



Faculty of Electronic and Computer Engineering

**WI-FI NAVIGATION USING MACHINE LEARNING WITH
CONSIDERATION OF CYCLIC DYNAMIC BEHAVIOUR**

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**WI-FI NAVIGATION USING MACHINE LEARNING WITH CONSIDERATION
OF CYCLIC DYNAMIC BEHAVIOUR**

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

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DECLARATION

I declare that this thesis entitled “Wi-Fi Navigation Using Machine Learning with Consideration of Cyclic Dynamic Behaviour” is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Doctor of Philosophy.

Signature :

Supervisor Name : Dr. Mohd Riduan Bin Ahmad

Date :

DEDICATION

I dedicate this thesis to Allah Almighty my creator, my strong pillar, my source of inspiration, wisdom, knowledge, and understanding. He has been the source of my strength throughout this program and on His wings only have I soared.

My great teacher and messenger, Mohammed (May Allah bless and grant him), who taught us the purpose of life;

My homeland Iraq, the homeland of civilization, glories, and tournaments;

The great martyrs, the symbol of sacrifice;

My great parents, who never stop giving of themselves in countless ways,

My beloved sisters;

My friend and elder brother Mohammed Hashem, who stands by me when things look bleak,

My friends who encourage and support me, especially;

Ahmed Ali Al-Saffar, Mohammed Ahmed Jubair, Mustafa Hamid Hassan, Taj-Aldeen Naser

Abdali, Fahad Taha Al-Dhief

All the people in my life who touch my heart,

I dedicate this research.

ABSTRACT

Wi-Fi based localization using machine learning has been proven to be an attractive approach for finding the location prediction with avoidance of accumulation of errors as other sensors such as odometry and inertial sensing. Researchers have developed various models to predict locations based on trained machine learning. A site survey is typically performed to collect fingerprints and a neural network is trained on those fingerprints. The trained model is then placed into operation. However, dynamic changes in the location and navigation behavior of users make the prediction process more challenging in terms of accurate prediction of location. One common mobility behavior of navigation runs is the cyclic dynamics or re-visiting the same place more than one time. Most machine learning models, developed for location prediction, lack sufficient handling of dynamic changes or leveraging them for better predictions. To fill this gap, this study builds a new simulator with two components: one for incorporating dynamic information of navigation in given Wi-Fi dataset and using them to generate the corresponding time series of any navigation run, it is named as Wi-Fi Simulator for Cyclic Dynamic (Wi-Fi-SCD) while the other is useful for converting any dataset to time series with cyclic dynamics, it is named as Cyclic Dynamic Generator (CDG). Furthermore, in this study, two novel location prediction machine learning models were developed. The first is Knowledge Preservation Online Sequential Extreme Learning Machine (KP-OSELM) and the second is Infinite Term Memory-based Online Sequential Extreme Learning Machine (ITM-OSELM). The KP-OSELM model is distinctive from other models cited in the literature, because it preserves knowledge gained in certain areas to restore again when the person re-visits the area again. In KP-OSELM, knowledge is preserved within the neural network structure and is enabled based on feature encoding. The ITM-OSELM model is distinctive from other models cited in the literature, because it carries external memory and transfers learning to preserve old knowledge and restoration. ITM-OSELM is more efficient than KP-OSELM when the percentage of active features is low. Meanwhile, KP-OSELM does not require any external blocks to be added to the neural network (unlike ITM-OSELM), which makes it much simpler. In area based scenarios, KP-OSELM and ITM-OSELM both achieved accuracies of 68%. Moreover, when evaluating KP-OSELM and ITM-OSELM on Wi-Fi-SCD, for three navigation cycles, the highest accuracies achieved were 92.74% and 92.76%, respectively. However, the execution time of KP-OSELM was 1176 second while much less time was needed for ITM-OSELM to be executed with a value of 649 second. Furthermore, when evaluating KP-OSELM and ITM-OSELM on CDG, for three cycles, 100% accuracy was achieved for both models. As a conclusion, this study has provided the literature of machine learning in general and Wi-Fi navigation in particular with various models to support the localization without any restriction on the type of Wi-Fi that is used and with consideration of the practical and dynamic behaviors that can be leveraged to improve the localization performance.

ABSTRAK

Pengenalpastian lokasi berasaskan Wi-Fi menggunakan pembelajaran mesin terbukti menjadi pendekatan yang menarik untuk mencari ramalan lokasi dengan mengelakkan kesilapan yang dilakukan oleh sensor lain seperti odometer dan penginderaan inersia. Penyelidik telah membangunkan pelbagai model untuk meramalkan lokasi berdasarkan pembelajaran mesin terlatih. Tinjauan tapak biasanya dilakukan untuk mengumpul cap jari dan rangkaian saraf yang telah dilatih menggunakan cap jari tersebut. Model yang telah dilatih kemudian diletakkan dalam sistem operasi. Walau bagaimanapun, perubahan dinamik di lokasi dan tindak balas navigasi pengguna membuatkan proses ramalan menjadi lebih mencabar dari segi ramalan ketepatan lokasi. Tingkah laku pergerakan umum navigasi adalah kitaran dinamik atau lawatan semula ke tempat yang sama lebih daripada satu masa. Kebanyakan model pembelajaran mesin, dibangunkan untuk melakukan ramalan lokasi, kekurangan pengendalian terhadap perubahan dinamik atau memanfaatkannya akan menjejaskan ramalan. Melalui kajian ini, simulator baharu dibina dengan dua komponen iaitu satu, untuk memasukkan maklumat dinamik navigasi dalam data set Wi-Fi yang diberikan dan menggunakannya untuk menjana siri masa yang sesuai bagi mana-mana jangka masa navigasi yang dikenali sebagai Wi-Fi Simulator for Cyclic Dynamic (Wi-Fi-SCD) manakala yang lain adalah berguna untuk menukar mana-mana data set kepada siri masa dengan dinamik kitaran yang dinamakan sebagai Cyclic Dynamic Generator (CDG). Dalam kajian ini, dua model pembelajaran ramalan lokasi telah dibangunkan. Yang pertama adalah Mesin Pembelajaran Terperinci Pengekalan Pengetahuan Dalam Talian (KP-OSELM) dan yang kedua ialah Mesin Pembelajaran Ekstrem Talian Terperinci Memori Tanpa Batasan (ITM-OSELM). KP-OSELM, memelihara pengetahuan dalam struktur rangkaian saraf dan berfungsi berdasarkan pengekodan ciri. Model ITM-OSELM adalah tersendiri berbanding model-model kajian lepas yang lain kerana membawa memori luaran dan melakukan pemindahan pembelajaran untuk memelihara serta memulihkan pengetahuan terdahulu. ITM-OSELM adalah lebih cekap daripada KP-OSELM apabila peratusan ciri aktif berada pada tahap yang rendah. Sementara itu, KP-OSELM tidak memerlukan sebarang blok luaran untuk ditambah ke rangkaian saraf (tidak seperti ITM-OSELM) yang menjadikan operasinya adalah lebih mudah. Dalam senario kawasan, KP-OSELM dan ITM-OSELM kedua-duanya mencapai ketepatan 68%. Penilaian ke atas KP-OSELM dan ITM-OSELM di Wi-Fi-SCD, bagi tiga kitaran navigasi, menunjukkan ketepatan tertinggi iaitu 92.74% dan 92.76%. Walau bagaimanapun, masa pelaksanaan KP-OSELM adalah 1176 saat manakala lebih sedikit masa diperlukan untuk ITM-OSELM dilaksanakan dengan nilai 649 saat. Selain itu, ketika menilai KP-OSELM dan ITM-OSELM menggunakan CDG, selama tiga kitaran, kedua-dua model telah mencapai ketepatan 100%. Kesimpulannya, kajian ini telah menyediakan kajian lepas mengenai pembelajaran mesin secara umum dan navigasi Wi-Fi khususnya dengan pelbagai model untuk mengenal pasti lokasi tanpa sebarang sekatan ke atas jenis Wi-Fi yang boleh dimanfaatkan untuk meningkatkan prestasi ketepatan pengenalpastian lokasi.

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LIST OF ABBREVIATIONS

AcMu	-	Automatic and continuous radio map self-updating service
AFKF	-	Adaptive fingerprint kalman filter
AMKL	-	Adaptive multiple kernel learning
ANNs	-	Artificial neural networks
AOA	-	Angle of arrival
APs	-	Access points
BLE	-	Bluetooth low energy
BS	-	Base station
CDG	-	Cyclic dynamic generator
COSELM	-	Constraint online sequential extreme learning machine
CSI	-	Channel state information
DA	-	Domain adaptation
DAELM	-	Domain adaptation extreme learning machine
DANN	-	Discriminant adaptive neural network
DBSCAN	-	Density-based spatial clustering of applications with noise
DCs	-	Discriminative components
DNN	-	Deep neural networks
DOS	-	Denial of service
DTMKL	-	Domain transfer multiple kernel learning
EDA	-	Extreme learning machine based domain adaptation
ELM	-	Extreme learning machine
EM	-	External memory
F1	-	F-measure
FA-OSELM	-	Feature adaptive online sequential extreme learning machine
FCR	-	Feature change ratio.
FN	-	False negative
FNR	-	False negative rate

FP	-	False positive
FPR	-	False positive rate
GPS	-	Global positioning system
GSM	-	Global system for mobile communication
HMM	-	Hidden markov model
ILBSs	-	Indoor location-based services
IM	-	Improvement in measure
IMU	-	Inertial measurement units
IoT	-	Internet of thing
IPS	-	Indoor positioning systems
IR	-	Infrared
ISM	-	Industrial, scientific and medical
ITM-OSELM	-	Infinite term memory online sequential extreme learning machine
JSD	-	Jensen-shannon divergence
KDD	-	Knowledge discovery and data mining
KDDA	-	Kernel direct discriminant analysis
k-NN	-	k-nearest neighbor
KP-OSELM	-	Knowledge preserving online sequential extreme learning machine
kWNN	-	k-weighted nearest neighbor
LEDs	-	Light emitted by diodes
LOS	-	Line of sight
LTE	-	Long-term evolution
LuMA	-	Localization using manifolds alignment
MAC	-	Maximum accuracy change
MAC	-	Medium access control
MDA	-	Multiple discriminant analysis
ML	-	Machine learning
MLP	-	Multi-layer perceptron
MN	-	Measure in new model
MO	-	Measure in old model
MU	-	Mobile unit

NA	-	Number of features in location A
NB	-	Number of features in location B
NC	-	Number of features in location C
NCF-AB	-	Number of common features between A and B
NCF-BC	-	Number of common features between B and C
NIC	-	Network Interface card
NLOS	-	Non line of sight
NN	-	Neural networks
OSELM	-	Online sequential extreme learning machine
PCA	-	Principle component analysis
PDR	-	Pedestrian dead reckoning
PGFE	-	Parameterized geometrical feature extraction
PNAF	-	Percentage of new active features
PNN	-	Probabilistic neural network
POAF	-	Percentage of old active features.
PoI	-	Point of interest
PSD	-	Power spectral density
R2L	-	Root to local
RBF	-	Radial basis function
RBF	-	Rank based fingerprinting
RELMs	-	Robust extreme learning machines
RF	-	Radio frequency
RFID	-	Radio frequency identification
RMM	-	Ratio-based map matching
ROWA	-	RandOm k-sample sets feature for the weighting approach
RP _s	-	Reference points
RSS	-	Received signal strength
RSSI	-	Received signal strength indication
RTT	-	Round trip time
RVR	-	Relevance vector regression
SD	-	Standard deviation
SDA	-	Stacked denoising autoencoder
SK	-	Segmental k-means

SLAM	-	Simultaneous localisation and mapping
SLFN	-	Feedforward neural network
STI	-	Similarity metric, termed signal tendency index
SVM	-	Support vector machine
TDOA	-	Time difference of arrival
TKL	-	Transfer kernel learning
TL	-	Transfer learning
TN	-	True negative
TNR	-	True negative rate
TOA	-	Time of arrival
TP	-	True positive
TPE	-	Target position estimation
TPR	-	True positive rate
TTP	-	Target tracking process
U2R	-	User to root
UWB	-	Ultra-wideband
VLC	-	Visible light communication
VLP	-	Visible light positioning
WAPs	-	Wireless access points
WELM	-	Weighted extreme learning machine
Wi-Fi-SCD	-	Wi-Fi simulator for cyclic dynamic
WinSMS	-	Wi-Fi-based non-intrusive sensing and monitoring system
WLAN	-	Wireless local area network
WSN	-	Wireless sensor network

LIST OF SYMBOLS

PT	-	Period of time
mp	-	Marker points
v	-	Velocities between each two stop points
N_1	-	Number of repeating the point of the pause in the time series
N_2	-	Number of repeating point p_t of the trajectory in the time series
FR	-	Framerate of the sensors
T	-	Pauses times at the stop points
p_t	-	Points in the path
$Res.x$	-	The x axis of grid granularity
$Res.y$	-	The y axis of grid granularity
TS	-	Time Series
D	-	Original dataset
D_t	-	Time series dataset
FCR	-	Feature change rate
NF	-	Number of features
$\langle B_t \rangle$	-	Number of ones in the vector
R	-	That represents the number of records
C	-	Number of classes
y_t	-	The class that is extracted from D at moment t