INDOOR LOCALIZATION TECHNIQUES USING WIRELESS NETWORK AND ARTIFICIAL NEURAL NETWORK

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To my beloved parents and siblings

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ABSTRACT

This research focuses on improving indoor localization using wireless network and artificial neural network (ANN). This involves strategic study on wireless signal behavior and propagation inside buildings, suitable propagation model to simulate indoor propagation and evaluations on different localization methods such as distance based, direction based, time based and signature based. It has been identified that indoor signal propagation impairments are severe, non-linear and custom to a specific indoor location. To accommodate these impairments, an ANN is proposed to provide a viable solution for indoor location prediction as it learns the location specific parameters during training, and then performs positioning based on the trained data, while being robust to severe and non-linear propagation effects. The versatility of ANN allows different setup and optimization possibilities to affect location prediction capabilities. This research identified the best feedforward backpropagation neural network configuration for the generated simulation data and introduced a new optimization method. Indoor-specific received signal strength data were developed with the Lee's in-building model according to a custom indoor layout. Simulation work was done to test localization performance with different feedforward backpropagation neural network setups with the generated received signal strength data as input. A data preparation method that converts the received signal strength raw data into average, median, min and max values prior to be fed into the neural network process was carried out. The method managed to increase location prediction performance using feedforward neural network with two hidden layers trained with Bayesian Regularization algorithm producing root mean squared error of 0.0821m, which is 50% better in comparison to existing research work. Additional tests conducted with six different relevant scenarios verified the scheme for localization performance robustness. In conclusion, the research has improved the performance of indoor localization using wireless network and ANN.

ABSTRAK

Kajian ini memberi tumpuan kepada menambah baik penyetempatan lokasi tertutup menggunakan rangkaian isyarat tanpa wayar dan rangkaian neural tiruan (ANN). Ini merangkumi kajian tentang kelakuan isyarat tanpa wayar dan perambatan dalam bangunan, model perambatan yang sesuai untuk simulasi perambatan dalam kawasan tertutup dan penilaian ke atas kaedah penyetempatan berbeza seperti kaedah berdasarkan jarak, kaedah berdasarkan arah, kaedah berdasarkan masa dan kaedah berdasarkan corak. Telah dikenal pasti bahawa ketaksempurnaan perambatan isyarat di lokasi tertutup adalah teruk, tidak sekata dan unik untuk lokasi tertutup tertentu. Bagi mengatasi ketaksempurnaan ini, satu ANN dicadangkan untuk memberikan penyelesaian baik kepada penyetempatan lokasi tertutup kerana ianya dapat mempelajari maklumat khusus lokasi semasa latihan dan melakukan jangkaan lokasi tertutup berdasarkan data latihan, sambil kekal teguh kepada kesan perambatan teruk dan tidak sekata. Kepelbagaian ANN membolehkan persediaan berbeza dan kemungkinan pengoptimuman bagi mempengaruhi kemampuan ramalan lokasi. Oleh itu, kajian ini mengenal pasti konfigurasi rangkaian neural suap depan rambatan balik terbaik untuk data simulasi yang dibangunkan sambil memperkenalkan kaedah penambahbaikan yang baharu. Data kekuatan isyarat penerima khusus untuk lokasi tertutup telah dibangunkan menggunakan model dalam bangunan Lee berdasarkan susun atur lokasi tertutup unik. Simulasi dijalankan untuk menguji prestasi penyetempatan menggunakan rangkaian neural suap depan rambatan balik berbeza menggunakan data kekuatan isyarat yang telah dibangunkan sebagai input. Satu kaedah penyediaan data yang menukarkan data kekuatan isyarat yang diterima kepada nilai purata, nilai tengah, nilai minimum dan nilai maksimum sebelum dimasukkan ke dalam proses rangkaian neural telah dilaksanakan. Penggunaan kaedah ini berjaya meningkatkan prestasi jangkaan lokasi menggunakan rangkaian neural suap depan rambatan balik dengan dua lapisan tersembunyi yang dilatih dengan algoritma pengaturan Bayesian, menghasilkan ralat min punca kuasa dua pada 0.08210 meter, iaitu 50% lebih baik berbanding kajian terkini. Ujian-ujian tambahan yang dijalankan dengan enam senario berbeza membuktikan keteguhan prestasi jangkaan lokasi menggunakan kaedah yang diperkenalkan dalam kajian ini. Kesimpulannya, kajian ini berjaya menambah baik prestasi penyetempatan lokasi tertutup menggunakan rangkaian isyarat tanpa wayar dan ANN.

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LIST OF ABBREVIATIONS

WSN	-	Wireless Signal Networks
GNSS	-	Global Navigation Satellite Systems
GPS	-	Global Positioning System
GLONASS	-	Global Navigation Satellite Systems
CNSS	-	Chinese Navigation Satellite System
QZSS	-	Quasi-Zenith Satellite System
IRNISS	-	Indian Regional Navigational Satellite System
LOS	-	Line of sight
NLOS	-	Non line of sight
RSS	-	Received signal strength
ISI	-	Intersymbol interference
TOA	-	Time of arrival
TDOA	-	Time difference of arrival
DGPS	-	Differential global positioning system
AOA	-	Angle of arrival
DOA	-	Direction of arrival
SMP	-	Smallest M-vertex polygon
SOM	-	Self organizational map
PCA	-	Principle component analysis
BP	-	Backpropagation
MLP	-	Multiple layered perceptrons
ART	-	Adaptive resonance theory
BAM	-	Bidirectional associative memory
RBF	-	Radial Basis Function

SVM	-	Support vector machine
FANN	-	Feedforward artificial neural network
LQI	-	Link Quality Indicator
CIR	-	Channel impulse response
PSO	-	Particle swarm optimization
FFBNN	-	Feedforward backpropagation neural network
RBFNN	-	Radial basis function neural network
BFGS	-	Broyden-Fletcher-Goldfarb-Shanno
LM	-	Levenberg-Marquardt
BR	-	Bayesian regularization
OSS	-	One step secant
RP	-	Resilient backpropagation
CG	-	Conjugate gradient
GD	-	Gradient descent
RAM	-	Random access memory

LIST OF SYMBOLS

P_t	-	Transmitted power
P_r	-	Received power
G_t	-	Transmitting antenna gain
G_r	-	Receiving antenna gain
L	-	Loss factor
λ	-	Wavelength
f	-	frequency
d	-	Distance
X_σ	-	Gaussian random variable
σ	-	Standard deviation
v	-	Speed
B_s	-	Bandwidth of transmitted signal
T_0	-	Time of arrival
T_s	-	Reciprocal bandwidth
σ_τ	-	RMS delay spread
B_H	-	Coherence bandwidth
R_S	-	Signal data rate
f_d	-	Doppler frequency
n	-	Refraction index
θ_1	-	Incident angle
θ_2	-	Reflected angle
a_h	-	Horizontal reflection coefficient

a_v	-	Verticle reflection coefficient
ε_c	-	dielectric constant
ε_r	-	permittivity
β	-	Brewster angle
h_c	-	Critical height of surface protuberance
Γ	-	Reflection coefficient of smooth surface
Γ_{rough}	-	Reflection coefficient of rough surface
ρ_s	-	Scattering loss factor
c	-	speed of light
τ	-	transmission time
α	-	Decay rate
b	-	Bias
D_c	-	close-in distance
h_t	-	height of transmitter
h_r	-	height of receiver

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CHAPTER 1

INTRODUCTION

1.1 Indoor Localization

Localization is a process of determining the position of devices within a specific area. It is also recognized as geolocation, radiolocation, parameter sensing or positioning [1]–[5]. Normally localization determines the coordinates of a target node in two or three dimensions, specifying the latitude and longitude of where the node is located. Localization leads to many pioneering application potentials which can be developed by utilizing this technology especially when the targeted device's coordinates can be identified wirelessly or even better, involving capability to engage mobile or non-static devices. Consequently, over the past decades a lot of research work have been done due to the interest of improving current systems in terms of accuracy performance, computational cost, complexity and production cost [6]. While resolving and finding solutions for many issues, research work also contribute in identifying new problems and limitations. This therefore introduces opportunities for further research work to be done.

In reference to Elliot D. Kaplan et. al [7], a popular method for localization would be through the implementation of the Global Navigation Satellite Systems (GNSS), which estimates the target node positions by calculating the transmitted data from multiple satellites to the receiver. The most well-known among currently available GNSSs is the Global Positioning System (GPS) which is managed by the United States government. Other options of GNSSs include the Global Navigation

Satellite System (GLONASS), Galileo, Chinese Navigation Satellite System (CNSS) named Compass/Beidou, Japanese Quasi-Zenith Satellite System (QZSS) and the Indian Regional Navigational Satellite System (IRNSS). In total more than 100 satellites are involved to operate GNSSs around the globe. These satellites transmit their time and position data continuously while the receivers on the ground monitor and process these data with equations that estimate location via calculations involving measurements of deviation with the true time relative to the satellites position. In order to achieve acceptable coordinating performance, a minimum of 4 satellites must be in view of the receiver for sufficient data computation [8].

As a result, particular limitations are introduced upon urban areas where satellite signals are most likely to be blocked by the high density of buildings and infrastructures. Therefore, an alternative method is required to apply localization especially in indoor situations where GNSSs do not work [9]. Many researchers are going through the route of using Wireless Signal Networks to achieve this as it is already widely used inside buildings for telecommunication and data transmissions [1]. However, various errors on location prediction are occurring due to non-linear propagation effects, which are more severe in indoor areas and are sensitive to the performance of the localization system [10].

Having an accurate and reliable GPS like system indoors would open up towards many possibilities of useful applications [11]. For example, during an emergency situation in a busy hospital, where a patient must be attended as soon as possible, having a system that would know the positions of every doctor or medical officer and call the closest one available may contribute to having an efficient personnel management in complicated environments while increasing the chances of being a life saver. This may also apply similarly to other situations where people can be quickly allocated and assembled for immediate meetings in business, government, educational or law enforcement organizations. On the other hand, asset or equipment management can be improved through parameter fencing system where attached nodes can be monitored on real-time basis preventing misplacement and also making sure the security is optimized by applying triggering mechanisms when the asset or equipment is taken out from a certain set of parameters. Additionally, an indoor navigation system would benefit users on finding desirable destinations more effectively and conveniently within a large building such as shopping malls, faculty buildings, stadiums or expo halls.

1.2 Problem Statement and Research Motivation

In order to understand the relationship between radio signal propagation and radio signal transmission distance, it is essential to know behavior of electromagnetic radiation relative to the space between the transmitter and receiver. According to David M. Pozar [12], research on the nature of electromagnetic radiation has started since the 18^{th} century where James Clerk Maxwell developed his theory stating that radio waves move through free space at finite velocity with an order of magnitude similar to the of speed of light while involving instantaneous propagation effects which were not consistent with ‘action at a distance’ theories. Maxwell’s theory was then verified by Heinrich Hertz whom undertook controlled experiments to confirm that the electromagnetic behavior predictions by Maxwell were indeed true.

Fundamental theories provide a basis of the understanding radio propagation with the assumption of radio signal transfer in free space or in a uniform dielectric medium. However, real live implementation requires further considerations as it involves contact with large variety of transfer medium which are different in properties, shapes, sizes and distribution. This results to radio signal impairments and distortion as it goes through the transmission process from the transmitter to the receiver. Subsequently, the impairments of radio signal transfer also contribute to error in location measurements based on radio propagation. The effects of radio propagation include reflection, diffraction, scattering and fading.

Indoor localization introduces a very tough environment for signal propagation. The signal distortion and impairments are more severe inside buildings due to the existence of multiple objects of different materials affecting the transmission of signal between the transmitting antenna and the receiving antenna. Different surface shapes and roughness, object sizes and composition and object location and distribution all lead to different propagation effects. Furthermore, the higher density of these objects indoors increases the complexity of signal propagation as non-line of sight (NLOS) situations are more likely. Indoor environments are very different at different locations. This means signal distortion and impairments are also different depending on the location. Therefore, in general, a parameter adaptive method of location estimation is necessary to solve non-linear propagation effects for indoor localization scheme.

The main motivation of this research is the profound ability of artificial neural networks to classify non-linear problems for pattern recognition. Artificial neural network mimics the brain function of learning and solving problems based on the information learnt. This concept can be applied directly for indoor localization which needs an adaptive mechanism to estimate position based on the parameters of a certain location. The signal propagation will provide a specific pattern for each location and these data will be taught and trained into the artificial neural network. Then during the online phase, the neural network will predict the location based on the training data. There are many ways to configure the neural network plus there are numerous optimization possibilities within the application of neural network process.

As severe indoor propagation causes non-linear and location specific signal patterns relative to the distance of signal transmission, this creates challenging input data for the neural network to process and utilize to predict the mobile node location. Therefore, there is a need of an effective optimization technique to allow the neural network to receive a more distinguishable pattern which would lead to better performance in mobile location prediction.

1.3 Objectives of Research

The paramount objective of this research is to provide a valid location prediction solution for the problems occurring during indoor parameter sensing using wireless networks, following the path of our research motivations, with the end goal of producing a better performance for indoor localization system by utilizing suitable artificial neural network processes. Specifically, the objectives of this research are stated in the list below:

i. To investigate for a feedforward backpropagation neural network configuration suitable for indoor localization using the developed simulation data.
ii. To optimize neural network based indoor localization with proposed data preparation strategy for improved location prediction accuracy.
iii. To conduct comprehensive performance evaluation on the proposed method of indoor localization.

1.4 Scope of research

The research focuses on WSN localization for indoor parameter sensing. Centralized localization method is used where the computation takes place at the receivers which are interconnected while mobile nodes only act as transmitters. The study is based on 5.8GHz radio frequency suitable for short range femtocell applications. The basic triangulation technique is adopted where the received signal strengths (RSS) from three different receiver base station locations provide input parameters for the neural network to process and conduct location prediction accordingly. The primary simulation tool is the Matlab software. The neural network toolbox is utilized to process the obtained simulation data with different types of Artificial Neural Network algorithm configurations for location prediction. With exemption to the max epoch and max validation error, all training parameters are according to default values of the neural network toolbox. Data preparation provides strategic input pattern to the Artificial Neural Network. The prepared data is limited to 100 values generated from 100 raw data. The research is based on static receivers and ignores the effect movements of the mobile transmitter nodes as indoor localization applications normally involve static or low velocity movements of the mobile transmitter nodes. The received signal strength data is developed using the Lee's in-building model according to a custom indoor layout. The indoor layout design is limited to an empty building structure.

1.5 Research Contributions

The research work done provide contributions by introducing methodologies which are compliant to improving indoor localization approach and application as listed below.

i. The research provides an indoor specific development of simulation data by utilizing the Lee's in-building model to provide received signal strength data in locations according to a custom indoor layout. In contrary to the log-normal shadowing model used by many research works related to indoor localization [13]–[17], the Lee's in-building model takes into consideration of additional indoor-specific parameters including wall thickness, wall material, floor material, height of the transmitter and the receiver, Fresnel zone distance between the transmitter and receiver, LOS and NLOS properties of the signal path and the number of rooms within the signal path to model the received signal strength accordingly. Therefore, a more relevant simulation data is produced which better simulates severe radio signal propagation in indoor environments.

ii. The research also proposes the application of a novel data preparation method on the RSS data to optimize location prediction with 2 hidden layer feedforward backpropagation neural network trained with Bayesian Regularization training algorithm. The proposed data preparation method involves manipulating the raw RSS data into min, max, median and average values which provide a more strategic input to be processed by the neural network for location prediction. This method is contrary to traditional filtering methods where portions of valuable RSS information is eliminated to create a desirable range of RSS data. The proposed data preparation method enables respectable location prediction accuracy with RMSE of 0.08210m which better than the most recent related research work [18]. This research also provides comprehensive analysis on indoor localization with the proposed data preparation method by evaluating several different scenario applications.

1.6 Thesis Organization

This thesis is organized into 6 chapters respectively. The first chapter provides introductory insight into the research by laying out the fundamental background of the research topic, the problem statements, the research objectives, the scope which limits the research and the contributions yielded by the completion of the research. The second chapter provides elaborate discussion on the theories and previous research work related to the research topic. By conducting critical review of relevant literatures, the research problem is magnified which consequently reveals existing research gaps providing reference for the direction of research. The third chapter establishes the general blueprint of the research. This is where the methodology framework is presented in detail, presenting actions taken to achieve the objectives of the research. The fourth chapter provides analysis discussions on the indoor localization performance of different feedforward backpropagation neural network configurations, the effects of the data preparation method to location prediction and comparison analysis between the proposed data preparation method and the weighted mean filter method. The obtained results are analyzed to verify that the fulfillment of objectives 1 and 2 of the research. Chapter 5 proceeds with location prediction performance evaluation analysis of the proposed method in different controlled scenarios to satisfy the third objective of the research. The last chapter synthesizes the overall research work into a complimentary conclusion and recommends future research works to further improve indoor location prediction.

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