Analysis of Device-Free and Device Dependent Signal Filtering Approaches for Indoor Localization Based on Earth's Magnetic Field System

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Abstract. In this study, Earth's magnetic field signals have been investigated to determine mobile user's location. In theory, Earth's magnetic field does not change during the day at a certain point. But, the various noise effects that are exposed during the measurement causes deviations in the measured signal. In this study; Kalman Filter, LOESS, Savitzky-Golay filters are adapted with two different approaches to purge Earth's magnetic field values from noise. K-Nearest Neighbour and Random Forest models have been trained with filtered signals and the locations of the mobile user are determined. Relevant systems have been tested by using RFKONDB which is existed in literature. The purpose of this study is to measure how these filters should be adapted to an Earth's magnetic field based indoor localization systems. Digital sensors, which are integrated mobile devices, can use different measurement techniques. In a heterogeneous environment, noise reduction filters can show a different effect. Two different test scenarios and two different noise reduction models, with the 3 noise reduction techniques, are developed to find the best case.

Keywords: Earth's Magnetic Field, Indoor Localization, Device-Free, Device-Dependent, Signal filter, Kalman, Savitzky-Golay, Locally Weighted Scatter Plot Smooth (LOESS) Filter

1 Introduction

Indoor localization is particularly difficult due to the high dynamics and obstacles of the environment. Therefore, there is no generally accepted positioning system in in-

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door areas. The methods used for localization in closed areas are considered as deterministic and probabilistic methods [1]. In deterministic methods, Triangulation and Trilateration methods are included. Probability methods include Particle Filter, Hidden Markov Model, Histogram Method, Kernel Learning method, but the most commonly used method is Fingerprinting. The fingerprinting method consists of two phases: online and offline. Using the data collected during the offline phase, the signal map of the environment is generated. In the online phase, the data collected from the mobile user is compared with the data in the signal map to determine the location of the mobile user. Fingerprinting method often uses WiFi, BLE, RFID, Infrared and Earth's magnetic field data [2]. It is particularly important that an indoor localization technique must not have a high-cost infrastructure. Technologies such as WiFi, BLE, and RFID, which are frequently used for indoor localization, need infrastructure installation and hardware support inside the building. For this reason, in this study position of a mobile user has been determined by using the geomagnetic field (Earth’s magnetic field) information. The determination of the Earth's magnetic field values is first carried out in 1600 by William M. Gilbert in the book “De Magnete” [3] [4]. The magnetic field that surrounds the Earth is formed by the rotation of the Earth through the nickel outer structure of the outer core of the Earth and the liquid iron contained therein [5].

At first glance, it seems to be the most logical way to use the Earth's electromagnetic field values in the design of a generally accepted indoor positioning system with a unique magnetic field value in every part of the Earth. However, the Earth's magnetic field information cannot be accurately measured due to disturbances caused by ferromagnetic objects in indoor locations [6]. Smartphones are often used for locating mobile users, especially in indoor areas. However, the sensors in mobile phones are exposed to two basic effects, which are hard and soft iron due to their hardware structure and which makes it difficult to accurately measure the electromagnetic values of the Earth.

At the same time, electromagnetic signals collected from an environment are exposed to the hard-iron effect caused by substances such as nickel-cobalt in the environment. According to this, it is aimed to eliminate the noise values in measured signals to create an indoor localization system independent from infrastructure hardware by using the magnetic field values of the Earth. For this purpose, the RFKONDB[7] signal map is used. The Earth’s magnetic field data is evaluated in a pre-processing step to be cleared of noise. Although there are different signal noise reduction methods [8], Kalman filter, Loess Filter and Savitzky-Golay Filter (SGF) are preferred in pre-process phase. Two different pre-processing model, Device-Free filtering and Device-Depended filtering, are proposed for analyzing noise effects.

The organization of the paper is as follows: In Chapter 2, indoor localization studies carried out by using Earth’s magnetic field values are detailed. The signal maps, filtering methods, filtering approaches and test scenarios used in the study are described in detail in Chapter 3. Finally, test results obtained from test scenarios are presented in Chapter 4.

2 Related Works

The use of earth's magnetic field signals in indoor localization systems provides a powerful approach, which can be designed completely without infrastructures and allows for continuous positioning. The design is difficult due to the electromagnetic noise in the environment affects the sensor measurements of electromagnetic data.

A fingerprint-based approach is proposed in the AMID [9] system, and the noise on the Earth's magnetic field values obtained in the online phase is classified using the Deep Learning method after noise is reduced by using Smoothing Filter. [10] proposes a fingerprinting based method that uses Earth's magnetic field values for indoor localization. EMF data are calibrated to reduce the noise from original EMFV obtained in the online phase and the location is determined by using Likelihood approach. [11] proposes a system that compares EMF valuesin the signal map by using the Gaussian Function. [12] determine locations using the Nearest Neighbourhood with Root Mean Square in their fingerprint-based study. [13] separate each grid in the signal map into sub-grids and detect similar mobile user with similarity calculation with an error of 3.3m. [14], the test area is divided into a stable and fluctuating area; positioning in indoor area is realized by using Earth's magnetic field. In related study, a mobile user is determined by an average of 3 m error. [15] obtain the feature extraction methods on the EMF values that 46 features are reduced to 5 features obtained by using the genetic algorithm, the possibility of the correct location detection of the mobile user is increased from 78.3% to 85.8%.

[16] used the magnetic field data to test the performance of the Particle Filter, Artificial Neural Networks and the FPM-MI proposed by the authors. In the proposed FPM-MI algorithm, it was measured by the nearest neighboring Euclidean distance from each sampling in the magnetic signal map using the KNN method. Measurements performed with accelerometers and gyroscopes in order to reduce errors that may be included in the magnetic signals have been used in the regulation of the position information. They predicted k paths through accelerometers and gyroscopes. Selection of the proposed route estimations was performed by particle filtering the information received from INS. Position detection was performed with an average of 90% probability and an accuracy of 1.1m.

[17] obtained an average accuracy of 1.06m using Recurrent Neural Network as a classification method in their fingerprint-based studies. [18] compared the classification methods KNN, MLE, and Naive Bayes by using Earth's magnetic field values on RFKON dataset they created. As a result of their tests, they determined that the methods can determine a mobile user's position with an accuracy of less than 6m with an average probability of 70%. [19] measured positioning performance using the Kalman Filter on the data they are collected via smartphones. In the tests performed, it is seen that a positioning error up to 40m is obtained with an average of 9.5m. The Kalman Filter is used based on the PDR technique and is used to estimate the position of the moving user in the EMFV and images collected by the smartphones in their fingerprint-based mobile user monitoring system. They have created a step-by-step model with gyroscope and accelerometer information collected via smartphones. The information in the step model they created is evaluated in artificial neural networks to

obtain the necessary attributes and then to perform positioning using a context-aware particle filter on a server. Tests are carried out in four different areas. In the positioning tests performed using only EMFV accuracy below 1 m is achieved with a probability of 77%. By using the author's proposed method, accuracy below 1m is obtained with a 91% probability.

3 Methodology

In this section, methods are introduced detailed.

3.1 K-Nearest Neighbors Classification Algorithm

K-Nearest Neighbour technique is a machine learning algorithm that has an easy implementation. It is a classification model based on finding the similarity rates between samples. The distance between samples is calculated with a Euclidean distance formula. If it is considered $x=x_1, x_2, \ldots, x_n$ and $y=y_1, y_2, \ldots, y_n$ as two samples taken from indoor areas the Euclidean distance calculation is presented in Equation 1.

$$\text{distance} = \sqrt[2]{\sum_i^n (x_i - y_i)^2} \tag{1}$$

Large Euclidean distance symbolizes that two samples are like each other, while a smaller distance symbolizes that two samples are less resembled. To classify sample data; The Euclidean distance value for all points in the data set is calculated. It is classified according to the majority vote of the nearest K neighbors.

3.2 Random Forest Algorithm

Random Forest is a tree-based classification method. It creates multiple decision trees in the dataset to be used for classification. The forest is formed with more than one decision tree. In the obtained forest, the subclass that represents the best value in the dataset is selected and graded. The decision tree algorithm tries to solve the problem by using tree representation. Each internal node of the tree corresponds to an attribute, and each leaf corresponds to the node class label. It places the best attribute of the dataset on the tree root. The subset divides the training set. Each subset is created to contain data that has the same value for an attribute. This process is done for all branches of the tree.

The primary challenge in implementing a decision tree is to determine which attributes should be considered as the root node and count of levels. The feature selection approach is adapted for this. Gini Index, entropy and twoing are metrics to determine how often a randomly selected item is detected incorrectly.

3.3 Kalman Filter

The Kalman filter is described as one of the most important discoveries of the 20th century. Although it is named as a filter, it is used in linear systems for estimating the next step. With its recursive structure (re-inputting the outputs into the filter) is the only filter that minimizes the estimation error in the existing filters. The Kalman filter has two equations for estimation and correction [20]. Prediction equation is presented in Equation 2.

$$x_k = Ax_{k-1} + Bu_k + w_{k-1} \tag{2}$$

$$Z_k = Hx_k + v_k \tag{3}$$

The measurement value of a signal is obtained in the previous case x_{k-1}. The control signal u_k and w_{k-1} are the previous operational noises. A, B and H are general representations of matrices. These values can be treated as numerical numbers. The A matrix is the state transition model, the B matrix is the control model, the H matrix is the measurement model. The measurable value of a signal is presented in Equation 3.

3.4 Svatzkiy Golay Filter (SGF)

Savitzky-Golay Filter (SGF) is presented in 1964 by Abraham Savitzky and Marcel J. E. Golay [21]. filtering techniques are used on average tend to flatten and expand peaks in the data spectrum. It has been developed to reduce the noise in the data and to ensure that the characteristics of the distribution such as relative maximum or minimum. In digital filtering, the following formula is used in order to smooth the average of the data 2n+1 neighbor at (y_k) point k.

$$(y_k)_{smooth} = \sum_{i=-n}^{n} (y_k + i)/(2n + 1) \tag{4}$$

In the SGF filter, the data is matched to a polynomial using its (2n + 1) neighbors. The width of the filter used is also called the window width. Smoothing is continued by sliding the window.

3.5 Locally Weighted Scatter Plot Smooth (LOESS) Filter

LOESS is one of the most popular kernel type smoothing filters. The LOESS filter is a nonparametric method for estimating regression surfaces and has great flexibility. There are no global assumptions about the parametric form of the regression surfaces. LOESS fits nonparametric models, supports the use of multidimensional data, supports multiple dependent variables and performs iterative reweighting to provide robust fitting when there are outliers in the data [22].

Assume that i=1,…, n and Y_i represents the measurement value of the corresponding x_i where f(x) represents an unknown function and ε_i represents a random error in the observations or variability from sources not included in the x_i.

$$Y_i = f(x_i) + \epsilon_i \tag{1}$$

The regression function f(x) can be locally approximated by the value of a function in some specified parametric class. Such a local approximation is obtained by fitting a regression surface to the data points within a chosen neighborhood of the point x [23].

LOESS is ideal for modeling complex processes as a very flexible filter. But it requires very large and densely sampled datasets to produce good models. Increasing the size of the dataset results in increases experimental costs.

3.6 Proposed Model

In this study, the effect of noise reduction/cleaning filters, which can be used in the localization/positioning systems based on Earth's magnetic field values in indoor areas, is investigated. In theory, the Earth's magnetic field may change in time referred to as short-term and long-term deviations. Long-term deviations caused by solar flares, the axis of the earth, etc. which are and ignored in this study. Short-term deviations caused

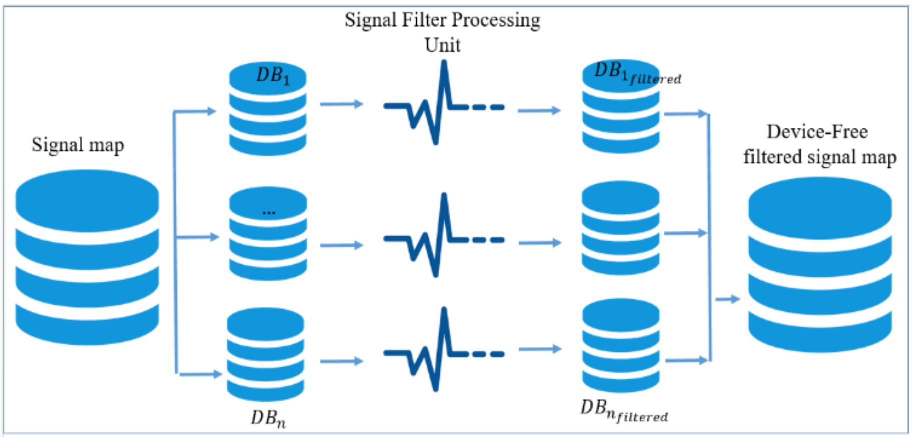

Fig. 1. Device-Free signal filtering model.

by the metal effects. We propose two different approaches: Device-Free and Device-Depended to clear/reduce the noise from the measured signals. Deviations caused by mobility, by building materials such as iron, nickel, etc. in the indoor area are considered as noise. To reduce the noise, it is recommended to filter only measurements at the reference points, as independent from the measuring devices. According to our theory, the magnetic field signals at the reference points should not change during the day and the deviation in the signals could be within a certain range. To examine this theory, signal measurements are grouped according to the reference points. the signal measurements in each group (DB *k=1,…, n*) are subjected to filtering independent from the measured device information shown in Fig 1. The signal map obtained after filtering ($DB_{kfiltered}$) is used for the training of the positioning model.

The Device-Depended approach recognizes that the noise source in the signals originates from the digital sensors of the devices which are used for measurements. The digital sensors are developed with four different approaches. Hence, the signal filtering process should be designed according to the device. The signal map (Fig. 2.) is divided into groups (DB_k *k=1,…, n*). Each subgroup data is grouped again according to the device information. The measurements of each device are filtered, and the noise is reduced. Then, it is used to train the positioning models.

70% of the signal maps are used in the training of KNN and RF positioning models. The remaining 30% of the dataset is used to test the models. Accuracy rates of the models are calculated according to the estimations on the test data. Accuracy is calculated by finding the percentage ratio of the correct estimates in the submitted test data size to the total test data size. In a well-trained model, high accuracy is expected. Two different test scenarios (Fig. 3) are proposed to test the models that are trained in this study.

In Scenario 1, user can measure magnetic field signals of the Earth and the measurements are sent to the filtering unit. This filtering unit may be located on a remote server or integrated into a mobile device. The related unit reduces noise according to the filtering approach. Noise-free signals are transmitted to the positioning module. The positioning module is a unit where the user's position is determined. The specified position information is transmitted to building supervisor, user or to another application. In this scenario, processing time for determining the user's location is represented as Δt.

$$\Delta t = t_{filter} + t_{classification} \tag{5}$$

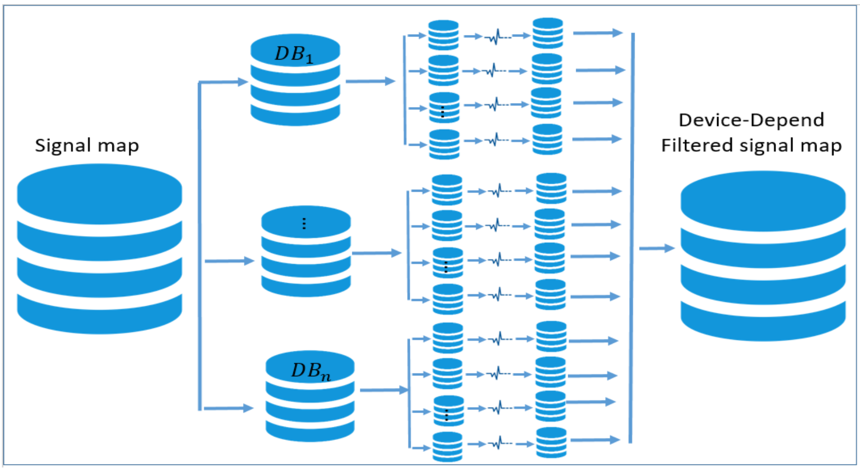

Fig. 2. Device-Depended filtering model

Δt is depended on filtering processing time and classification time (Eq. 6). In Scenario 2, user measures the magnetic field signals with his/her mobile device. The measured data is transmitted to the positioning module without any filtering process. The positioning module detects the position of the user and delivers to the relevant units.

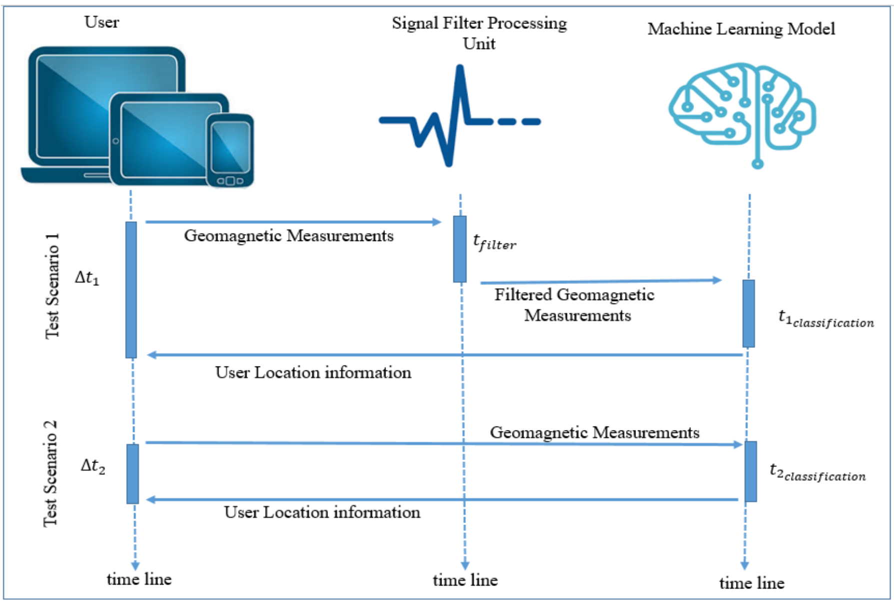

Fig. 3. Test scenarios

Delays in the network are ignored in both models. For the same positioning model, the absence of filtering time in Scenario 2 seems advantageous in terms of decreasing processing time.

4 Test results

In this study, RFKONDB is used which is obtained by the fingerprinting technique. Measured area of The RFKONDB is divided into 1.2 x 1.2 m2 squares and signals are captured from in the middle of related squares. Fingerprinting signal maps are divided into two parts as 30% for testing and 70% for training. Training data is used to train KNN and RF methods. Test data is used to test the accuracy of the trained models. While creating fingerprint signal maps, *NaN* values are not used in the training phase of the models. The number of neighbors in the KNN method is 1. In the RF method, the nodes of the tree are selected according to the Gini index.

The accuracy values obtained localization models by using the RFKON dataset with the Device-Free filtering approach are given in Table 1. Cross-validation accuracy rates obtained as 95% by using KNN and RF as classification methods.

In the Device-Free filtering approach, the accuracy rates of the models by using Kalman filter and SGL filter have decreased. The LOESS filter did not change the accuracy of the model but it is observed that Test Scenario 2 is more successful than the original situation. Test Scenario 2 reduces localization processing time because it contains unfiltered test data. Therefore, the LOESS filter is an advantageous filtering method.

Table 1. RFKONDB Device-Free Filtering Test Results

Filter Method	**10K Cross Validation**		**Validation Data Type**	**Validation Results**	
	KNN	RF		KNN	RF
Original Data	0.95	0.95	Scenario 2	0.95	0.95
Kalman	0.88	0,87	Scenario 1	0.89	0.88
			Scenario 2	0.95	0.88
LOESS	0,95	0.95	Scenario 1	0.95	0.95
			Scenario 2	0.96	0.98
SGF	0.92	0.90	Scenario 1	0.92	0.90
			Scenario 2	0.95	0.94

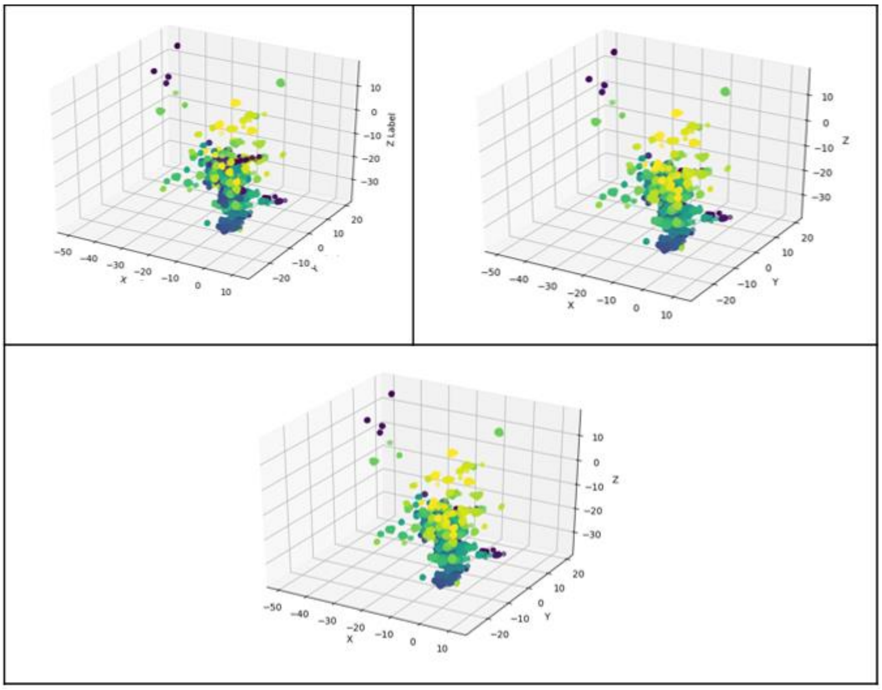

Fig. 4. 3D representation of RFKONDB signal map (top-left), Device-Free approach results by using SGF (top-right) and LOESS filter (below)

Device-Depended approach advocates that the cause of the noise in the signals is due to the measurements of the digital sensors. Therefore, to observe the accuracy rates of the filters, 6 different devices are used in the RFKON dataset. The signal measurements of the devices are grouped and filtered according to the device id value. The KNN and RF positioning models are trained by using 70% of the signal map obtained after filtering. The test results are shown in Table 2. The device-depended approach increased the accuracy of models. The Kalman filter is the most successful noise removal filter in this approach. 98% accuracy is obtained in the KNN and RF method SGF showed similar performance results to the Kalman filter. A decrease in accuracy values is observed in Test Scenario 2 by using Kalman and SGF in pre-process phase. It is observed that the models trained after LOESS filter are more successful in Test Scenario 2. Especially the RF method is a very successful localization method with a 98% accuracy rate.

Table 2. RFKON Device-Depended Filtering Test Results

Filter Method	**10K Cross Validation**		**Validation Data Type**	**Validation Results**	
	KNN	RF		KNN	RF
Original	0.95	0.95	Scenario 2	0.95	0.95

Data					
Kalman	0.98	0.98	Scenario 1	0.99	0.99
			Scenario 2	0.95	0.87
LOESS	0.95	0.95	Scenario 1	0.95	0.95
			Scenario 2	0.96	0.98
SGF	0.97	0.98	Scenario 1	0.97	0.98
			Scenario 2	0.96	0.93

The highest accuracy in the proposed localization models trained with RFKONDB data set is obtained by using SGF and LOESS filters with the Device-Free approach. Fig. 4 shows the 3D graph of the original measurements in the RFKONDB signal map and the 3D graph after the SGF and LOESS filters are used. Same colored dots symbolize measurements taken from the same reference points. The SGF and LOESS filters are provided similar results. When both filters are examined, it is seen that some measurements between the color groups are considered as noise and cleaned.

5 Conclusion

In this study; the filtering methods which are developed to clean the noise from the Earth's magnetic F]ield signal values and their usage with positioning models have been investigated. For this reason, Kalman filter, LOESS and SGF filters, which are frequently used for cleaning the signals, are preferred. Fingerprinting technique is chosen as the method of indoor positioning. In the fingerprinting technique, signals are measured with different devices from the same reference points and these measurements are used to create signal maps. Two different approaches have been studied to reduce/clear the noise in the signals. The first approach; the noisy measurements in the signals are based on the digital sensor which is used to collect signals and therefore the measurements of each device are filtered independently, and the fingerprint map is generated. The relevant approach is called Device-Depended. The second approach, called Device-Free, is intended to clean the measurement noise from the environment, depending on the time taken at the reference point. All the signals in the fingerprint map at the same reference point are passed through the respective filters together. The main purpose of this approach is to collect signal measurements at a reference point in a narrower range. KNN and RF algorithms are used in the localization phase. In order to realize the proposed positioning models, RFKONDB signal map is used. Two different test scenarios have been proposed to compare the accuracy of the developed systems. Obtained test results are analyzed and the propositions related to these analyses are presented.

The accuracy of the models tested with 10k cross-validation and the validity of the test data and the models are calculated. Two different scenarios are developed for validation test data. In the first scenario, a filtered validation data set is presented to the models that are trained with the filtered data set. The aim is to present the data to be used in the determination of the user position by eliminating the noise with the same filter. In this scenario, the processing time of the data spend on filtering is disadvantageous. The second scenario includes the transmission of measurements from the user whose location is to be determined without any pre-processing. Although it is advantageous in terms of time, its positioning success decreases due to noisy measurements caused by digital sensors.

In the Device-Free approach, by using the RFKONDB data set, the success of the models proposed by the Kalman Filter has decreased. The SGF filter reacted similarly to the Kalman filter. When using the LOESS filter, the accuracy is not affected. We recommend using the LOESS and SGF filters for indoor positioning methods in the Device-Free approach.

In the Device-Depended approach, it has been observed that all filters increase positioning accuracy. The highest accuracy value found at 99%. With this approach, we recommend that the Kalman filter and the KNN positioning model to be created according to Scenario 1 for the positioning model performed by filtering.

In both approaches, it has been observed that validation data (Scenario 1) should also be filtered. It can be provided to send the data to the model after filtering on the mobile user's device where the location would be determined. It is also possible to filter the measurement data of the same user after being sent to a central server. Due to the development of technology; due to the usage of fast and powerful hardware the filtering process time has ceased to be a major problem. If the positioning model based on Scenario 2 would be created, it is observed that the most suitable filter would be LOESS filter. The accuracy rate obtained from models developed by using this filter is higher than the unfiltered validation test results. Especially the usage of the RF method with the LOESS filter is recommended.

References

1. Z. Turgut, “Nesnelerin İnterneti için Hareketlilik Yönetimi,” İstanbul Üniversitesi, (2018).
2. Namiot, D., On indoor positioning. International Journal of Open Information Technologies, vol. 3, no. 3, pp. 23-26 (2015).
3. Bloxham, J., Sensitivity of the geomagnetic axial dipole to thermal core-mantle interactions. Nature, vol. 405, no. 6782, pp. 63–65, (2000).
4. Hulot, G., Finlay, C. C., Constable, C. G., Olsen, N., Mandea, M., The magnetic field of planet Earth. Space science reviews, vol. 152, pp. 159-222 (2010).
5. Bloxham, J., Gubbins, D. The secular variation of Earth's magnetic field. Nature, vol. 317, no. 6040 (1985).
6. Angermann, M., Frassl, M., Doniec, M., Julian, B. J., Robertson, P., Characterization of the indoor magnetic field for applications in localization and mapping. In 2012 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1-9 (2012).
7. Bozkurt, S., Yazıcı, A., Gunal, S., Yayan, U., Inan, F., A novel multi-sensor and multi-topological database for indoor positioning on fingerprint techniques. In 2015 International Symposium on Innovations in Intelligent SysTems and Applications (INISTA), pp. 1-7 (2015).
8. Dronyuk I., Nazarkevych M., Fedevych O. Synthesis of Noise-Like Signal Based on Ateb-Functions. In: Vishnevsky V., Kozyrev D. (eds) Distributed Computer and Communica-

tion Networks. DCCN 2015. Communications in Computer and Information Science, vol. 601 (2016). Springer, Cham https://doi.org/10.1007/978-3-319-30843-2_14.

9. Lee, N., Ahn, S., Han, D., AMID: Accurate Magnetic Indoor Localization Using Deep Learning. Sensors, vol.18, no. 5, pp. 1598 (2018).
10. Berkvens, R., Vandermeulen, D., Vercauteren, C., Peremans, H., Weyn, M., Feasibility of Geomagnetic Localization and Geomagnetic RatSLAM. International journal on advances in systems and measurements, vol. 7, no. 1, pp. 44–56, (2014).
11. Bilke, A., Sieck, J., Using the magnetic field for indoor localisation on a mobile phone. In Progress in Location-Based Services, pp. 195-208 (2013).
12. Chung, J., Donahoe, M., Schmandt, C., Kim, I. J., Razavai, P., Wiseman, M., Indoor location sensing using geo-magnetism. In Proceedings of the 9th international conference on Mobile systems, applications, and services, pp. 141-154 (2011)
13. Du, Y., Arslan, T., Magnetic field indoor positioning system based on automatic spatial-segmentation strategy. In 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1-8 (2017)
14. Du, Y., Arslan, T., Juri, A., Camera-aided region-based magnetic field indoor positioning. In 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1-7 (2016).
15. Galván-Tejada, C., García-Vázquez, J., Brena, R., Magnetic field feature extraction and selection for indoor location estimation. Sensors, vol. 14 no. 6, pp. 11001-11015 (2014).
16. Ma, Z., Poslad, S., Hu, S., Zhang, X., A fast path matching algorithm for indoor positioning systems using magnetic field measurements. In 2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC), pp. 1-5 (2017).
17. Jang, H. J., Shin, J. M., Choi, L., Geomagnetic field based indoor localization using recurrent neural networks. In GLOBECOM 2017-2017 IEEE Global Communications Conference, pp. 1-6 (2017).
18. Bozkurt Keser, S., Yazici, A., Gunal, S., An F-Score-Weighted Indoor Positioning Algorithm Integrating WiFi and Magnetic Field Fingerprints. Mobile Information Systems, (2018).
19. Li, Y., Zhuang, Y., Lan, H., Zhou, Q., Niu, X., El-Sheimy, N., A hybrid WiFi/magnetic matching/PDR approach for indoor navigation with smartphone sensors. IEEE Communications Letters, vol. 20, no. 1, pp. 169-172 (2015).
20. Welch, G., Bishop G., An introduction to the Kalman filter. (1995).
21. Press, W. H., & Teukolsky, S. A., Savitzky-Golay smoothing filters. Computers in Physics, vol. 4, no. 6, pp. 669-672 (1990).
22. Cohen, R. A., An introduction to PROC LOESS for local regression. In Proceedings of the twenty-fourth annual SAS users group international conference, vol. 273, (1999).