Automatic Calibration for Log-Normal Path Loss Model Based on Bluetooth Low Energy Beacons

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***Abstract*—This paper describes automatic calibration procedure for indoor lateration technique based on log-normal signal propagation model using Android-based mobile device. The usage of signal propagation models for indoor localization requires calibration phase because the path loss model parameters take into account multipath propagation, shadowing and fading influences. This phase of such indoor localization technique using signal propagation model can be eliminated by automated procedure of parameter calibration. For this objective Bluetooth Low Energy beacon proximity zones and smartphone built-in sensors can be used.**

I. INTRODUCTION

A number of indoor localization techniques and solutions have been suggested and developed for last ten years. Many people in science and business have been involved in this process. The result gotten from indoor localization solution development as a promising and complex task provides information to different context-aware and location-based services. Traditional, as examples of such services, airport, museum and shopping mall visitor localization services or personnel and equipment location detection services are considered. Development of some indoor localization solution requires map construction based on floor plans of indoor areas, accurate localization techniques and algorithms, deploying the appropriate equipment inside the buildings.

The problem of map construction for public indoor areas is being solved by Google using a service for indoor map applying by the building owners. Moreover, there are a lot of OpenStreetMap based map projects. In another case, the building owners use indoor localization system developed especially for their buildings like Accuware [1]. In addition, the simultaneous localization and mapping (SLAM) algorithm can be used for laser sensor, camera or Wi-Fi [2].

Various indoor sensing approaches used for localization may be classified into:

- Wireless technologies based approaches: This group of approaches is the most widespread and its methods are used in many localization services and solutions. Wireless information access is now widely available due to the growth of wireless networks and ubiquitous mobile devices usage. Wi-Fi, Bluetooth, RFID, ZigBee, NFC, A-GPS are widely used for indoor localization.
- Vision based approaches: Visual information can be collected for indoor navigation. Using one or more cameras one can collect image databases and analyze captured pictures, or capture the position of the laser points or QR-codes on the walls [1]. Vision based solutions can use laser-based range finder in the surrounding environment. These laser-based approaches are usually used for mobile robot navigation.
- Inertial navigation based approaches: Such approaches are used for calculations via dead reckoning the position, orientation and velocity using several motion and rotation sensors. The main drawback of inertial navigation is cumulative errors.
- Other approaches: Other approaches consider ultrasound, magnetic fields and FM radio based techniques.

The wireless technology based localization solutions developed last years can provide acceptable accuracy localization (about 1-3 m). These solutions can be a basis of several context-aware services that may provide a personalized content, location-specific data, statistic information for cloud users and other context-aware interactions. The methods, using Wi-Fi localization, are considered by many researchers as more preferred because Wi-Fi networks are prevalent in most public indoor areas and their usage doesn't require any additional infrastructure and allows to locate each user of mobile device [3]. In addition, the last 3 years Bluetooth Low Energy beacons have become very popular solution for indoor location sensing which can provide user proximity and location. Since Apple produced its own BLE data transfer protocol known as iBeacon in 2003, a lot of BLE beacon and BLE based indoor localization solution producers have risen. The release of Eddystone data transfer format for BLE developed by Google opened the possibility of additional location-specific information transmission. This idea is the base of Physical Web technology which provides an interaction between physical objects, locations and semantic information in the Web. The Physical Web provides a list of localized object URLs in an environment around a user.

There are many methods based on wireless signal information e.g. [4], [5], [6], [7] and [8]. Acceptable accuracy and deployment cost achievement is the main challenge of such methods. The present time Bluetooth and Wi-Fi based solutions are more promising due to these reasons. Therefore, the interest to use such indoor localization solutions is gained in many research communities. The wireless localization methods can be classified on signal propagation based techniques and scene analysis, also known as fingerprinting, which refers to feature of a scene collection and online data matching.

The outdoor localization techniques based on signal propagation use, for example, such methods like lateration (known as trilateration or multilateration in common case) and angulation. The ground of lateration techniques is the calculation of distances between reference points and mobile device to locate absolute or relative position of mobile device using circle geometry. These distances can be obtained by different signal information like, received signal strength (RSS), the time of arrival of the radio signals from transmitters (TOA), the time difference of the arrival of several radio signals (TDOA), the time-of-flight of the signal traveling from a transmitter to a receiver (RTOF), the received signal phase (POA). Several approaches based on angulation techniques use arriving signal angle measurements (AOA). Unfortunately, usage of these methods for indoor environments have different challenges like missing line-of-sight channel between the transmitter and the receiver, multipath signal propagation, scattering, shadowing and fading. Due to these effects TOF, AOA, RSS and other methods are affected, and localization accuracy could be decreased. Such effects could be caused by moving people and reflecting surfaces. Thus, the usage of these methods requires accurate signal propagation models (path loss models), prior RSS measuring to calibrate parameters of these models.

Fingerprinting is the effective technique based on signal data collection without using any radio signal characteristic based approaches and providing high accuracy. Fingerprinting uses fingerprint database, which consists of RSS values related to indoor coordinates. Fingerprinting consists of two phases: 'training' (offline phase) for database construction and 'positioning' (online phase). The positioning phase includes accessible radio signals measurement process and determine receiver's location using an appropriate search/matching algorithm [10], [11]. There are a number of problems like a vast number of RSS measurements at training phase, collisions and unstable radio signal, which induces errors during matching algorithm usage.

In this paper automatic calibration procedure for RSSI-based indoor localization method is considered. This method uses BLE signal strength lateration technique based on log-normal path loss model. Log-normal path loss model has several parameters that account multipath propagation and shadowing effects. Usually these parameters are determined empirically during the calibration phase. The auto-calibrated parameter procedure is needed to avoid calibration phase of log-normal path loss lateration. We considered BLE beacon based localization technique due to the beacon mobility, because we can move beacon within an area to achieve line-of-sight propagation channel, add new beacons to improve localization accuracy, and due to proximity zones of BLE signal. The proximity zone can be used to determine several initial values for auto-calibration procedure. In addition, we propose to use the internal smartphone sensors for distance auto-detection, which is necessary for auto-calibration.

The rest of the paper is structured as follows. Section II presents an overview of wireless indoor localization techniques. Section IV introduces auto-calibration procedure for log-normal path loss model. Main results are summarized in Section V.

II. Related work

There are a number of indoor localization techniques and solutions based on several wireless technologies like a Wi-Fi, Bluetooth and RFID. One of existing solutions for indoor localization is produced by Navigine [12]. This solution uses hybrid localization approaches including BLE beacons, Wi-Fi and internal mobile phone sensors. Indoor localization solutions produced by Navigine provide tools for advertising notifications, visitor activity analysis and tracking. Moreover, Navigine SDK is available for custom mobile application development using Navigine API. At the Navigine public repository [13] trilateration and pedometer localization algorithms are presented.

The next significant instance of indoor localization solutions is Google Beacons platform [14], which provides via Proximity Beacon API the possibility of register and support different type of beacons, attach and share location-specific data. In addition, Google Beacons platform provides Nearby Messages API and Places API for the client side. Nearby Messages API is a publish-subscribe API which can interact with BLE beacons and other Android or iOS based devices. The API can be used for advertising notification obtaining from several BLE beacons. Places API implements Physical Web paradigm and can be used for categorized search of locations, location-specific data obtaining and adding new locations.

The very old example of indoor positioning system using proximity-oriented infrastructure is the Smart museum project [15]. In scope of this project the location-based recommendation system for museum visitors has been developed. The main objective of Smart museum was provision some information related to various kinds of cultural objects and presenting to the user recommendation information about places of interest based on user's location. The system used RFID tags for proximity localization and GPS for outdoor localization. Each RFID tag stores the URL of the web page with information about the subject of an exhibit.

The second example of proprietary beacon based indoor localization system is Place Lab [16]. Place Lab can locate user indoor and outdoor. The system uses a number of radio beacons that can be Wi-Fi access points, fixed Bluetooth stations, and GSM towers. The system has its own protocol, which sets unique or semi-unique ID for each beacon.

In [17] the trilateration algorithm based on log-normal path loss model is proposed. This algorithm uses self-calibration procedure based on particle swarm optimization (PSO) for determining calibrated parameters of log-normal path loss model. The receivers are static, and their actual locations are prior known. Also PSO is used for obtaining the minimum of a function of distance error which is defined as the difference between actual distance value and estimated distance. It means that this auto-calibration procedure is applicable only to measurements and calculations RSS obtained by static receivers.

In [18] the fingerprinting tracking approach based on KNN-method is presented. The algorithm uses Kalman filtering to mitigate the effect of RSS fluctuations, which makes fingerprinting technique inapplicable. Then certain parameters for the presented fingerprinting transformation model are calibrated using recursive least square estimation or simple mean estimation for the case when the number of access points is small and one of the parameters is reduced.

In [19] three auto-calibration (virtual calibration) procedures for log-distance path loss model including floor and wall attenuation factors are presented. There are global virtual calibration, per-wall virtual calibration and ad-hoc calibration procedures. The procedures include parameters that take into account the number of walls crossed by signal, the attenuation factors of these walls. The actual distance value is defined by hands as the prior information. The computations are performed via least square estimation method.

The PiLoc indoor localization system [20] uses sensed RSS data contributed by a number of users. The system merges annotated walking segments related to certain indoor area to derive the map of walking paths. This system is based on fingerprinting technique and dead-reckoning calculations using built-in mobile phone sensors. The calibration procedure is the complex procedure of trajectory matching.

Also the proposed in this paper auto-calibration procedure uses the real distance to transmitter which is obtained dynamically by calculations using inertial smartphone sensor information during user movement through indoor area.

III. Wireless Indoor Lateration Overview

A. Lateration approach

The indoor localization in wireless networks is a process of position determination in a defined part of building area. As a result of the localization process, we consider the estimated position or the area obtained by performing a certain localization technique. In common case lateration method is based on knowledge of reference point positions within some area and the distances to them.

The wireless lateration method for indoors uses parameters of known wireless networks like a frequency of a signal, its signal strength (RSS), beacon MAC-addresses and real coordinates of transmitters (beacons) within the area. The signal strength received by mobile device can be used for distance estimation between beacons and mobile device. This dependency is the function of distance and can be shown as simple equation system:

$$\begin{gathered} d_1^2 = (x-x_1)^2 + (y-y_1)^2 \\ d_2^2 = (x-x_2)^2 + (y-y_2)^2 \\ \dots \\ d_n^2 = (x-x_n)^2 + (y-y_n)^2 \end{gathered} \quad (1)$$

where x_1, x_2, x_n, y_1, y_2, y_n are the coordinates of access points, d_1, d_2, d_n are the estimated distances.

The main goal is to determine the approximate radius by RSS values for each reference point. This problem corresponds to determining the distance between the transmitter and the receiver using a signal propagation model. Radio signal path loss is the largest and most variable quantity of gains and losses. It depends on frequency, antenna orientation, penetration losses through walls and floors, the effect of multipath propagation, the interference with other signals, signal shadowing and scattering among many other factors [27].

B. Indoor path loss models

Due to the indoor environment varies significantly from place to place, the simplest way to estimate the distance from transmitter to receiver is to perform some signal propagation formula. There are several path loss models, and one of them is ITU model, which is the site-specific model and includes parameters accounting floor penetration effect. The model is applicable to multiple floor signal prediction and allows one to reuse signal frequency characteristic. The model is defined by equation 2:

$$L = 20\lg f + N\lg d + P_f(n) - 28 \quad (2)$$

where L – total path loss, f – frequency of transmission (MHz), d –distance (m), N – distance power loss coefficient given by the ITU depending on the environment, n – number of floors between transmitter and receiver and $P_f(n)$ – floor loss penetration factor calculated by expressions from ITU propagation model.

Several researchers consider Hata-Okumara path loss model. In [29] the modeling a two-dimensional path loss model is described because calibrated Hata-Okumara model shows different results at different range of distance to transmitter. The model is defined by equation 3:

$$\lg d = \frac{1}{10n}(P_{TX} - P_{RX} + G_{TX} + G_{RX} - X_a + 20\lg\frac{\lambda}{4\pi} \quad (3)$$

where d – estimated distance between the transmitter and the receiver, P_{TX} (dBm) – transmitted power level, P_{RX} – power level measured at the receiver (dBm), G_{TX} (dBi) – antennae gain of the transmitter. Similarly, GTX (dBi) is the antennae gain of the receiver, λ (m) – wavelength, n – measure of the influence of obstacles, X_α – normal random variable with a standard deviation of α.

Both of the above described loss models should be calibrated by certain parameters, like a floor loss penetration factor $P_f(n)$ and the distance power loss coefficient N from (1) or measure of obstacle influence n from (2), that account errors due to the multipath propagation and other negative effects in non-line-of-sight environments. The calibration procedure usage can improve lateration process by adoption to a real environment particularities like walls, furniture and others. This procedure can be performed for many directions and regions within indoor area.

It is shown in [28] that this model is accurate as ITU model in testing indoor areas. Using of ITU model has several advantages, but we consider the signal propagation within one room. Originally, Hata-Okumara model is developed for suburban areas and reflection and shadowing effects are not included to it.

The log-normal path loss model for estimation of distance between receiver and transmitter is the simplest past loss model. We consider this model because it provides acceptable accuracy and is simple for calibration. The model is described by the equation below:

$$RSS = P_t - PL(d_0) - 10 \propto log_{10}\frac{d}{d_0} + X_{\sigma_{RSS}} \quad (4)$$

where *RSS* – the received signal strength (dBm), d – true distance from the sender to the receiver, α – path-loss exponent, P_t – transmitted power of the sender (dBm), $PL(d_0)$ – power loss (dBm) at a reference distance d_0. The quantity $X\sigma_{RSS}$ in dBm is a random variable representing the noise in the measured RSS and is often assumed to be a zero-mean Gaussian random variable with variance RSS.

Time varying and time-invariant sources can provide the noise $X\sigma_{RSS}$. Since there is no possibility to design path loss model for each wireless channel of each deployed network, the noise cannot be averaged by taking multiple measurements of RSS. These random effects of shadowing and multipath propagation may be presented by assuming the $X\sigma_{RSS}$ is Gaussian.

While RSS-based lateration localization technique the RSS from the BLE beacons on the floor in the building should be measured. This measured value RSS can be mapped to an estimated distance $\hat{d}$:

$$d = k\,10^{\frac{P_t - RSS + X_{\sigma_{RSS}}}{10 \cdot \propto}} \quad (4)$$

where k is a constant incorporating both $PL(d_0)$ and $\log10(d_0)$.

Given the empirical values of k and α, the resulting model in (4) can be used to compute a distance estimate $\hat{d}$ from a measured RSS as

$$\hat{d} = k\,10^{\frac{P_t - RSS}{10 \cdot \propto}} \quad (5)$$

Also, calculation of k and α parameters can be given by curve fitting [30]. The obtained by such approximation distance value could be used as a distances from receiver (user mobile device) to the transmitter (BLE beacons) by calculation localization area while lateration process.

As it pointed above the main goal of this research is to investigate the possibility of automatic calibration of log-normal path loss signal propagation model. This model has parameters k and α that should be defined empirically. It means that we should calibrate these parameters during the automatic calibration phase for each BLE beacon involved to the localization process. This technique may help to use BLE lateration method.

C. Two-dimensional log-normal path loss model

Since the RSS of received BLE beacon signal fluctuates and produces big errors in distance estimation, the RSS level decreases very high due to the human body if the user turns his/her back to the beacon keeping a smartphone in the hand. To reduce the influence of fluctuations one can use the Kalman filter or just simple averaging of real RSS measurements. The other challenges are the proximity zones of BLE beacons (Fig.1).

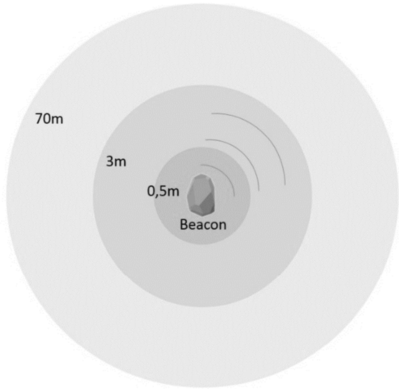

Fig. 1. BLE iBeacon proximity zones

It means that if we try to calibrate path loss model for all zones, the accuracy will be not applicable due to signal propagation differences in each zone. To resolve this disadvantage one can consider two-dimensional path loss model. The two-dimensional path loss model includes the break point that separates the propagation properties in near and far regions relative to the transmitter. This model can be described by two equation systems:

$$d_{11} = k\,10^{\frac{P_t - RSS_{11}}{10 \cdot \propto}}$$
$$d_{12} = k\,10^{\frac{P_t - RSS_{12}}{10 \cdot \propto}} \quad (6)$$

where d_{11}, d_{12}, RSS_{11}, RSS_{12} corresponds to near region.

$$d_{21} = k\,10^{\frac{P_t - RSS_{21}}{10 \cdot \propto}}$$
$$d_{22} = k\,10^{\frac{P_t - RSS_{22}}{10 \cdot \propto}} \quad (7)$$

where d_{21}, d_{22}, RSS_{21}, RSS_{22} corresponds to far region. The break point in this model corresponds to $d_{12} = d_{21}$.

D. Evaluation of two-dimensional log-normal path loss model

We are using Android based application to measure RSS and distance calculation by equations 6 and 7. We assume that first zone radiuses are 0.1 m and 1 m, for the second zone – 1m and 3.5 m. The iBeacon standard by Estimote are used. The beacon transmit power – -12 dBm as default Estimote transmit power. The calibration phase includes empirically determined parameters k and α. The measurements made for both described proximity zones in straightly allocated points on one chose direction. In each point are obtained at least 15 RSS measurements, and the averaged RSS level are calculated. Thus, the calibration procedure is performed to one direction of signal propagation for two BLE proximity zones within the indoor area in which BLE beacons are allocated. For the nearest zone are used points from 0.5 to 1 meters, and for medium zone – from 1 to 3 meters. The area of the room is 25 square meters. The in Table I results are presented. The results are presented in Table I for nearest zone and in Table II for medium zone.

TABLE I. THE COMPARISON REAL AND ESTIMATED DISTANCES FOR NEAR PROXIMITY ZONE

Distance, m	Estimated distance, m	Relative error, %
0.5	0.84	68.0
0.6	0.87	45.0
0.7	0.87	24.3
0.8	0.9	12.5
0.9	0.92	2.2
1	0.93	7.0

Results presented in Table II show that the signal propagation model is viable for using even within the indoor area with several obstacles on the signal line.

TABLE II. THE COMPARISON OF REAL AND ESTIMATED DISTANCES FOR MIDDLE PROXIMITY ZONE

Distance, m	Estimated distance, m	Relative error, %
1	0.84	16.0
1.5	0.87	42.0
2	0.9	55.0
2.5	1.5	40.0
3	2.22	26.0
3.5	2.5	28.6

As shown in the tables the significant errors are produced after 1 meter of distance where the near zone is allocated. The localization error of this approach is about 1 meter. Also, using this approach requires some improvements.

IV. LOG-NORMAL PATH LOSS AUTOMATIC CALIBRATION

In this section, we propose the two-dimensional log-normal path loss based lateration method which uses the automatic parameter calibration procedure. This procedure can be used for non-two-dimensional variant of log-normal path loss model. As it is shown in previous section, the parameters of log-normal path loss model k and α can be determined empirically while calibration phase. While this phase engineer should obtain a number of RSS measurements from BLE beacons to define the parameters. We propose auto-calibration to avoid this phase.

There are two important features to be considered as the basis of this approach:

1) BLE proximity zones lying on certain distances from the BLE beacon.
2) Android smartphone built-in inertial sensors like accelerometer and gyroscope.

It was assumed that the RSS level near the beacon is known. The measured RSS level of the beacons at a distance of 0.5 m was 45dBm. It was that the user moved on the tangent to the border of near proximity zone only, because we couldn't correctly determine the direction of user moving regarding the beacon (Fig. 2). We should consider straight moving of user only. Then if we register the certain value of RSS corresponding to near proximity zone, we consider that the user moves straight on the tangent to this zone. After this we can measure new value of distance by internal smartphone sensors and calculate the distance to BLE beacon (distance 2 on the Fig. 2). We still consider the equation 4 as the calibration equation. Generally it can be defined as:

$$d_1 = k\,10^{\frac{P_t - RSS_1}{10\cdot\propto}}$$
$$d_2 = k\,10^{\frac{P_t - RSS_2}{10\cdot\propto}} \quad (8)$$

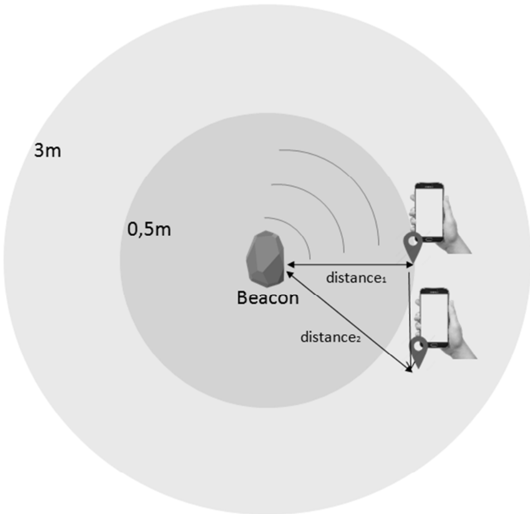

Fig. 2. RSS level measurements for the access point for one direction

Thus, we have defined the values of d_1 and RSS_1 and should obtain missing values. To obtain these values, we can use inertial sensor data to calculate velocity of moving user, and then the distance d_2. The velocity can be estimated using equation below:

$$d = \frac{t^2\sqrt{\Delta x^2 + \Delta y^2}}{2} \quad (9)$$

where d – distance (m), Δx – offset of x coordinate, Δy –offset of y coordinate, t – the time interval.

Using the equation 6 and Android smartphone sensors, we can estimate distance d_2. If d_2.value is 3m we can measure RSS to complete the parameter obtaining for calibration. Also we can transform the equation 5 for auto-calibration procedure:

$$\alpha = \frac{RSS_2 - RSS_1}{10\lg {d_1}/{d_2}}$$
$$\lg k = \lg d_1 - 10^{\frac{(P_t - RSS_1)\lg\frac{d_1}{d_2}}{RSS_2 - RSS_1}} \quad (10)$$

Also we can point several steps of this technique:

1) *Step 1:* Parameter initialization. The initialization of parameters d_1 and RSS_1 for near proximity zone determination. The parameters for near zone of two-

dimensional log-normal path loss are calibrated on this step;

2) *Step 2:* BLE beacon near proximity zone allocation detection. If the user enters the near proximity zone, his/her location is estimated as at the border of this zone;
3) *Step 3:* Calculate the distance via smartphone sensors only by direct moving. The beginning of steps counting. The calculated distance is used to obtain the distance to the beacon using the Pythagorean theorem;
4) *Step 4:* If the distance is 1 meter measure RSS level. Mesurment of RSS to obtain all necessary parameters for calibration;
5) *Step 5:* Using equation 10 calibrate the path loss model. By testing this technique, the average signal strength levels are measured by distance one beacon allocated in within one room. This data are measured to distance estimation for lateration method described above. These measurements are made for each point on the one direction at the 0.5 m interval within middle proximity zone. The near proximity zone doesn't need to be calibrated automatically. The measurements are made using developed Android application. This application found different beacons by addresses and measured the RSS levels of each access point. The RSS level changes at time therefore it is necessary to use its average value. The results for one of them are displayed in Table III.

TABLE III. THE COMPARISON OF THE REAL DISTANCES AND ESTIMATED DISTANCES AFTER AUTO-CALIBRATION PROCEDURE AND WITHOUT USING IT

Actual distance, m	**Two-dimensional model distance estimate, m**	**Relative error, %**	**Auto-calibration model distance estimate, m**	**Relative error, %**
1	0.84	16.0	0.95	5.0
1.5	0.87	42.0	1.01	32.7
2	0.9	55.0	1.12	44.0
2.5	1.5	40.0	1.61	35.6
3	2.22	26.0	2.09	30.3
3.5	2.5	28.6	2.43	30.6

The values estimated by distances 3 and 3.5 meters are worse than for the two-dimensional model. It is caused by start location point determination on the step 1. The drawback should be resolved while the future works. The method provides 1 meter accuracy depends on environment particularities like a wall, furniture and access point disposition within a small area whose radius is less than 4 meters.

V. CONCLUSION

The presented automatic calibration procedure for a log-normal path loss model and the two-dimensional signal propagation model can be used for several wireless technology based indoor localization methods. BLE beacon signal lateration method can localize a user within one room if the number of beacons is at least three. The test of described techniques showed that BLE beacon number allocated within indoor area should be more than three beacons. The calibration procedure is sensitive to built-in smartphone sensor errors. Due to this drawback user should move only in a straight line. Moreover, the user himself can be an obstacle that could lead to big errors. This means that naturally movements are impossible during the procedure. To improve this technique some filters for dead reckoning procedure to decrease errors could be used.

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