Assessment of Blind-Spots and Multi-Path Effects at Indoor Positioning by Multilateration

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Abstract

Indoor positioning techniques are utilized in many professional applications. However, aforementioned technique can provide positions with serious accuracy problems due to multipath and ill-conditioned station constellations. In the literature the effect of multipath is examined thoroughly but the ill-conditioned station constellations are omitted. In this study, indoor positioning accuracy is examined by simulation where white Gaussian noise is added to the exact distances between the location to be measured and the station points. Effect of station constellation is analyzed by trying two different station positions. In the first case all of the stations are located at the same side of the room causing nearly parallel lines among the location and station points. In the second case all of the stations are located at different sides of the room and ill-conditioned systems are avoided. The simulation results provided that when the location to be measured and the stations are located at the same line, the measurement errors are magnified by the ill-conditioned least square-adjustment equations which leads to significant positioning errors. Moreover, an algorithm for the detection of multipath is proposed and tested by simulation. The algorithm detected 31 multipath cases among the 35 multipath situations and significantly improved the resultant positioning accuracy. The simulation results illustrated that the proposed multipath detection algorithm can be utilized efficiently for indoor positioning applications.

1. Introduction

Indoor positioning applications have become increasingly widespread as the prices of the necessary sensors became affordable. Indoor positioning methods have a wide range of applications. To illustrate; efficiency of construction management process is increased with the location information obtained. Occupational health and safety issues can be controlled by real time monitoring the workers at construction sites. Quality inspection of materials brought to construction sites, and implementation of building information modelling (BIM) technologies can be given as two examples that necessitates real time positioning (Li et al., 2020).

One of the challenges of indoor positioning is determining a method that is robust to wide-ranging, environmental effects, simple enough, and accurate (Jiménez et al., 2020). In Ultra-Wideband (UWB) sensor technologies, signals provide precise distance estimation capability for wireless devices with high time resolution. In this way, it can theoretically provide range estimation with centimeter-level accuracy, but in practice, it is difficult to reach the theoretical limits in range estimation due to limitations such as computational complexity, power and cost (Güvenç et al., 2008). One of the most important advantages of UWB sensor technologies is their positioning capability with high accuracy. The wide bandwidth offers a high temporal multipath resolution to the propagation channel. Due to the aforementioned principles most UWB localization and ranging approaches are based on Time of Arrival (TOA) estimation (Althaus et al., 2005).

Indoor positioning systems can be classified based on the performance criteria of accuracy, precision, coverage, adaptability, scalability, cost and complexity. Accuracy of the indoor positioning systems is the distance between the estimated location and the actual location. Sensitivity refers to the speed at which the position estimate of a moving target is updated. Changes in environmental influences can affect the performance of positioning systems. The ability of positioning systems to cope with these changes is adaptability. An adaptive system can provide higher positioning accuracy and at the same time avoid the need for calibration (Farid et al., 2013).

In the literature accuracy of the position data obtained by using different sensor types has been examined, but the geometry of the sensors has not been taken into account. However, in order to achieve the desired positioning accuracy in triangulation technique, increasing the accuracy of distance measurements may not always provide satisfactory results. In this study, the effect of the distribution of station points on location accuracy is investigated by simulation. Moreover, multipath effects are also considered in the simulation.

2. Literature Review

Prevalent indoor positioning systems can be listed as UWB, zigbee, bluetooth, WiFi, RFID, Pedestrian Dead Reckoning (PDR) and visible light communication (VLC). UWB localization systems use time information instead of received signal strength indicator (RSSI) measurements and stand out with their precise positioning ability. Systems using RSSI measurements are affected by signal attenuation, so positioning accuracy is relatively low compared to the time of arrival (TOA) method. UWB sensor technology, which has the advantages of high accuracy and interference, has a range of 10-20 m. Thanks to short pulses; this technology easily penetrates solid objects that form obstacles indoors and is resistant to multi-path effects (Poulose et al., 2019; Dabove et al., 2018). Indoor positioning systems can provide precise positioning as much as sub-centimeter level accuracy (Alhadhrami et al., 2014; Alışkan at al., 2023).

Poulose et al. (2019) analyzed the positioning accuracy of UWB localization systems by considering and comparing line-of-sight (LOS) and non-line-of-sight (NLOS) environments. The evaluation of accuracy is executed by Linearized Least Squares Estimation (LLSE), weighted center of gravity estimation (WCE), and fingerprint estimation (FPE) methods. A model consisting of reference nodes (RNs) placed at fixed points with known coordinates was built and a blind node (BN) is used to measure the time of arrival (TOA) between the RNs.

LLSE algorithm estimates the location by minimizing the sum of the squared errors between the obtained measurements and the estimated measurements which is obtained by considering the estimated points and the station points. On the other hand FPE algorithm creates a fingerprint map and the tag position is estimated by matching. Positioning by FPE requires prior knowledge about the environment, as well as human intervention and endeavor to collect the fingerprint data. The WCE algorithm does not depend on any dynamic data to estimate the location, and it continuous position data can be obtained. Positioning is done using the locations of the stations and the assigned weights to the each station (Sookyoi et al., 2016).

Poulose et al. (2019) conducted positioning based on an environment which provides LOS between the rover tag and the station points. Average positioning error values are obtained as 0.7491 m, 0.7273 m and 0.7009 m for LLSE, FPE and WCE algorithms, respectively. The maximum error values are 1.01 m, 0.83 m and 0.96 m for LLSE, FPE and WCE algorithms, respectively. The minimum error values are 1.0017 m, 0.0053 m and 0.001 m for LLSE, FPE and WCE algorithms, respectively. The average computation times are recorded as 1.5136 s for LLSE, 1.4649 s for FPE and 1.4578 s for WCE.

UWB, Wi-Fi, Bluetooth and Zigbee can be used for short-range applications. However they consume low power. IEEE 802.15.1 is a wireless personal area network (WPAN) standard designed for short-range and low-cost devices where Bluetooth devices are produced in compatible with the aforementioned standard. UWB is compatible with IEEE 802.15.3 which is also suitable for multimedia connections requiring high bandwidth. Zigbee is compatible with IEEE 802.15.04, which is designed for reliable wireless monitoring and control networks. Wi-Fi is compatible with IEEE 802.11, which is designed to replace the extension of wired networks for computer-to-computer connections (Lee et al., 2007).

IEEE established the 802.15.4a standardization group to provide standards for the low data rate communications. UWB is an important technology that is compatible with this standardization. Angle of arrival (AOA)-based approaches are not suitable for UWB localization since the mentioned technique requires utilization of antenna arrays which would increase the cost of the overall localization system. Moreover, due to the high bandwidth, UWB signals are probable to follow multiple paths. Presence of indoors objects increases the difficulty of accurately estimating the angle due to the scattering of the signal between the objects (Gezici et al., 2005).

It is crucial to utilize different techniques and merge the information obtained from different sensors as each sensor and technique has its unique error source. Therefore, estimated position contains certain error which should be taken into account. Bayesian filter techniques are a powerful tool for multi-sensor fusion to manage measurement uncertainty. Bayesian filters probabilistically estimate the state of the system from a noisy array of sensor data. The most widely used variant of Bayesian filters is the Kalman filter, which approximates beliefs to unimodal Gaussian distributions represented by their variances and means. The mean value gives the expected position, while the variance value represents the prediction uncertainty. The main advantage of these filters is their computational efficiency. However, since Kalman filters represent unimodal distributions, they are best used when the uncertainty in a person's location is not very high. Bayesian filter techniques are a statistical tool to manage multi-sensor fusion, identity estimation and measurement uncertainty. It probabilistically estimates the state of a dynamic system of noisy observations. For positioning systems, the state of the system is the position of the object or person. The sensors used provide observations about the state (Fox et al., 2003).

Grid-based approaches divide the environment into cells for indoor location estimation. The advantage of this approach is that it can arbitrarily represent distributions over the state space, thus overcoming the limitations of Kalman filters. The disadvantage is computational complexity of the method (Fox et al., 2003).

In UWB-based positioning systems, errors caused by non-line-of-sight (NLOS) conditions pose a significant problem. In this context, Barbieri et al. (2021) detail a proposed Bayesian augmentation technique to mitigate the effects of NLOS states and experimentally evaluate this method in a real industrial setting. The proposed method uses a particle filter (PF) to determine the position of a moving tag and the conditions of appearance (LOS/NLOS) between access points (AP). The position of the tag changes with time and is modeled by a first-order Markov process.

The proposed method is tested with commercial UWB devices in various industrial environments. The positioning error is reduced from 2.10 meters up to 67 centimeters using time difference of arrival (TDOA) measurements. If AOA measurements are also integrated, the error can be reduced to 52 centimeters. The proposed Bayesian augmentation technique provides a system capable of positioning with high accuracy even in harsh industrial environments (Barbieri et al., 2021).

The localization process is generally divided into two phases: signal measurement and location computation. In the first stage, the receivers determine the arrival time, direction and signal strength of the signals transmitted between the reference and target nodes. In this way, signal parameters such as time of arrival (TOA), received signal strength (RSS), AOA and time difference of arrival (TDOA) are obtained. In the second stage, the position of the destination node will be determined using the previously obtained parameters. Moreover, since signal measurements are not completely accurate in real systems, especially indoors, optimization-based statistical methods are used to improve the accuracy of the results and filter out measurement noise (Zhang et al., 2010).

Radio frequency based systems can cover large distances as they can penetrate obstacles. Radio Frequency Identification (RFID), Ultra–Wideband (UWB), Bluetooth, and Wireless Local Area Network (WLAN) are based on radio frequency technology. UWB is used more commonly among the listed technologie due to its low error rate for indoor positioning (Zhang et al., 2010).

Alhadhrami et al., (2014) conducted a SWOT analysis to examine the strengths, weaknesses, opportunities and threats of UWB technology. Advantages of UWB technology were listed as free licensing, and low power consumption. Moreover it does not interfere with the existing radio systems and existence of high multipath can be detected. Opportunities of UWB were listed as widespread application areas such as robot guidance, medical applications, and implementations at the industrial warehouse.

UWB based techniques and ultrasound are classified as the most accurate indoor positioning techniques. Ultrasound can provide high accurate results but its approximately 10 meters limited range is a significant disadvantage. UWB localization systems have lower positioning accuracy compared to ultrasound technique but have wide coverage and high range (Jiménez at al., 2016). Ultrasound-based systems are relatively inexpensive but they are not as precise as infrared-based systems due to the reflection effect. In addition, the need to synchronize these systems with RF technologies increases the cost (Zhang et al., 2010).

High speed data communication is achieved by increasing bandwidth. As its name implies UWB has very high bandwidth which provides communication with high data rate. Its low cost also increases enables widespread. Besides the high data transmission rate, the advantages of UWB technology can be counted as robustness against multipath effects, low cost, low power consumption, high accuracy ranging and positioning. The Federal Communications Commission (FCC) issued the first regulations on UWB use in 2002, allocating the frequency range between 3.1 and 10.6 GHz for UWB use.

The main techniques used for measuring UWB channels are the time domain technique and the frequency domain technique. The time domain technique is based on the excitation of the channel with a short pulse. The frequency domain technique is based on frequency domain measurements using a vector network analyzer (VNA). Due to its high data rate and unique channel characteristics, UWB is used in various applications such as wireless sensor networks, information and indoor positioning. The use of short-pulse radio signals on the order of 1 ns makes UWB suitable for positioning with decimeter range accuracy. This is because the ambiguity of the time is multiplied by the speed of light.

High frequency of UWB systems shortens its range because of the high signal loss characteristics of high frequency waves. The range can be elongated by increasing the transmission power which increases the cost of the hardware. Utilization of MIMO can be another alternative to increase the communication range, but this increases the complexity of the system (Ngah et al., 2016).

Frequency modulated continuous wave (FMCW) and Ultra Wideband (UWB) ranging techniques can provide maximum resolution. UWB localization systems have a simple system design, low power consumption and good results in suppressing multipath interference. The UWB operating frequency can be adapted to allow see-through capability, including through walls and the human body (Zhang et al., 2006).

One of the prevalent indoor positioning techniques is smartphone-based systems that do not require any devices other than the phone used. Poulose et al., (2019) proposed a slope-based step detection algorithm for location estimation. In this method, the steps and step length of the pedestrian are estimated in order to determine the person's location. The experiments were conducted using a smartphone with magnetometer, accelerometer and gyroscope data. Since only gyroscope data is used in traditional methods, errors accumulate and deteriorate the positioning accuracy. A magnetometer was added to the system to eliminate the accumulated error.

Poulose et al., (2019), tested the proposed method by preparing three scenarios. A rectangular track is prepared for the first scenario, in which the person walks down through a corridor. In the second scenario, the person follows a straight line. In the third scenario, the person moves around a circle. In all three experiments, it is observed that the proposed algorithm provides high accuracy in position estimation and gives better results than the traditional method. The displacement errors for rectangular and circular motions are compared and it is found that the proposed algorithm has lower displacement errors than the conventional method. Furthermore, the positioning errors are evaluated by root mean square error (RMSE)., the maximum error of the proposed algorithm is measured as 2.6 m while the maximum error of the conventional method is detected as 3.8 m during the tests conducted for rectangle motion. Similarly, for straight line motion, the RMSE values are compared and it is observed that the proposed algorithm has lower error rates. These results show that the positioning performance of the proposed algorithm is better and gives more accurate results than traditional methods (Poulose et al., 2019). In order to monitor the positions of the pedestrians, the inertial measurement unit (IMU) consisting of a gyroscope and an accelerometer are utilized to measure the angular velocity and acceleration of the person. Inertial sensors make inaccurate measurements and the errors of the measurements accumulate and affect positioning accuracy. This is a significant problem for IMU-based positioning technologies. In addition, the deterioration of the positioning accuracy due to not taking the velocity of the movement into account throughout the position estimation process is one of the shortages of the proposed method. Also the requirement for a barometer to enable the tracking of complex movements such as walking up and down increases the cost of the system (Bai et al., 2020).

Doğan and Bettemir (2024), investigated the effect of the constellation of the station points. In this context 3 different station point constellations consisting of 4 sensors are formed and the resulting positioning accuracy is examined. Stations were placed in 3 different combinations: near the corners of the room, near the midpoints of the edges and all stations on the same edge. The effect of sensor locations with the same magnitude of noise on the positioning precision was analyzed Same noise magnitude of error is achieved by adding white noise to the distance measurements. As a result of the analysis, maximum positioning error is measured as 0.3495 m, which was obtained when the stations are placed on the same line. This error is approximately 35 times the added noise (Doğan and Bettemir, 2024).

As seen in the literature review, although important studies have been conducted on indoor positioning, the effect of the locations of the fixed station points used on the measured positioning accuracy has not been examined thoroughly. In this study, it is aimed to address the specified literature gap by measuring the effect of the distribution of station points on positioning accuracy.

3. Method

The effect of the distribution of station points and the obstacles inside the room which prevents the direct signal transmission from the stations were measured by simulation. The simulation is conducted by positioning five station points in different combinations whose coordinates are known exactly. The distances between the reference stations and the point whose coordinate is to be determined are computed. Throughout the simulation the position of the point is known priori. However, this information is only used to compute the distances between the considered point and the stations. White noise with 1 cm magnitude is added to the exact correct distances between the

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stations and the examined point. The obtained data simulates the real observation data acquired from the sensors. Then the location is estimated by utilizing linearized triangulation equations with least squares adjustment and the added white noises were compensated to obtain the location information. While three distance measurements from known points are sufficient to detect the coordinates of the unknown point in indoor positioning, five distance measurements are simulated to analyze the effect of redundant stations. The coordinate of the unknown point is estimated with the least squares adjustment as shown in Eq. 1.

$$\Delta\beta = (X^T X)^{-1} X^T \Delta Y \tag{1}$$

The vector expressed as ΔY in Eq. 1 represents the differences between the measured distances and the distances calculated according to the estimated location, as expressed in Eq. 2.

$$\Delta Y = \begin{bmatrix} d_1 \\ d_2 \\ d_3 \\ d_4 \\ d_5 \end{bmatrix} - \begin{bmatrix} \hat{d}_1 \\ \hat{d}_2 \\ \hat{d}_3 \\ \hat{d}_4 \\ \hat{d}_5 \end{bmatrix} \tag{2}$$

The matrix denoted as X contains the partial derivatives of the distances with respect to the estimated position. Exact distances are computed by as given in Eq. 3.

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{3}$$

In Eq. 3, x and y are the true coordinate values of the measured point and they are a priori known throughout the simulation. Estimated distances computed by considering the estimated positions are computed as given in Eq. 4.

$$\hat{d}_i = \sqrt{(\hat{x} - x_i)^2 + (\hat{y} - y_i)^2} + w_i \tag{4}$$

In Eq. 4 $\hat{x}$ and $\hat{y}$ are the coordinates of the estimated point, and i index represents the station points. In order to illustrate measurement errors a white noise represented by w_i is added which is a random number with zero mean and one standard deviation. The explicit form of the matrix X is expressed in Eq. 5.

$$X = \begin{bmatrix} \frac{\partial \hat{d}_1}{\partial x} & \frac{\partial \hat{d}_1}{\partial y} \\ \frac{\partial \hat{d}_2}{\partial x} & \frac{\partial \hat{d}_2}{\partial y} \\ \frac{\partial \hat{d}_3}{\partial x} & \frac{\partial \hat{d}_3}{\partial y} \\ \frac{\partial \hat{d}_4}{\partial x} & \frac{\partial \hat{d}_4}{\partial y} \\ \frac{\partial \hat{d}_5}{\partial x} & \frac{\partial \hat{d}_5}{\partial y} \end{bmatrix} \tag{5}$$

The vector represented by Δβ contains the corrections to be made to the initial position values. In order to linearize the Euclidean distance equations, they are linearized by first order Taylor series expansion. Taylor series expansion requires, approximate initial position information. The initial position estimates are shown in Eq. 6. Obtained Δβ vector is the correction to the initial position estimation.

$$\beta_0 = \begin{bmatrix} x_0 \\ y_0 \end{bmatrix} \tag{6}$$

The corrections are obtained after the solution of least squares adjustment given in Eq. 1. Corrections are added to the current solution obtained in the previous parameter estimation cycle as shown in Eq. 7. The iteration continues until the correction values decreases below the desired level.

$$\beta = \Delta\beta + \beta_0 \tag{7}$$

The approximated value is subtracted from the true value and the Euclidean distance of obtained values is reported as the error value. It is possible that many obstacles may exist in the room where indoor positioning is conducted. In this study, the effect of obstacles on the positioning accuracy is investigated by simulation. For this, the room with the geometry presented in Figure 1 is used.

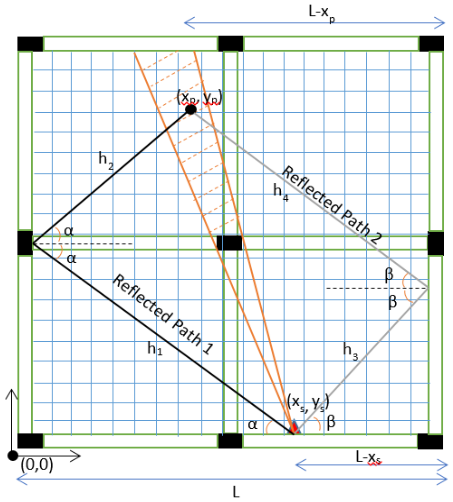

Figure 1. Geometry of the room to investigate the effect of blind spots.

In the middle of the room there is a column which prevents the direct reception of the signals from the station points. Figure 1 illustrates a particular sensor distribution to demonstrate the regions where direct measurements and measurements with multi-path can be conducted. The sensor will report the shortest distance measurements and the multi-path signals would have the path length represented in Eq. 8.

$$\tan(\alpha) = \frac{y_p - y_s}{x_s + x_p} \quad \tan(\beta) = \frac{y_p - y_s}{2L - x_s - x_p} \tag{8}$$

The shortest multi-path can arrive the measured point by bouncing the left or the right wall as shown in Figure 1. Therefore, Eq. 8 provides two bouncing angles represented by α and β. Corresponding path lengths are computed as given in Eq. 9 for the left bouncing and in Eq. 10 for the right bouncing path.

$$h_1 = x_1\sqrt{1 + (\tan\alpha)^2} \qquad h_2 = x_2\sqrt{1 + (\tan\alpha)^2} \tag{9}$$

where $L_{RP1} = h_1 + h_2$.

$$h_3 = x_3\sqrt{1+(\tan\beta)^2} \qquad h_4 = x_4\sqrt{1+(\tan\beta)^2} \tag{10}$$

where $L_{RP2} = h_3 + h_4$

L_{RP1} and L_{RP2} are the lengths of the reflected paths. The shortest of the indirect paths is taken as the simulated measured distance by min $\{L_{RP1}; L_{RP2}\}$. White noise is also added to the simulated multi-path distance.

Positioning accuracy is investigated for different location of the room. In order to systematically examine the spatial effect, the room is divided into 1 meter sized meshes and the positioning is simulated by conducting the Eq. 1 to 10. Least squares adjustment is implemented 25 times for every least square adjustment session. The number of iterations is adequate to ensure convergence.

The geometric relationship of the sensors with the column is evaluated according to locations of the sensors and the lines passing through different corners of the column.. The points formed by the lines passing through the two corners of the column and behind the column relative to the sensor are determined as the areas where the multipath effect is present.

If a point is not subject to multipath effects, path distance between the sensor and the point is computed by the Euclidean distance equations. However, if the station point is subjected to multipath effect, the shortest of the reflected paths of the signals is used as the distance between the sensor and the point. In this way, the multipath effect will be analyzed and distances will be calculated depending on the position of the sensors in the room. The above mentioned process ensures that the simulation handles the real life conditions correctly.

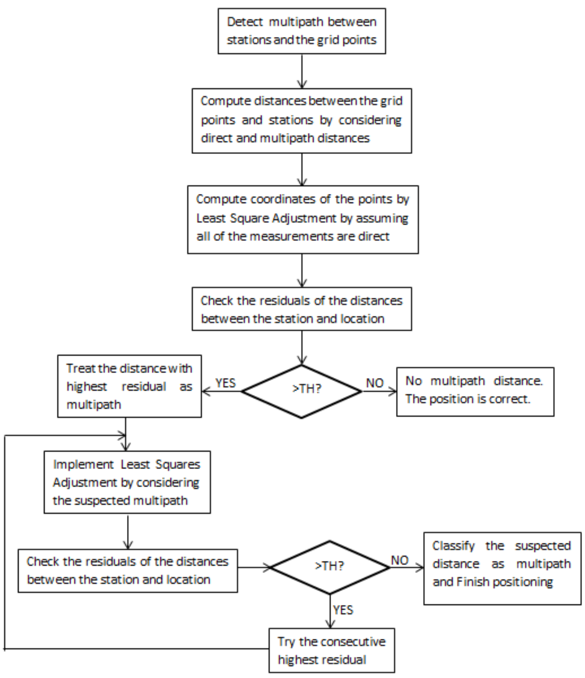

Figure 2. Flowchart of the multipath detection algorithm.

Least square adjustment is conducted by assuming that all of the distance values are direct measurements. The least squares adjustment process is implemented until the stopping criteria are met. If the magnitudes of the residuals of the distances are above a predetermined threshold value then the distance value with the highest residual is assumed to be an outlier and the distance between the station and the measured point is computed by implementing the multipath equations. Another least square adjustment process is implemented by computing the suspected distance between the location and the station point by multipath distance equations. The adjustment process is continued until stopping criteria are met. If the magnitudes of the resultant residuals are smaller than the initial result the suspected distance between the sensor and the point is classified as multipath. If the obtained residuals are higher than the initial solution, the suspected point is not classified as multipath and the residual with the second highest residual error is examined. This process is continued until all of the residuals are examined. The flowchart of the proposed multipath detection algorithm is presented in Figure 2.

4. Case Study

In this study, different combinations of sensor placement and the effect of multipath on positioning accuracy are investigated. As shown in Figure 3, five station points are fictitiously set up at points $(x_1, y_1) = (6, 0)$; $(x_2, y_2) = (10, 6)$; $(x_3, y_3) = (4, 10)$; $(x_4, y_4) = (0, 8)$, and $(x_5, y_5) = (0, 3)$. In the center of the room a column with dimensions 1.0m x 0.3m exists at location (5, 5). The positioning accuracy is examined in meshes with 1 meter mesh size. This ends up with 121 examined points. The existence of blind spots thus multipath effect is examined and the mesh locations represented as 0 are found to be receiving direct signal from all of the station points. In Table 1 mesh locations represented as 1 receives 1 multipath signal and direct signals. The blind spot positioning accuracy in blind spots in the areas where the column is located was investigated.

Table 1 shows the number of sensors identified as blind spots in the analysis for the corresponding grid points created at 1 meter intervals in a 10m x 10m room. The given numbers represents the number of obtained distances that are received by following multipath with respect to the geometry of a room given in Figure 2. Table 1 does not represent any value for the coordinate (5, 5) as it is inside the column and cannot be measured.

	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
0	0	0	0	0	1	0	0	0	0	0	0
1	0	0	0	0	1	0	0	0	0	0	0
2	0	0	0	0	1	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	1
4	0	0	0	0	0	1	0	1	1	1	1
5	1	1	1	1	1		1	1	1	1	1
6	1	1	1	1	1	0	0	0	0	0	0
7	1	0	0	0	1	0	1	0	0	0	0
8	0	0	0	1	0	0	1	0	0	0	0
9	0	0	1	1	0	0	0	1	0	0	0
10	0	1	1	0	0	0	0	1	0	0	0

Table 1. Number of distance measurements subjected to multipath for the corresponding grid points.

When the positioning was conducted without considering the multipath effect, the maximum error was determined as 2.6427 m at point (2,4). In this point signals from the station point 2 came by following a multipath direction. As a result of this the maximum difference between the calculated distances and the measured distances is observed at the 2nd row of the ΔY vector for this point.. The minimum error was 0.0007561 m at point (6, 6) where all of the measurements were direct. Throughout the aforementioned simulation Table 1 is not considered while computing the corrections to the initial position estimation.

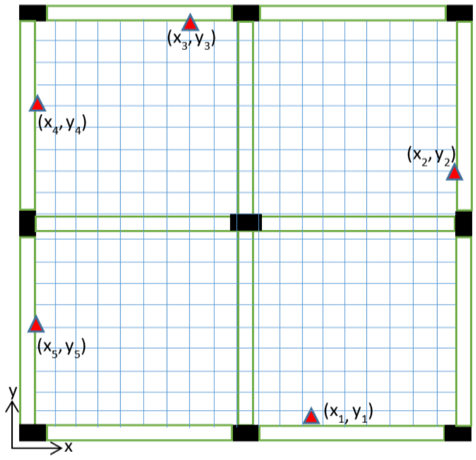

Figure 3. Location of the columns and positions of the station points.

When the signals cannot reach the blind spots directly, they follow reflected paths and the length of the followed path is measured. The positioning errors obtained as a result of the analysis are shown in Figure 4. Table 1 and Figure 4 are highly correlated that the points receiving signals with multipath have significant positioning error.

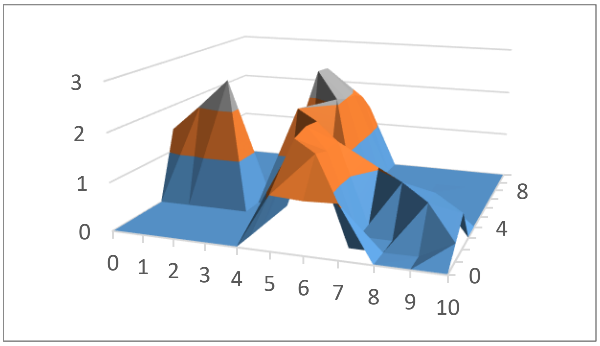

Figure 4. Error values obtained as a result of the analysis.

To examine the effect of station distribution on the position accuracy another analysis is conducted where the sensors are aligned on the same line. The sensors were placed at $(x_1, y_1) = (1, 0)$; $(x_2, y_2) = (3, 0)$; $(x_3, y_3) = (5, 0)$; $(x_4, y_4) = (7, 0)$ and $(x_5, y_5) = (9, 0)$. The sensor distribution is given in Figure 5.

The error amounts obtained as a result of this analysis are shown in the graph in Figure 6. When the geometric relationship between the positions of the sensors and the column is examined, the positioning error is high in those regions where the column causes blind to more than one sensor. Furthermore, if the station point arrangements are lined up on the same line, then extremely erroneous positioning can be experienced due to the ill-conditioned equations which magnify the added white noise.

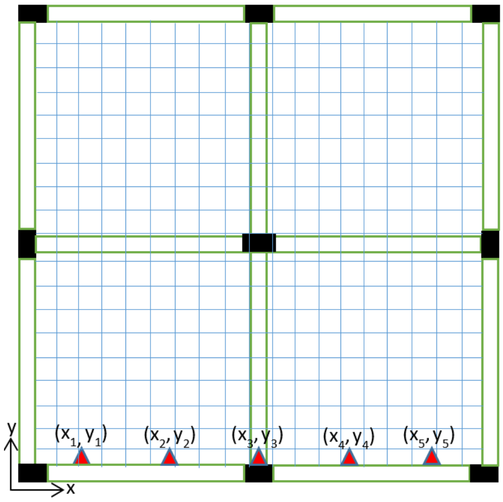

Figure 5. Positions of sensors placed on the same line.

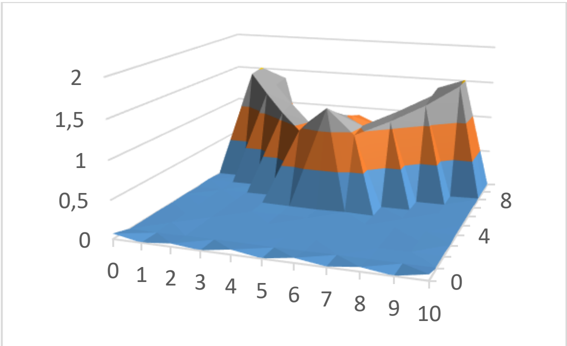

Figure 6. Error values obtained when sensors are positioned on the same line.

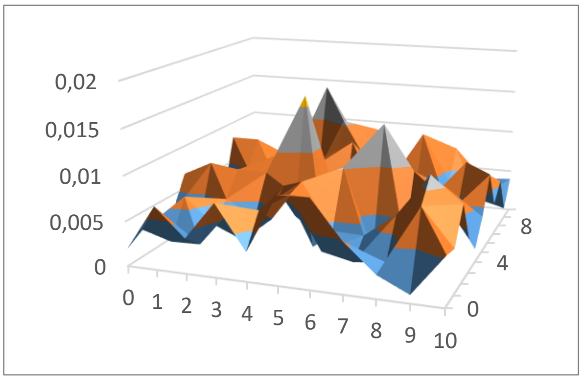

Figure 7. Magnitudes of the positioning error values when the multipath effect is considered.

The algorithm given in Figure 2 is executed for the positioning results given in Figure 4. The multipath detection algorithm corrects 31 erroneous positioning out of 35 erroneous points. At the end of the analysis maximum absolute positioning error is computed as 0.01627 m at point (4, 5). The multipath detection algorithm cannot improve the positioning accuracy of the 4 points since the computed residual values of those points were less than the predefined threshold value.

5. Discussion and Conclusion

According to the simulation results, sensor placement strategies significantly affect the accuracy of indoor positioning. In particular, blind spots in the areas where the column is located cause signal loss and the positioning accuracy is deteriorated seriously. Location errors increase in cases where signal transmission is interrupted in blind spots.

When the positioning accuracy of the stations was distributed in a spatially dispersed manner, the signals covered most of the space in the room and blind spots were minimized. In contrast, there was a significant loss of precision when the stations were aligned on the same axis. This can be explained by the fact that the effect of white noise is magnified due to poor conditioning of the equations and the geometry between the sensors and the column creates blind spots by more sensors.

Simulation results show that obstacles such as columns cause multipath effects and positioning errors increase when signals cannot reach them directly. In regions where the distances are measured by direct paths, the amount of error remains low, whereas when the shortest reflected path is used, the amount of error increases significantly. This is mainly due to the adjustments of the residuals of the distance values throughout the least squares adjustment process. In addition, in the regions behind the column the signals do not reach directly, which further increases the error in these regions. To illustrate, the maximum error was calculated to be 2.643 meters at a point located behind the column.

The occurrence of blind spots and the analysis of errors in these regions were related to the geometric layout of the sensors and the position of the sensors relative to the column. Blind spots were observed to occur due to obstacles such as columns blocking the field of view of multiple sensors. Blind spots are detected when the differences between the measured distances and the distances measured for the estimated locations show extreme values. In the distance calculation of a blind spot, the shortest of the reflected paths was taken into account and the calculations were revised using the proposed multipath detection algorithm.

In conclusion, the distribution of stations and the effects of environmental obstacles should be taken into account in indoor positioning systems. The effect of obstacles should be minimized by developing appropriate algorithms. Meanwhile the homogeneous distribution of the station points should be fulfilled which is a critical parameter to improve the accuracy of the positioning. More complex room geometries with different types of sensors should be investigated to reveal their effects on the positioning accuracy as future study. Furthermore, the development of more effective analytical representations and algorithms to detect the multipath and eliminate its adverse effects will improve the accuracy and reliability of indoor positioning systems. The results of this study reflect the importance of constellation of station points and investigate the detectability of multipath cases which are the important factors to be considered through the design of positioning systems.

Magnitudes of the differences between the measured distances and the observed distances that are stored in the ΔY vector are the main decision criterion for the detection of whether the estimated position is located in a blind spot. During the analysis some of the blind spots which causes multipath could not be detected by the developed algorithm. This is because even if a point is a blind spot, the measurement error remains lower than the predefined threshold value. This happens when the distance of the reflected paths and the distance of the direct path are close to each other. In the analysis based on the sensor locations in Figure 3, the algorithm successfully detected 31 blind spots out of 35 blind spots. By developing more comprehensive detection criteria, the performance of the algorithm can be improved in more complex scenarios.

The expected benefits of this study include the development of more reliable and precise positioning solutions for critical indoor applications. In addition, the development of positioning strategies that are sensitive to blind spots and multi-path effect can be beneficial to reduce the magnitude of the error of the location data.

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