

# Optimization of RSSI Based Indoor Localization and Tracking using Machine Learning Techniques

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## DECLARATION

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## ABSTRACT

Localization and tracking of persons in industrial environment is critical in terms of safety, privacy and security, particularly when there are hazardous zones. In this research, RSSI of RF signals were used to localize, track and uniquely identify a person in a cluttered environment with a case study into a doorway from a safe zone to a hazardous zone in a cluttered warehouse. Vision based localization was impractical both due to visual obstruction by moving large objects and privacy issues. There were three approaches in RF based localization reviewed in this work. This research uses the approach in which RF receivers are fixed and the transmitter is worn by the target person. RSSI data in a doorway area of  $420\text{ cm} \times 450\text{ cm}$  was analysed both in simulation and in a real test bed and it was proved that DNN and RNN based location prediction was feasible with an accuracy of over 80% even though the environment had noise in the range of  $\pm 2\text{ dB}$  to  $\pm 15\text{ dB}$  and  $\pm 7\text{ dB}$  on average for RF signals. The experiments carried out with a test bed consisting of Raspberry Pi-3 as receivers and Kontakt-io Tough Beacon TB15-1 module as transmitter connected over POE module to a centralized server. The results show that a bounded type RF receiver arrangement to cover the whole area with at least few receivers mounted at a high elevation to capture line of sight signals was effective in accurately localizing the person. The density of positions at which the RSSI data is collected to train the DNN also considerably affected the localization accuracy. The body attenuation was found to be another critical factor affecting the localization accuracy. When the DNN was trained with data captured at one orientation of the person, this DNN was successful in localizing a person with the same orientation but not in localizing a person in completely different orientations. This behaviour was used to detect the body orientation of a person using multiple neural network. A straight path traversed by a walking person at an average speed of  $25\text{ cm/s}$  was successfully tracked at a point-wise accuracy over 80% using time series RSSI data with a threshold of 25 cm. The threshold was reduced to half by averaging the data

over three consecutive predicted positions in the form a centroid. Lastly, Time-domain based RSSI data were used to train RNNs. Deep-LSTM model showed around 95% path-wise localization accuracy for constructed walking paths. Also, RNNs were able to detect the walking direction in single RNN network compared to multiple DNN approach. Finally, this research was able to uniquely identify, localize, detect body orientation and track the walking path of a person and since the person is uniquely identified and RSSI data is MAC addressed this work can be extended to localization of multiple persons.

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## LIST OF ABBREVIATIONS

GPS	Global positioning system
PPE	Personal protective equipment
OSHA	Occupational safety and health administration
RF	Radio frequency
TOF	Time of flight
TDOA	The Time difference of arrival
DOA	Direction of arrival
RSSI	Radio signal strength indication
LQ	Link quality
WSN	Wireless sensor network
RPI	Raspberry pi
ML	Machine learning
NN	Neural network
DNN	Deep neural network
BLE	Bluetooth low energy
NLOS	Non Line Off Sight
LOS	Line Off Sight
Hz	Hertz
RFID	Radio frequency identification
WPAN	wireless personal area networks
IEEE	Institute of Electrical and Electronics Engineers
WLANs	wireless local area networks
Mbit/s	megabit per second
CDMA	Code-Division Multiple Access
LF	Low Frequency
HF	High Frequency
UHF	Ultra-High Frequency
POE	Power Over Ethernet

CSIRO	Commonwealth scientific and industrial research organisation
MNN	Multiple neural network
LF-DLSTM	Local feature-based deep long short-term memory
BPANN	Feed-forward back propagation artificial neural network
RMSE	Root mean square error
IoT	Internet of Things
LoRaWAN	long-range wide-area network
UWB	Ultra Wideband
NN-HMM	Hierarchical neural network hidden Markov model
RBF	Radial Based Function
ReLU	Rectified linear units
COTS	commercial off-the-shelf
NTP	Network time protocol
CNN	Convolution neural network
RNN	Recurrent neural networks
MSE	Mean squared error
MAE	Mean absolute error

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