TAF
Journal of Advances in Technology and Engineering Research
JATER
2019, **5**(3): 135-141

PRIMARY RESEARCH

High precision location tracking technology in IR4.0

Alvin Ting [1*], David Chieng [2], Chrishanton V. Sebastiampi [3], Putri S. Khalid [4]
[1, 2, 3, 4] Mimos Berhad, National Applied R&D Centre, Kuala Lumpur, Malaysia

Keywords
High precision tracking
UWB
Industry 4.0
Internet of things

Received: 5 April 2019
Accepted: 8 May 2019
Published: 28 June 2019

Abstract

In the era of Industry 4.0, where factory efficiency is highly desired, knowledge about the position of the objects like tools, materials, and employees is indefensible for improving the processes and reducing idle times within the Smart Factory. The Smart Factory requires the real-time collection, distribution, and access of manufacturing relevant information anytime and anywhere. Indoor positioning systems (IPSs) can track objects such as assets or people in real-time and play a vital role. However, it is not easy to deploy such a system in a factory due to the obstacles and challenging environment. This paper shares the real experience of deploying Ultra-wideband (UWB) IPS in a manufacturing factory. The positioning system contains UWB anchors, tags, a backend system, and a frontend GUI. The deployment challenges and methods to overcome the challenges in factory environments are discussed. Techniques to improve accuracy such as implementing Kalman Filter, best practice of tag wearing and battery life consideration are also shared. Generally, a solution of providing indoor positioning in a smart factory is shared.

I. INTRODUCTION

Recent manufacturing industry advancement has led to the systematical deployment of Cyber-Physical Systems (CPS) [1], which allows monitoring and synchronization of information from all related perspectives between the physical factory floor and the Internet of Things (IoT) software. Such a trend is transforming the manufacturing industry to the next generation, namely Industry 4.0 [2, 3, 4] or Smart Factory.

Smart Factory concept enables the real-time collection, distribution, and access to manufacturing relevant information anytime and anywhere. Manufacturers have to gather real-time data from all parts of the manufacturing process for fast and accurate decision-making which is vital to successful manufacturing in a global economy. In order to be context-aware, the applications in the Smart Factory have to answer the following three questions [5].

- How is an object identified?
- Where is an object located in the factory?
- What is the situation or status of an object?

One of the Smart Factory requirements, as stated above, is about the real-time location information of employees, machines, and materials. For example, tracking of every worker's movement marked the building into zones to track movements inside/outside each zone and duration or the number of hits in the zone, tracing the path used by a worker to complete a task, searching for employees or important equipment on the building map and tracking the material in the manufacturing process and estimating the job completion time and so on.

In order to realize indoor tracking and tracing, indoor location positioning technologies are needed. There are several types of indoor location positioning technologies commonly used [6], such are WiFi, BLE, RFID and UWB. Each of the technologies has its strengths and weakness which will be discussed in the following session, but the focus of the paper will be on the UWB positioning due to its excellent positioning accuracy.

The following of the paper is organized in such a way that section II compares the existing wireless indoor positioning technologies. Section III presents the software framework of UWB IPS. Deployment challenges in factory floor and hardware requirements are discussed in Section IV and Section V, respectively. Section VI concludes the paper and

[*]Corresponding author: Alvin Ting
[†]email: kee.ting@mimos.my

gives future research directions.

II. WIRELESS INDOOR POSITIONING TECHNOLOGIES

Different environments and requirements need different types of indoor positioning technologies. The technologies that are suitable for the manufacturing factory must be cost-effective and able to provide blanket coverage on the wide factory area. Thus, wireless/RF-based technologies are best to be considered as they have the capability of penetrating walls and obstacles, which leads to wider coverage area, ease of deployment and, hence, cost-effectiveness [7]. The brief discussion of those technologies and their pros and cons are as follows.

A. UWB

UWB is defined by Federal Communications Commission (FCC) as an RF signal occupying a portion of the frequency spectrum that is greater than 20% of the center carrier frequency or has a bandwidth greater than 500 MHz. UWB uses short pulses typically less than 1 nanosecond, which enables it to achieve a positioning accuracy of 30cm or better with averaging [8]. UWB for positioning mainly utilizes the Time of Arrival (TOA) or Time Difference of Arrival (TDOA) [9] of the Radio Frequency (RF) signal to do the ranging between the target and reference point. Since the UWB communication channel spreads information out over a very wide frequency spectrum, it requires very little transmit energy; thus, it is good for battery life.

B. Radio Frequency Identification (RFID)

RFID [10] is a system that transmits the identity of tags wirelessly using radio waves. RFID systems fundamentally consist of two elements: the transponder or tag which is located in the object to be identified and the readers. There are mainly two types of tag, i.e., passive and active tags. Passive tags provide a less range compared to active tags, but it is attractive due to minimal maintenance required. Active RFID tags actively transmit their identification and other information; it is normally battery-powered and provides a larger coverage area. Due to that, the cost of tags is higher.

The RFID technology is most frequently deployed in the production and logistics sector to track objects in the production chain. For real-time indoor positioning, RFID relies on proximity approach where readers have to be installed in desired locations to detect the tags when the tags move within their reading range. Since it highly relies on signal strength to determine the location accurately, the deployment will be challenging in the area with a very Little Line of Sight (LOS).

C. Wireless Local Area Network (WLAN)

WLAN is popular and has been deployed almost everywhere nowadays. WLAN-based IPS relies on the existing WLAN infrastructures. Thus, it is cost-effective. WLAN coverage is good and is normally up to 50m-100m. There are two common techniques for WLAN indoor positioning called propagation approach and fingerprint approach. The propagation approach depends on knowing the location of a list of wireless Access Points (APs) in the area in which the IPS operates. The positioning is then done by measuring the Received Signal Strength (RSS) from each AP and estimating the location using a wireless propagation model and trilateration [11]. This approach is less accurate as signal fluctuations introduce high positioning error during the calculation. The fingerprinting approach is carried out in two phases called offline and online phases [12]. The offline phase involves pre-collecting wireless signatures or RSS of all detected WiFi APs at different Reference Locations/Points (RPs). Thus, at each RP, the RSS signature will be unique due to the spatial differences of those RP to surrounding APs. Hence, each RP is represented by its fingerprint. In the online or positioning phase, the real-time RSS signature collected will be compared to the offline fingerprint to predict the location. Calculations can be done with well-known machine learning algorithms, such as K-Nearest Neighbour (KNN) [13], Bayesian Algorithm [14], Linear Regression or Neural Network [15] to name a few.

The accuracy of the fingerprinting approach is typically 5 to 10 meters, which is better than the propagation approach. However, the fingerprint approach required a huge effort to pre-collect the fingerprint and is susceptible to fingerprint changes due to the addition, removal or changing of Aps' locations [16].

D. Bluetooth Low Energy (BLE)

BLE is designed to be a very low power technology for peer-to-peer communications, which operates in the 2.4-GHz ISM band. Compared to WLAN, the BLE has a shorter range due to low energy transmission and its range is approximately 1 to 10 meters. Due to their low energy characteristic, BLE beacons are particularly attractive because of long battery lives that last many years with low maintenance requirements.

Location positioning using BLE is typically based on proximity measurement, where distance is measured using RSS. A BLE tag will transmit signals and pick up by the reader. This approach provides high accuracy when the tag-reader range is close, such as within a meter. However, the accuracy degrades rapidly with range. Thus, in order to main-

ISSN: 2414-4592
DOI: 10.20474/jater-5.3.4

tain accuracy, more readers are required [17]. Proximity method is very expensive for a large coverage area due to a high number of readers needed. However, fingerprint approach which is similar to WiFi-based positioning system can also be applied to BLE. With this approach, the number of BLE readers can be reduced and it provides better accuracy than WiFi-based positioning system giving the accuracy between 1 and 2 meters [18].

Performance of various IPSs is compared in Table 1, where the definition of performance metrics is defined as follows:

1) Accuracy and precision: Accuracy (or location error) is the most important requirement of the positioning system. It means distance error which is the average Euclidean distance between the estimated location and the true location. Accuracy only considers the value of mean distance errors. However, location precision considers how consistently the system works by considering the variation in its performance over many trials. Usually, the Cumulative Probability Functions (CDF) of the distance error are used for measuring the precision of a system. In Table 1, we group both accuracy and precision under performance metric Accuracy.

2) Coverage: Coverage is defined as the extent of the area to which the wireless signals are transmitted.

3) Scalability: The scalability character of a system ensures the normal positioning function when the positioning scope gets large. Here scalability means the system can scale in terms of coverage and deployment density.

4) Cost: The cost of a positioning system is considering factors, such as the cost of the hardware, the time needed to deploy the system and ease of maintenance.

TABLE 1
PERFORMANCE OF VARIOUS IPS

Performance Metrics	UWB	RFID	WiFi	BLE
Accuracy	High	High	Low	Medium
Coverage	High	Low	High	Medium
Scalability	High	Medium	High	Medium
Cost	High	High	Low	Medium

III. SOFTWARE FRAMEWORK FOR INDOOR POSITIONING SYSTEM

Figure 1 shows the network architecture of UWB IPS, where UWB hardware consists of UWB anchors and tags communicate with each other, calculating the tag position at the desired time interval. The positions of UWB tags are then sent to the upper layer through a preferred interface, such as UART, SPI, HTTP or MQTT, where raw positioning data will be managed and filtered to reduce the position errors. Finally, the processed position data is stored in a database and at the same time, it is also sent to the map manager for displaying the position of tags on the dashboard.

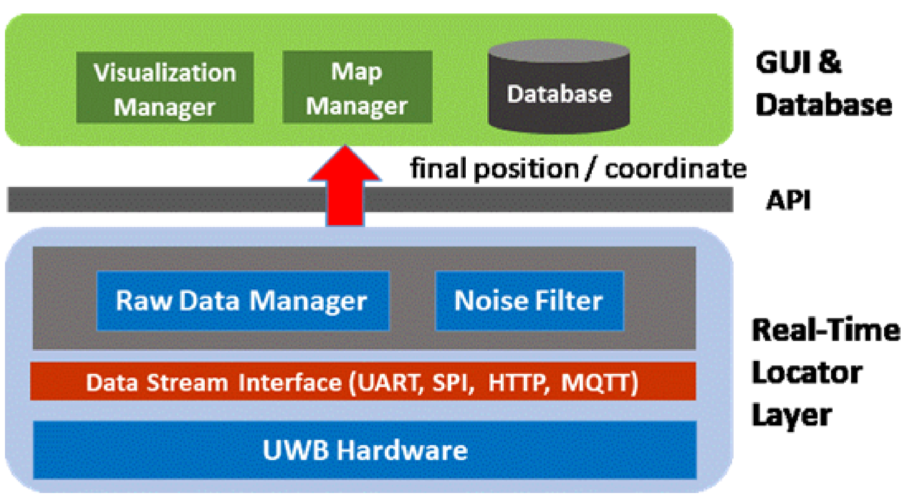


Fig. 1. Architectural diagram of the UWB IPS

IV. DEPLOYMENT CHALLENGES IN FACTORY

A. *Reflective Surface of Metal Room*

For the factories which require clean or hygiene environment, such as food processing factories, any porous material means bacteria can grow in those hard-to-clean pockets, such as concrete, and will be avoided. Typically, Insulated Metal Panels (IMP) are used to build the wall and ceiling because they are quick to install, cost-efficient, and cleanup-friendly. Such an environment is very challenging for UWB deployment as there will be too many reflections of UWB signals on the metal walls and ceiling. Besides, it is very difficult for the signal to penetrate through the wall due to the attenuation of the signal by metal walls. Positioning accuracy will be greatly compromised in such an environment.

ISSN: 2414-4592
DOI: 10.20474/jater-5.3.4

One of the solutions to such an environment is to deploy denser UWB sensors and properly place them at a strategic location. Besides, sensors can be placed at the windows or doorway between two rooms where the signal from one sensor can be probably received in both rooms. This will greatly reduce the number of sensors required, hence reduciing the cost. RF absorption material [19] is also useful to block the undesired signal or reduce the reflections. Those steps are helpful to reduce the positioning error but cannot get rid of them entirely.

B. Sensors Placement Considerations

UWB IPS uses TOA or TDOA for accurate positioning. Thus, LOS from sensors to a tag is vital for accuracy. Any signal blockage or reflections will potentially cause an error in location positioning. In some buildings such as factories with many large machines, LOS from tag to anchors can be obstructed. The tag needs to range to at least 3 anchors to be able to calculate a position. If such a requirement is not met due to LOS disruption and the ranging is based on reflected signal, then the position reported will not be accurate. In order to make sure the best LOS conditions are there, the anchors need to be installed higher up, ideally close to the ceiling of the building so that they are cleared from obstacles. Depending on the physical setup of the building, typically in the case of very tall racks or machines, more anchors are needed to improve the accuracy.

C. Tag Wearing Considerations

Similar to metals, liquids are a great absorber of the UWB signal, resulting in reduced range. Besides, radio waves travel slower in liquids which may increase positioning error due to the fact that UWB positioning relies on the time of flight of the signal. The severity of the liquid affecting the signal is directly related to its volume. The typical human body will significantly reduce the time of flight and result in range measurements that appear to be further away. For human tracking, the UWB tag needs to be worn by workers and the accuracy will be affected if the human body blocks the signal. Due to that, it is best to wear the tracking tag on the shoulder or embed the tag in the helmet so that it will not be obstructed by the human body. If the tag, inevitably, has to be worn at the body area which will block the tag from seeing sensors directly, the solution is to strategically install the UWB sensors in the locations where the tag will not be blocked most of the time based on user's movements.

D. Positioning Accuracy

Due to the obstruction as well as signal fluctuation, positioning is an error prompt. One of the techniques applied to reduce the error is to use the Kalman Filter [20]. Kalman Filter consists of two phases, i.e., Time Update or Predict phase and Measurement Update phase as shown below:

a) Time Update ("Predict")

• Project the state ahead

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_k \tag{1}$$

• Project the error covariance ahead

$$P_k^- = AP_{k-1}A^T + Q \tag{2}$$

b) Measurement Update ("Correct")

• Compute the Kalman Gain

$$K_k = P_k^- H^T \left(HP_k^- H^T + R\right)^{-1} \tag{3}$$

Update estimate wit measurements Z_k

$$\hat{x}_k = \hat{x}_k^- + K_k\left(z_k - H\hat{x}_k^-\right) \tag{4}$$

• Update the error covariance

$$P_k = (I - K_k H)\, P_k^- \tag{5}$$

Where:

x is an estimated location. A is state transition matrix, a difference equation related to the state at the previous time step $k-1$ to the state at the current state k. Matrix B is the control input related to the state $x.u$ is a motion vector. Q is the process noise. P is uncertainty covariance. z is the measurement from the sensor. H is measurement function-the matrix in the measurement Equation 4 relates the state to the measurement z_k and K is Kalman Gain.

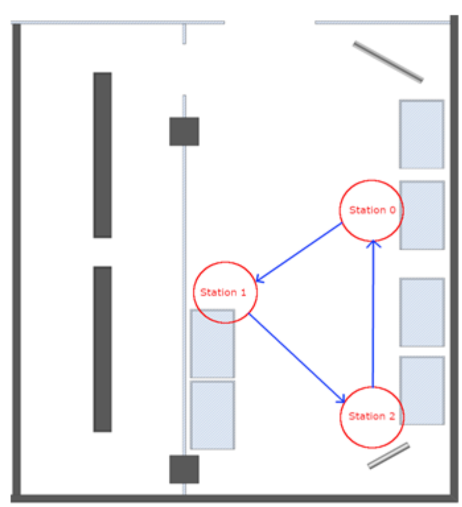


Fig. 2. Floor plan with indoor positioning tracking stations

ISSN: 2414-4592
DOI: 10.20474/jater-5.3.4

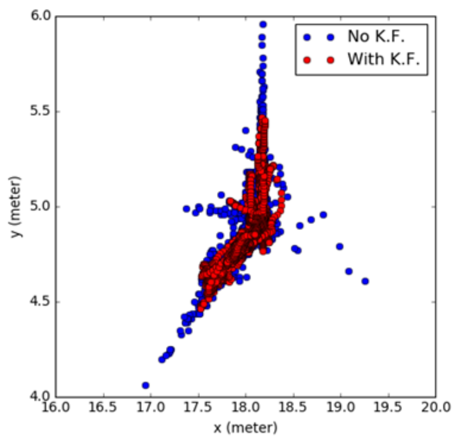


Fig. 3. Positioning sample collected with and without Kalman Filter

The system is tested in our lab, which is a 5x6 square meters room as in Figure 2. Three stations namely Station 0, Station 1 and Station 2 in Figure 2 are virtual stations used to track whether the tag is inside or outside of the station. In the experiment, a tag is placed at the center of the station which is the ground truth. One thousand samples are collected with and without applying Kalman Filter. Figure 3 shows the results plotted with and without Kalman Filter; results show that the positioning is more stable with less spreadout when the Kalman Filter is applied. The plots in Figure 4 show the number of false detections that indicate the tag is outside of the station instead of inside the station. Obviously, Kalman Filter has successfully reduced false detection.

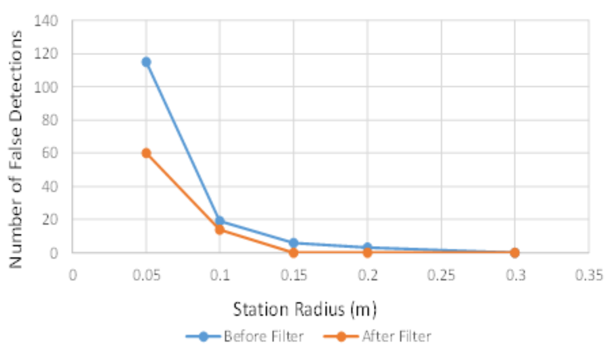
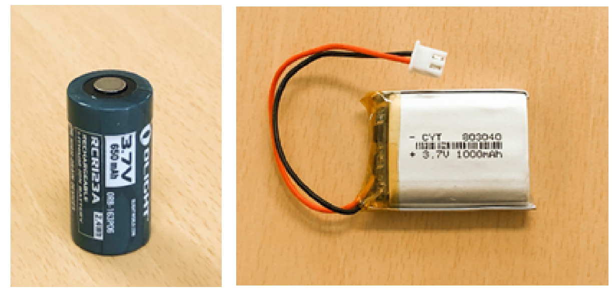


Fig. 4. Detection error vs. station size

V. HARDWARE CHALLENGES

A. Tag Battery Life

One of the concerns of using an active UWB tag is its battery life, even though the UWB tag was designed to be recharged conveniently using USB cable through micro-B plug. Ideally, battery life needs to last as long as possible. Tests were carried out to test battery life as a function of battery capacity and frequency of positioning update. Clearly, the higher the battery capacity, the longer the battery life and the battery life is inversely proportional to the rate of positioning update. Figure 5 shows two types of rechargeable battery used for testing and Figure 6 shows the measurements done for the battery under various settings.



(a) (b)

Fig. 5. Two types of lithium-ion battery used in the test (a) 650 mAh (b) 1000 mAh

From the test result, it can be concluded that battery life is not a big concern for UWB IPS unless very high update frequency, i.e., 5Hz -10Hz, is desired. For normally tracking, the battery can be recharged once in three months or less if an update frequency of 1Hz or lower is used.

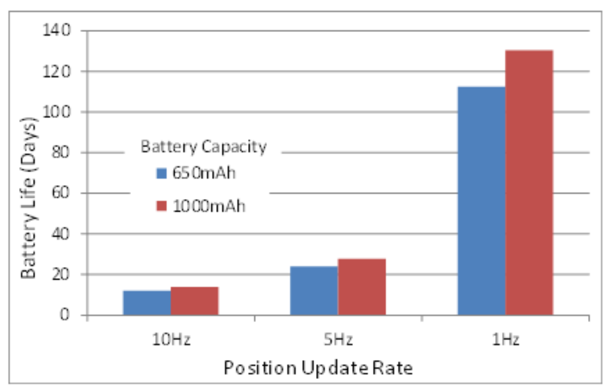


Fig. 6. Battery life as a function of position update rate and battery capacity

B. UWB Tag's Form Factor

(a) (b)

Fig. 7. Tags for (a) worker tracking and (b) material tracking

Tag for tracking workers and material is designed differently based on the need. For worker tracking, the tag has to be lightweight, small and convenient to be carried or worn by the worker. Figure 7(a) shows the design of the tag for worker which is about a name card size. As for material

ISSN: 2414-4592
DOI: 10.20474/jater-5.3.4

tracking, the tag is required to be attached to the material-carrying tray; thus, the tag is designed to be durable with hardened casing and can be conveniently mounted on the tray as shown in Figure 7(b).

VI. CONCLUSION

UWB IPS, including its software system architecture, hardware such as tag design, battery life consideration and battery life testing, has been shared. Besides, the real experience of deploying UWB IPS in a manufacturing factory has also been shared and its deployment challenges and methods to overcome the challenges in factory environments are discussed. Those deployment techniques, such as UWB anchors and tags placement, are detailed. Furthermore, the implementation of the Kalman Filter for noise reduction is also discussed. Future works will explore other possible use cases besides factories, such as office, hospital, conference hall, etc.

REFERENCES

[1] J. Lee, B. Bagheri, and H.-A. Kao, ``A cyber-physical systems architecture for industry 4.0-based manufacturing systems,'' *Manufacturing Letters*, vol. 3, pp. 18-23, 2015. doi: https://doi.org/10.1016/j.mfglet.2014.12.001

[2] H. Lasi, P. Fettke, H.-G. Kemper, T. Feld, and M. Hoffmann, ``Industry 4.0,'' *Business & Information Systems Engineering*, vol. 6, no. 4, pp. 239-242, 2014. doi: https://doi.org/10.1007/s12599-014-0334-4

[3] G. Schuh, C. Kelzenberg, J. Wiese, and F. Stracke, ``Industry 4.0 implementation framework for the producing industry,'' *Journal of Advances in Technology and Engineering Studies*, vol. 4, no. 2, pp. 79-90, 2018. doi: https://doi.org/10.20474/jater-4.2.4

[4] Y. L. Chia, Y. L. Jia, and I. C. Ray, ``Improve quality and efficiency of textile process using data-driven machine learning in industry 4.0,'' *International Journal of Technology and Engineering Studies*, vol. 4, no. 1, pp. 64-76, 2018. doi: https://doi.org/10.20469/ijtes.4.10004-2

[5] D. Lucke, C. Constantinescu, and E. Westkämper, ``Smart factory-a step towards the next generation of manufacturing,'' in *Manufacturing Systems and Technologies for the New Frontier*. London, UK: Springer, 2008.

[6] H. Liu, H. Darabi, P. Banerjee, and J. Liu, ``Survey of wireless indoor positioning techniques and systems,'' *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 37, no. 6, pp. 1067-1080, 2007. doi: https://doi.org/10.1109/tsmcc.2007.905750

[7] Y. Gu, A. Lo, and I. Niemegeers, ``A survey of indoor positioning systems for wireless personal networks,'' *IEEE Communications Surveys & Tutorials*, vol. 11, no. 1, pp. 13-32, 2009. doi: https://doi.org/10.1109/surv.2009.090103

[8] Z. Sahinoglu, S. Gezici, and I. Guvenc, *Ultra-Wideband Positioning Systems*. New York, NY: Cambridge University Press, 2008.

[9] W. Sakpere, M. Adeyeye-Oshin, and N. B. Mlitwa, ``A state-of-the-art survey of indoor positioning and navigation systems and technologies,'' *South African Computer Journal*, vol. 29, no. 3, pp. 145-197, 2017. doi: https://doi.org/10.18489/sacj.v29i3.452

[10] A. Bekkali, H. Sanson, and M. Matsumoto, ``RFID indoor positioning based on probabilistic RFID map and Kalman filtering,'' in *Third IEEE International Conference on Wireless and Mobile Computing, Networking and Communications,* Beijing, China, 2007.

[11] J. Yim, C. Park, J. Joo, and S. Jeong, ``Extended kalman filter for wireless LAN based indoor positioning,'' *Decision support systems*, vol. 45, no. 4, pp. 960-971, 2008. doi: https://doi.org/10.1016/j.dss.2008.03.004

[12] S. He and S.-H. G. Chan, ``Wi-fi fingerprint-based indoor positioning: Recent advances and comparisons,'' *IEEE Communications Surveys & Tutorials*, vol. 18, no. 1, pp. 466-490, 2015. doi: https://doi.org/10.1109/comst.2015.2464084

[13] W. Lan and H. Li, ``A modified KNN indoor wifi localization method with K-median cluster,'' in *IOP Conference Series: Materials Science and Engineering,* California, CA, 2019.

[14] F. Zhao, T. Huang, and D. Wang, ``A probabilistic approach for wifi fingerprint localization in severely dynamic indoor environments,'' *IEEE Access*, vol. 7, pp. 116 348-116 357, 2019. doi: https://doi.org/10.1109/access.2019.2935225

[15] T. Zhang and M. Yi, ``The enhancement of WiFi fingerprint positioning using convolutional neural network,'' in *DE Stech Transactions on Computer Science and Engineering,* New Dehli, India, 2018.

[16] K. Yeo, A. Ting, S. Ng, D. Chieng, and N. Anas, ``Wi-fi indoor positioning fingerprint health analysis for a large scale deployment,'' *International Journal on Advanced Science, Engineering and Information Technology*, vol. 8, no. 5, pp. 1411-1416, 2018. doi: https://doi.org/10.18517/ijaseit.8.4-2.6837

ISSN: 2414-4592
DOI: 10.20474/jater-5.3.4

[17] M. Ji, J. Kim, J. Jeon, and Y. Cho, ``Analysis of positioning accuracy corresponding to the number of BLE beacons in indoor positioning system,'' in *17th International Conference on Advanced Communication Technology (ICACT),* Rome, Italy, 2015.

[18] R. Faragher and R. Harle, ``An analysis of the accuracy of bluetooth low energy for indoor positioning applications,'' in *Proceedings of the 27th International Technical Meeting of The Satellite Division of the Institute of Navigation,* New York, NY, 2014.

[19] Z. Zhou, K. Chen, J. Zhao, P. Chen, T. Jiang, B. Zhu, Y. Feng, and Y. Li, ``Metasurface salisbury screen: Achieving ultra-wideband microwave absorption,'' *Optics Express*, vol. 25, no. 24, pp. 30 241-30 252, 2017. doi: https://doi.org/10.1364/oe.25.030241

[20] G. Welch and G. Bishop, *An Introduction to the Kalman Filter*. North Carolina, NC: University of North Carolina Press, 1995.