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The Effects of Dynamic Environment on Channel Frequency Response-based Indoor Positioning

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***Abstract*—Indoor Positioning Systems should be able to locate an object or person in a dynamic environment. In this research work, we present experimental results when performing indoor positioning in a dynamic environment when using channel frequency response as the indoor location's fingerprint. Dynamic environments introduce varying channel frequency responses for a given indoor location, which makes it difficult to locate desired indoor objects. According to our experiments, we find that indoor fingerprints become uncorrelated within a 15-min window. To bridge the gap between daily fingerprints, we propose three quick remedies in updating the CFR database. These updates allow indoor localization even in the presence of dynamic environmental changes (e.g., people movement, interference of other wireless signals, etc.) and are able to 100% localize indoor locations separated by at least five (5) centimeters. We highlight that in the experiments, there is only one anchor node used to estimate the desired indoor location.**

Index Terms–Indoor Positioning, Channel Frequency Response, Dynamic Environment, Fingerprint Averaging

I. Introduction

Global Positioning System (GPS) cannot be employed for locating a point of interest in an indoor environment since satellite signals do not penetrate walls very well [1]. Instead, Indoor Positioning System (IPS) is developed to address the accurate, reliable and real-time localization of static or mobile person, or device [2] with the aid of wireless communication infrastructures, specifically the WLAN IEEE 802.11 technology [3] in an indoor environment. Others combine this wireless technology with ultrasonic sensors [4] and Bluetooth [5]. Various applications of IPS can be found in robotic indoor surveillance [6], navigation assistance for the disabled [7], and indoor people tracking and monitoring [8]. Indoor positioning systems are termed in as *automatic object location detection* in [9]. With the emergence of gadgets capable of communicating with each other through wireless technology, thus, developing the Internet of Things (IoT), indoor positioning is playing an important role in sharing location and other pertinent information for better service and user experience.

Modeling radio propagation in an indoor environment is difficult to obtain due to the presence of multipath, non-line-of-sight conditions and indoor parameters such as room layout and moving people. Triangulation, scene analysis and proximity are three commonly used measuring principles and positioning algorithms. Triangulation uses geometric properties for target estimation from measuring the received signal strength (RSS), time of arrival (TOA) or time difference of arrival (TDOA). Scene analysis or location fingerprinting relies on collecting desired indoor location features. These features are called fingerprints and stored in a database. Like human fingerprints, these features are unique characteristics of a given indoor location. Thus, scene analysis estimates the target location by matching the online measurements to those measured in real time. Finally, proximity techniques work like cellular networks in estimating the targets location. A mobile handset location is approximated by knowing which cell site is used at a given time. This technique obviously relies on the dense deployment of antennas in known positions.

TABLE I
Comparison of IPS Technologies [10]

Technology	Existing Hardware?	Min Anchors	Low Cost?	Res. LOS (m)	Res. NLOS (m)	Commercial Examples
RSSI	YES	3	–	1–3	5–10	iBeacon, Active RFID, SPIRIT Navigation, Modulated LEDs
TOA TDOA	NO	3	NO	0.2–0.4	1–5	UWB, Zebra, Decawave, Time Domain, Nanotron
AOA	YES	2	–	0.4	1–5	None
Time Reversal	YES	1	YES	0.02	0.02	Origin Wireless

Indoor positioning systems are evaluated in terms of accuracy, precision, complexity, scalability, robustness and cost. Table I summarizes the most common technologies used in indoor positioning and emphasizes the resolution achieved under the line-of-sight (LOS) and non-line-sight (NLOS) conditions.

The Time Reversal technique uses only a single anchor to implement fingerprint analysis based on Channel Frequency Response (CFR). The collected fingerprints are matched to those stored in the database to determine the estimated location. This technique can localize an object up to the centimeter-level.

This research work implements CFR collection and processing as described in [11]. However, we found out through experiments that a dynamic environment greatly impacts the CFR of an indoor location, which is in contrast to the results in [11].

Overall, the major contributions of this paper are as follows:

1) When using only one anchor point for localization, the effects of a dynamic environment on CFR collection are highlighted, e.g., fingerprint correlation between the same indoor location is at a low level and bandwidth increase does not necessarily improve indoor detection accuracy. These variations in the collected CFRs makes it impractical to use them in Time Reversal-based indoor positioning systems.
2) Having the effects of a dynamic environment in mind, three quick remedies are proposed to further improve CFR-based fingerprint matching for more robust indoor localization. These methods, in effect, transform a dynamic environment into a quasi-static environment, making the Time Reversal technique still applicable for indoor localization.

This paper is organized as follows: Section 2 briefly discusses the experimental setup and how fingerprints are processed. Section 3 presents the results and discussion obtained from the experiments. Section 4 then proposes three elementary improvements for better localization. Finally, this paper is concluded in Section 5. Future research directions are also discussed in this section.

II. Experimental Setup

The experimental setup in obtaining the desired CFR fingerprint of a target indoor location is shown in Figure 1. Two Universal Software Radio Peripheral (USRP) N210s, each employing single antenna, are used as the anchor point (AP) and targeted indoor location (IL) in the experiments. The fingerprints to be collected are the Channel Frequency Responses (CFRs) [11]. Figure 2 illustrates the grid showing where the 10 Indoor Locations (IL) are situated. Adjacent ILs are separated by 5 cm.

The parameters used in the experiments are given in Table II. The length of the cyclic prefix, N_g, is 16. There are N = 64 subcarriers with 53 usable subcarriers. The total length of the OFDM frame, N_s, is 80 which is equivalent to $N + N_g$.

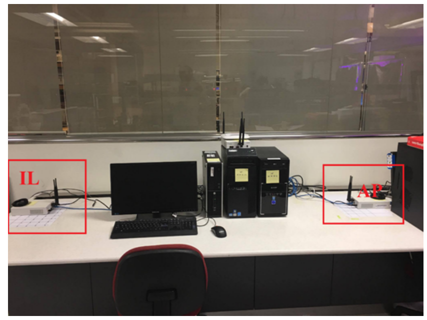


Fig. 1. Experimental Setup for Fingerprint Collection of Desired Indoor Locations.

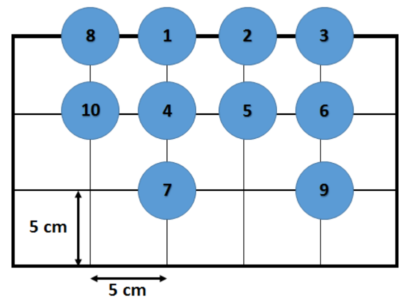


Fig. 2. Positions of the 10 Indoor Locations (IL) where the CFRs were obtained.

TABLE II
Indoor Localization Experimental Settings

Setting	Value
Tx/Rx Gain	15/15 dB
Sampling Rate Tx/Rx	12.5 MHz
Frequency Band	2.51 – 2.61 GHz
Number of Channels Used	11
Channel Bandwidth	10 MHz

In obtaining the CFR database measurements, the USRPs are set to a frequency and capture the channel response depending on the desired number of measurements before switching to the next center frequency. There are 11 center frequencies used in the experiment each with an effective bandwidth of 10 MHz. In the experiments, the frequency band is swept from 2.51 – 2.61 GHz, effectively having a total bandwidth of 110 MHz.

When collecting the CFRs, the transmitter USRP is turned ON before the receiver USRP. The receiver USRP receives the signal for a few seconds so that not too much data are stored. On average, using the 12.5 MHz sampling rate, a 5-second received signal approximately needs 200 MB of storage. For each saved file, the first and second long training preambles defined in the OFDM signal are used to estimate the channel and extract the CFR.

Figure 3 shows a sample processed channel frequency response from USRP IL to USRP AP. The raw data are compensated by mitigating the carrier frequency offset (CFO), symbol frequency offset (SFO) and symbol timing offset (STO). The CFO is due to the oscillator inaccuracies between the transmitter and receiver oscillators, while the SFO is introduced by the sampling interval mismatch at the transmitter and receiver. STO, on the other hand, is caused by the receiver's imperfect timing synchronization [11].

For each of the $L = 10$ locations, we collect 10 CFR measurements, where five will be stored in the database and the rest will be used as the online measurements that are to be localized. These CFR measurments are sanitized, sifted, averaged, and concatenated according to the steps provided in [11].

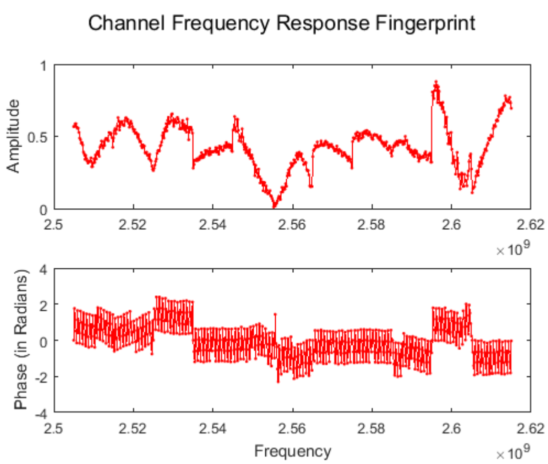


Fig. 3. Processed CFR (IL $\rightarrow$ AP) at location 1.

To determine whether a fingerprint belongs to any of the target indoor locations, we use the Time Reversal Resonating Strength (TRRS) [11] defined by:

$$\eta[\hat{\mathbf{H}}, \hat{\mathbf{H}}'] = \frac{|\sum_{k=1}^{K} \hat{H}_{u_k} \hat{H}'_{u_k}|^2}{\langle \hat{\mathbf{H}}, \hat{\mathbf{H}} \rangle \langle \hat{\mathbf{H}}', \hat{\mathbf{H}}' \rangle} \quad (1)$$

where $\hat{\mathbf{H}} = [\hat{H}_{u_1}, \hat{H}_{u_2}, \cdots, \hat{H}_{u_K}]^T$ and $\hat{\mathbf{H}}'$ defined similarly the processed real-time and online CFRs, respectively. To determine which location the fingerprint under test corresponds to, define $l^* = \arg\max_{l=1,2,\cdots,L} \eta[\hat{\mathbf{H}}[l], \hat{\mathbf{H}}'[l']]$. The estimated location index L' is

$$L' = \begin{cases} l^* & \text{if } \eta[\hat{\mathbf{H}}[l^*], \hat{\mathbf{H}}'[l']] \geq \Gamma \\ 0 & \text{Otherwise} \end{cases} \quad (2)$$

When l^* is obtained and found to be greater than or equal to the tunable variable Γ, we say that indoor localization is achieved for the fingerprint under test and this estimated location index is denoted as L'.

III. Results and Discussion

The experimental setup shown in Figure 1 is situated in one of the laboratory rooms in the university. We collected fingerprints (CFRs) on these 10 locations from May 8 to May 17, 2017. In this interval, research students are going into the office and using different equipment during weekdays. On weekends, there are few or no people working in the lab and functioning devices.

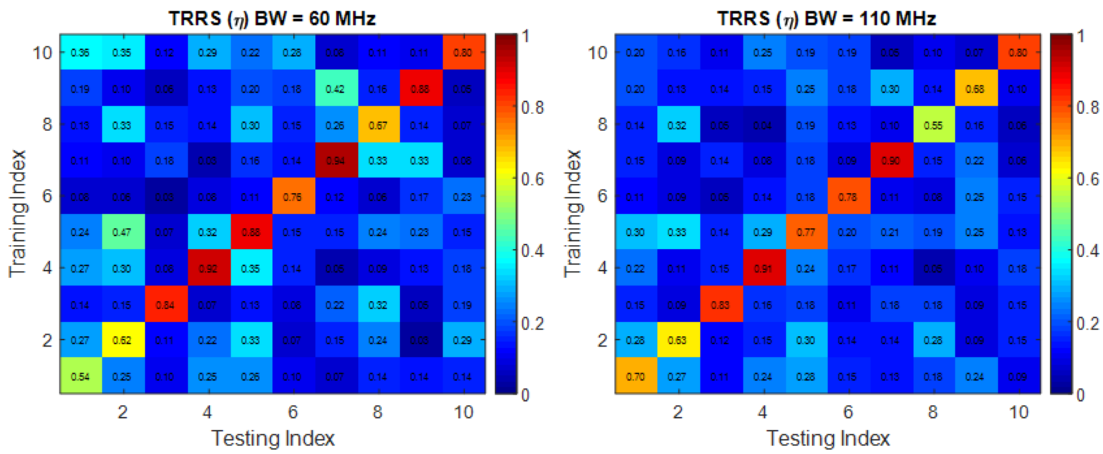
The fingerprints that are collected used bandwidths equal to 60 MHz and 110 MHz. From the collected CFR measurements, the TRRS η's are calculated using (1). Figure 4 illustrates the obtained TRRS from testing and training fingerprints, with a separation of 10 seconds of each other, on a Sunday. Indoor positioning for the said day is achieved by setting the over-all tunable values of $\Gamma \geq 0.54$ and 0.55 when using 60- and 110-MHz CFRs respectively. These show that target locations separated by 5 cm can be distinguished.

Due to the dynamic nature of the environment, we observe that extending the bandwidth from 60 MHz to 110 MHz does not necessarily translate to a better localization via TRRS. This finding is verified in the other nine days. However, one thing consistent is that the off-diagonals from this dataset tends to decrease when there is more bandwidth. The additional bandwidth introduces more of the environment's dynamics, thus, lowering the similarities between CFR measurements, even for the same indoor location.

TABLE III
TRRS Values Obtained from the 10-Day Experiment using BW = 110 MHz

Day	Main Diagonal TRRS Values	Off-Diagonal TRRS Values	Γ Values for Localization
May 8, 2017	0.45–0.94	≤ 0.37	≥ 0.45
May 9, 2017	0.39–0.89	≤ 0.47	—
May 10, 2017	0.26–0.88	≤ 0.35	—
May 11, 2017	0.29–0.89	≤ 0.37	—
May 12, 2017	0.54–0.92	≤ 0.36	≥ 0.54
May 13, 2017	0.52–0.92	≤ 0.39	≥ 0.52
May 14, 2017	0.55–0.91	≤ 0.33	≥ 0.55
May 15, 2017	0.23–0.96	≤ 0.32	—
May 16, 2017	0.49–0.97	≤ 0.38	≥ 0.49
May 17, 2017	0.44–0.92	≤ 0.39	≥ 0.44

Table III summarizes the indoor localization TRRS measurements for the 10-day experiment when using a 110-MHz bandwidth. For each day, there is a wide range of TRRS values that should be used to locate an indoor position (see Main Diagonal Values), while there are days where localization cannot be achieved since the Off-Diagonal values coincide with the Main Diagonal values, e.g. May 9–11, and 15, 2017. On these days, only one indoor location is difficult to localize and the TRRS value is the lower bound of the Main Diagonal TRRS values of each respective day.



(a) (b)

Fig. 4. TRRS matrices of fingerprints with (a) 60 MHz and (b) 110 MHz Bandwidths when CFRs are taken on a Sunday, May 14, 2017.

Each column of the TRRS matrix is the similarity measure between the online and stored CFRs. To determine the suitable Γ value for positioning, we first obtain the maximum TRRS in each column. Among all these maximum TRRS values, we identify the minimum one and set this to be the Γ value for localization.

The daily CFRs are compared with each other to test the indoor locations' stationarity during the 10-day interval. The average TRRS η_{ave} of the 10-day CFRs is shown in Figure 5. It is evident that there is no channel stationarity. Therefore, the difference in the environment gives rise to quite different CFRs to be used for positioning. We also highlight that there are no two days that exhibited a high correlation between them, even when two same days are compared, e.g. May 8 and May 15, 2017, which are both Mondays.

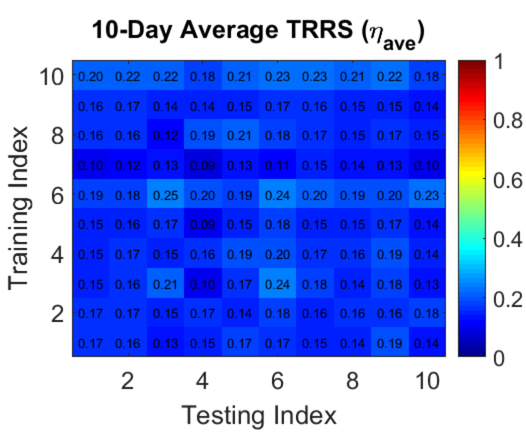


Fig. 5. Average TRRS matrix of the fingerprints obtained from May 8–17, 2017.

Brought about by this finding, we collected one indoor location's fingerprints every 15 minutes for two (2) hours to investigate how channel stationarity varies over time. This is illustrated in Figure 6. We observe that channel stationarity is not achieved because of the low correlation between measured CFRs. This justifies the results shown in Figure 5. To achieve stationarity so that TRRS can be used for indoor positioning, CFRs must be measured in short intervals (seconds interval), just like what was done to obtain Figure 4.

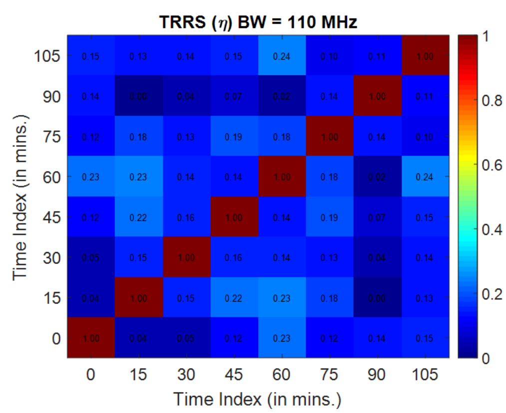


Fig. 6. TRRS matrix of IL 8 when each of its CFR fingerprints is obtained every 15 minutes.

IV. Quick Remedies for Eliminating the Effect of the Dynamic Environment

From Figures 5 and 6, we saw that an indoor location exhibiting stationarity is hard to establish, thus, there is a need to update the fingerprint database to ensure that localization can still be achieved with a possibly high value of TRRS η even though there may be changes in the environment.

We implement three quick remedies for improving the indoor localization scheme on a daily basis, namely (1) Continuous Fingerprint Appending (CFA), (2) Fin-

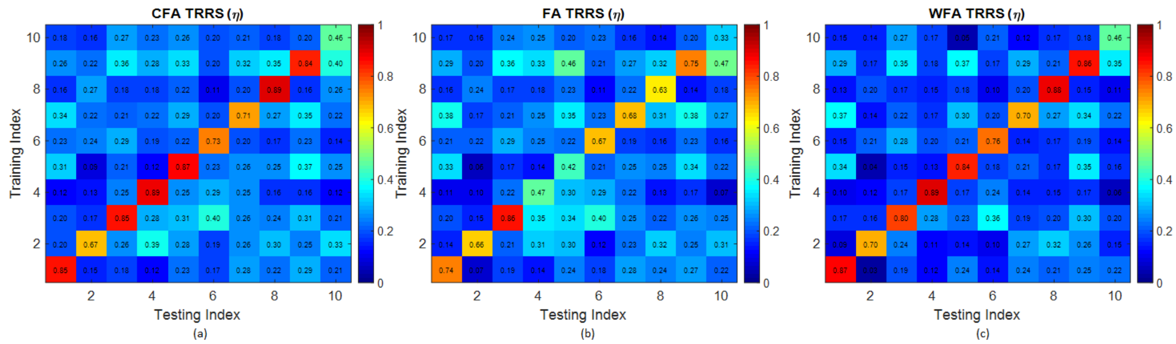


Fig. 7. TRRS matrix derived using Method (a) Continuous Fingerprint Appending, (b) Fingerprint Averaging and (c) Weighted Fingerprint Averaging.

gerprint Averaging (FA), and (3) Weighted Fingerprint Averaging (WFA).

In the CFA method, the latest fingerprint after tested for localization is automatically added to the current database. The localization is determined by getting the maximum among all TRRS η's, i.e.

$$l^* = \text{argmax}\{\eta_1[\hat{\mathbf{H}}_1[l], \hat{\mathbf{H}}'[l']], \cdots, \eta_M[\hat{\mathbf{H}}_M[l], \hat{\mathbf{H}}'[l']]\} \quad (3)$$

where M is equal to the total number of fingerprints which are already stored in the database.

We present M = 9 fingerprints already stored in the database and a 10th fingerprint is to be matched. The TRRS's $\eta_{i=1,\cdots,9}$ between the stored fingerprints and the new fingerprint are calculated. Equation (3) is then used for all the TRRS $\eta_1, \cdots, \eta_9$. This is shown in Figure 7 (a).

CFA allows the database to grow by storing newly acquired fingerprints after localization while retaining the older fingerprints. Possible applications of this method in indoor localization are:

1) Fingerprint data size is in the range of KB or a few MB. For the 10 locations, the testing or training dataset size is approximately equal to 100 KB (Matlab *.mat file size).
2) Targeted indoor locations are only a few. For example, in an indoor location of size 100 cm by 100 cm, only 10% is of critical importance. Outdated fingerprints that have been kept for a long time can also be removed.

If storing new fingerprints to the database will be a disadvantage or if there are many possible indoor locations to be tracked, such that data storage becomes critical, then averaging the fingerprints is considered. FA and WFA can overcome this disadvantage. Averaging the fingerprints using FA is done by:

$$\hat{\mathbf{H}}_M = \frac{\hat{\mathbf{H}}_1 + \cdots + \hat{\mathbf{H}}_M}{M} \quad (4)$$

On the other hand, averaging the fingerprints using WFA is done by:

$$\hat{\mathbf{H}}_M = \frac{\hat{\mathbf{H}}_M}{2} + \cdots + \frac{\hat{\mathbf{H}}_1 + \hat{\mathbf{H}}_0}{2^M} \quad (5)$$

Localization for FA and WFA becomes:

$$l^* = \text{argmax}\{\eta[\hat{\mathbf{H}}_M[l], \hat{\mathbf{H}}'[l']]\} \quad (6)$$

The FA and WFA propositions allow storing fingerprints by using a data size equivalent to a single fingerprint data size. Since for the 10 locations above consume approximately 100 KB each, then averaging the old and new fingerprints will also approximately need this much of space. Unlike FA that gives equal weights to all fingerprints, WFA gives more significance to the most recent fingerprint. This is done to allow storing the most recently acquired environment changes. Localization when using the averaging methods is shown in Figure 7 (b) and (c).

CFA and WFA allow perfect localization with $\Gamma \geq$ 0.46, while FA suffers from incorrect estimation at some indoor locations, e.g. location 5 and 10.

For the three methods stated above, we compare each TRRS to the ideal localization results, i.e. a square matrix $\mathbf{I}$ where the main diagonal is equal to 1 and the off-diagonals equal to zero. A "1" means there is a perfect localization via the spatial-temporal focusing effect [12] and a "0" means otherwise. The mean-square error (MSE), given below, is obtained.

$$\text{MSE} = \frac{1}{\lambda}\sum_{i=1}^{L}\sum_{j=1}^{L}(I_{i,j} - \eta_{i,j})^2 \quad (7)$$

where, for all elements, $\forall i$ and $\forall j$, λ = L^2, for diagonal elements only, i = j, λ = L, and for off-diagonals, $i \neq j$, λ = $L^2 - L$. The resulting MSEs are shown in Table IV.

Between the averaging methods (FA and WFA), WFA provides the least MSE during localization. This

TABLE IV
COMPARISON OF THE THREE METHODS USING MSE

Method	All Elements	Diagonal	Off-Diagonal
CFA	0.0604	0.0670	0.0597
FA	0.0708	0.1678	0.0600
WFA	0.0463	0.0664	0.0441

implies that the target and non-target indoor locations can be discriminated from each other while using only weighted-averaged fingerprints.

On the other hand, CFA performs better than FA since all fingerprints are stored in the database. There is a high probability that one of those fingerprints is a replica of the fingerprint currently being tested for localization.

Also, we highlight that in CFA, the total required storage is 1 MB since there are 10 stored fingerprints, each requiring 100 KB. For FA and WFA, only 100 KB is needed for storing the averaged fingerprints for all positions. CFA will also suffer to a longer processing time when compared with the other two methods for improving indoor localization since it needs to compute for M TRRS. For this experiment, using an Intel(R) Core(TM) i7-4770 CPU @ 3.40 GHz for post-processing the CFRs, the processing times are shown in Table V.

TABLE V
ELAPSED COMPUTATIONAL TIME FOR THE THREE QUICK REMEDIES

Method	Processing Time (in seconds)
CFA	0.031381
FA	0.001567
WFA	0.010787

V. CONCLUSION AND FUTURE WORK

In this work, we have been able to verify indoor localization of target locations separated by five (5) cm using the Channel Frequency Response (CFR) as the location's fingerprint. However, we found out through experiments that indoor location stationarity is difficult to achieve due to the dynamics of the environment. It has been shown that a minutes-interval depicts the non-stationarity of the environment.

From these findings, we have presented three quick remedies to provide robust localization when CFRs are collected in seconds-interval. CFA allows instantaneous updates of location fingerprints, but requires more data storage and processing time. FA and WFA update the location fingerprint by averaging the fingerprints and assure that there is an up-to-date indoor location fingerprint, especially FWA since more than 50% of the averaged value come from the latest fingerprints.

In the future, we will explore how to extract distinct features of an indoor location using deep learning or nonlinear processing techniques. The features extracted are the fingerprints for that indoor location even if there will be uncontrollable environment changes introduced, such as people walking around and rearrangements in the indoor setup.

VI. ACKNOWLEDGMENT

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