the requirements for the degree of Master of Science
in Electronic Engineering**



Faculty of Electronics and Computer Technology and Engineering

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2023

DEDICATION

I dedicate this thesis to my supervisor Ts. Dr. Abd Shukur Ja'afar who was the backbone in helping me throughout the journey. Next is to my beloved parents who have always given a big support for me to complete my research. Besides that, I would like to dedicate this thesis my friends who had always motivated me whenever I'm down.



ABSTRACT

Positioning systems can be utilized both indoors and outdoors, however their precision varies since the environment seems to have a significant influence on localization. There are positioning system for respective environments for example, at outdoor GPS is used whereas for indoor positioning Wi-Fi and BLE are used but there is no positioning system that can be adaptive to different types of environments which leads to huge positioning error. LoRa positioning has good performance in terms of accuracy however the positioning error is high due to the Received Signal Strength Indicator (RSSI) heavy fluctuations and the selection of the parameters depending on different the type of environment. In this research, an adaptive LoRa based Positioning system is developed which consists of LoRa Transmitters and LoRa Receiver. Next, RSSI and Signal-to-Noise Ratio (SNR) that is measured is being classified whether it is LoS or NLoS environment based on the sequence-based Bi-LSTM model. Furthermore, an analysis of classification using different sequence length is done. Then, a new positioning algorithm is developed which incorporates distance estimation, Kalman Filter and trilateration technique according to the classification with different sequence length data and the positioning error is being analysed. It is concluded, having a sequence length of 100 dataset gives 100% accuracy due to the length is shorter, it is faster to be trained. The CDF gives 90% of positioning error less than 2.9m in LoS scenario whereas NLoS scenario is less than 2.41m. Comparing with the traditional trilateration method, the proposed algorithm gives higher positioning accuracy in which the estimated positions are near to the actual position. Proposed method improves the positioning error up to 28.92% for the LoS scenario meanwhile for the NLoS scenario the positioning error is improved by 32.68%. Meanwhile when the user moves from NLoS to LoS environment, the positioning error was improved to 72.16% whereas when it is was from LoS to NLoS environment, the accuracy improved 99.81%.

ALGORITHMMA PENENTUDUDUKAN BAHARU BERASASKAN LORA MENGUNAKAN TEKNIK URUTAN PEMBELAJARAN MENDALAM

ABSTRAK

Sistem penentududukan boleh digunakan di dalam dan di luar bangunan, tetapi keadaan persekitaran mempunyai pengaruh yang besar ke atas penentududukan seseorang. Sistem penentududukan semasa hanya untuk keadaan persekitaran spesifik; misalnya GPS digunakan di luar, Wi-Fi dan BLE digunakan di dalam bangunan. Walau bagaimanapun, tiada satu sistem penentududukan yang boleh disesuaikan terhadap keadaan persekitaran yang berbeza dan ini menyumbang kepada ralat yang besar. Penentududukan LoRa mempunyai prestasi yang baik dari segi ketepatan, namun ralat penentududukan adalah tinggi disebabkan oleh turun-naik Indikator Kekuatan Isyarat yang Diterima (RSSI) dan pemilihan parameter berdasarkan jenis persekitaran yang berbeza. Dalam penyelidikan ini membangunkan pemancar LoRa dan penerima LoRa untuk sistem penentududukan LoRa yang adaptif. Berdasarkan model jujukan Bi-LSTM, RSSI dan nisbah isyarat-hingar (SNR) yang diukur diklasifikasikan sebagai persekitaran LoS atau NLoS. Selanjutnya analisis pengkelasan dilakukan dengan panjang jujukan yang berbeza. Kemudian, algoritma penentududukan baharu telah direkabentuk menggabungkan anggaran jarak, penapis Kalman dan teknik trilaterasi mengikut klasifikasi dengan data panjang jujukan yang berbeza. Rumusan awal mendapati bahawa dataset dengan panjang jujukan 100 memberikan kejituan 100% dengan latihan rangkaian lebih cepat serta panjang jujukan yang lebih pendek. Dalam senario LoS, bacaan CDF 90% memberikan ralat penentududukan kurang daripada 2.9m, manakala dalam senario NLoS, ia adalah kurang daripada 2.41m. Berbanding dengan kaedah trilaterasi tradisional, algoritma yang dicadangkan memberikan ketepatan penentududukan yang lebih tinggi di mana kedudukan yang dianggarkan adalah lebih hamper kepada kedudukan sebenar. Ralat penentududukan dalam senario LoS bertambahbaik sebanyak 28.92% dengan kaedah yang dicadangkan, manakala dalam senario NLoS bertambahbaik sebanyak 32.68%. Apabila pengguna bergerak dari persekitaran NLoS ke LoS, ralat penentududukan bertambahbaik kepada 72.16%, manakala kejituan meningkat sebanyak 99.81% apabila pengguna berpindah dari persekitaran NLoS ke persekitaran LoS.

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LIST OF ABBREVIATIONS

AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
AoA	-	Angle of Arrival
AP	-	Access Point
BDS	-	Bei Dou Navigation System
Bi-LSTM	-	Bidirectional Long Short-Term Memory
BLE	-	Bluetooth Low Energy
CDF	-	Cumulative Distribution Function
CNN	-	Convolutional Neural Network
DNN	-	Deep Neural Network
GNSS	-	Global Navigation Satellite System
GPS	-	Global Positioning System
GRU	-	Gated Recurrent Unit
LoRa	-	Long-Range Low Power Network Technology
LoS	-	Line-of-Sight
LPWAN	-	Low Power Wide Area Network
LSTM	-	Long Short-Term Memory
NLoS	-	Non-Line-of-Sight
PAN	-	Personal Area Network
RMSE	-	Root Mean Square Error
RNN	-	Recurrent Neural Network
RSSI	-	Received Signal Strength Indicator
SF	-	Spreading Factor
SNR	-	Signal-to-Noise Ratio
TDoA	-	Time-Difference of Arrival
ToA	-	Time of Arrival

WAN - Wide Area Network
Wi-Fi - Wireless Fidelity



LIST OF SYMBOLS

A	-	reference value of RSSI at 1m away
d	-	distance
n	-	Path Loss Exponent
N	-	total number of sampled data
x	-	coordinate at X-axis
y	-	coordinate at Y-axis



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LIST OF PUBLICATIONS

1. Ja'afar, A. S., Suseenthiran, K., Saipullah, K. M., Aziz, M. Z. A. A., Khang, A. W. Y. and Salleh, A. 2023. Development of real-time monitoring BLE-LoRa positioning system based on RSSI for non-line-of-sight condition. *Indonesian Journal of Electrical Engineering and Computer Science*, 30(2), pp. 972–981. doi: 10.11591/ijeecs.v30.i2.pp972-981
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3. Suseenthiran, K., Ja'afar, A. S., Heng, K. W., Aziz, M. Z. A. A., Isa, A. A. M., Husin, S. H. and Hashim, N. M. Z. 2021. Indoor positioning utilizing bluetooth low energy (BLE) RSSI on LoRa system. *Indonesian Journal of Electrical Engineering and Computer Science*, 23(2), pp. 927–937. doi: 10.11591/ijeecs.v23.i2.pp927-937.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

To decide the location of an object at any place, a positioning scheme is necessary. Creations for this mission range from worldwide meter precision coverage to workspace surveillance with sub-millimeters accuracy. Positioning system has been used in many sectors such as navigation, military, tracking devices, logistic and health care monitoring (Zhuang et al., 2018). Positioning system can be used indoor as well as outdoor, but the accuracy will not be the same as the environment has a direct impact on localization. Signal Based Positioning System consists of different types of systems such as Satellite Based Positioning, Cellular Network, Wi-Fi based Positioning System, Bluetooth Low Energy (BLE) based Positioning and LoRa Positioning. Satellite based Positioning is mainly called the Global Navigation Satellite System (GNSS) where it has a few technologies which are the Global Positioning System (GPS), Global Navigation Satellite System (GLONASS) and BeiDou Navigation Satellite System (BDS)(Mendoza-Silva, Torres-Sospedra and Huerta, 2019). GPS has been one of the positioning technologies used for outdoor environment. GPS is recognized mostly as navigation satellite method for identifying the location of a user mostly on the ground. GPS receivers are included in several existing products such as automobiles, smartphones, smart watches and Geographic Information System (GIS) devices. Meanwhile the Wi-Fi-based, BLE-based and LoRa-based positioning system is used with its own device for example Wi-Fi based positioning utilizes Access Point (AP) to transmit and receive data, BLE-based positioning utilizes

BLE beacons to send and receive signal while LoRa positioning system uses LoRa node to transmit and receive signals.

LoRa is a Low-Power Wide-Area Network (LPWAN), a non-cellular networking technology that facilitates long-range communication through low-power, low-cost IoT devices and encourages machine-to-machine communication (M2M) network. Regardless of its low bandwidth limit, LPWAN connectivity is therefore perfectly suggested for long-range wireless IoT applications. LoRa uses four types of frequencies worldwide which are 433MHz, 868MHz, 915MHz and 923MHz. In Malaysia the allocation of LoRa frequency band is 915MHz (Lam, Cheung and Lee, 2019). LoRa enables a long-range transmission with a distance of 5 kilometers in urban areas while 15 kilometers in rural areas with low power consumption. There are only a number of research that comprehends LoRa technology's efficiency and characterization in positioning system. Wi-Fi based positioning which is under WAN has the drawback of unstable transmission of data as it penetrates through heavy objects while BLE-based positioning that is under PAN can only be used in short range transmission of approximately 20 meters.

As LoRa is a revolutionary technology throughout Malaysia, there are only a few studies to comprehend LoRa technology's characterization and efficiency in positioning system. Most of the researchers used LoRa in development of their IoT network and utilized GPS to identify the location (Podevijn et al., 2018)(Choi et al., 2018). Previous researches in the positioning system have studied different techniques such as fingerprinting, Time of Arrival (ToA), Time-Difference of Arrival (TDoA) and trilateration. In development of LoRa positioning, usually trilateration and fingerprinting are the preferred techniques due to the easiest of development and implementation(Lin and Zeng, 2019)(Andersen et al., 2020).

1.2 Problem Statement

The main drawback of GPS technology is its accuracy in critical environments such as indoor, tunnel and urban canyon. The reasons causing GPS technology to not work precisely are weak signal strength, attenuation of signal caused by multipath effect and signals sometimes are totally blocked by the building (Oderwald and Boucher, 2003). GPS signals are always blocked at high-rise buildings and there are not enough satellite signals available to locate a user's position (Cui and Ge, 2001).

There are a few types of alternative technologies to satellite based that are used in positioning system nowadays, for example Wi-Fi based positioning, BLE based positioning and LoRa based positioning. According to Wi-Fi based positioning system, it can cover a long-range making it the ideal option for indoor positioning system and also the data are more secured due to its advanced encryption method. However, Wi-Fi has a higher center frequency so it can penetrate through heavy objects like buildings causing it to be unstable due to its multipath fading effect or noise (Pascacio et al., 2021). Also, the ranging frequency's connectivity of Wi-Fi is limited to approximately 45 meters. Whereas for BLE based positioning, which is initiated by Bluetooth special interest group, it uses less amount of energy in contrast to Wi-Fi positioning system. BLE's usage has rapidly increased in various applications. The disadvantage of this system is that it can only be used in a short range transmission with a maximum of 20 meters with a small amount of data only (Kalbandhe and Patil, 2017). When tracking an asset in a large environment, BLE cannot be used as it cannot support long range transmission of data. BLE and Wi-Fi technologies are only suitable for indoor transmission of data and not suitable for both indoor and outdoor environment as the range of data transmission is small.

Another technology that is used in the positioning system is LoRa based positioning system. LoRa is a new technology which is mostly used for the industrial and geographical

type of IoT networks where its demand has been increasing nowadays. Moreover, it supports long range data transmission with low power consumption. Alternative solution for the indoor GPS detection is LoRa Positioning System. Basic LoRa positioning system gives a good performance in terms of accuracy but it also has the positioning error due to RSSI fluctuation and the environment plays a major part in estimating the position of the object (Cui and Ge, 2001). The determination of LoS and NLoS scenarios is important as the path loss exponent affects the distance and location estimation. Looking at the trend of deep learning models for positioning, it mostly uses fingerprinting technique. This technique uses more manpower for collecting data at each point of the environment which is a major drawback. There is no single positioning algorithm that can adapt to different types of environment which leads to a huge positioning error. As LoRa is used in a long range transmission of data which ranges up to 5 kilometers, it can be used in both indoor and outdoor environment. Hence, the type of environment is crucial in order to have a high positioning accuracy or a small positioning error. Furthermore, basic trilateration technique mostly used in a static environment and not a for a dynamic environment. This technique depends on a fixed path loss exponent when evaluating the user's position. Change of environment during the positioning analysis directly impacts the positioning accuracy. To the best of the knowledge of the researcher, there is no single positioning algorithm that adapts both indoor and outdoor environment condition.

1.3 Research Objectives

This research is developed with the aid of the three objectives which are:

- To design a deep learning layer based on sequence-based Bi-LSTM to classify Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS).
- To integrate sequence-based Bi-LSTM model with Kalman Filter and trilateration technique.