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Indoor Localization Based Wi-Fi and Bluetooth Low Energy Technologies

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Abstract

Indoor positioning has attracted commercial developers and researchers in the last few decades. This paper presents an indoor localization system based on both Wi-Fi and BLE technologies at 2.4 GHz. The proposed system uses fingerprinting method with existed advertising channel of Wi-Fi and BLE, 63 reference points and 17 test points. The mean error achieved of 1.6795 m in a very complex indoor environment of 9.2 m x 8.4 m, is a good result compared to similar model considering the equivalent complexity of the region.

***Keywords**: Indoor localization, ILS, Wi-Fi, BLE.*

Symbols

Symbols	Units	Description
d_i	m	Euclidean distance
RSS	dB	Received Signal Strength
Ω_k		Weighted of each point
L	m	Distance

Abbreviations

KNN	K-Nearest Neighbor
W-KNN	Weight K-Nearest Neighbor
BLE	Bluetooth Low Energy
UHF	Ultra high frequency
RF	Radio frequency
RFID	Radio frequency identification
UWB	Ultra-Wideband
GPS	Global Positioning System
AP	Access point
LSTM	Long Short-Term Memory
DNN	Deep neural Network

Tóm tắt

Định vị trong nhà đã và đang thu hút các nhà phát triển và các nhóm nghiên cứu trên thế giới trong vài thập kỷ qua. Bài báo này trình bày giải pháp định vị trong môi trường hẹp dựa trên công nghệ Wi-Fi và BLE ở dải tần 2.4GHz. Hệ thống định vị đề xuất sử dụng phương pháp lấy dấu vân tay, khai thác tham số RSS từ các trạm phát Wi-Fi và BLE với 63 điểm tham chiếu và 17 điểm thử nghiệm. Sai số trung bình đạt được là 1.6795m trong môi trường rất phức tạp 9.2m x 8.4m, là một kết quả tốt đáng để so sánh với các hệ thống tương đồng có xét đến độ phức tạp của vùng không gian định vị.

1. Introduction

Positioning is determining the position of an object in an area that is coordinated by a given frame. A positioning system must have the function of determining the position of equipment in a given area with a certain accuracy.

Along with the development of technology, the global positioning system GPS has been pre-installed on most mobile devices, making outdoor positioning and navigation easier and more popular than ever. However, in large buildings, the GPS global positioning system faces difficulties such as weak signal, large noise, making the accuracy of the results significantly reduced. Such difficulties are mainly encountered in indoor environments, basements, and underground environments of large buildings. Therefore, there is an inevitable need to build indoor positioning systems independent of the GPS global positioning system.

Location information plays an important role in industrial systems including agriculture, healthcare, security, transportation, telecommunications, entertainment and other services in smart homes, smart cities that help improve people's quality of life. The indoor localization research is attracting the attention of many research groups and technology companies around the world with potential applications such as locating objects in the office/supermarket; Positioning and navigation systems for people/robots in commercial centers, buildings, warehouses, smart treatment rooms.

Indoor localization is not only a raising topic of research but also a necessity of the market which open up a promising research area [1]. In fact, there has been a lot of researchers to develop indoor localization systems using different technologies with different objectives such as reducing costs, increasing the accuracy of positioning results. According to a survey by the research team with the main author Christian Esposito in [2]: RF radio technology accounts for 66% (Wi-

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Fi 24%; Bluetooth 17%; Zigbee 8%; UHF 4%); RFID 7%; combination 6%) infrared technology 9%, UWB technology 6%, GPS 4%, imaging technology 1%, magnetic field technology 1%.

In this paper, we deploy a positioning system based on Wi-Fi or BLE (Bluetooth Low Energy) technologies and combination technology (Wi-Fi + BLE). RSS parameter is recorded as the database for fingerprinting method to identify objects positioning with many obstacles.

This paper is organized as follows. In section 2, related works about existing indoor localization systems and recent trends are presented, the deployment of locating systems: theoretical basis, structure, components, and localization algorithm is elaborated upon in section 3. Section 4 summarizes experimental results and compares with other works, and section 5 is the author's conclusion.

2. Related works

There are various methods relate to indoor localization system based on electromagnetic wave namely ILS. The following list briefly introduces the most common techniques employed in ILS [3].

• Time of Arrival (TOA): It measures the time of arrival of the signal from an emitter, as recorded by the receiver. It is used for estimating the distance to each emitter, as the propagation speed of the signal (sound, radio frequencies) is known for the transmission medium (air).

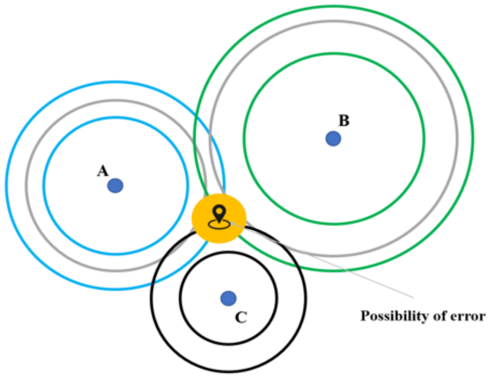
• Time Difference of Arrival (TDOA): It is similar to TOA. It measures the differences in the time of arrival of signals from different emitters. It is used for estimating differences in distances to each emitter.

• Angle of Arrival (AOA): It refers to the angle at which the signal reaches the sensor. Angles are then used to obtain a position fix.

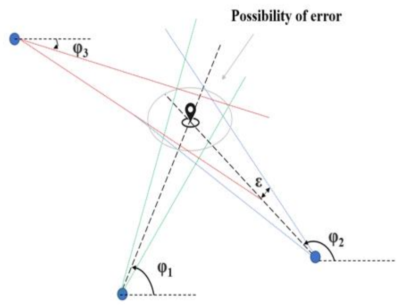
• Received Signal Strength (RSS): It is the intensity at which the signal from an emitter is measured. The signal strength decreases as the distance to the emitter increases, although their relation may be affected by attenuation and interference.

The technique employed for a solution determines how the position is estimated. TOA, TDOA, and RSS are used for estimating distances to signal emitters. The estimated distances to a set of emitters are then used in what is called lateration to find the position estimate that best fit the set of distances (see Figure 1a). Lateration is called trilateration if three distances are used, while it is called multilateration if more than three are used. The angles obtained in AoA are used to compute a likely fix on the target position, as shown in Figure 1b, in what is known as angulation. Both lateration and angulation are commonly classified as range-based or ranging- methods, and they require the previous knowledge of the positions of the emitters.

The RSS technique is also employed for a range-free method, very popular in ILS, called fingerprinting or sometimes scene analysis. The fingerprinting encompasses two stages. In the first stage, also known as offline stage, the signal quantity of each detected emitter at a given time and position (a fingerprint) is measured at several places the target scenario and stored to create a characterization of the signals in that scenario as comprehensive as possible. The collected database is called the training database. If the measured signals are radio frequencies (RF), the database is also called radio map. In the second stage, also known as online stage, the position corresponding to new measured signal quantities is estimated using the positions associated with the stored fingerprints that are the most similar when compared to the new measurements (see Figure 1c). Table 1 present the advantages and disadvantages of localization techniques [4]:



(a) Lateration



(b) Angluation

(c) Fingerprinting

Figure 1: Most common methods used in ILS.

Table 1: Advantages and disadvantages of different localization techniques

Technique	Advantages	Disadvantages
RSS	Easy to implement, cost efficient, can be used with a number of technologies	Prone to multipath fading and environmental noise, lower localization accuracy, can require fingerprinting
AoA	Can provide high localization accuracy, does not require any fingerprinting	Might require directional antennas and complex hardware, requires comparatively complex algorithms and performance deteriorates with increase in distance between the transmitter and receiver
ToA	Provides high localization accuracy, does not require any fingerprinting	Requires time synchronization between the transmitters and receivers, might require time stamps and multiple antennas at

		the transmitter and receiver. Line of Sight is mandatory for accurate performance.
TDoA	Does not require any fingerprinting, does not require clock synchronization among the device and RN	Requires clock synchronization among the reference nodes, might require time stamps, requires larger bandwidth
Fingerprinting	Fairly easy to use	New fingerprints are required even when there is a minor variation in the space

Regarding RSS-based system, the other claimed systems exploiting RSS parameter are taken into comparison with our system. Lateration and Fingerprinting are the most popular method used in such systems.

Article [5] used Bluetooth technology with lateration method, using 4 transmitters, in the locating space is classroom of 6.0m* 8.0m, there are only tables and chairs, the locating error is 0.5m - 1.5m. [6] used BLE technology, the positioning method is the fingerprinting with 6 transmitter stations in an empty laboratory, only a few tables, an area of 14.0m * 8.0m, achieving an error of 0.246 - 1.272 m. [7] used Wi-Fi technology, 3 transmitter stations, the positioning area on the laboratory of 10.8*7.3m is quite complicated, the corridor is wide, reached an error of 1,6472m with the KNN algorithm. The article [8] achieved an error of 1.2 m on the positioning area as a fairly simple reading room 8*8m with 4 BLE transmitters. [9] Experimented on a complex 7*11m laboratory with 3 Wi-Fi stations, used lateration method with an error of 0.5-3.5m. For improving WKNN algorithm, the authors in article [10] deploy Long Short-Term Memory (LSTM) in combination with WKNN in a measuring area of 308.4 m^2, in a library with multiple bookshelves, achieving an error of 1.99 m on average. Another Assemble Learning technique states in article [11], which using Deep Neural Network to enhance traditional WKNN algorithm, achieve average positioning error about 1.69 m, with most positioning errors were less than 3 m.

3. Deploying the Indoor localization system

3.1. System configuration

For each positioning technology, we use the same configuration as in Figure 2 with 3 fixed stations – the minimum number of stations for a navigation system. The experimentation system is described as bellow:

- 3 APs (access points) using Wi-Fi technology are fixed using ESP32-S module.
- 3 APs (access points) using BLE technology based on nRF52840 module. Each Wi-Fi AP is placed at the same position with BLE AP as in Fig. 3.
- Target device is using Wi-Fi and BLE technologies.
- One station access point (STA) acts as a master which can communicate both BLE and Wi-Fi technologies for pushing data to Server. The data will be processed at the Server to indicate the position of target device based on information of RSS, collected database and positioning algorithm.

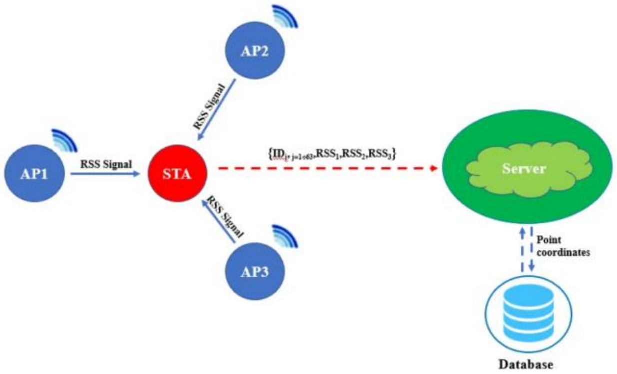


Figure 2: Configuration of positioning system

The system consists of 6 fixed AP nodes with 3 BLE AP nodes and 3 Wi-Fi AP nodes. In the combination of two technologies scenario as in Figure 3, one Wi-Fi AP and one BLE AP are placed at each AP*i*. With that combination, we overcome the limitation of number of BLE or Wi-Fi hardware devices, more AP nodes are available which results in better localization accuracy.

3.2. Tested scenairo

The selected location for implementation and evaluation of results is 328 room, C1 building, Hanoi University of Science and Technology. The room is divided into 4 areas as in Figure 3: Lab 1 activity area, Lab 2 activity area, Microprocessor area, server area. Mesh of 7*9 points in 8.4m*9.2m positioning space, mesh spacing is 1 m.

In the offline stage, we create a database with 63 fingerprinting points arranged in Figure 3. In the online phase, we conduct a test with 17 test points using the W-KNN positioning algorithm.

Both of the selected positioning technologies use the same measurement model, which forms the basis for the evaluation of the positioning results, and the combination model is conducted later.

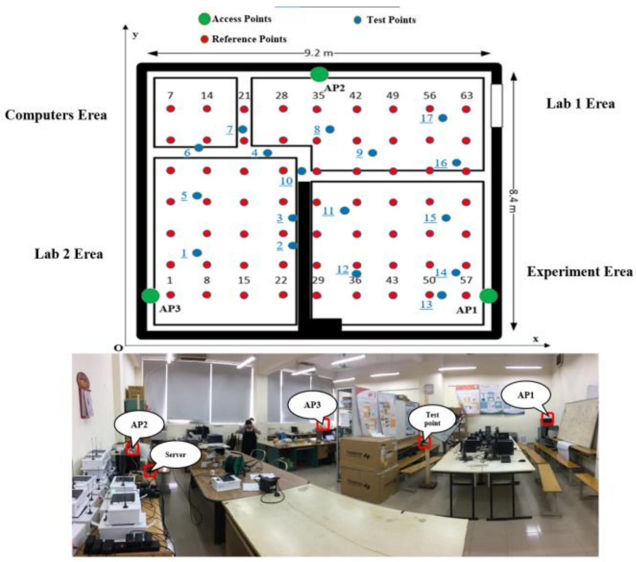


Figure 3: Locating room C1-328 (for dataset self-gathering)

The RF3I Lab area (C1 - 328) is chosen as the testing environment due to its complex environmental conditions, many obstacles and electrical devices that turn on and off at different times, creating great challenges for indoor positioning and increasing value for error improving efforts. That contributes to the advantage of this paper and creates a basis for comparison with similar works taking into account the complexity of the environment.

3.3. Positioning method

Fingerprinting is a positioning method based on comparing the current signature of the object with the existing signature in the sample database, thereby drawing conclusions about the location of the locating object. The positioning parameter commonly used in this method is the received signal strength RSS indicator. This method can estimate the position of the device with high accuracy.

The determination of the device's position assumes that the RSS obtained at each point in the geolocation space are different and that these values are stable over time. The device's position within the locating area is determined by matching or comparing the observed signal value with signal values previously stored in the sample database. The accuracy of this method does not depend on the location of the signal stations, in other words, we do not need to know the coordinates of the signal stations in advance, but still determine the position of the positioning object.

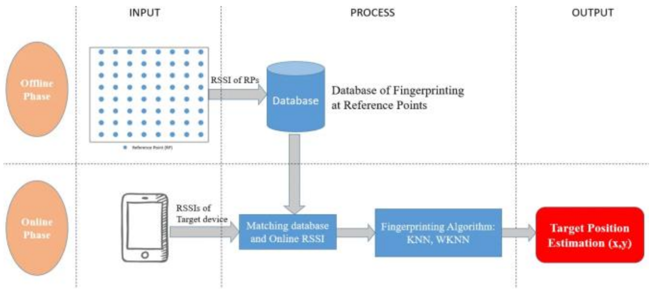


Figure 4: Fingerprinting phases

The process of implementing fingerprint method consists of 2 stages:

- Phase 1: Select test points in the implementation area of the problem and measure the RSS of the transmitting stations received at these test points. These are the unique features or signs that distinguish one location from another. Through the measurement results, we will build a sample database for the test points. This process is also known as signal mapping of the positioning area.
- Phase 2: Compare the value of the received signal strength (RSS) indicator of the object with the signal map of the positioning area built in stage 1. Using algorithms such as KNN, WKNN, ... to estimate the position of the object to be located.

The fingerprinting requires considerable effort and time to build a database for each test site and should be updated when there is a significant change in signal strength. In general, the challenges of signal tracing and mapping are mainly the time-consuming and computationally intensive process of imprinting.

This method does not require any specialized hardware, just commercially available radio transceivers such as beacons, APs, smartphones, RFID, etc. The disadvantage of this method is the low accuracy if there are many unusual noise in the environment that have not been recorded in the database.

3.4. W-KNN algorithm

3.4.1. *Basic kNN*

KNN algorithm [12] helps to classify samples based on measurement, calculating available samples. Here, the set of Euclidean distances D_i between the measurement of RSSs in real time $S=\{S^1_i, S^2_i, \dots S^m_i\}$ and the measurement of RSSs in the grid of real reference fingerprints $R=\{R^1_i, R^2_i, \dots R^m_i\}$ will be calculated. The set of distances D_i is sorted to find K based on the smallest D_i intervals. Finally, the coordinates of the test subject will be calculated based on the average coordinates of the K fingerprints mentioned above (online phase). Specifically, we have the following formula to calculate the Euclidean distance:

$$d_i = \sqrt{\sum_{j=1}^{N} \left| RSS_j - RSS_{ij} \right|^2} \quad \text{with } i=1,2,3,\dots,M \qquad (1)$$

In there, RSS_{ij} represents the average value of received signal strength on the j^{th} test point calculated with the i^{th} reference point on the reference fingerprint map and $RSSj$ represents the RSS value of the AP_j obtained during the online testing period. M and N represent reference points (RPs) and test points, respectively. Next, by selecting the k smallest outcomes in the set D_i, we get k coordinates of the reference points (RP). From there, determine the coordinates of the object's position by the formula:

$$(x, y) = \frac{1}{k}\sum_{i=1}^{k}(x_i, y_i) \qquad (2)$$

Where (x,y) is the coordinates of the test point to be found. k can be estimated and given empirically.

3.4.2. *Weight K-Nearest Neighbor*

The distribution of RSS is not always a normal (Gaussian) distribution for complex indoor environments with many obstructions. To solve this problem, the Weighted KNN (WKNN) algorithm [12] is introduced. Assuming the test point has coordinates L, we represent L according to the coordinates of K nearest neighbor points as follows:

$$L = (\hat{x}, \hat{y}) = \sum_{i=1}^{k} \omega_i * (x_i, y_i) \qquad (3)$$

where ω_i is the weighting factor of each reference point among the K nearest points of the test point, used to determine the coordinates of the point to be found, calculated by the formula:

$$\omega_i = \frac{\frac{1}{d_i}}{\sum_{j=1}^{h} \frac{1}{d_j}} \quad (4)$$

Finally, the location of the test point is given by the formula:

$$L = (\hat{x}, \hat{y}) = \sum_{i=1}^{k} \frac{\frac{1}{d_i}}{\sum_{j=1}^{h} \frac{1}{d_j}} * (x_i, y_i) \quad (5)$$

4. Experimental result

Applying the positioning algorithm with 17 test points at the online stage, we considered and selected k=4 for the W-KNN algorithm as the most optimal coefficient for this measurement data. We synthesize the positioning error of the system using Wi-Fi, BLE technologies and propose a solution of multi – technologies localization system that combine Wi-Fi and BLE technologies, so that each survey point will receive 6 RSS Vectors to improve the accuracy for the system.

4.1. Localization result

The topic has conducted experimental locating system with Wi-Fi technology (3 stations) and BLE (3 stations) and applied the W-KNN positioning algorithm (K=4). The results in Table 2 show that BLE technology gives better results with an error of 0.26 m - 4.6 m, the average error is 1.69 m on the locating area of 9.2m x 8.4m. Some test points have abnormally high errors due partly to errors in data collection, mainly because these points are located at the edge of the positioning area or in an area with many obstacles, or the effect of electrical devices, so there is difference between the offline and online phases.
Combining both Wi-Fi and BLE technologies (6 stations) reduces the average error to 1.6795 m and reduces the error range to 0.3807 - 3.8810 m, the quality of the locating system is significantly increased.

Table 2: Summary of localization results

Technology	Error		
	Min error	*Max error*	*Mean error*
Wi-Fi	0.5279	4.6382	1.8524
BLE	0.26	4.6	1.69
Wi-Fi + BLE	0.3807	3.8810	1.6795

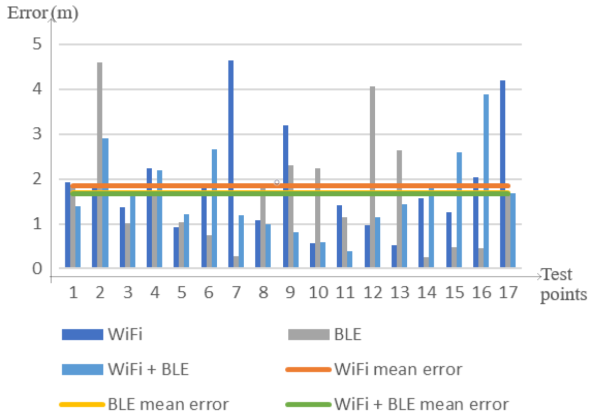


Figure 5: Summary of localization results

4.2. Comparison with the related works

There have been many groups deploying single-modal indoor localization system, Table 3 and 4 present the comparison between the proposed system with the related work in term of accuracy, locating area and the complexity of locating environment. The advantage of this paper is using 3 stations, which is the minimum number of stations, simple hardware and low cost. It can be applied to a rather large and complex indoor localization area.

Table 3: Comparison with related indoor localization systems

Sample		Algorithm	Area (m^2)	Error (m)	Mean error/ Area
Our system	Wi-Fi	K-nearest Neighbor	77.28	Min: 0.5229 Max: 4.6382 Mean: 1.8524	0.0240
	BLE	K-nearest Neighbor		Min: 0.26 Max: 4.6 Mean: 1.69	0.0219
	Wi-Fi + BLE	K-nearest Neighbor		Min: 0.3807 Max: 3.8810 Mean: 1.6795	0.0217
Other articles	[5]	Least Square Centroid Positioning Three-border	48	0.5 ÷ 1.5	0.0104÷0.0313
	[6]	K-nearest Neighbor	112	0.246 ÷ 1.272	0.0022 ÷0.0114
	[7]	Least Square	78.84	3.7358	0.0474
		K-nearest Neighbor		1.6472	0.0209
		Naïve Bayes		2.7390	0.0347
	[8]	K-nearest Neighbor	64	1.2	0.02
	[9]	Least Square	77	0.5÷3.5	0.006 ÷0.045
	[10]	WKNN + LSTM	308.4	1.99	0.006
	[11]	WKNN + DNN	117	0.4 ÷ 4 Mean: 1.67m	0.014

Criteria for assessing environmental complexity:

- Environment with lots of furniture and obstacles with different heights: 1*/5*
- Narrow and complicated navigation corridor: 1*/5*
- Obstacles, partitions made of many different materials: 1*/5*

- There are many machines that can cause interference: 1*/5*
- Many passersby: 1*/5*

Table 4: Assessment of complexity of environment

Sample		Description	Scenario	Complexity rating
Our system		- The laboratory has many tables and chairs, many operating machines, many furniture. - There are glass cabinets, partitions, narrow aisles, many obstacles with complicated materials - There are people passing by. - Area of 77.28 m^2.	- 3 stations - mesh spacing: 1m - 63 finger-printing sample points - 17 random test points	4.8/5
Other articles	[5]	- Classroom has desks and chairs with a height of less than 1.2m. - Area of 48 m^2.	- 4 stations - 7 test points	1.5 /5
	[6]	- The laboratory is mostly empty, has only a few tables. - Area of 112 m^2.	- 6 stations - mesh spacing: 1m - there are 73 finger-printing sample points - 15 random test points	1/5
	[7]	- Laboratory with tables, chairs, BLE and Wi-Fi devices. - Wide corridor, the test area takes place in an area of the lab (no walls or obstacles). - Area of 78.84 m^2.	- 3 stations - 40 fingerprinting points - mesh spacing: 1m - 16 random test points	3.5 /5
	[8]	- Reading room with bookshelf, reading table. - Area of 64 m^2.	- 4 stations - mesh spacing: 1m -32 random test points	2 /5
	[9]	- The laboratory has tables, chairs, partitions, and machines. - Area of 77 m^2.	- 3 stations.	4 /5
	[10]	- A Library with multiple bookshelves and people around. - Area: 308.4 m^2	- 448 APs - 63504 measurement in 15 months	4/5
	[11]	- A classroom of 13*9 m^2	- 210 APs - grid: 1.1m * 1.1m - 20 random test points	4/5

5. Conclusion

This paper has presented and analyzed current indoor positioning trends, thereby building a locating system based on Wi-Fi and BLE technologies with simple configuration, low cost, easy to deploy and simple algorithm, easy to extend and improve. The result achieved an average error of 1.8524 m with Wi-Fi and 1.69 m with BLE by fingerprinting method on a locating area of 77.28 m2.

This paper also proposed a multi-technology locating system based on Wi-Fi and BLE with an average error of 1.6795 m and reduced error margin.

The experimental space located in a complex environment of RF3I Lab (C1 - 328) with many partitions, obstacles and electrical devices that can be turned on or off at different times which effect the radio signals. To limit interference, samples should be taken at different times of the day. In the near future, we will test the system with increasing the number of grid points according to the prediction instead of the actual measurement so that we can increase the amount of database without increasing the sampling time in the offline phase. With further developments, the system can improve the accuracy of the current results.

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