



**HUMAN LOCALISATION IN AN OUTDOOR
ENVIRONMENT USING RADIO FREQUENCY
TOMOGRAPHY**

by

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A thesis submitted in fulfillment of the requirements for the degree of
Doctor of Philosophy

**Faculty of Electrical Engineering Technology
UNIVERSITI MALAYSIA PERLIS**

2022

ACKNOWLEDGEMENT

Praise be to Allah, the Most Gracious and the Most Merciful, who has given me the strength and will to complete this work. The blessings and mercy of Allah be upon his messenger, Prophet Muhammad S.A.W, and his family.

I would like to thank my research supervisor, Assoc. Prof Ir. Dr. Mohd Hafiz bin Fazalul Rahiman, co-supervisors Assoc. Prof. Dr. Latifah Munirah binti Kamarudin and Assoc. Prof. Dr. Hiromitsu Nishizaki gave me the opportunity to do this research and always provided support and guidance. Without the guidance and support of my supervisors, I may not have been able to complete this research work successfully. They always spent their time, were patient, and always offered their hands to help when I faced difficulties in this research. May Allah bless them till Jannah.

I would like to thank the Ministry of Education Malaysia for their sponsorship and financial support. Appreciation and gratitude also to the Japan Science and Technology Agency, University of Yamanashi, and Center of Excellence for Advanced Sensor Technology (CEASTech), Universiti Malaysia Perlis for offering research collaboration opportunities under the Sakura Exchange Program in Science. Many thanks to postgraduate members of the Department of Mechatronics, Yamanashi University, for their help and support in this project.

I'm very thankful for my colleagues, who always give their love and support no matter where they are. Only Allah can repay their kindness.

Last but not least, thank you to my lovely family for their love and patience, which always encourage me to be better and more enthusiastic going through this research study period.

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LIST OF ABBREVIATIONS

AE	Area error analysis
CNN	Convolution Neural Network
DFL	Device-free localisation
DNN	Deep Neural Network
DL	Deep learning
GPS	Global positioning system
GSM	Global System for Mobile Communication
HRTI	Hybrid Radio Tomographic Imaging
IoT	Internet of thing
KNN	K-Nearest-Neighbor
LBP	Linear back projection
LOS	Line of sight
MSSIM	Mean Structural Similarity Index Measure
MSE	Mean Squared Error
NLOS	non-line of sight
PSNR	Peak signal-to-noise ratio
RF	Radio Frequency
RFT	Radio Frequency Tomography
RTI	Radio Tomographic Imaging
RSSI	Received signal strength indicator
RFID	Radio-frequency identification
RNN	Recurrent Neural Network
ROI	region of interest
SIE	spatial image error analysis
SVM	Support vector machine
SSIM	Structural Similarity Index Measure
TSV	Thresholding Sensor Value Method
UT	Ultrasonic Tomography
UCT	Ultrasonic Computerized Tomography
WSN	Wireless sensor network

LIST OF SYMBOLS

P_a	direct transmission link
P_b	reflection link
P_c	reflection link
T_x	transmitter
R_x	receiver
P_i	Transmitted power in decibels (dB)
L_i	Static losses due to distance, in dB
$S_i(t)$	Shadowing loss due to the object that attenuates the RF signal, in dB
$F_i(t)$	Fading loss
$V_i(t)$	Measurement of noise
L	Path loss
dB	decibel
λ	wavelength
c	speed of light
f	frequency
$y^{(k)}$	feed-forward networks

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Penyetempatan Manusia Dalam Persekitaran Luar Menggunakan Tomografi Frekuensi Radio

ABSTRAK

Penyetempatan manusia di persekitaran luar dapat menawarkan kemampuan yang besar terutama dalam aplikasi keselamatan dan pengawasan perimeter. Walau bagaimanapun, penyetempatan manusia dalam persekitaran bukan linear adalah satu cabaran. Walaupun, GPS dan CCTV berjaya mengesan lokasi manusia, namun kedua-dua teknik ini memberikan ketepatan penyetempatan yang rendah kerana kehilangan isyarat dan keterbatasan pandangan kamera. Penyetempatan bebas peranti (DFL) telah diperkenalkan bagi mengatasi masalah ini. Ini kerana pendekatan DFL mempunyai keupayaan untuk mengesan tubuh manusia secara wayarles dalam semua keadaan persekitaran dan tiada masalah kehilangan isyarat seperti yang dihadapi oleh GPS. Walaupun begitu, ketepatan pendekatan DFL ini masih rendah disebabkan oleh masalah variasi dalam penunjuk kekuatan isyarat yang diterima. Untuk mengatasi masalah ini, teknik Pengimejan Tomografi Radio (RTI) telah diperkenalkan. Pada dasarnya, pendekatan ini mencirikan perbezaan tindak balas frekuensi radio (RF) dengan memanfaatkan pelemahan frekuensi radio. Perbezaan tindak balas RF berlaku kerana isyarat terhalang oleh tubuh manusia. Secara konvensional, RTI menggunakan algoritma Unjuran Balik Linear (LBP) untuk membina semula imej tomografi. Walau bagaimanapun, ia menghasilkan imej berkualiti rendah disebabkan oleh masalah songsang yang ditimbulkan oleh unjuran belakang dan kesan calitan akibat imej yang bertindih. Beberapa pendekatan regularisasi telah diperkenalkan oleh penyelidik lain untuk meningkatkan kualiti gambar tomografi. Teknik regularisasi ini telah digunakan untuk menghilangkan kesan pemburukan pada gambar RTI. Namun, gambar yang dihasilkan masih kabur kerana sasaran hanya menempati sedikit ruang berbanding dengan keseluruhan kawasan yang dipantau. Oleh itu, algoritma pembinaan semula imej baharu yang dikenali sebagai Teknik Pengimejan Tomografi Radio Hybrid (HRTI) dan Teknik Pengimejan Tomografi Radio Hibrid Ubahsuai (HRTI-M) telah dicadangkan. Melalui teknik ini, skor analisis ralat kawasan untuk HRTI adalah kurang daripada 3% dan kurang daripada 1% bagi pendekatan HRTI-M. Kelebihan menggunakan kaedah yang dicadangkan ini adalah lokasi titik manusia boleh dikenal pasti dengan jelas daripada imej yang dibina semula dan ini akan menyumbang kepada peningkatan ketepatan penyetempatan. Data RTI ini diperkenalkan kepada pendekatan klasifikasi Rangkaian Neural Dalam (DNN) untuk meningkatkan ketepatan penyetempatan. Pendekatan ini dikenali sebagai pendekatan RTI-DNN. Dalam sistem ini, HRTI-M digunakan untuk menghapuskan variasi data sensor dan meningkatkan kualiti gambar RTI. Sementara itu, DNN digunakan untuk mengurangi kesalahan klasifikasi kerana variasi data sensor dan meningkatkan ketepatan penyetempatan. RTI-DNN ini kemudiannya dibandingkan dengan RTI berdasarkan pendekatan Rangkaian Neural Buatan (RTI-ANN) untuk menilai prestasi kaedah yang dicadangkan. Daripada hasil klasifikasi didapati prestasi RTI-DNN adalah lebih baik berbanding RTI-ANN iaitu 88% berbanding RTI-ANN hanya 64% ketepatan.

Human Localisation in An Outdoor Environment Using Radio Frequency Tomography

ABSTRACT

Localisation of humans in an outdoor environment can offer great capabilities especially in security and perimeter surveillance applications. However, localizing humans in a nonlinear environment is a challenge. Although, GPS and CCTV successfully detect human location, these two techniques provide low localisation accuracy due to signal loss and camera view limitations. Device-free localisation (DFL) technique has been introduced to overcome these problems. This is because the DFL approach has the capability to detect the human body wirelessly in all environmental conditions and there is no losing signals problem as faced by GPS. Despite that, the accuracy of the DFL approach is still low due to the problem of variation in radio signal strength indicator. To overcome this problem, Radio Tomographic Imaging has been introduced. Basically, this approach characterized the differences in radio frequency (RF) response by exploiting the radio frequency attenuation. The differences in RF response occur due to the signal obstructed by the human body. Conventionally, RTI uses the Linear Back Projection algorithm (LBP) to reconstruct the tomographic image. However, it produces a low-quality image due to the ill-posed inverse problem caused by back-projection and the smearing effect due to the overlapping image. Several regularization approaches have been introduced by other researchers to improve the quality of tomographic images. These regularization techniques have been used to eliminate the smearing effect on the RTI image. However, the resulting image is still blurred because the target occupies only a small amount of space compared to the entire area monitored. Therefore, the new image reconstruction algorithms called as Hybrid Radio Tomographic Imaging Technique (HRTI) and Modified Hybrid Radio Tomographic Imaging Technique (HRTI-M) have been proposed to solve the RTI problem. Through these techniques, the area error analysis score for HRTI is lower than 3% and lower than 1% for HRTI-M. The benefit of using the proposed methods is the point location of the human can be identified from the reconstructed image and this will contribute to increasing the localisation accuracy. These RTI data are introduced to the Deep Neural Network (DNN) classification approach to improving localisation accuracy. This approach is known as the RTI-DNN approach. In this approach, the HRTI-M is used to eliminate the variation of sensor data and improve the quality image of RTI. While, the DNN is used to reduce the classification error due to variation in sensor data and increase the accuracy of localisation. This RTI-DNN was then compared with RTI based on the Artificial Neural Network (RTI-ANN) approach to evaluate the performance of the proposed method. From the classification results, it is found that the performance of RTI-DNN is better than RTI-ANN which is 88% compared to RTI-ANN with only 64% accuracy.

CHAPTER 1 : INTRODUCTION

This chapter discusses the application of human localisation in sub-chapter 1.1 and its research background in sub-chapter 1.2. The problem statements in sub-chapter 1.3 are listed based on the background of the study, for which the problem is related to the method to be developed. So, from this problem statement, several objectives have been discussed to address the issue of localisation applications. All the research works and constraints are discussed in sub-chapter 1.5. The organization of the report is stated in sub-chapter 1.6.

1.1 Human Localisation Application

Localisation is the process of determining the location of an object. Nowadays, human localisation applications play an important role in emergency cases such as rescue, health monitoring, and even safety monitoring. The benefit of human localisation application is it can provide information about a person's location for monitoring purposes. However, human localisation becomes challenging in certain situations such as in crowded, dark areas and restricted areas.

For instance, in certain areas like toilets and dressing rooms, Closed-Circuit Television (CCTV) or cameras cannot be installed due to privacy issues. So, it is not easy to know if something is happening in the area. Meanwhile, localisation is used in surveillance applications to perform specific tasks, e.g. person tracking, people counting, and crowd analysis. However, it becomes more challenging when involved with cluttered and crowded areas. Since indoor and outdoor localisation can offer excellent

capabilities in security and perimeter surveillance applications (e.g. in prohibited areas), thus, a lot of researches has been done to address the problem of human localisation in both environments.

1.2 Background Research on Human Localisation

The application of mobile technology in human localisation offers excellent capabilities, especially in environmental monitoring and surveillance applications. However, the problem of time-varying multipath created by environmental noise and coverage area of satellite becomes a major challenge in outdoor localisation (Cesare Alippi, Bocca, Boracchi, Patwari, & Roveri, 2016).

Visual-based localisation technique and signal-based localisation technique are two categories applied to outdoor localisation. In the case of visual-based localisation, for example, a video surveillance system; the coverage area of cameras and night vision problem becomes a challenging issue to be solved.

Because of the high demand for outdoor security and surveillance system, most of the places have been installed with video surveillance systems like CCTV to prevent crime, and to monitor people such as patients, the elderly, and children. However, this single-camera vision of CCTV is limited to small coverage areas (C Alippi, Bocca, Boracchi, Patwari, & Roveri, 2016). Due to this limited coverage area of vision, occasionally, the scene is not fully covered by CCTV and resulting in low quality of the recording images (Ashby, 2017). CCTV only can display the object image which appears in front and within the lens coverage area; unable to detect and visualize an

object located behind the wall or trees. Therefore, when dealing with large outdoor monitoring areas, a huge range of sensors is required. The alternative solution to overcome the limitation of the visual-based localisation technique is by implementing the signal-based localisation techniques.

The application of signal -based localisation techniques can provide information about objects in the monitoring area, including hidden objects by analyzing signal responses. Several conventional approaches are categorized in this localisation technique such as GPS, GSM, and RFID.

GPS is a conventional approach that has use successfully in localisation and it provides high accuracy in human localisation. However, it cannot locate people in places that are sheltered from satellite access, especially if the location of humans is within the building (Du et al., 2018). Meanwhile, mobile localisation using a a GSM network resulting in low accuracy due to the limitation of cell size (Huiyu Liu, Zhang, Su, Li, & Xu, 2015). Due to these reasons, the researchers start to seek alternative ways to overcome these weaknesses by introducing radio frequency-based localisation to estimate human position (Vo, Member, De, & Member, 2016) (Stella *et al.* 2012). Since the radio frequency (RF) wave can penetrate walls and insulating objects, it has the ability to detect hidden targets. There are many localisation techniques based on propagation wave signal has been proposed for the outdoor environment in the past few years. Radio-Frequency Identification (RFID) is one of these techniques.

Typically, RFID is a common device that is used in detection and localisation application. It is also known as infrared-based localisation approach. Although infrared

-based localisation systems do not require terminal devices, performance can be easily influenced by the surrounding environment (Sun et al., 2018). However, due to the limited tag capacity in terms of energy and memory, this system only suitable for short-range communication and centralized system (Zafari *et al.* 2017).

Nowadays, the localisation over Wi-Fi networks has becomes a trend due to its ability to penetrate walls and objects. Device-free localisation (DFL) technique makes human localisation easier without any touch with the target (human) (Y. Zhao, Patwari, Phillips, & Venkatasubramanian, 2013). DFL characterized the differences of RF response by exploiting the radio frequency attenuation due to obstruction of the human body. However, the identification of the human position become inaccurate due to a large variation in RSSI (Gupta, 2013; Y. Zhao & Patwari, 2015). Meanwhile, if there are small changes in multipath components, e.g., node position changes and environmental factors, the value of RSSI measurements will be affected (Kaltiokallio et al., 2014; Shukri & Kamarudin, 2017).

Based on the fundamental of radio propagation, the received signal power varies as a function of space, frequency, and time. The variation of the received signal in small free space outdoor environment can be classified as small-scale fading because it deals with a small distance between transmitter and receiver (Sequeira *et al.* 2017). The strength of the received signal depends on the distance between the two sensors (transmitter and receiver), and it is influenced by the propagation of multiple paths of electromagnetic waves. It causes the average local power of the received signal to decrease slowly if the distance between the transmitter and receiver increases. The

multipath problem created by environmental noise cause variation in RSSI signal which contribute to low accuracy of localisation (Alippi et al., 2016; Patwari, 2010).

To overcome the problem of DFL, radio tomographic imaging (RTI) with wireless network has been proposed by Patwari et al. in 2010. In their previous research work, they could revealed that the human's position can be estimated from the RF attenuation in the sensing area of the Wi-Fi network and interpret them in tomographic image. However, the quality of reconstructed image is poor due to despite experiencing back- projection problems and, hence, incapable to represent the exact location of human as shown in Figure 1.1. From this image, it is known that the reconstructed image still contains noise and needs to be improved. It requires the regularization technique to improve the quality of reconstructed image. Figure 1.2 shows the RTI image reconstructed using Tikhonov regularization method proposed by Xu et al. (2019). From Figure 1.2, the RTI image is clearer compared to the image in Figure 1.1. However, it still contains noise in the image.

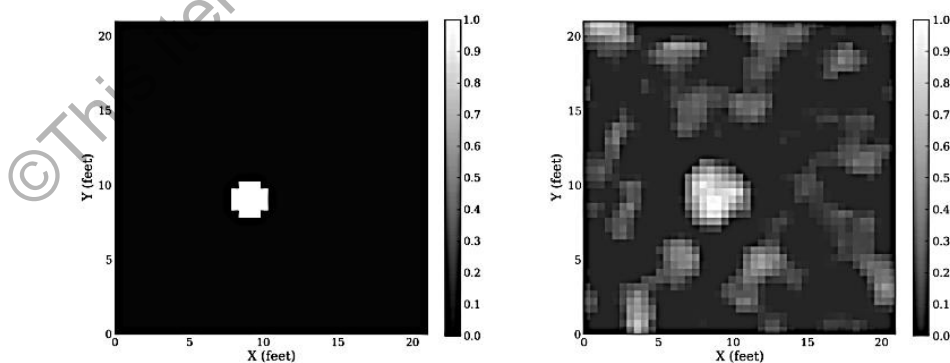


Figure 1.1 RTI image reconstructed by (J. Wilson & Patwari, 2010a)

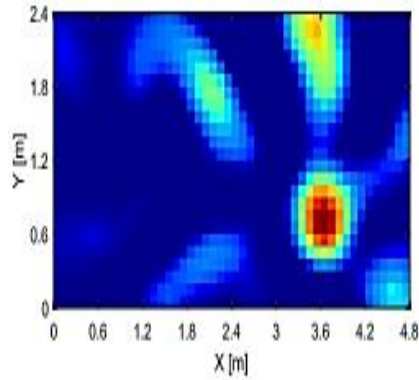


Figure 1.2 RTI image reconstructed using Tikhonov regularization method (Xu et al., 2019)

Suppose a low -quality RTI image is used in the classification of deep learning. It will result in high classification errors and reduced localisation accuracy due to noise or large smeared areas on the RTI image. Although there are weaknesses in tomographic imaging techniques, due to the large potential of RTI in localisation, it is worth exploring it in improving the quality of reconstructed images.

In this thesis, the design of the RTI system based on RF sensor network has been discussed. This system is designed to detect the target in the outdoor environment. Each of RF sensor in this network acts as a transceiver in order to increase the number of measurements and increase the coverage area of detection. Further, a new image reconstruction algorithm is proposed in order to improve the quality of the reconstructed image and increase the localisation accuracy. These RTI data were then tested as an input for the deep learning classification approach. This test is performed to determine the suitability or potential of RTI data in reducing classification errors and evaluate the accuracy of the classification.

1.3 Problem Statement

The following problems need to be considered when designing RTI and deep-learning classification approach for human localisation application.

- i. The measurement area must be viewed from as many angles as possible to obtain complete information of the monitoring space characteristics (Fazalul Rahiman, 2013). Therefore, transceiver sensing procedure will be used in order to perform all the measurements on the perimeter of the monitoring area.
- ii. In RF transmission approach, the challenges are to distinguish between the signal that carries the information and noise due to reflections and scattering waves. The effective solution is to use the RTI (K. Huang, Tan, Luo, Guo, & Wang, 2017). However, this technique is suffering from the ill-posed problem and smearing effect due to the overlapping image caused by back-propagation algorithm (Kaltiokallio et al., 2012).
- iii. The quality of RTI image is depends on the number of sensor node. If the number of nodes is inadequate, target size does not cross enough links to allow RTI to determine its location due to a reduced link density; resulting in an unclear tomographic image (Patwari, 2014; J. Wilson & Patwari, 2010b).
- iv. Blurred or unclear tomographic image will contribute to the low localisation accuracy. To solve this problem, a new image reconstruction algorithm is required to minimize the smeared area on the RTI.

1.4 Objectives of the Study

The research aims to design a localisation technique to improve the accuracy of human localisation. The specific objectives of this research as follows:

- i. To design a tomographic measurement system for human localisation using RF sensors network.
- ii. To propose a new image reconstruction algorithm in improving the quality of reconstructed image and reconstruct the tomographic image for human localisation.
- iii. To enhance the localisation accuracy for specific target location.
- iv. To design an RTI-deep learning classification approach in reducing classification error and increase the localisation accuracy.

1.5 Scope of the Study

The scope of this research is focusing on the possibility of implementing the human localisation system based on RTI and deep learning approach. The focus has been highlighted as follows:

- i. The tomographic sensor consists of twenty RF sensor units arranged around an outdoor monitoring area with dimensions of 5 meters x 5 meters. For the initial study, the detection coverage of twenty RF sensor units was sufficient to cover the entire space of the monitoring area. It is known that, increasing the number of sensors will increase the data collection time and computation time for RTI image reconstruction. Meanwhile, if the number of sensors used is too small, it will contribute to low quality images.
- ii. Experiments were conducted in outdoor environment to avoid the confined space of indoor environment and minimize the reflection and scattering effect. In