

## **UNIVERSITI PUTRA MALAYSIA**

# A NOVEL PATH PREDICTION STRATEGY FOR TRACKING INTELLIGENT TRAVELERS

## **OMID REZA ESMAEILI MOTLAGH**

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## A NOVEL PATH PREDICTION STRATEGY FOR TRACKING INTELLIGENT TRAVELERS

By

OMID REZA ESMAEILI MOTLAGH

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

October 2009



To my Parents

For their Love and Support



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

> A NOVEL PATH PREDICTION STRATEGY FOR TRACKING INTELLIGENT TRAVELERS

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October 2009

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There are various technologies for positioning and tracking of intelligent travelers such

as wireless local area networks (WLAN). However, the loss of actual positioning data is

a common problem due to unexpected disconnection between tracking references and

the traveler. Disconnection of the mobile terminal (MT) from the access points (AP) in

WLAN-based systems is the example case of the problem. While enhancement of the

physical system itself can reduce the risk of disconnections, complementary algorithms

provide even more robustness in localization and tracking of the traveler.

This research aims to develop a novel path prediction system which could keep track of

the traveler during temporary shortage of actual positioning data. The system takes the

advantage of the past trajectory information to compensate for the missing information

during disconnections. A novel decision support system (DSS) is devised with the

ability of learning decisional as well as kinematical behaviors of intelligent travelers.

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The system is then used in path prediction mode for reconstructing the missing parts of the trajectory when actual positioning data is unavailable.

An ActivMedia Pioneer robot navigating under fuzzy artificial potential fields (APF) and blind-folded human subjects are the two types of intelligent travelers. The reactive motion of robots and path planning strategies of the blinds are similar in that both of them locally acquire knowledge and explore the space based on route-like spatial cognition. It is proposed and shown that route-like intelligent motion is based on a combination of decisional and kinematical factors. The system is designed in such a way to integrate these two types of motion factors using causal inference mechanism of the fuzzy cognitive map (FCM). The FCM nodes are a novel selection of kinematical factors. Genetic algorithm (GA) is then used to train the FCM to be able to replicate the decisional behaviors of the intelligent traveler.

Experimental works show the capabilities of the developed DSS in human path prediction using both simulated and actual WLAN-based positioning dataset. Locational error is set to be limited to 1 m which is suitable for wireless tracking of human subjects with up to 10% improvement compared to the most related works. Both simulation and actual experiments were also carried out on the Pioneer platform. The accuracy in prediction of robot trajectory was obtained about 83% with considerable improvement compared to the recent methods. Apart from the positioning algorithm of this dissertation, there are several applications of this DSS to other areas including assistive technology for the blind and human-robot interaction.



Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

SATU STRATEGI INOVATIF UNTUK MERAMALKAN PERJALANAN SUBJEK YANG PINTAR

Oleh

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Rangkaian kawasan setempat tanpa wayar atau wireless local area networks digunakan

untuk mengenal pasti peletakan dan kedudukan terminal bergerak (MT) dengan

menggunakan parameter gelombang elektromagnetik yang pelbagai. Namun, terdapat

masalah yang timbul dalam sistem ini iaitu kekerapan MT terputus daripada sudut akses

atau access points (AP). Penambahbaikan sistem fizikal tersebut dapat merendahkan

risiko MT terputus, manakala algoritma dan perisian dalam sistem membolehkan

kedudukan dan pergerakan MT dikenal pasti dengan lebih utuh.

Kajian ini bertujuan membina satu sistem ramalan pergerakan yang baru yang mampu

mengenal pasti kedudukan MT apabila jaringan tanpa wayar terputus. Sistem yang baru

ini memperoleh maklumat trajektori MT yang lepas untuk menggantikan maklumat

yang hilang semasa jaringan MT-AP terputus. Sistem sokongan keputusan yang baru

(DSS) telah diperbaharui dengan kebolehan membuat keputusan secara bijak serta

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perilaku kinematikal subjek pintar yang berperanan sebagai MT. Sistem ini kemudiannya digunakan untuk meramal perjalanan bagi membina semula bahagian trajektori MT yang hilang semasa jaringan terputus.

Robot *ActivMedia Pioneer* yang mengemudi di bawah bidang berpotensi buatan kabur (APF) dan subjek manusia yang ditutup mata merupakan dua jenis subjek pintar yang berperanan sebagai MT. Sementara proses pembuatan keputusan manusia berlaku dalam otak, bagi robot mobil proses ini berlaku pada algoritma berasaskan pergerakan. Pergerakan reaktif robot mobil dan strategi perancangan perjalanan manusia buta adalah serupa dari segi perolehan pengetahuan secara tempatan dan menjelajahi ruang berdasarkan kognisi ruang yang seperti jalan. Jenis pergerakan ini telah ditunjukkan bahawa ia berdasarkan gabungan pemikiran rasional dan faktor kinematikal.

DSS ini telah direka sebegitu rupa untuk mengintegrasikan faktor kinematikal dan pemikiran rasional dengan menggunakan mekanisma inferens penyebab bagi peta kognitif kabur (FCM). Nod-nod FCM merupakan pilihan konsep-konsep pergerakan baru. Algoritma genetik (GA) digunakan untuk melatih FCM agar boleh mereplikakan perilaku pembuatan keputusan MT. Dengan itu, FCM yang terlatih mampu meramal trajektori MT apabila jaringan terputus.

Penyelidikan membuktikan keutuhan DSS dalam meramalkan perjalanan manusia menggunakan set data WLAN secara simulasi dan sebenar. Kesilapan lokasi telah dihadkan kepada 1 m, yang sesuai untuk mengenal pasti kedudukan subjek manusia



dengan pembaikan sehingga 10% berbanding dengan kebanyakan strategi yang sedia ada. Hasil penyelidikan telah dijadikan sebagai projek perintis. Ketepatan sistem dalam meramal perjalanan robot adalah dalam lingkungan 83% dengan kadar pembaikan yang lebih baik berbanding dengan pendekatan yang lain. Selain peletakan algoritma dalam kajian ini, terdapat beberapa aplikasi DSS dalam bidang-bidang yang lain termasuk teknologi bantuan untuk orang buta dan interaksi antara manusia dengan robot.



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## **DECLARATION**

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#### LIST OF ABBREVIATIONS

**AP** Access Point

**AHL** Active Hebbian Learning

AOA Angle of Arrival AI Artificial Intelligence

**AI-DSS** Artificial Intelligence-Decision Support System

APF Artificial Potential Fields
AGV Automated Guided Vehicle

**BHL** Blind Human Locomotion

**BBD** Brain-based Device

**CBR** Case-Based Reasoning

**DR** Dead Reckoning

**DSS** Decision Support System

EEG Electro-Encephalography
EKF Extended Kalman Filter

**FHSS** Frequency Hopping Spread Spectrum

FCM Fuzzy Cognitive Map FLC Fuzzy Logic Control

**GA** Genetic Algorithm

GPS Global Positioning System
GUI Graphical User Interface

**HCI** Host Control Interface

**IMU** Inertial Measurement Unit

IR Infrared

**KF** Kalman Filter

**KBS** Knowledge-based System

**LQ** Link Quality

**LBS** Location-based Service

MAB Malaysian Association for the Blinds

MT Mobile Terminal



NN Neural Network
NLP No Light Perception

PDA Personal Digital Assistant
PSO Particle Swarm Optimization

**RF** Radio Frequency

**RFID** Radio Frequency Identification Devices**RSSI** Received Signal Strength Indication

RPY Roll-Pitch-Yaw
RMS Root Mean Square

**SNR** Signal to Noise Ratio

**SW** Straight Walk

**SWSR** Straight Walk and then Straight Return

**TOA** Time of Arrival

**UDP** Undetectable Direct Path

**WF** Wall Following

WLAN Wireless Local Area NetworkWHO World Health Organization



#### CHAPTER 1

#### INTRODUCTION

#### 1.1 Background

There are various techniques for tracking intelligent travelers, i.e., subjects whose motion involve deliberative as well as reactive behaviors. Motion tracking has wide range of applications in security, surveillance, etc. However, due to partial or total loss of actual positioning information, motion prediction techniques have to be employed using simulation tools to predict the future motion. There are many algorithms developed for motion prediction of intelligent and non-intelligent travelers (Bennewitz et al., 2002; Bruce and Gordon, 2004; Iglesias and Luengo 2007; Vasquez and Fraichard, 2004; 2005; Ciurana et al., 2007; 2007b).

As the first approach, there are different kinematical models of path prediction for moving objects such as dead reckoning (DR) (Randell et al., 2005; Warren and Fajen, 2004). But when it comes to intelligent subjects e.g., human or any biological mechanism, there is no mathematical solution to take the challenge of motion prediction that is due to inherent uncertainties and variability of such systems. Kalman filter



(Kalman, 1960) and other recursive filters, as well as Markov localization (Fox, 1998) have been widely used to minimize DR errors. However, they require continuous supply of actual data for update stage of the filter or update of the transition matrix.

In these situations, another approach is to resort to statistical models (Vasquez and Fraichard, 2004). However, the main problem of statistical methods is in the stage of clustering and generation of path patterns (Jain et al., 1999) which requires lots of experimental work with subjects of the same type that is not always possible.

The third approach is to use the knowledge of the past trajectory to predict the future motion based on kinematical (Ciurana et al., 2007a; 2007b), statistical (Vasquez et al., 2005), or artificial intelligence models (Luengo and Iglesias, 2004). The future trajectory of an intelligent subject can be estimated by learning its motion behaviors from the past trajectory. However, in the related works, identification of the motion factors involved in generation of the past trajectory has been based on either kinematical characteristics, or decision making behaviors.

Wireless local area network (WLAN) systems are used for indoor tracking of human and other intelligent travelers e.g., mobile robots, automated guided vehicles (AGV), which are equipped with wireless mobile terminals (MT). Traditionally, the wayfinding behaviors of these travelers have been investigated from a single point of view. The traveler has been either treated as a moving object based on kinematical analysis of motion factors, or as a truly intelligent subject based on decisional factors of motion.

