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Modelling of Indoor Positioning Systems Based on Location Fingerprinting

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Abstract

In recent years, localization systems for indoor vicinity using the present wireless local area (WLAN) network infrastructure have been proposed. Such positioning systems create the usage of location fingerprinting instead of direction or time of arrival techniques for deciding the location of mobile users. However experimental study associated to such localization systems have been proposed, high attenuation and signal scattering related to greater density of wall attenuation still affecting the indoor positioning performance. This paper presents an analytical model for minimizing high signal attenuation effect for WLAN fingerprinting indoor positioning systems. The model employs the probabilistic algorithm that using signal relation method.

Keywords: WLAN; Fingerprinting; Indoor positioning; Probabilistic.

1. Introduction

Location detection systems are becoming important as a result of wide speared of wireless technology. Localization services are in different form based on positioning techniques. Localization systems facilitate context aware computation with position awareness [1, 2].

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They are as well essential for catastrophe services. In the recent years, position fingerprinting methods based on present WLAN planning infrastructure have been recommended for indoor environs where the global positioning system (GPS) is not executing well [3, 4]. Such system can bring additional services for present WLANs [5, 6]. The fingerprinting method is comparatively easy to deploy as compared to other methods such as time-of-arrival (ToA) and angle-of arrival [7, 8]. Location detection systems are becoming important as a result of wide speared of wireless technology. Localization services are in different form based on positioning techniques. Localization systems facilitate context aware computation with position awareness [1, 2]. They are as well essential for catastrophe services. In the recent years, position fingerprinting methods based on present WLAN planning infrastructure have been recommended for indoor environs where the global positioning system (GPS) is not executing well [3, 4]. Such system can bring additional services for present WLANs [5, 6]. The fingerprinting method is comparatively easy to deploy as compared to other methods such as time-of-arrival (ToA) and angle-of arrival [7, 8]. Commonly, the establishment of fingerprinting localization systems can be clustered into two phases. The training phases (offline), the position fingerprints are gathered by accomplishment a site-survey of the received signal strength (RSS) coming from several access points (APs). The complete area is concealed by a rectangular network (grid) of points [9-11]. Currently, high signal attenuation still remains to hinder the indoor WLAN fingerprinting location accuracy. Therefore, effort should be made to design a model that can minimize such effect. In this paper an analytical mathematical model to examine the accuracy performance of indoor localization systems on WLAN fingerprinting was designed. The suggested model may be applied to form a simple framework for better system deployment and performance investigation. The effects of the access point power and access point height are considered. This paper is organized as follows. In section 2, the model experiment set up was explained. A mathematical model of the operation of indoor positioning system was explained in section 3. This model enables to compute the probability density function (PDF) in signal space among the detected RSS and the position fingerprints as two different types of random variables. The discussion of the model implementation and performance was explained in section 4. Conclusions and recommendation of future work are explained in Section 5.

1.1. Related work

The study in [24] presented an analysis of the applicability of using walk test data theory to model the localization capabilities of access points (APs). The authors put their effort on quantifying the amount of localization information provided by individual APs during the training phase. The performance of this method is based on the measurement model training where the probabilistic equation was used to relate output and input parameters. Although the proposed probabilistic equation does not suffer from sum of squared error, authors did not consider the challenges of amount of data and low signal relation which poses computation overhead as well as accuracy problem. The study in [25] proposed the floor localization method used for indoor WLAN fingerprinting analysis. The floor localization method is based on the fact that the APs have a significant effect on its surrounding area. Therefore, the APs analysis is carried out in a surrounding area without considering the quantity of data and low signal relation problem in the localization system. This method is efficient in terms of floor estimation for indoor fingerprinting localization analysis in an area where multi-floor should be deployed. The study in [26] presented a mathematical programming (MP) model based on propagation approach for RSS location system. The aim of the approach was to design an optimization model that minimizes the SSE of signal strength. The suggested method in the study is basically in three steps. In the first step, the regression analysis was applied to find the relationship between the signal strength and distance. The second step is based on applying Kalman filter to smooth noise in the original data. The third step is based on minimization of SSE of the distance into the model. Lastly, the MP model is examined to validate the model performance. The authors struggled to minimize the SSE and computation overhead challenge by introducing two additional parameters into the proposed modelling equation. Though the issue of SSE seems to be reduced, the proposed equation still poses a challenging problem of sum of squared error. The study in [27] presented a Euclidian distance method that uses WLAN fingerprinting with post-processing analysis scheme for indoor location system. The aim of the approach was to design an optimization system that preserving battery life of a mobile device by shifting a complex algorithm to the server side of the positioning system. The suggested method in the study is mainly in three steps. In the first step, the RSSI values of fixed Wi-Fi access points are collected in known calibration points for constructing radio map. The second step is based on operational phase, where mobile device's current locations RSSI values and additional data from sensors are measured and stored in the local database. The third step is based on post-processing phase, where all the information obtained in operational phase is processed in the server to calculate users' moment position. Lastly, the scheme is examined with android application to validate the scheme performance. The proposed technique has been able to shift the computation overhead from client side to server side. The proposed method did not consider SSE and computation overhead at the server side which can affect the client side as well.

2. Experiment design

The experiment conducted in service is estimated to be 350 m^2 with total number of 74 training locations. Five APs are configured at specified height and related configuration in the testing environment. The sampling RSSI during offline learning is collected on grid-shape RPs at distance of (1-1.5) meter and stored in the database after being analyzed as explained in [12]. The implementation of algorithm was guided through the flow chart shown in Figure 1.

3. Modelling of the positioning system

Consider an indoor localization system covered on an indoor WLAN on a particular single floor in a classified building. The assumption that there are N-IEEE 802.11b access points in surroundings and they are all detectable throughout the surroundings under study. A four-sided grid is well-defined and completed the two-dimension surface plan and any approximate of a mobile position is restricted to the points over this defined grid. Supposing that the grid layout results in L points alongside the x and y axes, it expected to have $L \times L = L^2$ locations in the study area. Any point can be characterized by a triplet with marker (x, y, z) where x and y denote the 2-D coordinates on the surface floor plane whereas z denotes the altitude of the antenna at that specific grid location. In this study, z = constant for all coordinates except where mentioned otherwise. A total estimate of $K= L^2$ entries was stored in the database. Each individual entry in the database comprises a mapping of the grid point coordinate (x, y) to the corresponding vector of RSS values coming from all access points in the surrounding area. RSS is suggested as it reveals a stronger association with position compared to signal-to-noise ratio (SNR [13-15].

3.1. Mathematical model

Two vectors are generally employed in approximating the position of the mobile user location. The initial vector comprises of samples of the RSS collected at the planned area from N APs during online session. It named as RSS sample vector for this study. This vector is represented as: $(x, y) = (s' AP_1, s' AP_2, s' AP_3, s' AP_4 ... s' AP_N)$. The indoor localization system estimates the mobile's location using the combination of this RSS sample vector. Each element in this RSS vector is presumed to be a random variable with some assumptions as detailed here. The random variables $s' AP_i$ (in dBm) for all *i* are commonly independent. The random variables $s' AP_i$ (in dBm) are normally distributed. The another vector, that creates the fingerprints of the location, comprises of the real means of all the RSS random variables at the planned area from N APs and it is detailed in the position database. It named as the position fingerprints or location fingerprints or RSS vector for the this paper and denoted it by $\mu_y = (\mu_{y1,} \mu_{y2,} \mu_3 ... \mu_{yn})$. The justification for considering that the RSS is a normally disseminated random variable is supported by different studies [13, 14]. The goal of the study is to reduce computation overheard and increases accuracy of the WLAN fingerprinting indoor positioning system. Thus, the method where instead of using all beacon signal strengths is devised, the model finds K-RPs, where K=3 with smallest mean average before compare signal relations of online and offline APs signal strengths. Basically the model uses probabilistic method with APs RSS relations and mean average filter instead of normal RSS. To demonstrate the idea of mean average filter and signal relations with an example. Assume $\mu_{x_i}, \mu_{x_2}, \mu_{x_3} .... \mu_{x_n}$ = Offline RSSI Mean at Reference Point 1 for different APs $\mu_{y_i}, \mu_{y_2}, \mu_{y_3} .... \mu_{y_n}$ = Online RSSI Mean at Reference Point 1 for different APs Then average mean filter (AMF) from Reference Point 1 for N APs is given by equation 1.

$$\text{AMF}=(\mu_{x_1} - \mu_{y_1}) + (\mu_{x_2} - \mu_{y_2}) + (\mu_{x_3} - \mu_{y_3}) + ...(\mu_{x_n} .... \mu_{y_n}) \tag{1}$$

Then from the radio map best three K with the lowest AMF are selected to apply signal relations. This implies that, other RPs will not be included in the next step which expects to reduce computation overheard of the model. The level of relation is controlled by scaling up the relation of the signal by comparing these relations between user send values and database values is in the compassion of algorithm. If A = 80 dBm and B = 78 dBm the relations are given as in equation 2.

$$Z = A - B = 80\ dBm - 78\ dBm = 2\ dBm \tag{2}$$

Because, it is reality that terminal device at a particular RP gets signal strength values are clearly higher than in anywhere else. This information concept used to establish the model algorithm. If AP signal strength is detected high enough, it known that the position is very near to that AP, and thus can increase the positions probability to be chosen. If there are two signal strengths X and Y that are Gaussian distributed, then the random variable in probabilistic relation based method is the difference between them: Z = X - Y, that is also Gaussian distributed.

Mean of the random variable Z is then defined by equation 3

$$\mu_z = \mu_x - \mu_y \tag{3}$$

And variance is defined by equation 4

$$\delta_z{}^2 = \delta_x{}^2 - \delta_y{}^2 \tag{4}$$

The method works so that for every candidate position, it computes probability density function values of individual common relation that is established among user retrieved beacons and database beacons. The word 'common' in this sense means that the relations have the same MAC addresses. Then for every position, it sums up those probability density function values and divides it with the amount of relations. From user signals, it also determines what the required number of common relations that a position in database requires to be selected as candidate position. This way we can discard positions that The enough number of signals with appropriate relation should determine before the probabilistic equation is applied. This is achieved by introducing the technique of iteration in such a way that if in the first-time relation computation k=3 then, in the next step *k =k+3*. Finally, the probability density function method uses is the normal difference distributions density function as shown in equation 5 and 6. The general flow chart of the proposed algorithm is as shown in Figure 1.

$$f(z) = \frac{e^{\left(-\frac{(\mu_x - \mu_y)^2}{2(\delta_x{}^2 + \delta_y{}^2)}\right)}}{\sqrt{1 + (\delta_x{}^2 - \delta_y{}^2)}} \tag{5}$$

$$P(L) = \frac{\sum_{i=1}^{n} f(z_i)}{n} \tag{6}$$

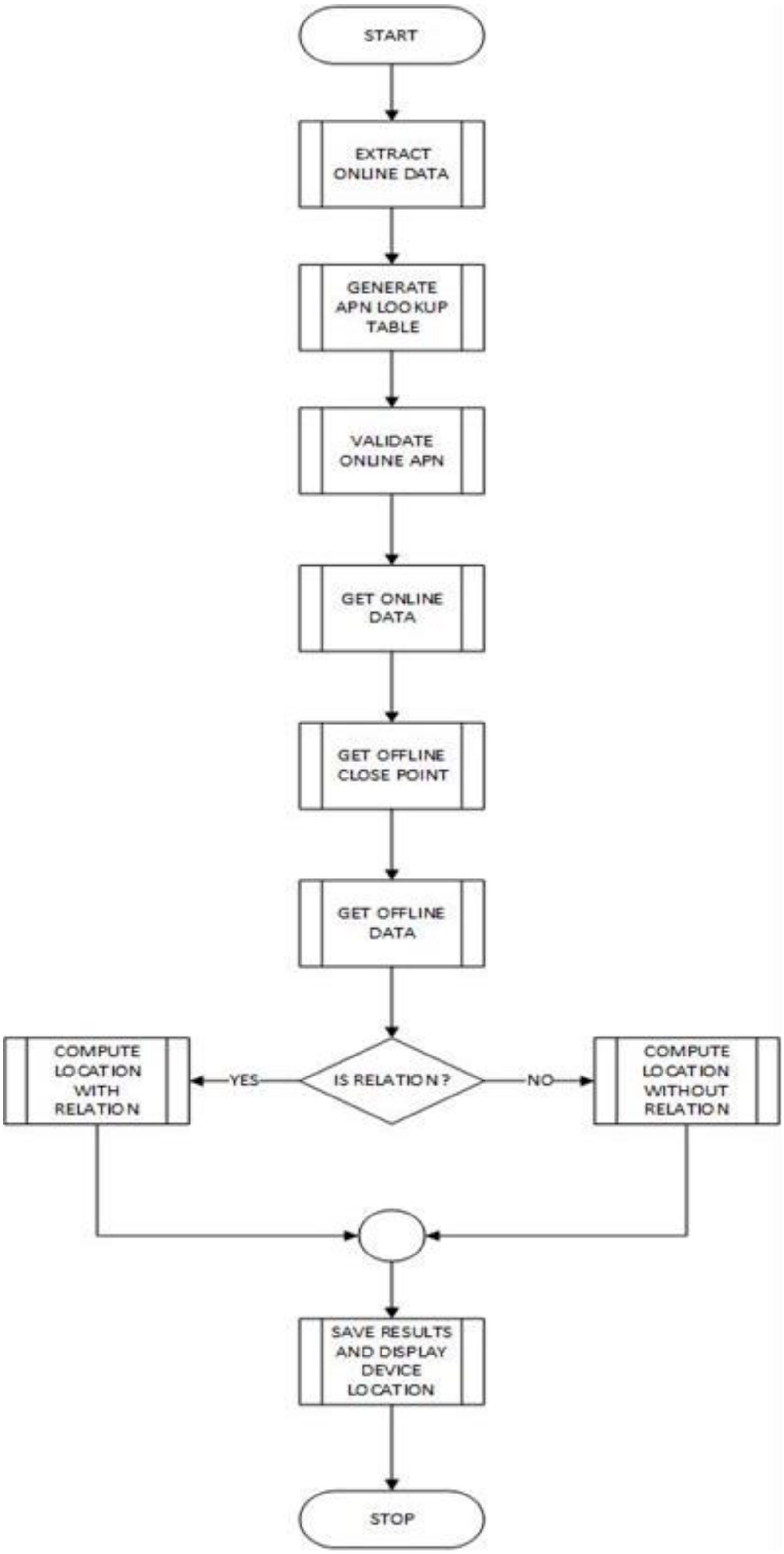

Figure 1: The general flow chart of the indoor WLAN fingerprinting algorithm model with signal relation

4. Results and discussion

4.1. Model implementation

In this section, flow chart used in converting the model into the software is described. The software was implemented based on a systematic approach as presented in various algorithm flow chart in section. Each flow chart block is explained in details in this section consistently. Compute Location with Relation: The computation of location through signal relation should be carried consistently, the minimal required valid signal should be encountered to ensure better IPS performance. Figure 2 and Figure 3 illustrate the algorithm for location probability computation through signal relation. Inadequacy to this procedure will cause poor positioning. The algorithm should determine if minimal signal was met or not. In case the signal was not met the algorithm should set signal to false and decrease the signal relation parameter to allow more signal to be allocated as the best one as shown in Figure 4. If the minimal limit is reached, the further step is considered.

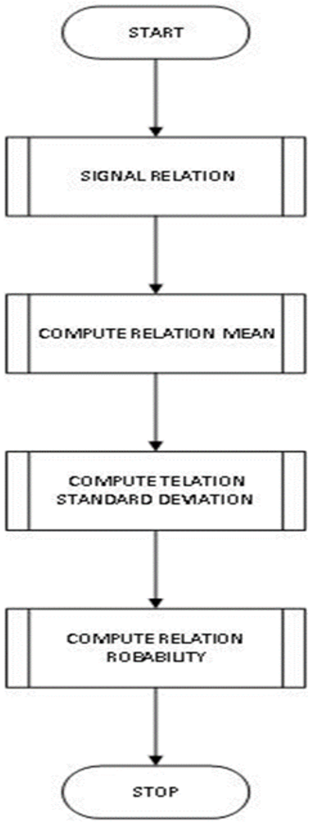

Figure 2: Flow chart for location with signal relation computation activity

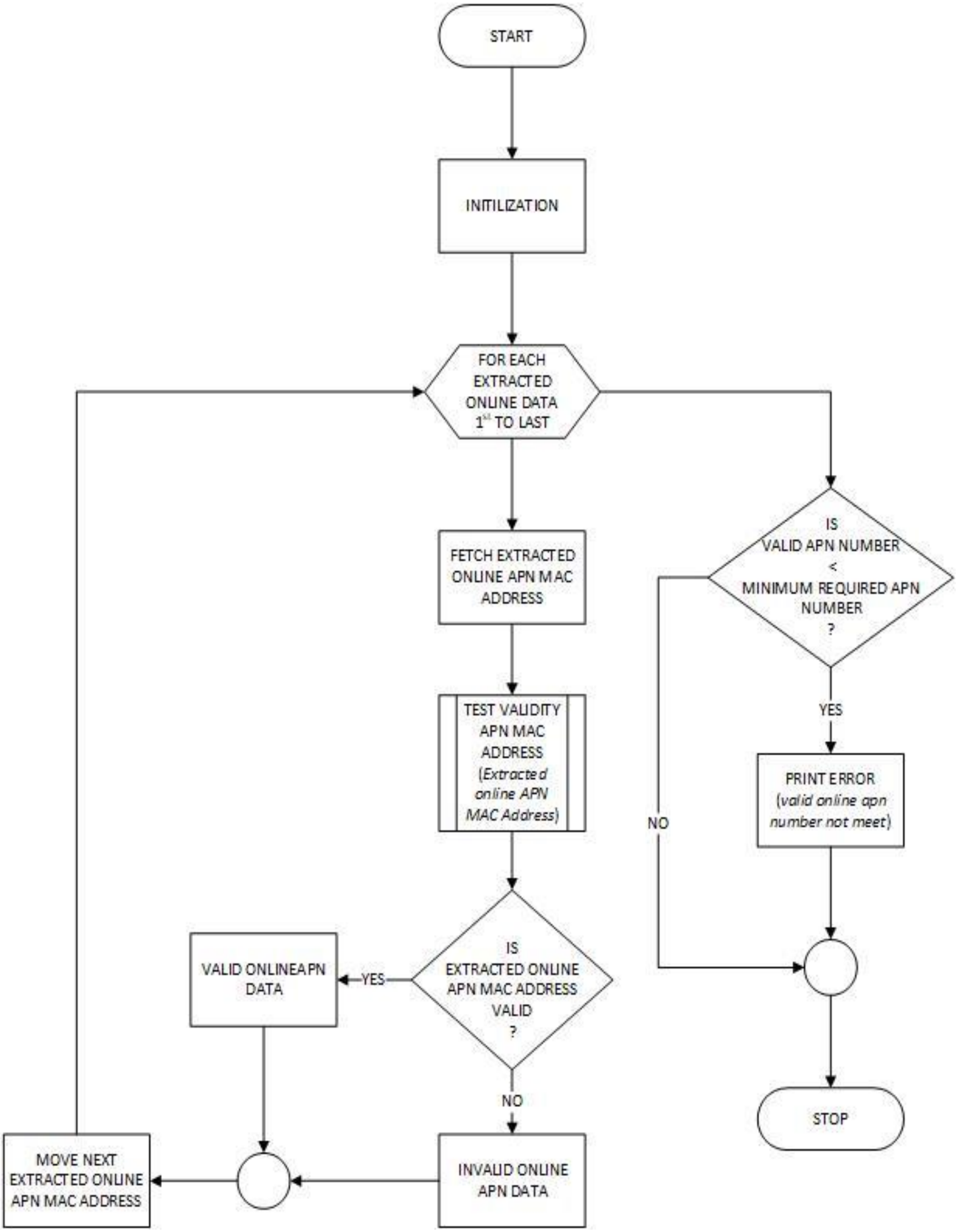

Figure 3: Flow chart for location with signal relation computation

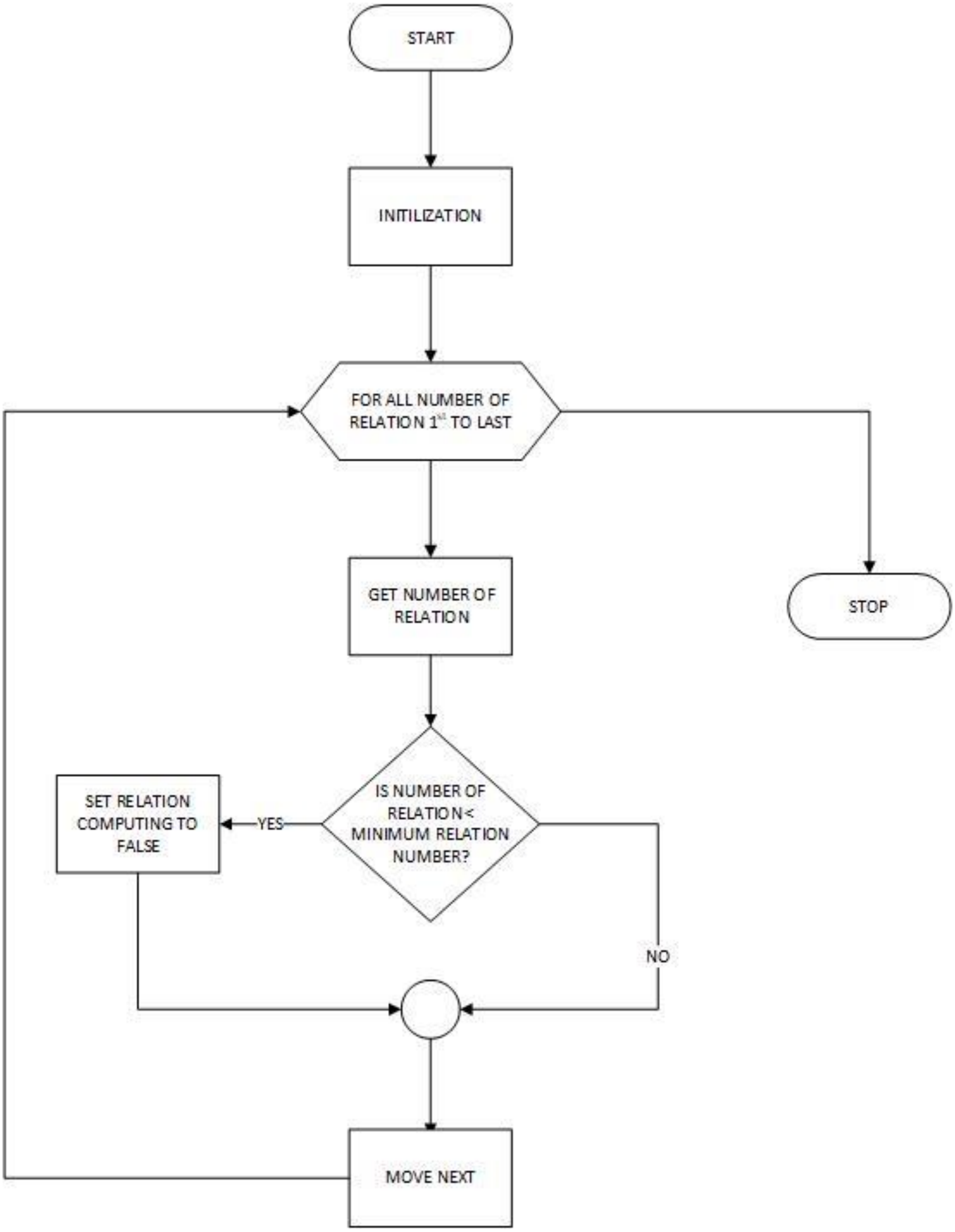

Figure 4: Flow chart for signal relation comparison

Compute Location without Relation: The computation of location without signal relation disregard the signal relation parameter while the remaining part works as in relation algorithm. Figure 5 illustrate the activity under non relation for location probability computation. The mean and standard deviation are estimated without signal relation techniques as shown in Figure 6 and Figure 7.

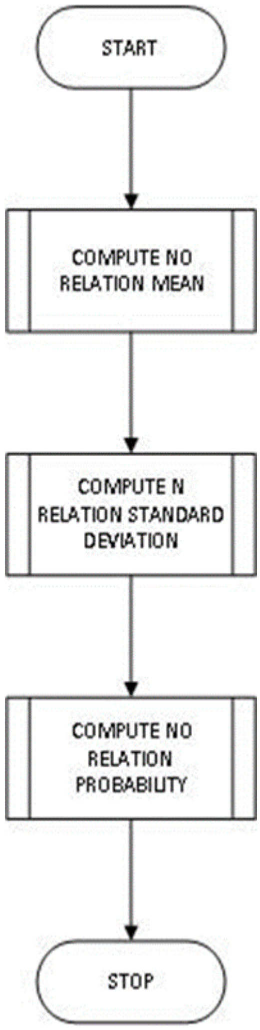

Figure 5: Flow chart for activity under non-relation probability computation

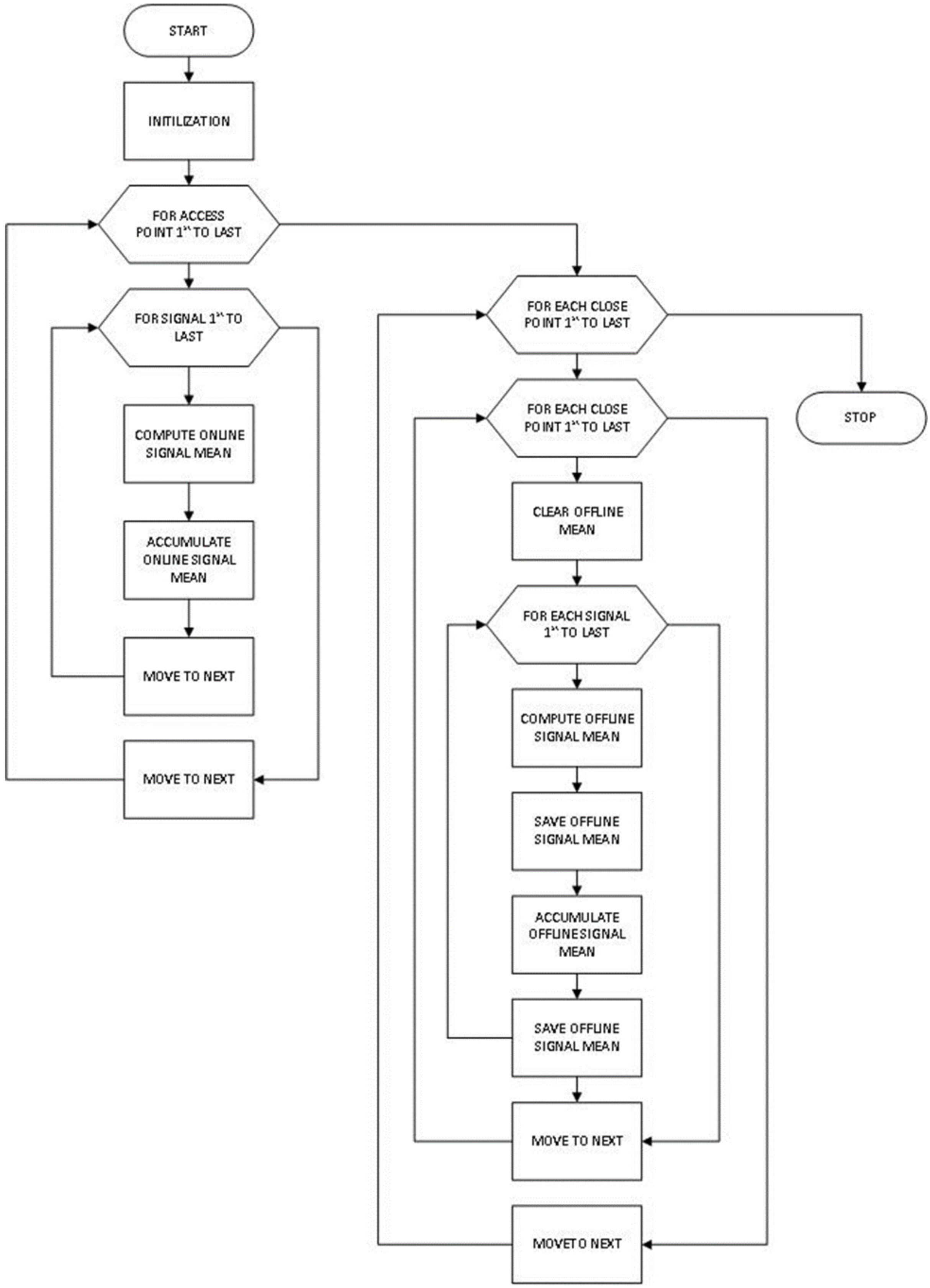

Figure 6: Flow chart for location probability mean computation

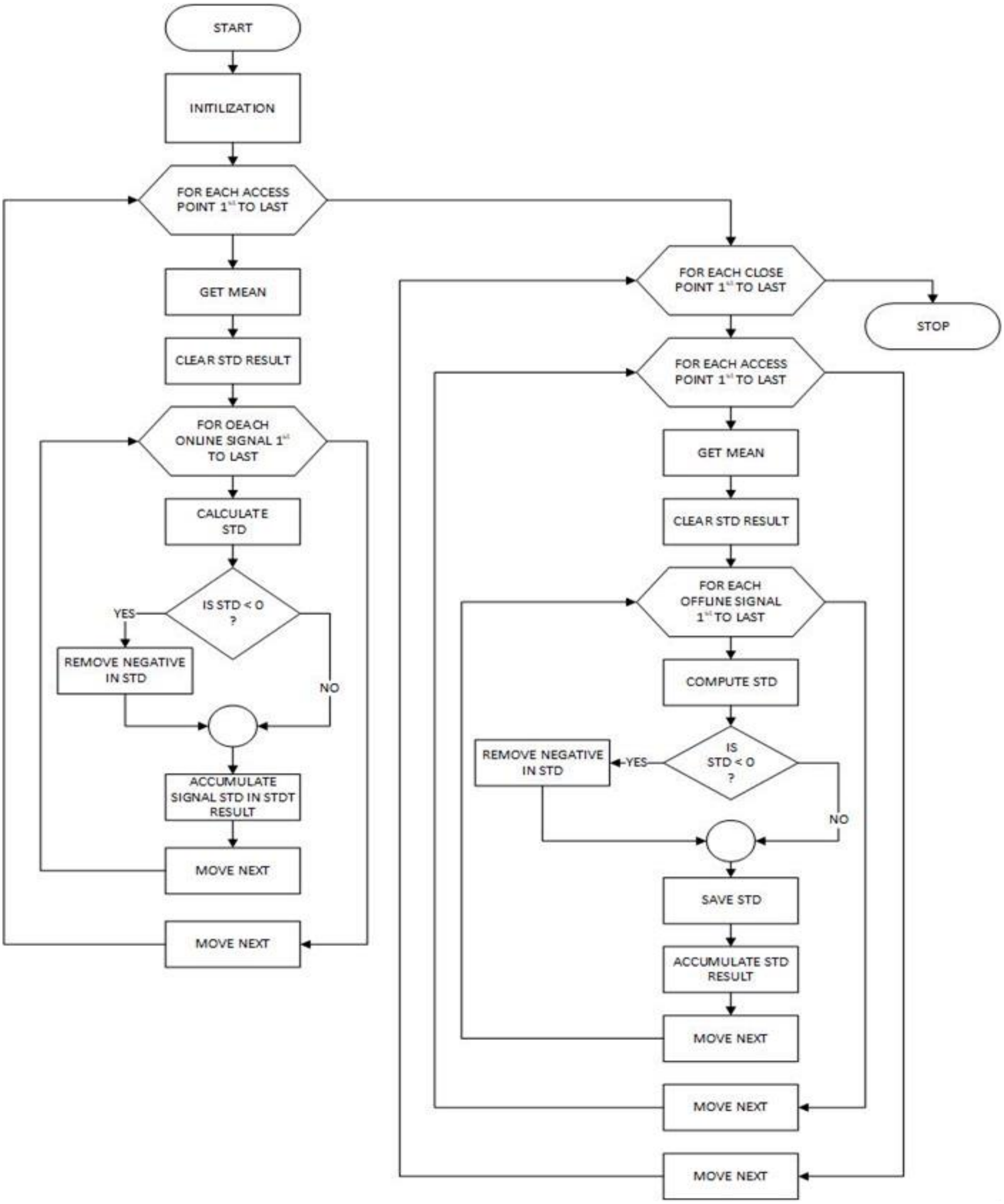

Figure 7: Flow chart for location probability computation standard deviation

Save and Display Device Location: The save and display device location should be carried consistently, the location with highest location probability should be kept as best cluster of location probability. Inadequacy to this procedure will cause poor positioning. The algorithm should determine if current location probability is great or less than the next location probability before save and display the result. In case if the current location probability is less than the next location probability, the next one will be considered as the best user location. compared to the other should be regarded as the best user location. Figure 8 illustrate the algorithm for best location probability.

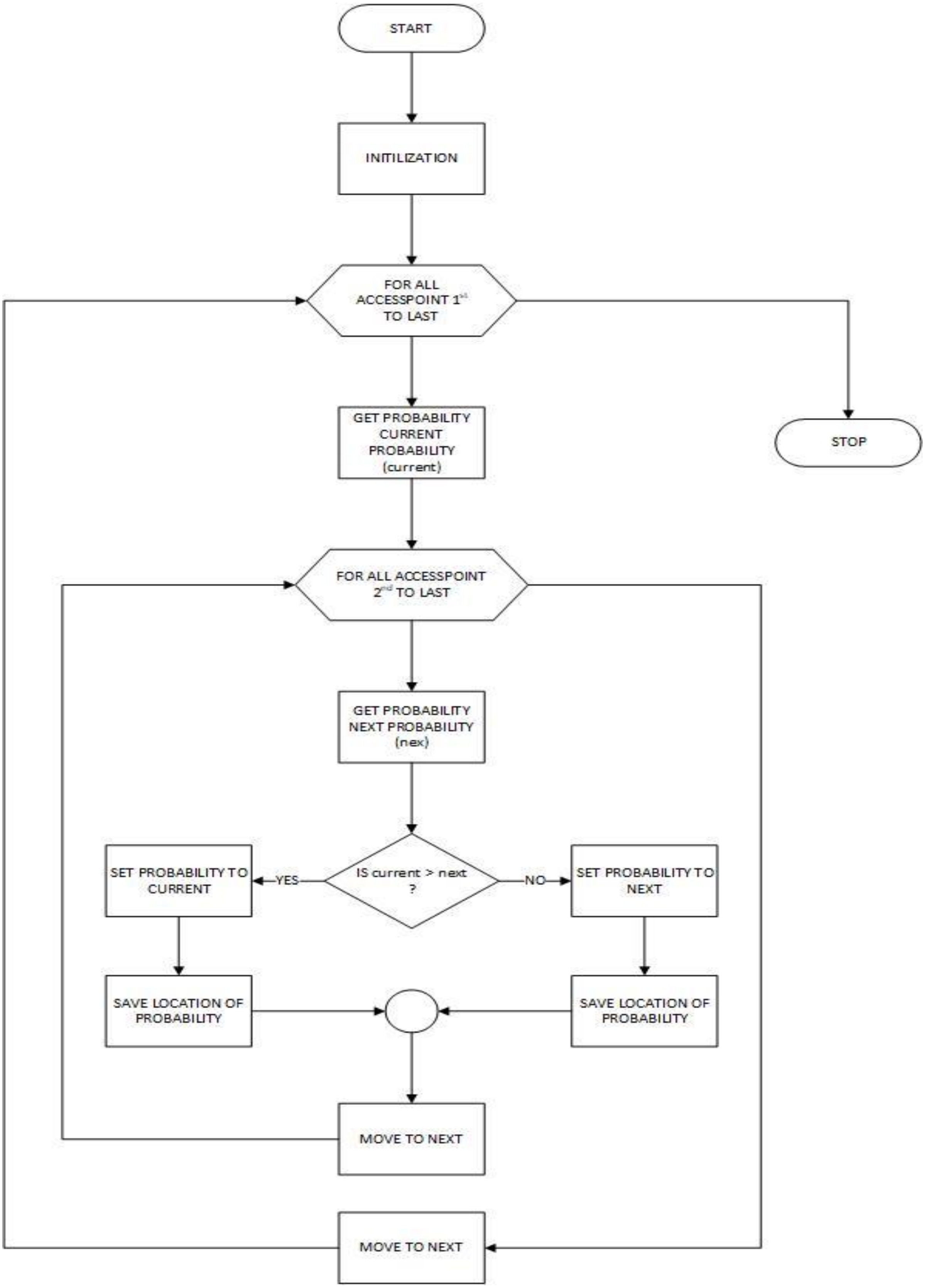

Figure 8: Flow chart for determining best location probability algorithm

4.2. Results on analysis model design

The model was designed based on the analysis of fingerprints reported by an IEEE 802.11b/g/n. All the fingerprints data and positioning algorithms are stored to the server. The server is responsible to run positioning algorithms and MySQL database for storing fingerprints. The fingerprinting database keeps access point information, device request information, indoor positioning user information and map information. For this study the service area and grid spacing permits 74 locations points; all of these 74 points were fingerprinted and the algorithm is expected run over 74 RPs as shown in Figure 9. Also, the results obtained after requesting the location is shown Figure 10 and 11 where returned point and coordinate observed clearly. Important parameter such as power configuration, relational configuration, AP height configuration and close point configuration should be determined before submitting online RSS for location probability computation from the model. The returned location is a result of submitted online RSS after combined with offline fingerprints in the database. This results reveals that the model can specify and determine the correct location with a given RSS and map detail.

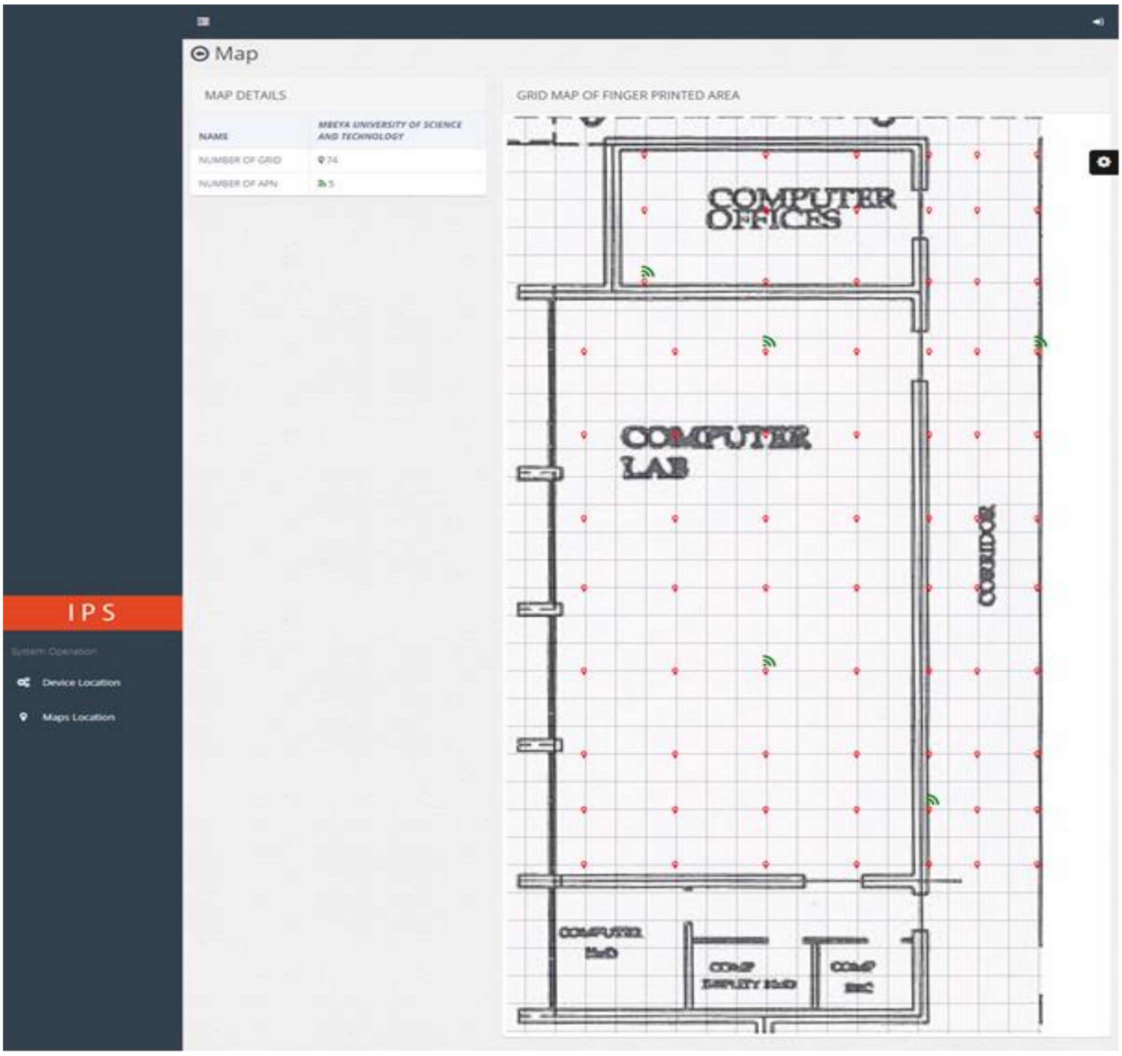

Figure 9: Map for grid and fingerprinted reference points

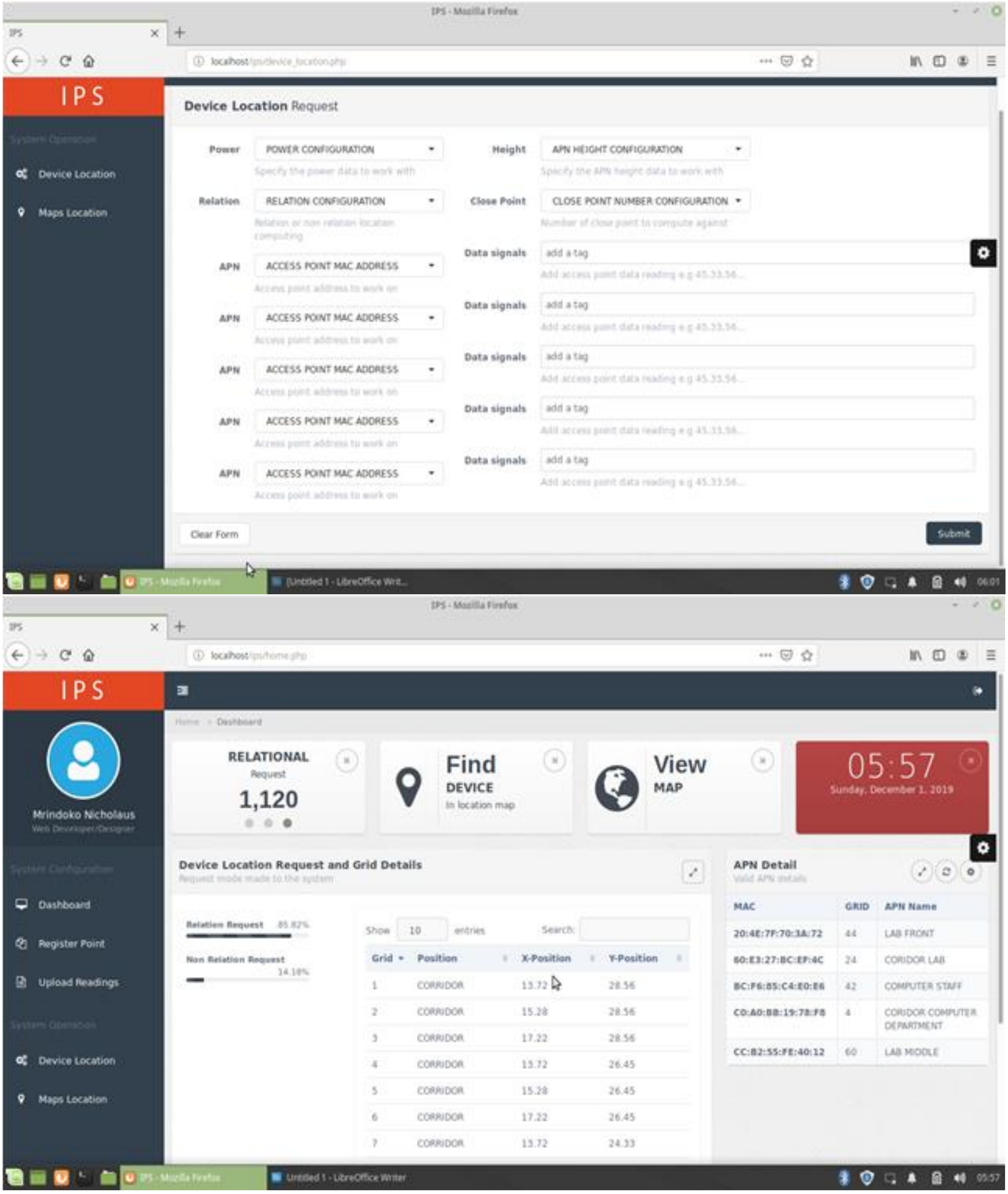

Figure 10: Model configurations input parameter

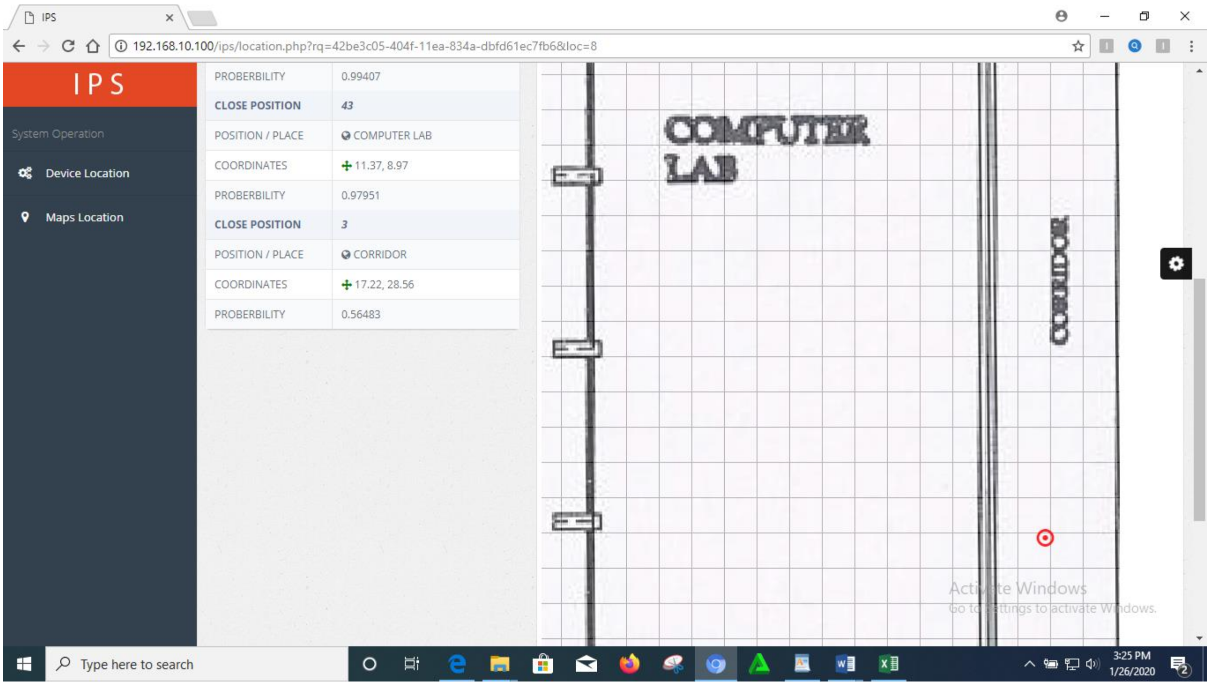

Figure 11: Result of the returned user position as a result of submitted input signal

4.3. Performance Comparison of Indoor Positioning System

This subsection briefly outlines performance of the WLAN IPS model for both signal relation and non-signal relation. Additionally, the model compared with recently indoor positioning system based on WLANs fingerprinting localization. The main performance metrics studied in various systems are positioning accuracy which reported in form of error measurement. The accuracy of the position information is commonly reported as an error distance among the estimated location and the actual mobile user location. The system parameters used and results obtained are summarized in Table 1. Though the accuracy performance varies from one system to another in Table 2, the differences among them are not very significant. It is easier to compare the performance if one of these metrics is fixed, the system that reports smallest distance (accuracy) is the best. It is essential to point out that each system has used different parameter settings; thus, comparison results could not be very fair. For such reason, the designed model was compared with the model that designed in the same environment as shown in Table 1 before compared with other recent work as shown in Table 2 Generally, it is expected that a system that has higher number of access points can perform better due to the higher dimension of the location fingerprint vectors which result in better pattern separability [15]. To guarantee that the proposed model is feasible to be applied, the accuracy of the position estimation has to be equal or fairly better compared to the existing model. Table 1 indicates the statistical results of the observed performance of the model. As revealed, the proposed model has returned an AME of 0.007251585 m and 1.1794305 m when power setting is medium respectively as shown in Table 1. This results of signal relation algorithm outperformed non signal relation algorithm and many existing systems as it can be seen in Table 1 and Table 2. Thus, it clearly proves that WLAN fingerprinting using signal relation technique improved accuracy of the proposed model.

Table 1: Performance comparison for signal relation and non-signal relation technique

Maximum Accuracy with Signal Relation Algorithm in AME meter			
Power Setting	Height= 1 meter	Height= 2 meter	Height= 3 meter
Medium	0.007251585	0.7488555	0.9623775
Maximum Accuracy without Signal Relation Algorithm AME meter			
Power Setting	Height= 1 meter	Height= 2 meter	Height= 3 meter
Medium	1.285515	1.1794305	1.192083

Table 4.2: Performance Comparison with Different Existing IPS

Authors	Positioning Algorithm	Number APs Used	Single Base Station Setup	Test Bed Area	Accuracy	Proposed Features
[16]	Probabilistic	AP × 10	Single AP	16 m × 40 m	1.69 m (ME-kernel)	Probabilistic approach
[17]	Probabilistic	AP × 4	Single AP	25.9 m × 68.3 m	90% accuracy within 2.1 m	Joint clustering technique
[18]	Probabilistic	Test bed 1: AP × 21 Test bed 2:	Single AP	Testbed 1: 68.2 m × 25.9 m Test bed 2:11.8 m × 35.9 m	Test bed 1: 0.42 m (ME) Test bed 2: 0.64 m (ME)	Horus, high accuracy and low computational requirement
[19]	WKNN	AP × 8	Single AP	12 m × 35 m	1.46 m (ME)	Map-aided fingerprint
[20]	WKNN	AP × 5	Single AP	9 m × 8.5 m	2.29 m (ME)	Training less fingerprint with EM field simulation
[21]	NN	AP × 26	Single AP	70 m × 23 m	1.5 m (Median)	LiFS with trajectory matching
[22]	Compressive sensing	AP × 26	Single AP	30 m × 46 m	1.5 m (ME)	Compressive sensing
[23]	OS-ELM	AP × 8	Single AP	35.1 m × 16.6 m	1.973 m (ME)	OS-ELM localization algorithm
Proposed IPS Model	Probabilistic	AP×5	Single AP with varying AP, Power level, Height	23 m × 15 m	Test 1, P= High: 0.9990495 m (AME), Test 2, P= Medium: 0.007251585 m (AME),	High accuracy and low computational requirements

5. Conclusions

The paper presents preliminary design of the WLAN indoor fingerprinting analysis model using RSS value as accounted by an 802.11 NIC. Provided with a number of system factors and radio distribution features, which are grid point, number APs, RSS, the accuracy performance of a WLAN positioning system may be estimated in relations of the probability of giving the correct location using the model offered in this study. A maximum grid layout of 1.5 meter is considered to be an appropriate value related to this model and experimentation. The system showed that, it does not need a vast number of APs to enhance the accuracy performance as only five APs utilized in this study. The number of APs and their position depend much on the network set-up and the economic issues. The IEEE 802.11b cost of APs is quickly going down and it cannot be a difficult to add more APs to provide supplementary coverage for WLAN indoor positioning fingerprinting. A system designer must compromise all of these system factors by regulating the number of APs a height of the APs and Power of the APs in order to provide a reasonable accuracy performance. In the future work, the model will be practiced using different AP power and varying number of APs to provide the guideline for designer of the WLAN indoor fingerprinting. This study elevates an essential aspect of WLAN fingerprinting analysis model.

6. Limitations of the Study

The study was restricted to the investigation of static mobile devices data. The indoor positioning is supposed to be superimposed on top of existing infrastructure. Therefore, the performance of the localization system might depend on the availability of WLAN infrastructure. The study was not considered the positioning algorithm analysis, but was considered probabilistic algorithms as baseline of the study. Hybrid approaches that combine multiple sensor technologies are not considered for this study. The position system was considered only on one floor of a building and room level accuracy in term of meters.

7. Recommendations for the Future

In the future work, the model will be practiced using different AP power and varying number of APs to provide the guideline for designer of the WLAN indoor fingerprinting. This study elevates an essential aspect of WLAN fingerprinting analysis model. Also more indoor parameter can be included into the model to understand how will affect the design. Multi- floor and propagation study is another important area in the future.

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