

**STUDY OF HAND GESTURE RECOGNITION  
USING IMPULSE RADIO ULTRA WIDEBAND (IR-  
UWB) RADAR SENSOR**



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**FACULTY OF ENGINEERING  
UNIVERSITI MALAYSIA SABAH  
2023**

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USING IMPULSE RADIO ULTRA WIDEBAND (IR-  
UWB) RADAR SENSOR**

**TERENCE JEROME DAIM**



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**THIS IS SUBMITTED IN FULFILMENT OF THE  
REQUIREMENTS FOR THE DEGREE OF  
DOCTOR OF PHILOSOPHY**

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## DECLARATION

I hereby declare that the material in this thesis is my own except for quotations, equations, summaries, and references, which have been duly acknowledged.

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## CERTIFICATION

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A handwritten signature in black ink, appearing to read 'Razak', is written over a horizontal line.

## **ACKNOWLEDGEMENT**

I am grateful to God for His abundant blessings.

I extend my heartfelt gratitude to my family: my father, Jerome; my mother, Irene; my sisters, Sylvia and Eliza, for their unwavering prayers, love, and support.

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I would also like to dedicate this work to the memory of my late brother-in-law, Thien Tet Soon (Ah Soon), and my late aunt, Elisabeth Ting Geok Sun (Fuan Ah Yee), both of whom have departed from this world. I regret not being present during their final moments. May their souls find eternal peace. Amen.

Terence Jerome Daim

29 August 2023

## ABSTRACT

Hand gesture recognition technology has gained significant attention in recent years due to its potential to revolutionize human-computer interaction by offering a natural and intuitive means of communication. This work addresses the limitations of existing systems and focuses on developing a novel hand gesture recognition system that leverages Impulse Radio Ultra-Wide Band (IR-UWB) radar sensors. The primary objective of this work is to create a comprehensive hand gesture recognition system capable of accurately recognizing a wide range of hand gestures while distinguishing between them based on gesture speed. To achieve this, this work defines three key objectives. First objective is to determine the optimal setup for IR-UWB radar sensor data acquisition, considering factors such as sensor placement and configuration. Second objective is to develop and assess hand gesture recognition models using seven different classifiers to achieve accurate and reliable recognition of hand gestures. Third objective is to analyse the performance of the developed classifiers in comparison to existing research in the field, with a focus on recognizing both hand gestures and their associated speeds. The work begins by providing insights into the state of the art in hand gesture recognition and IR-UWB radar sensor technology. Data collection experiments yield a diverse dataset of hand gestures, including variations in speed, essential for algorithm development. The developed algorithms interpret raw IR-UWB radar sensor data and associate it with specific hand gestures, addressing the core objective of gesture recognition. Speed recognition integration further enhances the system's ability to distinguish between gestures performed at different speeds. The resulting hand gesture recognition system is rigorously evaluated and compared to existing methods, demonstrating its effectiveness. Documentation of the development process ensures the methodology and findings are well-documented for reference and replication. While this research makes significant contributions to the field of hand gesture recognition, it also identifies several areas for future work. These include exploring recognition of gestures performed by two hands simultaneously, scalability to different environments, optimal sensor placement, and addressing user variability. Seven classification algorithms (K-Nearest Neighbour, Logistic Regression, Naive Bayes, Gradient Boosting, AdaBoost, Bagging, and Linear Discriminant Analysis) were meticulously explored for hand gesture recognition. The evaluation, based on macro F1 scores to balance precision and recall, aimed to assess their effectiveness. Linear Discriminant Analysis proved most accurate, especially in fast hand gestures, emphasizing its significance in real-time applications. In contrast, AdaBoost exhibited weaker performance, indicating areas for improvement. A slight accuracy decrease for "Up-Down" and "Down-Up" gestures compared to existing literature. However, it significantly outperforms certain literature by 16.28% for "Left-Right" gestures at slow speeds, showcasing improved recognition and robustness. Additionally, the research enhances system functionality, enabling intricate interactions. A developed application allows users to visualize executed hand gestures, paving the way for future integration of complex interaction sub-systems in various gesture recognition applications. In summary, this work advances the field of hand gesture recognition by introducing a novel IR-UWB radar-based system that accurately recognizes hand gestures and distinguishes their speeds, offering improved performance and usability for a wide range of applications.

## **ABSTRAK**

### **KAJIAN PENGESANAN ISYARAT TANGAN MENGGUNAKAN SENSOR RADAR ULTRA WIDEBAND IMPULSE RADIO (IR-UWB)**

Teknologi pengesanan isyarat tangan telah menarik perhatian sejak kebelakangan ini disebabkan potensinya untuk mengubah interaksi manusia-komputer dengan menawarkan cara komunikasi yang semulajadi dan intuitif. Kajian ini bertujuan untuk mengatasi batasan sistem-sistem sedia ada dan memberi tumpuan kepada pembangunan sistem pengesanan isyarat tangan yang baharu dengan menggunakan sensor radar Ultra-Wide Band Impulse Radio (IR-UWB). Objektif utama kajian ini adalah untuk menghasilkan sistem pengesanan isyarat tangan yang komprehensif yang mampu mengesan pelbagai isyarat tangan dengan tepat di samping mampu membezakan kelajuan isyarat tangan. Untuk mencapai tujuan ini, kajian ini menetapkan tiga objektif utama. Objektif pertama adalah untuk menentukan susunan optimal bagi pengumpulan data sensor radar IR-UWB, dengan mempertimbangkan faktor-faktor seperti penempatan dan konfigurasi sensor. Objektif kedua adalah untuk membangun dan menilai model-model pengiktirafan isyarat tangan menggunakan tujuh pengelas yang berbeza untuk mencapai pengiktirafan isyarat tangan yang tepat dan boleh dipercayai. Objektif ketiga adalah untuk menganalisis prestasi pengelas yang telah dibangunkan berbanding dengan penyelidikan sedia ada dalam bidang ini, dengan tumpuan kepada pengiktirafan isyarat tangan dan kelajuan yang berkaitan dengannya. Kajian ini bermula dengan penyelidikan ke atas kemajuan dalam pengesanan isyarat tangan dan teknologi sensor radar IR-UWB. Kemudian, eksperimen pengumpulan data menghasilkan dataset isyarat tangan, termasuk variasi dalam kelajuan, penting untuk pembangunan algoritma dijalankan. Sistem pengesanan isyarat tangan yang dihasilkan dinilai secara teliti dan dibandingkan dengan kaedah-kaedah sedia ada. Dokumentasi proses pembangunan memastikan metodologi dan penemuan disimpan dengan baik untuk rujukan dan replikasi. Walaupun kajian ini memberikan sumbangan yang signifikan kepada bidang pengesanan isyarat tangan, ia juga mengenal pasti beberapa bidang untuk kajian masa depan. Ini termasuk meneroka pengesanan isyarat yang dilakukan oleh dua tangan secara serentak, skalabiliti ke persekitaran yang berbeza, penempatan sensor yang optimum, dan mengatasi variasi pengguna. Tujuh algoritma klasifikasi (K-Nearest Neighbour, Regresi Logistik, Naive Bayes, Gradient Boosting, AdaBoost, Bagging, dan Analisis Diskriminan Linear) telah disiasat dengan teliti untuk pengenalan isyarat tangan. Penilaian berdasarkan skor F1 makro untuk seimbangkan ketepatan dan ingatan bertujuan untuk menilai keberkesanan mereka. Analisis Diskriminan Linear terbukti paling tepat, terutamanya dalam isyarat pantas. Sebaliknya, AdaBoost menunjukkan prestasi yang lemah, menunjukkan bidang yang perlu diperbaiki. Terdapat penurunan sedikit ketepatan untuk isyarat "Atas-Bawah" dan "Bawah-Atas" berbanding dengan literatur sedia ada. Walau bagaimanapun, ia mengatasi beberapa literatur dengan ketara sebanyak 16.28% untuk isyarat "Kiri-Kanan" pada kelajuan perlahan, menunjukkan peningkatan pengenalan dan ketangguhan. Secara ringkasnya, kajian ini menyumbang kepada pembangunan bidang pengesanan isyarat tangan dengan memperkenalkan sistem berdasarkan radar IR-UWB yang baharu yang mampu mengesan isyarat tangan dengan tepat disamping menawarkan prestasi yang lebih baik untuk kegunaan pelbagai aplikasi.

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## LIST OF SYMBOLS

$Z_s$	-	Complex ratio of sound pressure
$p$	-	Sound Pressure
$v$	-	Particle velocity
$c$	-	Speed of sound
$T(t)$	-	Transmitted radar signals
$\omega_0$	-	Fundamental angular frequency
$t$	-	Time
$R(t)$	-	Received radar signals
$d_0$	-	Range between a target and the transmitter
$d(t)$	-	Shift due to hand gesture movement
$A$	-	Amplitude of the received signal
$\lambda$	-	Signal's wavelength
$I(t)$	-	I phase
$Q(t)$	-	Q phase
$DC$	-	DC offset
$A_i$	-	in-phase amplitude
$A_q$	-	quadrature-phase amplitude
$\phi_0$	-	Phase noise
$\theta_0$	-	Phase delay
$f_{min}$	-	Minimum frequency
$f_{max}$	-	Maximum frequency
$f_c$	-	Carrier frequency
$B$	-	Chirp bandwidth

$\pi$	-	Pi constant
$j$	-	Eigenvalues
$\Delta f$	-	Frequency difference between higher frequency and lower frequency
$\eta_0$	-	Fractional bandwidth
$f_H$	-	Higher frequency
$f_L$	-	Lower frequency



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<b>2D</b>	-	2-Dimensional
<b>3D</b>	-	3 Dimensional
<b>ACMA</b>	-	Australian Communications and Media Authority
<b>AdaBoost</b>	-	Adaptive Boosting
<b>AR</b>	-	Augmented Reality
<b>ASL</b>	-	American Sign Language
<b>CEPT</b>	-	European Conference of Postal and Telecommunications Administrations
<b>CMOS</b>	-	Monochrome Complementary Metal-Oxide Semiconductor
<b>CMSVHG</b>	-	Control MS Windows through Hand Gesture
<b>CRTC</b>	-	Canadian Radio-Television and Telecommunications Commission
<b>CSL</b>	-	Chinese Sign Language
<b>CW</b>	-	Continuous Wave
<b>DARPA</b>	-	Defense Advanced Research Projects Agency
<b>EC</b>	-	European Commission
<b>ETSI</b>	-	European Telecommunications Standards Institute
<b>FCC</b>	-	Federal Communications Commission
<b>FMCW</b>	-	Frequency Modulated Continuous Wave
<b>ICNIRP</b>	-	International Commission for Non-Ionizing Radiation Protection
<b>IDA</b>	-	Info-Communications Development Authority
<b>IEC</b>	-	International Electrotechnical Organization
<b>IEEE</b>	-	Institute of Electrical and Electronics Engineers
<b>IP</b>	-	Internet Protocol

<b>IR</b>	-	Infra-Red
<b>IR-UWB</b>	-	Impulse Radio Ultra Wide Band
<b>ISL</b>	-	Indian Sign Language
<b>ISO</b>	-	International Standard Organization
<b>ITU</b>	-	International Telecommunication Union
<b>KNN</b>	-	K-Nearest Neighbors
<b>LCD</b>	-	Liquid Crystal Display
<b>LDA</b>	-	Linear Discriminant Analysis
<b>LED</b>	-	Light Emitting Diode
<b>MCMC</b>	-	Malaysian Communication Multimedia Commission
<b>OpenCV</b>	-	Open Source Computer Vision Library
<b>OSD</b>	-	Office of Special Development
<b>PSD</b>	-	Power Spectral Density
<b>PSL</b>	-	Peruvian Sign Language
<b>RGB</b>	-	Red, Green and Blue
<b>SFCW</b>	-	Single-Frequency Continuous Wave
<b>SIBI</b>	-	Indonesian Sign Language
<b>SRSP</b>	-	Standard Radio System Plan
<b>UAV</b>	-	Unmanned Aerial Vehicles
<b>USB</b>	-	Universal Serial Bus
<b>UWB</b>	-	Ultra-wideband
<b>VHF</b>	-	Very High Frequency
<b>VR</b>	-	Virtual Reality
<b>WiFi</b>	-	Wireless Fidelity

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# CHAPTER 1

## INTRODUCTION

### 1.1 Background

Hand gesture recognition technology has emerged as a significant area of research due to its potential to enhance human-computer interaction and user experience. It involves using various sensors technology, such as vision, wearables, and other sensors, to detect and interpret the gestures and movement of the human hand and fingers (Kumar *et al.*, 2017). Human-computer interaction refers to a combination of methods and instruments that allows people to connect with machines and computers (Laurel & Mountford, 1990; Yeo *et al.*, 2015). It is also occasionally referred to as human-machine interaction (Ahmed *et al.*, 2020) or man-machine interaction (Garg *et al.*, 2009; Fakhreddine *et al.*, 2008). Conventional human-computer interaction technologies include the use of a keyboard, mouse, and touch-screen sensors. These technologies, however, are becoming a constraint in the development of user-friendly interfaces (Yeo *et al.*, 2015).

The field of human-computer interaction is currently experiencing a shift towards more natural and intuitive interfaces, as noted by scholars Kim *et al.* (2019) and Yasen *et al.* (2019). Consequently, there has been a growing interest in incorporating alternative forms of human-to-human communication in human-computer interaction. This has resulted in a range of novel approaches that utilize human arm and hand movements, or hand gestures, as means of interaction, as discussed by Dix (2016) and Nandakumar *et al.* (2015). Hand gestures are a nonverbal form of communication that humans use in their daily interactions, ranging from basic pointing gestures to more complex movements that convey emotions. Given their ubiquity, it is natural to explore the potential of utilizing hand gestures as

an intuitive and natural interface for human-computer interaction.

Human-computer interaction based on hand gesture recognition delivers an inherent contactless interface, bringing people nearer to a natural manner of engagement (Kiliboz *et al.*, 2015; Rempel *et al.*, 2014; Haria *et al.*, 2017; Cremer *et al.*, 2016). The application of hand gesture recognition technology in human-computer interaction has attracted significant interest owing to its multiple benefits, which include usability, non-intrusiveness, and accessibility. This technology has become integral to several fields, including sign language, gaming, augmented and virtual reality, robotics, medical, and many more.

Hand gesture recognition in sign language applications has the potential to dramatically help the deaf and hard-of-hearing population by enhancing sign language communication. Sign language is a visual language that conveys meaning via hand gestures, facial expressions, and body language, and it is the main language used by many deaf and hard-of-hearing people. Hand gesture recognition technology may be used to interpret sign language gestures into text or voice, enabling sign language users and non-signers to communicate in real time. This technology may be used in a range of situations, including healthcare, education, and public transportation, to facilitate communication between sign language users and the broader public.

Hand gesture recognition technology may also be utilized for interactive sign language learning systems. The users of such systems may get feedback and advice while they practice various signs, which assists them in learning how to sign and helps them improve their abilities to perform sign language. Hand gesture recognition may also be used to operate virtual avatars that sign in real-time, which can be utilized for online communication between people who use sign language and others who do not sign. This may give a communication experience that is more immersive and engaging, enabling users of sign language to express themselves more completely and allowing non-signers to learn sign language in a manner that is more participatory and intuitive.

In gaming, one of the major benefits of hand gesture recognition technology is that it improves the game experience for the user. The evolution of video games from basic, two-dimensional interfaces to highly interactive, immersive experiences that demand natural user participation. Using hand gesture recognition technology, game designers are able to include movements that gamers are already used to. In addition, hand gesture recognition technology improves the accessibility of video games for those with physical limitations who are unable to use traditional input devices such as keyboards and controllers. Augmented and virtual reality are the other applications where hand gesture recognition technology has gained interest. Augmented and virtual reality technologies are used to improve the user experience by delivering an immersive and interactive environment. Hand gesture recognition technology is essential in these environments as it enables natural interactions with virtual objects. For instance, in augmented and virtual reality settings, users may handle virtual objects using hand movements, boosting their sense of presence and immersion.

In robotics applications, hand gesture recognition technology plays a vital role in the control and operation of robotic systems. By adopting hand gestures, operators may interact more naturally and intuitively with robots. This permits more accurate control of robotic systems and decreases the needed learning curve for operating these systems. Hand gesture recognition technology also has the potential to enhance the quality of patient care in the medical field. During rehabilitation, for instance, hand gesture recognition technology may be used to monitor and evaluate a patient's hand movements. This may give significant insights into the progression of the rehabilitation process and assist healthcare providers in tailoring treatment programs to the specific needs of individual patients.

Impulse Radio Ultra-Wide Band (IR-UWB) radar sensors provide various benefits over standard hand gesture recognition sensors such as camera and depth sensors, which are both vision-based. Lighting conditions that are both bright and dark have a negative impact on the overall accuracy of such sensors, besides having the potential disadvantage of privacy invasion concern (Schi *et al.*, 2009). To