Statistical Approach for Robust Indoor Positioning against Signal Variations

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Abstract—There are various methods for indoor positioning, but achieving precise accuracy in the presence of signal variations caused by diverse factors in indoor spaces is challenging. Robust indoor positioning methods are required to handle irregular and unpredictable signal changes. In this paper, we propose a statistical approach to indoor positioning, aiming to provide robustness against signal variations.

Keywords—Indoor Positioning, Wi-Fi, RSSI, Statistical Approach, Standard Deviation, Normal Distribution

I. INTRODUCTION

The importance and necessity of precise positioning for various applications have been continuously increasing. Various technologies are being developed to estimate the user's current point. For outdoor environments, positioning using Global Navigation Satellite System (GNSS) signals is available.[1] However, in indoor environments like underground areas, tunnels, and buildings, GNSS signals are not accessible, leading to radio shadow area, and alternative methods for positioning need to be explored.[2]

In indoor environments, it is possible to perform positioning using different wireless signals. The representative ones are Wi-Fi and Bluetooth Low Energy (BLE), which are already established for other purposes, resulting in low implementation costs. And there exist various methods for constructing systems using these signals and conducting similarity comparisons. And there exist various methods for building systems and performing similarity comparisons using these signals. For instance, many studies have been conducted to build databases for fingerprinting or trilateration, and to perform similarity comparisons using machine learning algorithms such as k-Nearest Neighbor and Random Forest.[3][4] Among the Indoor Positioning Systems (IPS) that utilize these wireless signals, fingerprint-based techniques are widely used for signal-based positioning. Fingerprint-based IPS requires similarity search. However, during the similarity search process, there may be errors that degrade the accuracy of positioning due to the presence of data containing variations in each signal.[5] Therefore, a similarity search method that is robust to such signal variations is needed. In this paper introduces a robust indoor signal positioning method using Wi-Fi signal strength to address the challenges posed by signal variations.

II. OVERVIEW OF FINGERPRINT PROCESS AND LIMITATIONS OF EXISTING WORKS

Fingerprint-based indoor positioning involves collecting wireless signal information such as Wi-Fi or Bluetooth Low Energy (BLE) as possible points and storing it in a database (DB). When positioning, the method involves comparing the signal information collected at the current point with the stored signal information for each possible point in the DB.[6] The similarity search utilizes the Received Signal Strength Indicator (RSSI) of each Access Point (AP) stored in signal information.

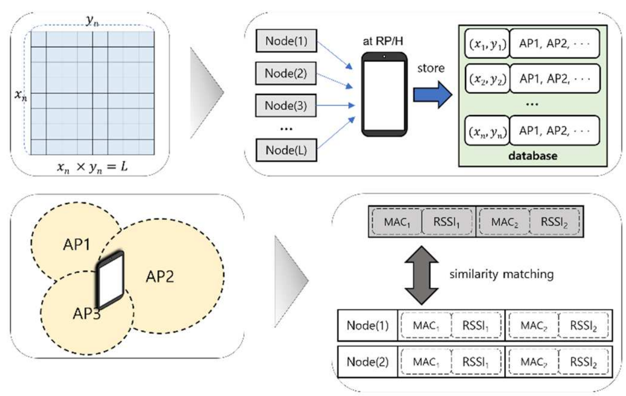

Figure 1. Indoor Positioning System based on Fingerprinting[7]

When collecting the signal information to construct the fingerprint DB, there are variations in signal strength caused by various reasons, such as existence of moving objects and temporal changes of the transmission power. Figure 2 shows the signal variations between the minimum and maximum values at each point. The x-axis represents a specific point, while the y-axis represents the RSSI values acquired at the point. Existing researches using Wi-Fi or BLE signals as resources for the positioning do not consider such signal variations, potentially resulting in reduced positioning accuracy at points.[8][9]

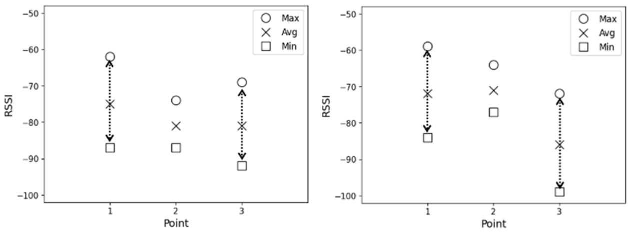

Figure 2. The Minimum and Maximum values of RSSI for a specific AP

III. Statistical Approach for Robust Similarity Calculation Against Variations of RSSI

To compare RSSI values against variations, this paper makes two assumptions: 1) The changes in Wi-Fi signals with specific MAC addresses follow a normal distribution, and 2) the standard deviation is a good measure of the signal variations. In addition, to consider the possible non-linear relation on the difference between $RSSI_{\mu}(X)$ and $RSSI_{cur}$, we use the area of the standard normal distribution function as a factor of the comparison between two RSSI values.

TABLE I. BASIC NOTATIONS FOR RSSI AND SIMILARITIES

Notation	Definition and description
$RSSI_{cur}$	The RSSI of a specific Wi-Fi AP scanned by the user's device trying to determine the point X.
$RSSI_{\mu}(X)$	The average RSSI of a specific Wi-Fi AP built in the fingerprint database for point X.
$RSSI_{\sigma}(X)$	The standard deviation RSSI of a specific Wi-Fi AP built in the fingerprint database for point X.
$RSSI_{cur-\sigma}(X)$	$RSSI_{\mu}(X) + \lvert RSSI_{\mu}(X) - RSSI_{cur} \rvert / RSSI_{\sigma}(X)$, where $\mathbf{RSSI_{cur-\sigma}(X)} \geq RSSI_{\mu}(X)$, $RSSI_{\mu}(X) - \lvert RSSI_{\mu}(X) - RSSI_{cur} \rvert / RSSI_{\sigma}(X)$, where $\mathbf{RSSI_{cur-\sigma}(X)} < RSSI_{\mu}(X)$,
$RSSI_{cur-pdf}(X)$	$\int_{\mathbf{RSSI_{cur-\sigma}(X)}}^{\infty} \mathbf{pdf}$, where $\mathbf{RSSI_{cur-\sigma}(X)} \geq RSSI_{\mu}(X)$, $\int_{-\infty}^{\mathbf{RSSI_{cur-\sigma}(X)}} \mathbf{pdf}$, where $\mathbf{RSSI_{cur-\sigma}(X)} < RSSI_{\mu}(X)$, where the pdf is the normal distribution on RSSIs of a specific Wi-Fi AP at a point X

Table 1 summarizes important notations with the definition and descriptions, which are used for the robust positioning against the signal variations, suggested in this paper. According to the second assumption mentioned earlier, instead of comparing two simple RSSI values, we compare the adjusted RSSI values based on the standard deviation ($RSSI_{cur-\sigma}(X)$). In addition, to put a non-linear relation on the amount of difference between $RSSI_{\mu}(X)$ and $RSSI_{cur}$, the standard probability distribution function (PDF) values are used as shown in Figure 3 ($RSSI_{cur-pdf}(X)$).

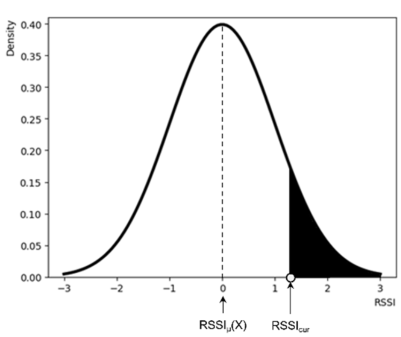

Figure 3. Definition of $RSSI_{cur-pdf}(X)$

Table 2 shows examples of the calculated differences using $RSSI_{\mu}$ and $RSSI_{\sigma}$ at Point 1, 2 and 3, presented in figure 2. As shown, As shown, compared to $\lvert RSSI_{\mu}(X) - RSSI_{cur} \rvert$, $\lvert RSSI_{\mu}(X) - RSSI_{cur-\sigma} \rvert$ shows lower differences in signal strength. In points with high standard deviation, even if the difference values are high, dividing by the standard deviation can narrow down the differences. Therefore, by incorporating the standard deviation, this method allows for stable utilization of signal strength values with significant variations.

TABLE II. EXAMPLES OF DIFFERENCES WHEN $RSSI_{CUR}$ = -76

Point			$\lvert RSSI_{\mu}(X) - RSSI_{cur} \rvert$	$\lvert RSSI_{\mu}(X) - RSSI_{cur-\sigma} \rvert$
1	$RSSI_{\mu}$	-75	1	0.2496
	$RSSI_{\sigma}$	4.0069		
2	$RSSI_{\mu}$	-81	5	2.3736
	$RSSI_{\sigma}$	2.1065		
3	$RSSI_{\mu}$	-81	5	1.3623
	$RSSI_{\sigma}$	3.6703		

Based on the examples in Table 2, it can be observed that the difference values reflecting the standard deviation are smaller than the typical difference values between $RSSI_{\mu}$ and $RSSI_{cur}$. Therefore, the method incorporating standard deviation exhibits greater robustness to variations in signal strength.

In general, in one point, there are multiple Wi-Fi APs present. Therefore, the positioning using the Wi-Fi fingerprint database involves comparing multiple RSSI values to determine the position. For the comparison in this paper, the cosine similarity is used on the common Wi-Fi sets between fingerprint DB and currently scanned one, because it is one of the most widely used similarity measure.[10]

$$Cosine\ Similarity\ (D_x, C_x) = \frac{D_x \cdot C_x}{||D_x||\ ||C_x||} \tag{1}$$

where

$D_x = RSSI_{\mu}(X)$

$C_x = RSSI_{cur}$ or $RSSI_{cur-\sigma}(X)$ or $RSSI_{cur-pdf}(X)$

In this paper, indoor positioning robust to signal variations is implemented using $RSSI_{cur-\sigma}(X)$ and $RSSI_{cur-pdf}(X)$, as defined in Table 1, along with cosine similarity.[11] The implemented methods for comparison and analysis are summarized in Table 3.

TABLE III. IMPLEMENTED POSITIONING METHODS USING COSINE SIMILARITY

Method	Description
$SIM_{cos}(X)$	Cosine Similarity between $RSSI_{\mu}(X)$ and $RSSI_{cur}$
$SIM_{cos-\sigma}(X)$	Cosine Similarity between $RSSI_{\mu}(X)$ and $RSSI_{cur-\sigma}(X)$
$SIM_{cos-cdf}(X)$	Cosine Similarity between 0.5 and $RSSI_{cur-pdf}(X)$

IV. EXPERIMENT AND ANALYSIS

A. Test Environment and implementation

The signal was collected and the positioning experiment was conducted in the No.12 building of the Electronics and Telecommunications Research Institute (ETRI). We have developed a signal collection and positioning app to run on Android devices. The app was implemented in Java and tested on a Galaxy S21+. We collected data from 7 different locations, each with 20 data points, and used this data to build the fingerprint database. We calculated the average, standard deviation, and other relevant metrics from this data, which are used for positioning.

Figure 4. Map of the test site and Positoning Device

B. Experimental Result and Analysis

Figure 5 shows the distance error graph between the actual positions and the estimated positions based on cosine similarity results. The probability distribution function-based cosine similarity does not necessarily exhibit the best accuracy at all points. However, compared to the other two methods that particularly show poor accuracy at points 4 and 6, the probability distribution method demonstrates better accuracy. As evident in Figure 2 at Point 1 and Point 3, points with significant signal variations impact the accuracy of positioning, but the probability distribution method shows greater robustness to signal variations.

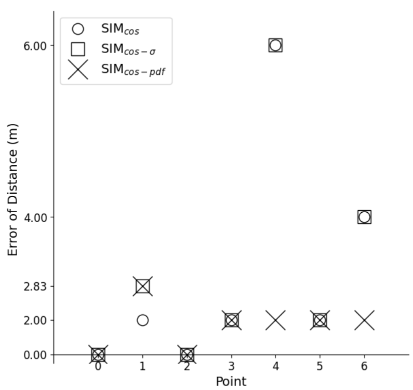

Figure 5. Indoor Positioning Distance Error Graph

V. CONCLUSION AND FUTURE WORK

In this paper presents a statistical approach for RSSI-based indoor positioning and explains the process in detail. The newly introduced method, incorporating standard deviation into the existing approach, demonstrates improved positioning accuracy, particularly in areas with significant signal variations. Such areas indicate signal instability due to various factors, and the statistical approach proves to be more effective in such regions.

Future research will explore and compare different distributions beyond the normal distribution and attempt to apply the approach to other signal values such as BLE, Long Term Evolution (LTE), etc. Moreover, we can also try using larger datasets from wider areas to make the method more scalable.

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REFERENCES

[1] Jens Einsiedler; Ilja Radusch; Katinka Wolter, "Vehicle indoor positioning: A survey", 2017, 14th Workshop on Positioning, Navigation and Communications, IEEE

[2] Pavel Puricer; Pavel Kovar, "Technical Limitations of GNSS Receivers in Indoor Positioning", 2007, 17th International Conference Radioelektronika, IEEE

[3] E. Jedari, Z. Wu, R. Rashidzadeh and M. Saif, "Wi-Fi based indoor location positioning employing random forest classifier", 2015 Int. Conf. Indoor Position. Indoor Navig. IPIN 2015, pp. 13-16, 2015.

[4] Jacqueline Lee Fang Ang; Wai Kong Lee; Boon Yaik Ooi, "GreyZone: A Novel Method for Measuring and Comparing Various Indoor Positioning Systems", 2019, International Conference on Green and Human Information Technology(ICGHIT)

[5] Guoquan Li; Enxu Geng; Zhouyang Ye; Yongjun Xu; Hongyu Zhu, "An Indoor Positioning Algorithm Based on RSSI Real-time Correction 2018 14th IEEE International Conference on Signal Processing (ICSP)

[6] Zhenghua Chen; Han Zou; JianFei Yang; Hao Jiang; Lihua Xie, "WiFi Fingerprinting Indoor Localization Using Local Feature-Based Deep LSTM", 2020, IEEE Systems Journal

[7] Sungil Kim; Sunhwa Ha; Alshihri Saad; Juho Kim, "Indoor positioning system techniques and security", 2015, Forth International Conference on e-Technologies and Networks for Development (ICeND)

[8] Yuhong Liu; Yaokuan Wang, "A position system of multi-Aps based on RSSI", 2012 2nd International Conference on Consumer Electronics, Communications and Networks (CECNet)

[9] Son, Sanghyun; Park, Youngjoon; Kim, Beomjun; Baek, Yunju, "Wi-Fi Fingerprint Location Estimation System Based on Reliability, 2013, The Journal of Korean Institute of Communications and Information Sciences (KICS), pp.531-539

[10] Jieyu Gao; Xiaohui Li; Yuemin Ding; Qian Su; Zhenxing Liu, "WiFi-Based Indoor Positioning by Random Forest and Adjusted Cosine Similarity, 2020, Chinese Control and Decision Conference(CCDC)

[11] Sham Firdaus Md. Ali; Rosilah Hassan, "Local Positioning System Performance Evaluation with Cosine Correlation Similarity Measure", 2011 Sixth International Conference on Bio-Inspired Computing: Theories and Applications (BICTA)