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RESEARCH ARTICLE

Indoors Smartphone Positioning Enhancement Using Wi-Fi and Magnetometer

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ABSTRACT

When smartphone holders are entering to the urbane area or indoors, the performance of GPS service will be degraded or sometime cannot retrieve location information due to blocking the GPS signals through the roofs or walls of the buildings. Beside this, many onboard smartphones wireless chipsets or sensors' readings can be used as alternate technologies to provide location information including Wi-Fi, Bluetooth, cellular, and inertial sensors. However, these technologies during positioning process will faced its own limitations such as: none-line-of-sight signals, multipath signals, and sensor drift or accumulated error. For these reasons, it is very difficult to provide a good positioning accuracy, when only a single technology is utilized alone. The aforementioned limitation of positioning technologies motivated us to propose a new positioning solution based on hybridize two different technologies measurements including received signal strength (RSS) of the Wi-Fi access points and onboard smartphone magnetometer readings within fingerprinting positioning technique. The hybridization of these technologies is based on taking their advantaged and mitigating their drawbacks. In addition to that, this study also provided an improved version of matching algorithm of the fingerprinting technique by applying the concept of boosting-dataset records. A set of real trial experiments are conducted to prove the validity of the proposed solution. The obtained results of the experiments show that the proposed positioning solution can provide an enough positioning accuracy, up to 0.13 meter.

1. INTRODUCTION

Utilizing onboard smartphones wireless chipsets and sensors provide a huge number of services and/or applications. The health care services, billing, navigations, shopping recommendations, advertisements, and sport activities, news and weather predictions are the most famous applications of the smartphone holders (Ali et al., 2019a). The main unique feature of these services is utilizing smartphone's position information. Further, since the people's life is spent indoors more, the demand of using location-based services (LBS) by smartphone holders for indoors has been increased day-by-day (Ninh et al., 2020). To run these services, many smartphones technologies and techniques have been used. For example, fingerprinting positioning technique with Bluetooth and Wi-Fi RSS values, triangulation via cellular signals, dead-reckoning by using inertial sensor measurements, and trilateration via GNSS.

Furthermore, the positioning solutions based on RSS values can be divided into two classes: 1) distance-based technique which is based on RSS propagation model and 2) fingerprinting based technique. The distance-based technique needs the path loss calculation and the location information of each Wi-Fi access points (WAPs). While, the fingerprint positioning technique doesn't need such information, it only needs the survey of the area/buildings to construct dataset positioning. Also, when the fingerprint technique is applied, smartphone position can be calculated by implementing a matching algorithm between current RSS values and the stored RSS values in the constructed dataset (Mendoza-Silva et al., 2018).

Basically, the fingerprint positioning technique is implemented by applying both offline and online stages (Ashraf et al., 2019). With the offline stage, the area of the buildings is surveyed by collecting WAPs RSS values and storing this information as a record in the dataset. Each record of the RSS values contains the RSS values of the WAPs in the vicinity and the corresponding location coordinates of each fingerprint. While with the online stage, the current RSS values of the WAPs are compared with the pre-stored RSS values via implementing the matching algorithms (Ali et al., 2019b). However, the accuracy of the fingerprint positioning technique is relying on the quality and stability of the measured RSS values. This is due to the fact that when indoors, scattering, absorption, and diffraction events will have an impact on the RSS values as they propagate through the buildings. Additionally, when RSS values are used with fingerprinting technique, 1) the coverage of WAP signals, 2) the instability of calculating RSS values via onboard smartphone chipsets within 4 dBm, and 3) WAPs signal interference with other wireless technologies within the same frequency channels are another drawback (Hosseini et al., 2021). Therefore, relying solely on RSS data for positioning solutions won't result in good positioning accuracy.

In another vain, many positioning solutions have been proposed based on using magnetic field via magnetometer measurements instead of using WAPs RSS values. Note, due to having different values of magnetic field at each point in the buildings, such information can be used to identifying location information for each fingerprint in the indoors (Kuang et al., 2021). However, indoor structures and materials like steels or noisy objects will have an impact on the magnetic field (Yeh et al., 2019). The advantages of RSS and magnetic measurements might be used to integrate or hybridize the RSS data and magnetic fields within the fingerprint positioning technique as a viable remedy for these restrictions (Hanley et al., 2021).

Therefore, in this work, the advantages of both technologies have been taken and the weaknesses are mitigated via combing their measurements in the fingerprint technique. The key contributions of this work are:

- A comparison of the advantages of hybrid magnetometer sensor measurements and Wi-Fi RSS values for positioning with the fingerprint technique.
- Improving the fingerprinting technique by applying statistical equation and dataset record-Boosting concept. Further, statistical approach is to apply the mean values of the WAPs RSS and magnetometer measurement records as extra records into the collected.

The next section of this article are structured as the following, section 2 surveyed on the current indoors positioning solution based on fingerprinting technique and investigate the weaknesses of the current solutions. The details of the proposed approach is explained in section 3. While section 4 demonstrated how the dataset is constructed as well as the conducted real trial experiments with the obtained result is explained in section 5 and section 6. At the end, section 7 concluded the contributions and the achievements of the proposed approach.

2. Related Works

Thanks for existing other wireless technologies such as Wi-Fi signals and onboard smartphone sensor including inertial sensors which can be utilized for indoor positioning. However, most of the available positioning suffers from positioning accuracy. For example, RSS-based techniques provide unstable positioning accuracy due to existing of interference issue, multipath/non-line-of-sight signals, and obstacle reflection. Also, inertial sensor measurements, such as magnetometer sensor, are learning by fluctuation and drift experiences. Therefore, in this section some recent solutions related to indoor positioning based on RSS (specifically via fingerprinting technique) and magnetometer measurements are investigated.

Wi-Fi fingerprint localization methods based on important access points (IAP) have piqued the interest of certain researchers who want to develop a dataset of location fingerprints and estimate location interior placement (Dari et al., 2018).The IAP is the Wi-Fi access point with the strongest received signal (RSS). The positioning algorithms were presented to improve positioning accuracy by determining location. However, the average positioning inaccuracy was larger than 2 m in the testing findings of positioning algorithms.

Authors in (Keser et al., 2018) proposed an F-score-weighted indoor location technique that incorporated Wi-Fi-RSS and Magnetic field (MF) fingerprints. Note, the MF has been converted to world coordinate phase in combined with accelerometer and gyroscope measurements and then to calculate smartphone rotation with the north-pole. In the offline phase, the recommended solution was to generate an IPS training dataset based on Wi-Fi-RSS and MF fingerprints values at each RP location. The F-score weighted indoor positioning technique was utilized to estimate the indoor positioning outcome in the online phase. However, their experimental data showed that in the best scenarios 91% of the average placement error was less than 3 m.

There are still some concerns with the aforesaid research projects, as follows: To begin with, it is unable to handle Wi-Fi signal errors while collecting data in the offline mode. Second, calculating placement in the online phase takes far too long (Pérez-Navarro et al., 2019). While Magnetic-field changes and abnormalities inside buildings have a big impact on compass readings, which are one of the most basic navigation tools (Ashraf et al., 2020). For example, in (Gozick et al., 2011) authors created maps for indoor navigation using mobile phones with built-in magnetometers. The maps show landmarks and guideposts, as well as several floors of a building's hallways. Different phones with different sensitivity rates were utilized to achieve similar findings. This method is effective for creating maps based on magnetic fields. Unfortunately, the accuracy of its location results has not been investigated.

In other vain, authors in (Shahidi and Valaee, 2015) propose a geomagnetic indoor positioning system for smartphones (GIPS), a new infrastructure-free method based on magnetic pattern matching using smartphone sensors (accelerometer, gyroscope, and magnetic field sensor). The method was put to the test in real-world circumstances, and it was able to achieve a median error distance of less than 2.5 meters. Indoor positioning, on the other hand, sometimes necessitates a higher level of precision in order to deliver more powerful applications.

As it can be noticed, that the main challenges of indoor positioning solutions are either they needed extra-hardware and incurs huge cost or they provided low positioning accuracy. Therefore, according to our knowledge, till now there is no a good solution to provide low cost and accurate positioning solution. To tackle this issues, this article proposed a hybrid positioning solution to provide accurate positioning solution and low cost via integrating features from both Wi-Fi RSS values and magnetometer sensor measurements.

3. THE PROPOSED ALGORITHM

This article proposed a new solution by hybridization of WAPs RSS values and magnetic field sensor measurements within fingerprint positioning technique. The general procedure of how the proposed solution is working, is shown in Figure 1. As it can be seen, the procedure includes two main stages which are offline stage and online stage. With offline stage, the WAPs RSS values and the onboard smartphone magnetic field of all three directions are surveyed along the area (or test-bed) and stored them in a dataset-map. This means, the RSS values of the WAPs in the vicinity and the magnetometer sensor measurements are used as features with its corresponding location information (i.e. x and y coordinates). The same application is used to read and collect the values, and the same environment is used as a testbed during the offline and online stage. A snapshot of the stored record features during collecting the WAPs RSS values and the magnetic field values are expressed in equation (1).

$$rec_{fea}(x_{cor}, y_{cor}, RSS_{wap1}, RSS_{wap2}, \ldots .. RSS_{wapn}, Mag_x, Mag_y, Mag_z) \quad (1)$$

Where x_{cor} and y_{cor} are the coordinate information at the fingerprint survey,

$RSS_{wap1}, RSS_{wap2}, \ldots .. RSS_{wapn}$are the WAPs RSS values in the vicinity, and finally the

Mag_x, Mag_y, Mag_z are the three axis magnetic field values.

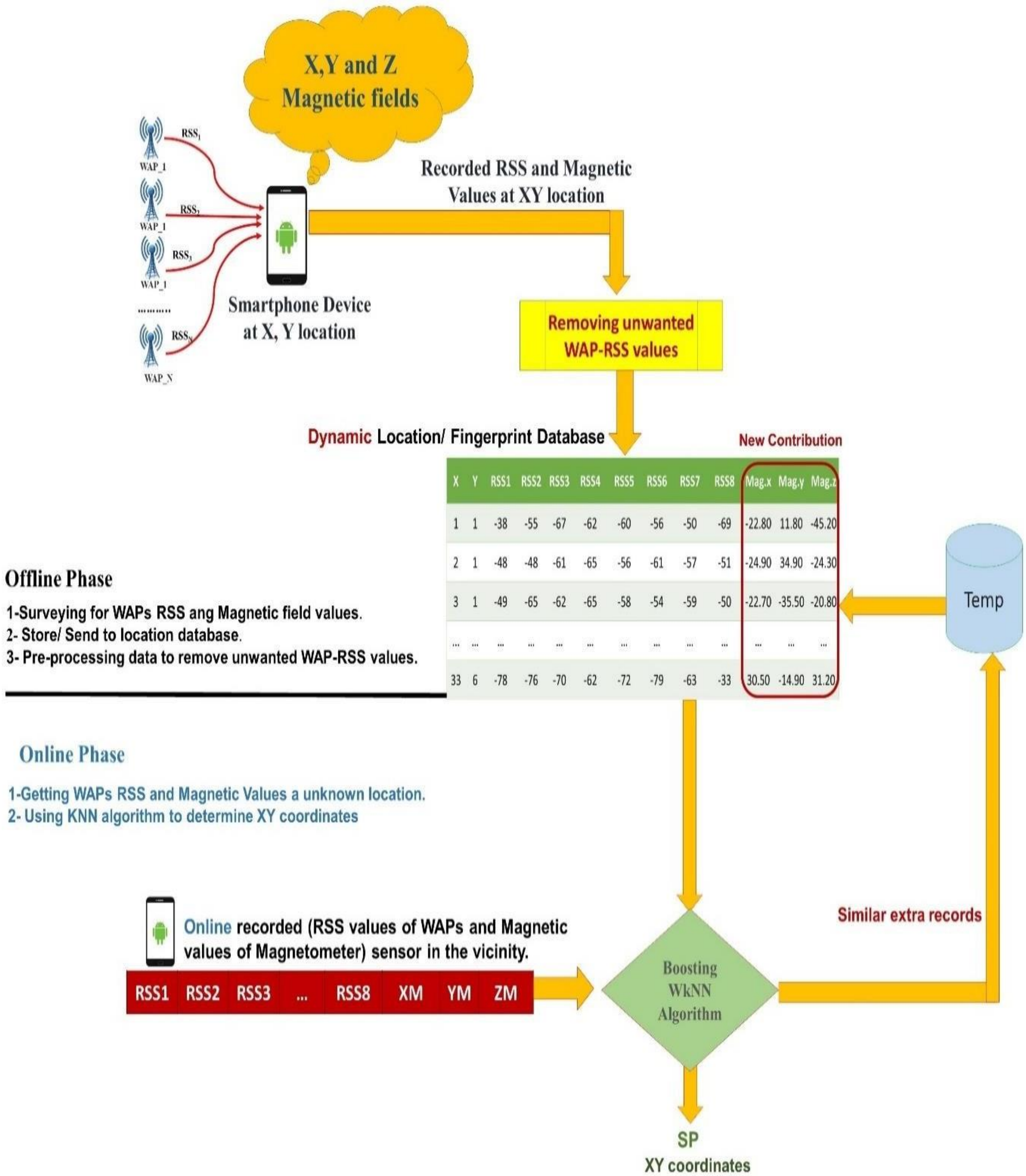

Figure 1. Diagram of Proposed Approach

While with the online stage, the process of matching between the current WAPs RSS values and magnetic field values with the pre-stored records in the dataset will be started via using proposed boosting Wk-NN algorithm. The boosting algorithm is the matching algorithm to make a comparison between the current RSS and magnetic field features with the previous stored features. The comparison is made based on calculating the distance or similarity between the online/current features and store features. Note, the Euclidean distance method is used to calculate the distance, as expressed in equation (2).

$$d_i = \sqrt{(ON\_RSS\_Mag - OF\_RSS\_Mag_i)^2} \quad (2)$$

Where d_{ij} is the similarity/distance between the online and offline features for the ith record,

ON_RSS_Mag is the online record features and $OF\_RSSi\_Mag_i$ is the offline features at i[th] record.

In the next step, the calculated similarities are sorted in ascending order. This means that the most similar records have the nearest probabilities. In this work, different k values (i.e. to select k values in Wk-NN algorithm) k=1, k=2, k=3 are tested and the results that the k=3 is much better than the k=1 and k=2 in terms of positioning error. Therefore, three most similar records are selected, i.e. the value k is equal to 3. However, with this study, this phenomenon of Wk-NN is improved and modified. The improvement is to select the best k value dynamically based on the boosting records. The best k value selection is relied on two different empirical-thresholds. The thresholds are calculated, via a set of experiments, and results showed that the threshold should be equal to 10 and second threshold will be 5. Through this threshold, if the minimum similarity between online features and database features exceeds 10, then the other next two records will be re-added into the main dataset (boosting concept records). Else, if the minimum similarity between online features and database features exceeds 5, then only the next first record will be re-added into the main dataset. Thus a new dataset will be generated and it is called dynamic dataset (or boosted dataset).

In the next step, each record should have its own weight. The weight values are calculated based on the inverse of similarity divided by the sum of all the three similarity records (since initially the k values equal to 3) the proposed algorithm is shown in figure 2. The method of calculating weights is illustrated in equation (3).

$$Wi = \frac{\frac{1}{dis(i)}}{\sum_{j=1}^{k} \frac{1}{dis(j)}} \qquad (3)$$

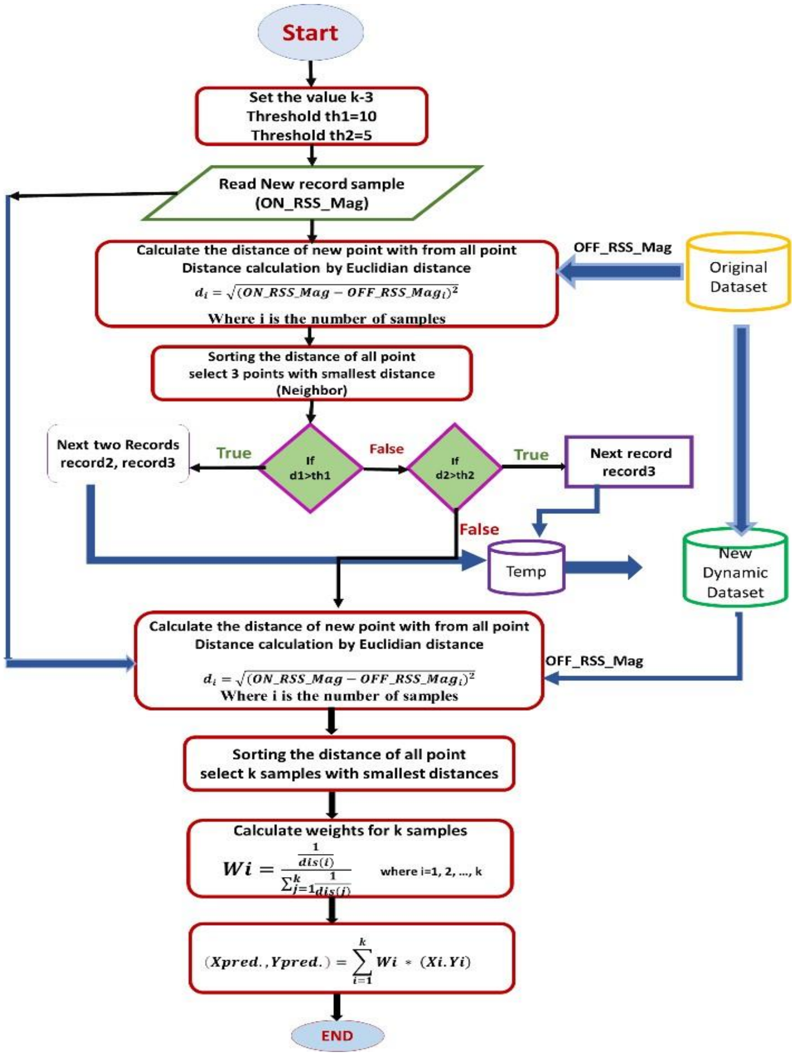

Figure 2. Flowchart of the Boosting WkNN Algorithm (The Proposed Algorithm)

4. Dataset Construction and Experiments

The other uniqueness of this study is to having new and real dataset to prove the performance of the proposed solution. The dataset is created via the survey in Koya Private Institute for Computer science building (only first floor). Figure 3 shows an image from the building during the work.

Figure 3. Snapshoot of The Survey at Koya PICS Building.

The surveyed floor is 33 meter by 6 meter, also 8 WAPs are used in the testbed environment during the survey. At nearly each 8 meter one WAP is installed and established to get WAPs RSS values through the smartphone. The whole area is divided into one meter squares (i.e fingerprints). Therefore, the number of the fingerprints of this study is equal to 198 samples. However, to ensure that the dataset has the ability of holding instability RSS values and magnetic field values, at each fingerprint, the WAPs RSS values and magnetic fields are collected three time. Thus, the number recorded features, at offline stage, will be 198 multiply by 3 (594) records. An example of a collected features is shown in equation (1). For collecting the RSS values and magnetic fields, the onboard smartphone WiFi chipset and the magnetometer sensor are utilized. Amon the smartphones, android-based smartphone is used. A snapshot of the Android-based application is shown in figure 4. Note, the Android-based smartphone is used. This is because the Android is powerful, portable, free to do the modifications and its source code is fully available. In addition to that, the collected RSS values and the magnetic fields are then stored in a CSV file. This file, then will be used during the testing of the proposed solution as the dataset.

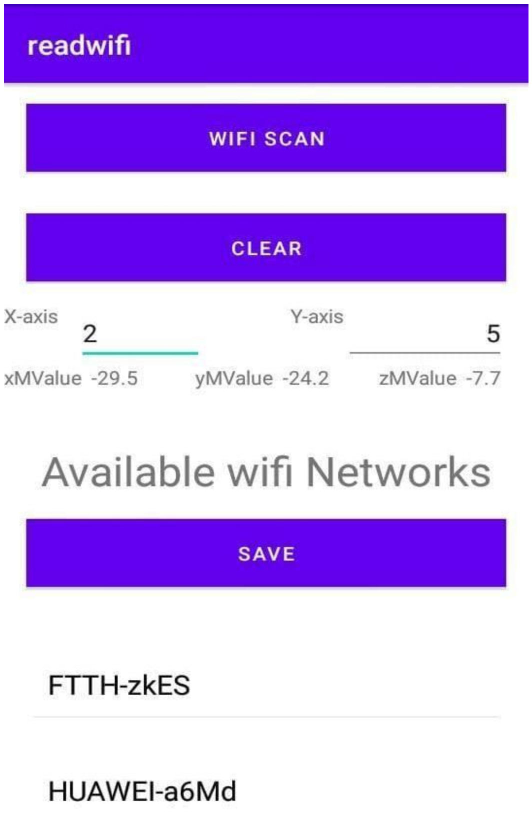

Figure 4. Snapshoot of Android Application.

Furthermore, MATLAB packages are used to evaluate the performance of the proposed approach.

A set of experiments are carried out via the packaged to show the validity of the dataset. For example, first, Figure 5 shows a MATLAB-based graph of the surveyed floor via the real-collected location coordinates (i.e. truth fingerprints).

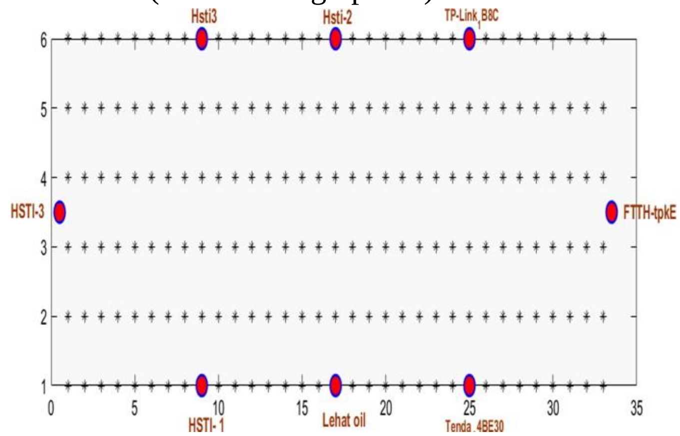

Figure 5. Simulated-MATLAB Graph of The Real Survey for the Koya-PICS Building.

$(Xpred,$

The next experiment is to show how the WAPs RSS values are recorded in terms of the fluctuations during the entire surveying. Figure 6 shows the recorded WAPs RSS values, as it can be seen, eight different graph lines are depicted with different colors. Further, each graph line is labeled with its WAPs name.

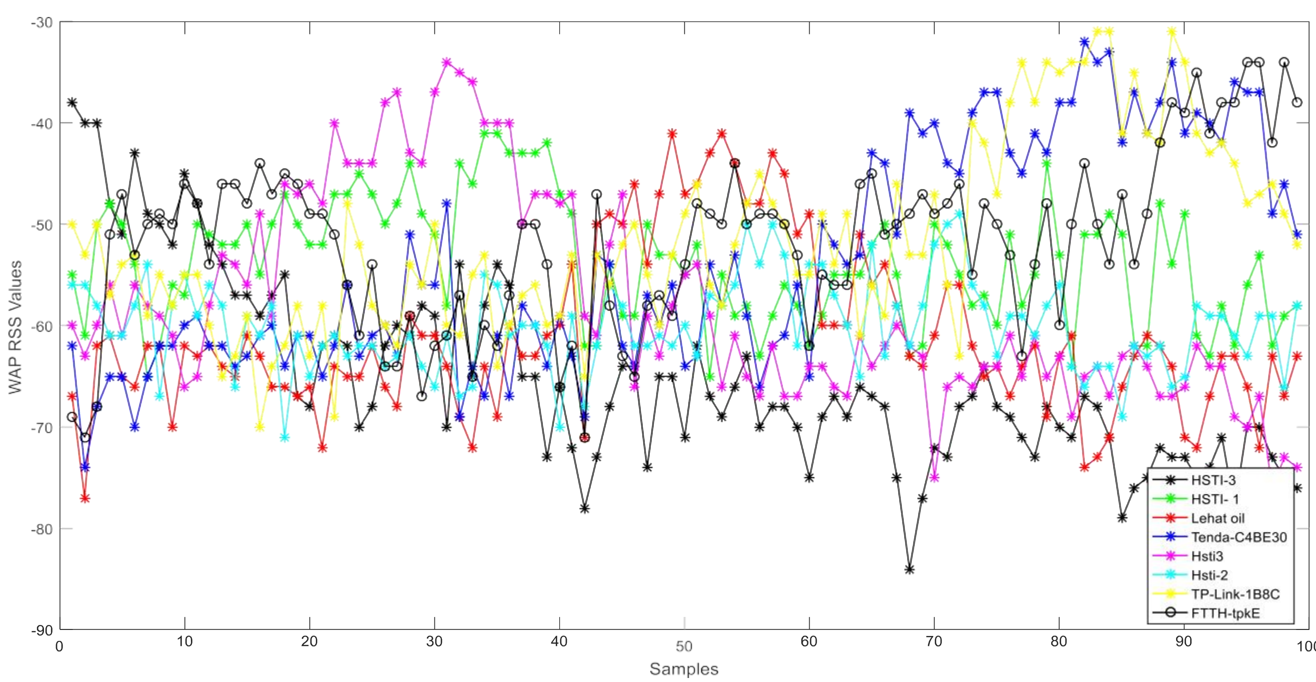

Figure 6. Eight WAPs RSS Values Along the Survey Path

Also, to further understanding on how the proposed solution is working, three trail experiments or scenarios are applied. The first scenario is conducted to show how Wk-NN is accurate when only the WAPs RSS values is used. The second scenario is to show how the Wk-NN is accurate when only magnetic field values of the collected dataset is used. Finally, the third scenario is the hybrid of WAPs RSS values and magnetic field values and to show the Wk-NN is working. Basically, the last scenario is to prove the validity of the proposed solution. Note, as it is mentioned before, Wk-NN is used as a matching algorithm in the fingerprinting technique. Further, regarding the proposed solution, the Wk-NN is modified based on the boosting dataset concept. Finally, the smartphone's positon is normally calculated via the equation (4).

Where $Xpred, Ypred$ are the predicted x-y coordinated of each unknown fingerprint during online stage, and Wi is the weight of ith selected record, and $Xi. Yi$ are the true coordinates of the nearest/selected records of the known fingerprints.

Note, simply to evaluate the proposed solution, the root mean square error (RMSE) is used as a positioning accuracy. Since, as a fact, the positioning accuracy has been used as a positioning performance evaluation. The formula of the RMSE is expressed in equation (5).

$$pos_{err} = \sqrt{\frac{1}{2}(X_{es} - X_t)^2 + (Y_{es} - Y_t)^2} \qquad (5)$$

Where pos_{err} is the positioning accuracy, X_{es} and Y_{es} are the estimated X and Y location coordinates, and X_t and $Y_t$are truth values of X and Y location coordinates respectively.

However, the another metric to evaluate the performance of the positioning algorithm is the precision of the positioning. Therefore, in this study, the positioning precision is also used. The position precision is determined through below equation 6:

$$\mathrm{Pos}_{\mathrm{S.}} = \sqrt{\frac{\sum_1^N (xi - \bar{x})^2}{N-1}} \qquad (6)$$

Where pos_s is the position precision (Standard deviation equation) of the points, N is the number of data points, xi is each of the values of the data and $\bar{x}$ is the mean value of the observed data. All of these calculation steps are done in the online stage of the proposed approach.

5. Experiments Setup and Results Without Adding Extra Mean Records

Each technology (including Wi-Fi and magnetometer) has its own strengths and limitations based on its own qualities for the execution of the proposed integration. For instance, location information based on various positioning algorithms can be obtained from magnetometer measurements and WAPs signal readings. However, the issue of interference induced by building structures or steel barriers is the main difficulty with employing magnetometer sensor data in indoor contexts. Additionally, complicated indoor structures like thick walls, doors, and ceilings will interfere with WAP signals. Furthermore, the WAP signal will be impacted by moving objects, including nearby humans. By incorporating the technology measurements into the fingerprinting technique based on their attributes, it may take advantage of their strengths in contrast to the limits of a single technology-based localization system. This study will first go over how each technological measurement in the suggested positioning strategy delivers positioning accuracy as well as how the suggested algorithm influences the system's accuracy.

According to the trials, using eight WAPs RSS data from eight access points, the WAPs RSS-based fingerprint technique may estimate the location of a smartphone. While using the closest neighbor (NN) matching algorithm, there is an average placement error of 1.64 meters and a precision of 2.05 meters. When the k-NN (k=3) method is tested, the average positioning error and precision are 1.59 meters and 1.45 meters, respectively. The positioning error is slightly improved (minimized) by providing 1.54 meters and the position precision was 1.47 meters after weights were added to the k-NN algorithm. The accuracy of the system significantly increased and positioning error of all technologies dramatically decreased when the improved algorithm (i.e. Boosting WkNN) is used for matching between online and offline stages. When WAP RSS data is used to test this improvement, the positioning error is decreased to 0.53 meter and precision is 1.22 meter. Additionally, Figure 7 displays the cumulative distribute functions (CDF) of the positioning accuracy (positioning error) attained, and Figure 8 displays the positioning error at each fingerprint in the dataset.

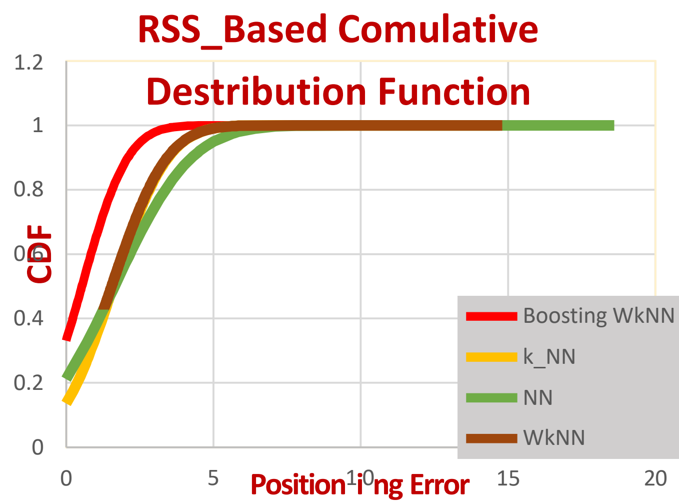

Figure 7. Cumulative Distributions Function of the Positioning Error When Only WAPs RSS Values is Used.

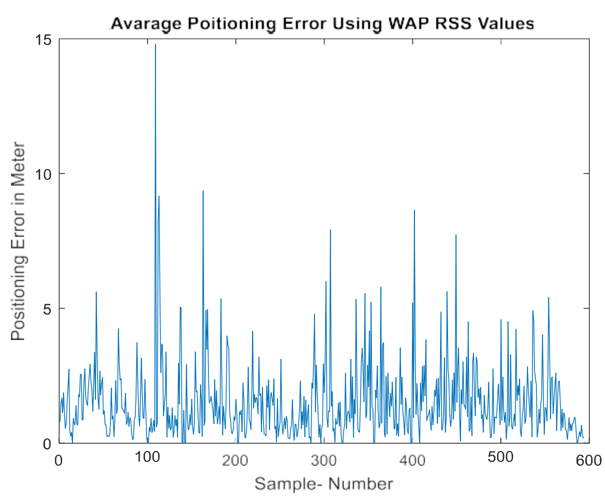

Figure 8. Positioning Error for All the Fingerprints of the Dataset for Wk-NN When Only WAP RSS values is Used.

When using the NN technique in the second scenario, the average error of the positioning accuracy is up to 3.48 meters when only magnetometer measurements containing (x, y, and z) are employed. This indicates that utilizing WAPs RSS values to determine location is more accurate than using magnetometer measurements. Further, when k-NN technique is used as matching algorithm the positioning accuracy was 3.99 meters and standard deviation was 3.69 meters, but these values are decreased to 3.76 for positioning accuracy and 3.73 meters for standard deviation when weights are added to the k-NN algorithm. while the contribution of this study is used (Boosting Wk-NN), the positioning error of the system was 3.42 meters and position precision became 3.8 meters. Further, the cumulative distribute functions (CDF) of the achieved positioning accuracy (positioning error) and the positioning error at each fingerprint of the dataset are shown in figure 9 and figure 10, respectively.

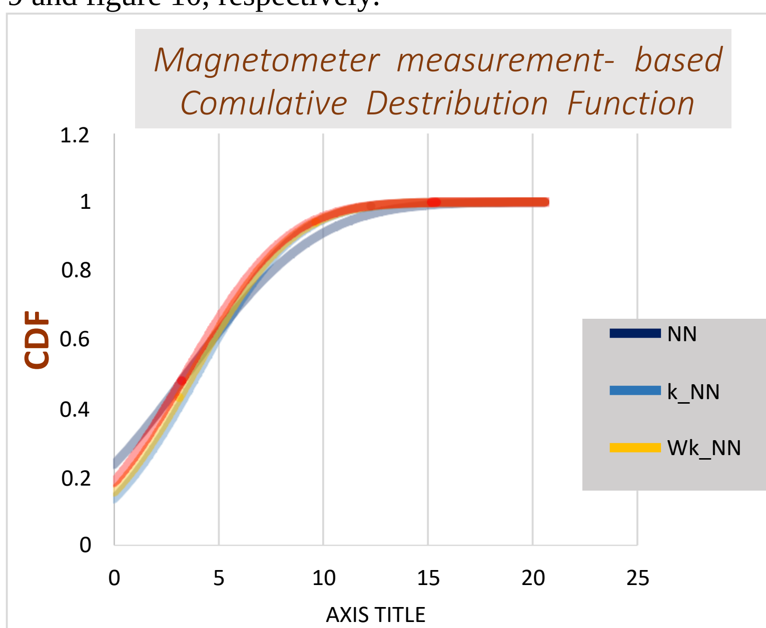

Figure 9. Cumulative Distributions Function of the Positioning Error When Only Magnetometer Values is Used.

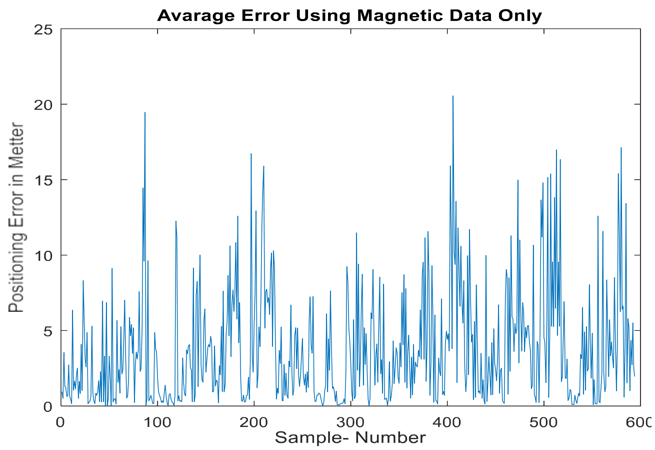

Figure 10. Positioning Error for All the Fingerprints of the Dataset for Wk-NN When Only Magnetic Values is Used.

The third scenario is to test the integration positioning approach by combining the two localization technologies measurements, as it is mentioned earlier. The integration is based on taking the advantages of both Wi-Fi technologies and magnetometer sensors measurements. In the first experiments NN is used as a matching algorithm for testing the system, the error positioning decreased 0.75 meters and the precision of the system became 1.29 meters. After that, the positioning error of the proposed approach is slightly increased when k-NN is used, that is up to 0.85 meter, but the precision is decreased to 0.89 meter compared to the NN algorithm. With adding weights to the k-NN technique, the accuracy of the positioning is somewhat better than k-NN, as the positioning error and precision are slightly decreased to 0.81 meter and 0.85 meter, respectively. Figure 11 and figure 12 shows the cumulative distribute functions (CDF) of the achieved positioning accuracy (positioning error) and the positioning error at each fingerprint of the dataset respectively. Table 1. shows the result of positioning accuracy and precision of all experiments and scenarios, in meters.

In order to compare our proposed methods with the related methods in the literature we reimplemented two method proposed in (Yu et al., 2019) and (Hanley et al., 2021) based on our environments (dataset). Table 1 shows the results of two related methods and the proposed methods in this study. We can clearly note that the proposed methods provided significant results and outperform other related methods.

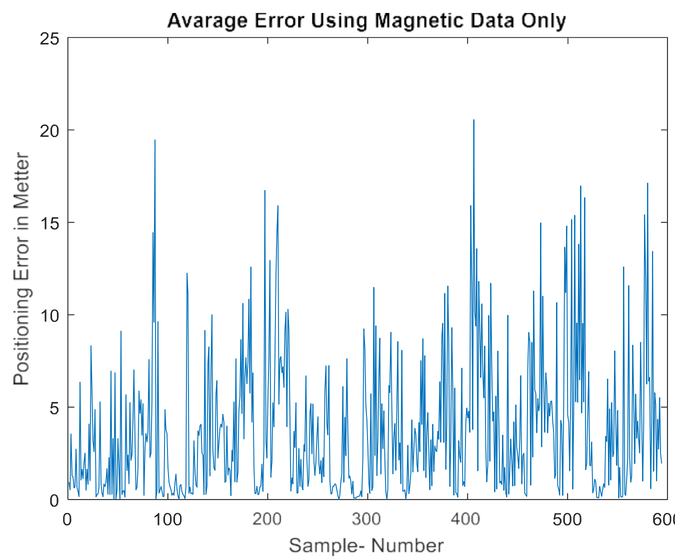

Figure 11. Cumulative Distributions Function of the Positioning Error When Combination of WAPs RSS and Magnetometer sensor Values is Used.

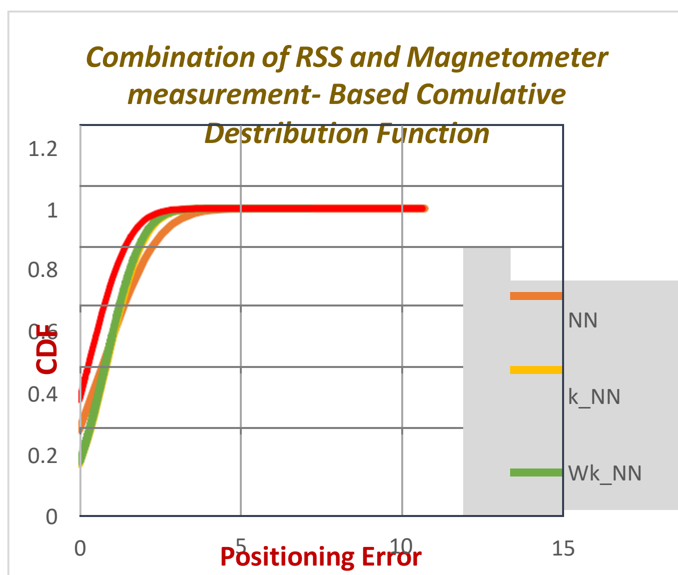

Figure 12. Positioning Error for All the Fingerprints of the Dataset for Wk-NN When Combination of WAPS RSS and Magnetometer Values is Used.

Table 1. Result of all test Experiments (Positioning accuracy and standard deviation in meters).

Approach	NN		kNN (k=3)		WkNN (k=3)		Boosting WkNN	
	Position Error	**Position Precision**	**Position Error**	**Position Precision**	**Position Error**	**Position Precision**	**Position Error**	**Position Precision**
WAP_RSS Only(Yu et al., 2019)	1.64	(2.05)	1.59	(1.45)	1.54	(1.47)	**0.53**	**(1.22)**
MAG Only (Hanley et al., 2021)	3.48	(4.84)	3.99	(3.69)	3.76	(3.73)	**3.42**	**(3.8)**
WAP_RSS and MAG	**0.75**	**(1.29)**	**0.85**	**(0.89)**	**0. 81**	**(0.87)**	**0.29**	**(0.96)**

6. Experiments Setup and Results with Adding Extra Mean Records

To improve the proposed algorithms, an extra mean value for 3 neighbor records (one after the other) of WAP RSS and magnetometer measurements of all records in the dataset is calculated. These records are added to the dataset as extra records. Extra mean-records have a high impact on the accuracy of the system. With the first scenario when the nearest neighbor (NN) algorithm is tested with these extra records, the experimental results shows that the accuracy (i.e. the positioning error) of the system is improved by providing 0.84 meters and the precision of the system became 1.62 meters. Furthermore, when k-NN algorithm is tested, the positioning error and precision of the system are 1.12 and 1.05 meters respectively. Moreover, these values are decreased to 1.2 meter for positioning error with WkNN algorithm and precision enhance to 1.19 meter. After testing all the algorithms and presenting the results, then this study's improvement is tested, the average positioning error decreased to 0.42 meter and standard deviation was 1.18 meter. As it is observed that the error rate is much lower than all other algorithms before. The CDF of this algorithms are depicted in figure 13 and the positioning error of weighted k-NN of WAP_RSS values is illustrated in figure 14.

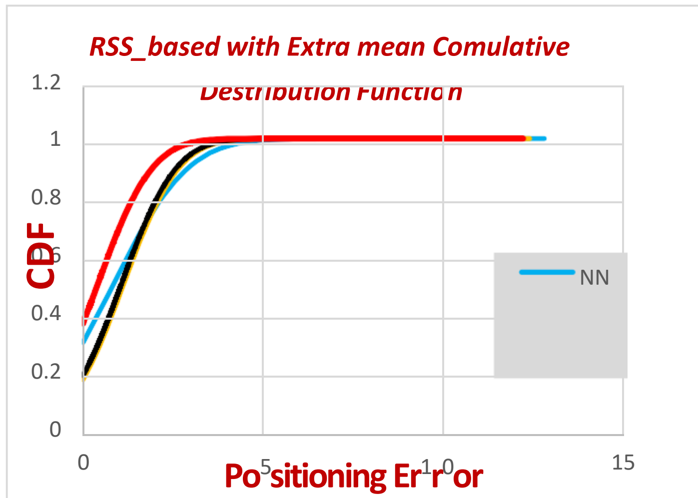

Figure 13. Cumulative Distributions Function of the Positioning Error When Only WAPs RSS Values is Used.

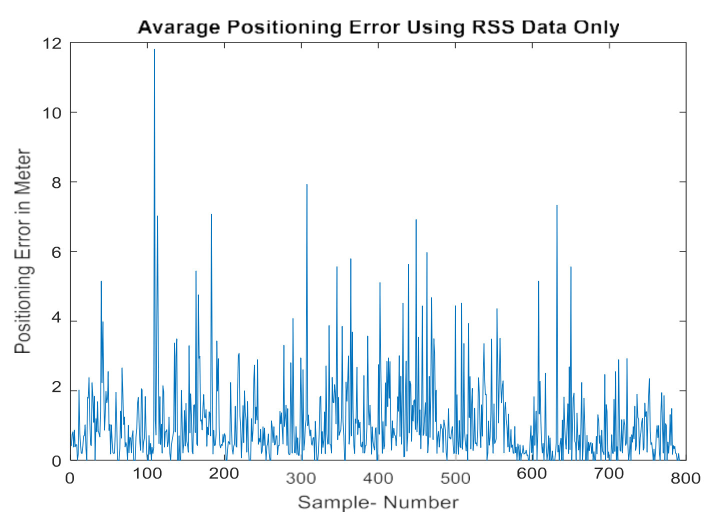

Figure 14. Positioning Error for All the Fingerprints of the Dataset for Wk-NN When Only WAPS RSS Values is Used.

With the second scenario, while only magnetometer-based measurement is tested, the positioning error of the proposed approach is 2.84 meters and the precision is 4.63 meters using NN algorithm. With k-NN algorithm, the positioning error is increased to 3.33 meters and precision is 3.76 meters, while with adding weights to the k-NN algorithm, this value decreases to 3.18 meters for positioning accuracy and precision of the algorithm is 3.70 meters. When this improvement is tested the positioning error is decreased to 2.98 meters and precision is 3.72 meters this is still very low compared to other techniques. Further, the cumulative distribute functions (CDF) of the achieved positioning accuracy (positioning error) is showed in figure 15 and the positioning error at each fingerprint of the dataset is shown in figure 16.

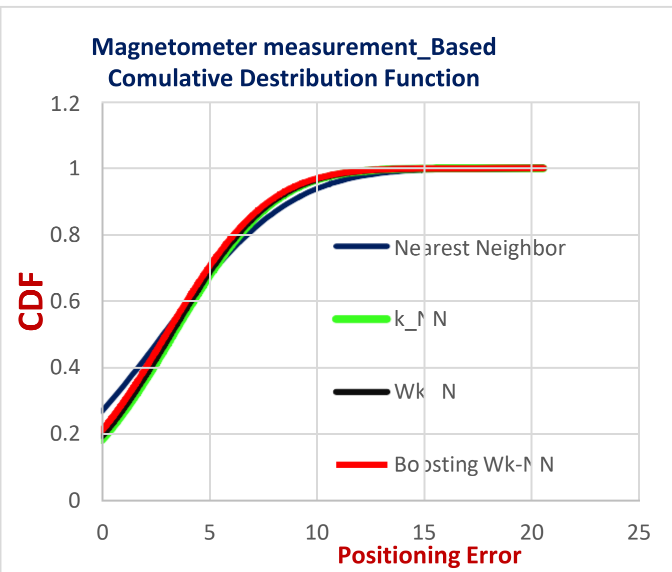

Figure 15. Cumulative Distributions Function of the Positioning Error Only Magnetometer Sensor Values is Used.

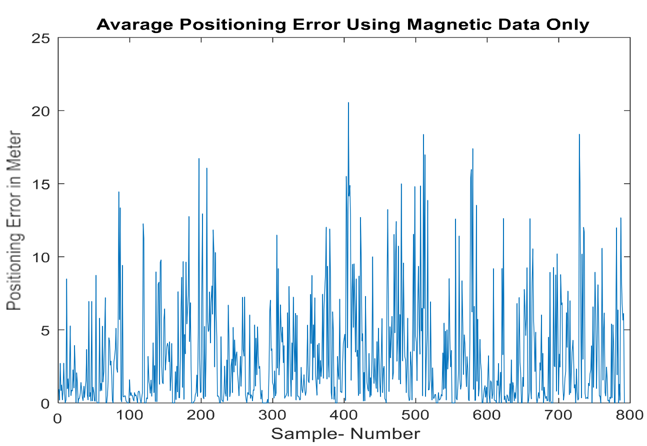

Figure 16. Positioning Error for All the Fingerprints of the Dataset for Wk-NN When Only Magnetometer Values is Used.

With adding extra mean values to the integration of RSS values and magnetometer measurements (third scenario), the accuracy of all the techniques is improved significantly and the positioning error of the techniques is decreased to 0.25 meter for using the nearest neighbor NN algorithm, while for using k-NN algorithm, the average positioning error is 0.52 meter and the standard deviation is 0.72 meter, but with using the WkNN algorithm, these values decreased to 0.47 meter for positioning error and 0.71 meter for standard deviation. Applying the Boosting weight k-NN to the combination of technologies (WAP_RSS and magnetometer) caused the accuracy of the system to increase significantly, and positioning errors have a minimum value of 0.13 meters, while the precision of the system is maximized when standard deviation is 0.62 meters. CDF and positioning error of this scenario is showed in figure 17 and 18 respectively.

It is clear that the integration of two technologies (WAPs RSS and magnetometer sensor) has a significant impact on system performance. The results of applying all of the previously utilized algorithms for indoor positioning shows that combining these two technologies has a favorable impact on estimating smartphone locations. During testing, the proposed Boosting WkNN algorithm resulted in significantly lower positioning error and increased positioning precision in all three scenarios, particularly in the third scenario, which is a combination of both technologies, the system's performance is higher than in the other two scenarios. Table 2 shows the results of two related methods and the proposed methods in this study after adding extra mean record to the dataset and developing a dynamic dataset. We can clearly note that the proposed methods with extra mean records to the dataset provided significant results and outperform other related methods.

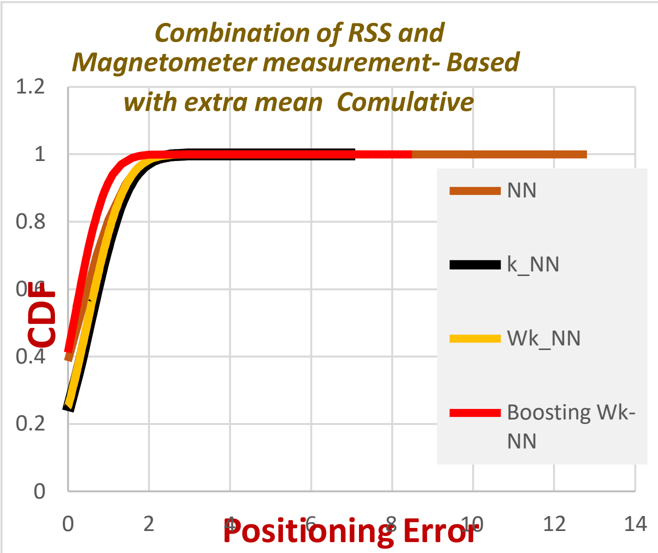

Figure 17. Cumulative Distributions Function of the Positioning Error When Combination of WAPs RSS and Magnetometer sensor Values is Used

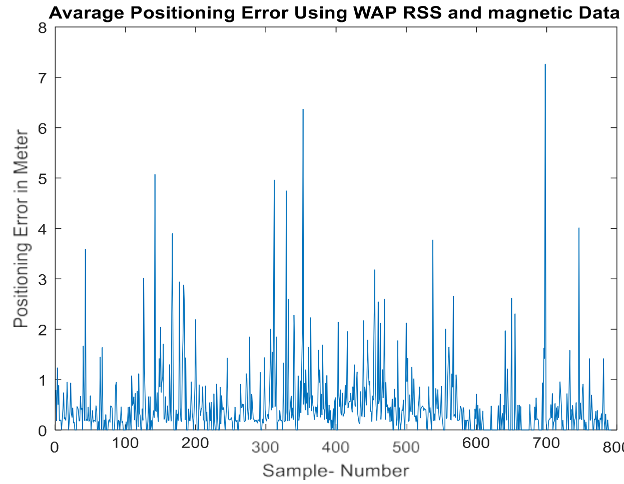

Figure 18. Positioning Error for All the Fingerprints of the Dataset for Wk-NN When Combination of WAPS RSS and Magnetometer Values is Used.

Table 2. Result of all test Experiments (Positioning accuracy and standard deviation with extra mean records).

Approach	NN		kNN (k=3)		WkNN (k=3)		Boosting WkNN	
	Position Error	**Position Precision**	**Position Error**	**Position Precision**	**Position Error**	**Position Precision**	**Position Error**	**Position Precision**
WAP_RSS Only (Yu et al., 2019)	0.84	1.62	1.12	1.2	1.05	1.19	**0.40**	**1.18**
MAG Only (Hanley et al., 2021)	2.84	4.63	3.33	3.67	3.18	3.70	**2.98**	**3.72**
WAP_RSS and MAG	**0.25**	**0.86**	**0.52**	**0.73**	**0.47**	**0.71**	**0.13**	**0.62**

7. Conclusions

In this article, a hybrid indoors positioning solution is proposed via using WAPs RSS values and magnetometer measurement within the fingerprinting technique. The solution is to provide better positioning accuracy and provide low cost solution, since the solution doesn't need extra-hardware. To prove the validity of the proposed solution, the fingerprint technique is implemented in three different ways, when only Wi-Fi RSS values is used, only magnetometer measurements is used, and both Wi-Fi RSS values and magnetometer. In all ways, the extra-hardware or any additional infrastructure doesn't need. Further, a set of real trial experiments with different scenarios are conducted. Moreover, an improved boosting WkNN algorithm, as a matching algorithm, is modified for improving the fingerprint techniques. The obtained results from the conducted experimental showed that the positioning accuracy is up to 1.6 meters when only Wi-Fi RSS values is used alone; and positioning accuracy is up to 3.74 meters when only magnetometer sensors alone is utilized. While, when the hybrid of Wi-Fi RSS values and magnetic measurements as well as when the proposed Boosting Wk-NN algorithm (as an improved matching algorithm) is applied, the obtained positioning accuracy is up to 0.13 meter.

Future work of this article could be based on modifying the threshold values to automatically select the best values which increase the accuracy of the system. Also, it is targeted to test and modify the proposed algorithm to be robust when it will be running in harsh environments or in complex indoors structure. This means, the algorithm will be modified to be adopted with the multi-path and NLOS environment.

8. References

ALI, M. U., HUR, S. & PARK, Y. J. S. 2019a. Wi-Fi-based effortless indoor positioning system using IoT sensors. 19**,** 1496.

ALI, W. H., KAREEM, A. A. & JASIM, M. J. C. U.-E. S. J. 2019b. Survey on wireless indoor positioning systems. 3**,** 42-47.

ASHRAF, I., HUR, S. & PARK, Y. J. S. 2019. Indoor positioning on disparate commercial smartphones using Wi-Fi access points coverage area. 19**,** 4351.

ASHRAF, I., ZIKRIA, Y. B., HUR, S. & PARK, Y. J. I. A. 2020. A Comprehensive Analysis of Magnetic Field Based Indoor Positioning With Smartphones: Opportunities, Challenges and Practical Limitations. 8**,** 228548-228571.

DARI, Y. E., SUYOTO, S. & PRANOWO, P. J. I. J. I. M. T. 2018. CAPTURE: A Mobile Based Indoor Positioning System using Wireless Indoor Positioning System. 12**,** 61-72.

GOZICK, B., SUBBU, K. P., DANTU, R., MAESHIRO, T. J. I. T. O. I. & MEASUREMENT 2011. Magnetic maps for indoor navigation. 60**,** 3883-3891.

HANLEY, D., DE OLIVEIRA, A. S. D., ZHANG, X., KIM, D. H., WEI, Y., BRETL, T. J. I. T. O. I. & MEASUREMENT 2021. The impact of height on indoor positioning with magnetic fields. 70**,** 1-19.

HOSSEINI, K. S., AZADDEL, M. H., NOURIAN, M. A. & AZIRANI, A. A. Improving Multi-floor WiFi-based Indoor positioning systems by Fingerprint grouping. 2021 5th International Conference on Internet of Things and Applications (IoT), 2021. IEEE, 1-6.

KESER, S. B., YAZICI, A. & GÜNAL, S. J. M. I. S. 2018. An F-Score-Weighted Indoor Positioning Algorithm Integrating WiFi and Magnetic Field Fingerprints. 2018**,** 7950985:1-7950985:8.

KUANG, J., LI, T. & NIU, X. J. I. S. J. 2021. Magnetometer bias insensitive magnetic field matching based on pedestrian dead reckoning for smartphone indoor positioning.

MENDOZA-SILVA, G. M., RICHTER, P., TORRES-SOSPEDRA, J., LOHAN, E. S. & HUERTA, J. J. D. 2018. Long-term WiFi fingerprinting dataset for research on robust indoor positioning. 3**,** 3.

NINH, D. B., HE, J., TRUNG, V. T. & HUY, D. P. J. F. G. C. S. 2020. An effective random statistical method for Indoor Positioning System using WiFi fingerprinting. 109**,** 238-248.

PÉREZ-NAVARRO, A., TORRES-SOSPEDRA, J., MONTOLIU, R., CONESA, J., BERKVENS, R., CASO, G., COSTA, C., DORIGATTI, N., HERNÁNDEZ, N. & KNAUTH, S. 2019. Challenges of fingerprinting in indoor positioning and navigation. *Geographical and Fingerprinting Data to Create Systems for Indoor Positioning and Indoor/Outdoor Navigation.* Elsevier.

SHAHIDI, S. & VALAEE, S. GIPSy: Geomagnetic indoor positioning system for smartphones. 2015 International Conference on Indoor Positioning and Indoor Navigation (IPIN), 2015. IEEE, 1-7.

YEH, S.-C., HSU, W.-H., LIN, W.-Y., WU, Y.-F. J. I. T. O. I. & MEASUREMENT 2019. Study on an indoor positioning system using Earth's magnetic field. 69**,** 865-872.

YU, J., NA, Z., LIU, X., DENG, Z. J. E. J. O. W. C. & NETWORKING 2019. WiFi/PDR-integrated indoor localization using unconstrained smartphones. 2019**,** 1-13.