Monte Carlo Localization Algorithm for Indoor Positioning using Bluetooth Low Energy Devices

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***Abstract*— This paper presents a technique for indoor localization using the Monte Carlo localization (MCL) algorithm. The MCL was upgraded from Markov localization, with both belonging to the family of probabilistic approaches. Throughout the last decade, laser rangefinders and gyroscopes have been applied to MCL-based robotic localization systems with remarkable success. However, the utilization of MCL-based indoor localization for mobile devices, by applying Bluetooth low energy (BLE) sensors, is still being researched. In this paper, we present a technique that utilizes MCL that exploits two sensors, namely, the accelerometer and compass, with commonly deployed BLE beacons to localize people with mobile devices indoors. Experimental results illustrate that, by applying MCL with BLE beacons using an accelerometer and compass, the error of the calculated coordinates for the user position is less than 1 m in line of-sight (LOS) environments, while in a complex non-LOS environment, the average error is 3 m. Meanwhile, the proposed MCL system does not demand a high deployment density of BLE beacons compared with triangulation and trilateration-based indoor positioning algorithms.**

Keywords—Monte Carlo localization (MCL), Bluetooth low energy (BLE), indoor positioning.

I. INTRODUCTION

Sensor-based localization has increasingly attracted the attention of researchers in areas such as mobile robotics and civilian facilities [1]. In addition, in tandem with the development of positioning technologies, operators and manufacturers have begun to focus on indoor positioning. As human beings spend a large amount of time in both private and public indoor areas, providing an accurate indoor positioning service is of significant practical importance.

Within the area of robotics, researchers have developed a substantial number of algorithms to solve the robot location problem. One example is Monte Carlo localization (MCL) [2]. The primary purpose of MCL is to compute a robot's location by generating a group of particles that denote the possible position of a robot. Bayes' rule and the method of convolution are applied to update the position of particles whenever the robot senses or moves.

Since the development of Bluetooth Low Energy (BLE) [3] and the rise in popularity of mobile smartphone devices with the BLE function, Bluetooth sensor-based indoor localization systems have increasingly gained attention [3]. In an indoor setting, BLE-based positioning systems track the position of mobile devices or robots by referring to the received signal strength indicator (RSSI) value from BLE beacons.

Throughout the last decade, laser rangefinders and gyroscopes have been applied to Monte Carlo (MC)-based robotic localization systems with remarkable success. However, the application of MC-based indoor localization for mobile devices, by applying BLE sensors, is still being researched. In this paper, BLE beacons as well as mobile devices integrated with BLE, accelerometers, and compass-based sensors are exploited by a specially tailored MCL algorithm. In the first section of this work, the principle of Markov localization is described. The second section presents the theory behind MCL, which has been developed from Markov localization. Experimental results are analyzed in the third section of this work, followed by the conclusion in the fourth section.

II. MARKOV LOCALIZATION

This section gives a brief outline of the basic Markov localization algorithm upon which our algorithm is based. Markov localization algorithms are applied to address the challenge of estimating different user states from the data provided by different sensors. Specifically, the key method of Markov localization is to compute a probability distribution over the space of all possible locations, which is different from triangulation and trilateration-based localization algorithms [4].

Let $l =< x, y, \theta >$ express the user's position.

where:

x and y are the coordinates of user's position, and θ is the orientation of the user.

Initially, the user does not know the accurate starting position. Hence, $be(l)$, which expresses the user's belief of being at position l, is applied to denote the probability of the user's state. Normally, $be(l)$ is distributed uniformly with same probability to present the uncertainty of the user's position. The probability of the user's location is corrected incrementally by the updated sensor reading and the estimation of the user's motion.

In Markov localization, two different stages are applied to update the value of $be(l)$ [2]: the estimation update, which is the user's motion in this proposed method to update the movement of the user's estimated probability and the observation update, which is the sensor reading to correct the belief of the user's position.

Estimation update

When the user's location changes from the previous location l′ to l, with a measured movement action a, the $be(l)$ is then updated by the modelled motion$P(l\ |l', a)$, according to the following formula [2]:

$$bel(l) \leftarrow \int P(l\ |l', a) bel(l') dl' \qquad (1)$$

Observation update

When the user moves, an updated sensor reading is received. Then, the $be(l)$ is updated by the sensor readings$s$, which is integrated with Bayes' rule. The relationship between $(s|l)$, the likelihood of sensor reading s, and the $bel(l)$ is given by [4]:

$$bel(l) \leftarrow \alpha P(s|l) bel(l) \qquad (2)$$

where α is applied to normalize the $bel(l)$ to 1.

Both update steps must follow the rule of Markov chains [5]. Being Markovian means that the previous states are independent from the current and future states. Specifically, the past sensor has a relationship with the current and future readings. Recent research [6] has proved that a non-Markovian environment can be subject to the MCL approach; in this situation, the environment in this paper will be assumed to be Markovian.

III. Monte Carlo Localization

The main theory of MCL is similar to Markov localization [2]. Instead of computing the probability of the user's position in each grid, the key idea of MCL is to represent $bel(l)$ with a group of weighted, random particles $S = \{si|i = 1..N\}$ [2]. A group of samples is applied to present the probability distribution of the user's location. A sample in MCL is shown below:

$$\ll x, y, \theta >, p >$$

where:

$< x, y, \theta >$ is the user's position, and p is the weight value, which should be no less than 0.

In this research, MCL proceeds in two steps.

A. *Estimation update -User Motion*

Currently, most smart mobile devices implement an accelerometer sensor and compass, which can be utilised to provide the estimation update for the MCL algorithm. When mobile devices move, MCL generates N new samples that represent the user's possible coordinates. New particles are deployed by randomly deploying a sample from the previous location with the likelihood determined by the previous weight values p.

Figure 1 gives an example of this sampling method. The user starts at an initial and unknown position. As can be seen, because of the increasing uncertainty caused by the accelerometer sensor error (step counter), the position information (samples) is lost step by step with approximate distributions.

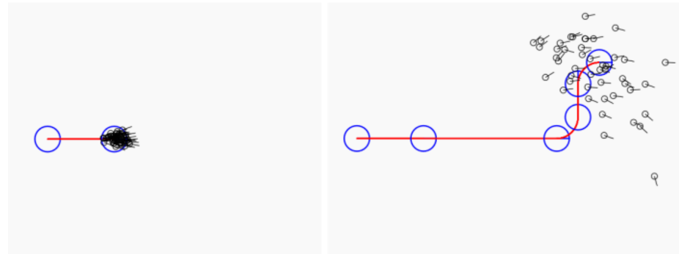

Fig. 1. Sampling-based estimation of user's position without BLE sensor.

B. *Observation update -BLE Sensor Reading*

Sensor readings are incorporated by reweighting the particle set, which is based on the Markov localization implemented by Bayes' rules. In this project, BLE beacons are employed to provide the observed information and redeploy the sample according to the RSSI value.

The RSSI value received by BLE beacons is a power value measured in mW, which can be applied to represent the electromagnetic energy of the transmission medium. According to the pass loss model, a known distance $r0$ and the received power at this distance $P\ (r0)$ have the following relationship [7]:

$$\frac{P(r_0)}{P(r)} = \left(\frac{r}{r_0}\right)^n \qquad (3)$$

where:

r_0 is the known reference distance; and

n is the pass loss coefficient with a range from 2 to 6.

This equation can be extended to a Gaussian distribution with the unit dBm. The equation is [7]:

$$P\ (r)\ =\ P\ (r_0)\ - 10n \times lg\ (r/r_0)\ + X\sigma \qquad (4)$$

where:

$P\ (r)$ is the signal transmit power at distance r (RSSI value);

$P\ (r_0)$ is the received signal strength at reference distance r_0 (normally 1 m); and

$X\sigma$ is a zero mean Gaussian random variable.

Figure 2 shows an example of the RSSI value at 3m.

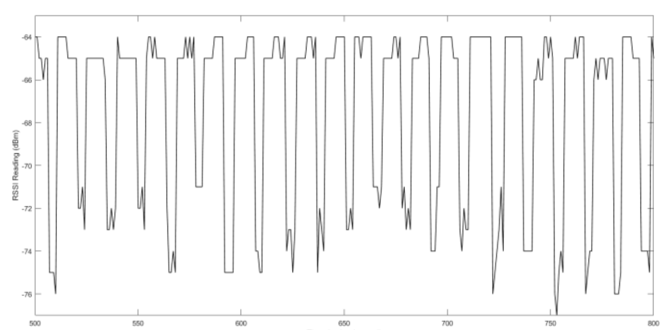

Fig. 2. The received signal strength indication (RSSI) reading under a line of sight (LOS) environment at 3 m.

In a real environment, the RSSI value is dynamic under the observation of the receiving end, which is mobile devices in this study. As can be seen in Eq. 4, a Gaussian distribution is applied to explain this phenomenon. According to the experimental results, in an indoor line-of-sight (LOS) area, a distance of 5 m is normally implemented with a ± 5 to ± 7 dBm fluctuation, while, in an indoor non-LOS area, the value of this fluctuation is decreased to ±3 to ±5 dBm. Consequently, an uncertain observation update is applied when computing the MCL. In such a case, pairs of concentric circles are generated due to the Gaussian distribution. A higher weight value will be given to the particles that are inside the concentric circles. Because the fluctuation error acts as a Gaussian distribution, most of the inserted particles are in the middle of the two circles.

Otherwise, in a complex environment, the accurate determination of the pass loss coefficient n is difficult to achieve. This is because the indoor map information of obstacles, such as tables, chairs, and moving people, is difficult to measure accurately. In addition, moving people will increase the fluctuation of the RSSI value, while fixed obstacles will decrease the standard deviation value. In the paper by Arief et al. (2016) [8], a method was proposed to detect whether the area between the transmitter and receiver is in the LOS or not by analyzing the value of the standard deviation. In this research, the standard deviation analysis from [8] is applied to decrease the uncertainty of the transmitted media determination; however, it still needs to be improved to increase its validity.

Before reweighing the particles using RSSI values, some of the samples were removed for the preparation of redeployment. Let $< l, p >$ denote a sample. The weight factor p and sample $< l, p >$ have the following relationship:

$$p \leftarrow \alpha P(s|l) \tag{5}$$

where:

s is the BLE sensor reading;

$P(s|l)$ is the likelihood of s; and

α is applied to normalise the p value to set $\sum_{n=1}^{N} p_n = 1$ [2].

In this experiment, it is necessary to give some particles random coordinates following each estimation step. Those replaced samples are applied for re-locating the user's position when mobile devices lose their position. Otherwise, it may appear that, in some cases, there is no sample located inside the weighted area, which means that no samples are located near the actual location. Hence, MCL could not re-locate the user's position. By applying these randomly replaced samples, MCL can effectively re-locate the users' position. An example of MCL with 3,000 particles is shown in Fig. 3. Fig. 3(a) shows the initialization of MCL. In Fig. 3(b), particles are crowded by the weighted framework. Finally, in Fig. 3(c), the users' position was successfully localized accurately.

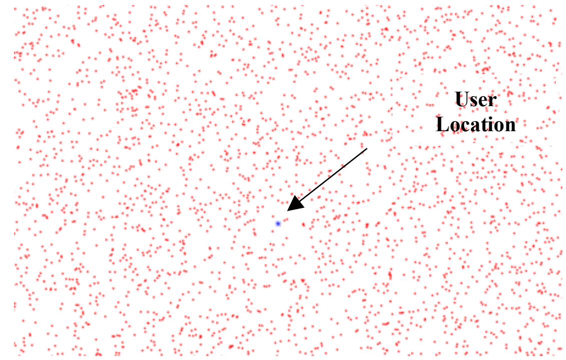

Fig. 3. a) Initialization.

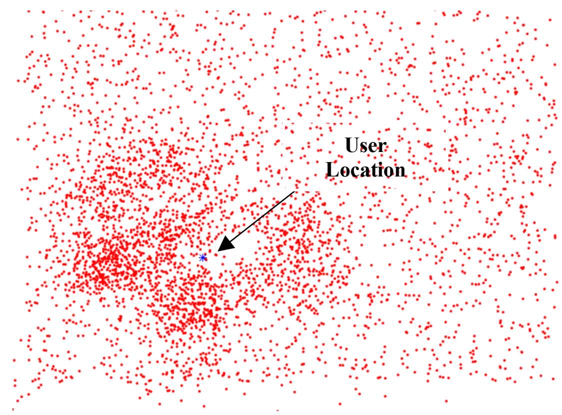

Fig. 3. b) Uncertain location due to symmetry.

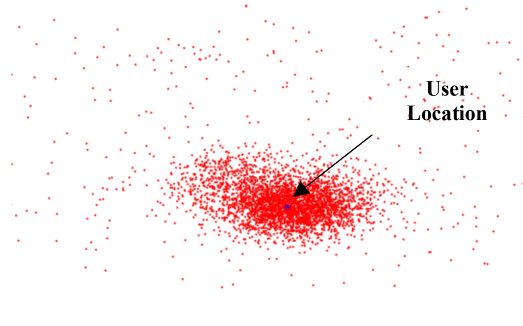

Fig. 3. c) Successful localization with high accuracy.

IV. Experimental Results and Analysis

Two experiments were conducted in an indoor environment that included both LOS and non-LOS cases. The location, shown in Fig. 4, is a laboratory and an office space within Kings Building Campus at the University of Edinburgh. The first experiment was to undertake a comparison between the two methods, MCL and Markov localization. The aim of the second experiment was to compare the performance of MCL and other localization algorithms. Google Nexus 6 device was used in these experiments. Two types of BLE beacons (TI BLE beacons [9] and Estimote BLE beacons [10]) were used to provide RSSI values. These are shown in Fig. 5.

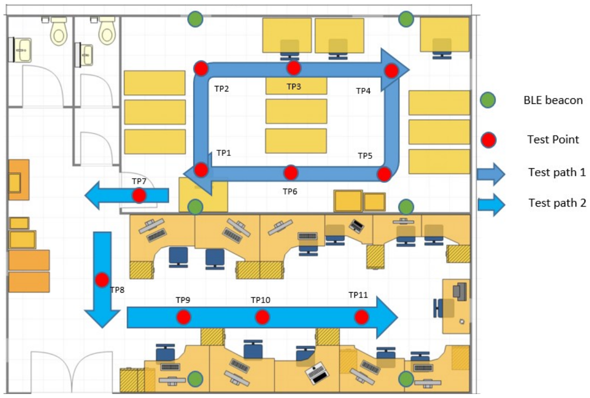

Fig. 4. Experimental environment.

Fig. 5. TI BLE beacon (Top) and Estimote BLE beacon (bottom).

The first experiment has illustrated a difference in performance for MCL, compared to the grid-based Markov localization [2]. Figs. 6 and 7 show the localization error for the grid-based Markov localization with different grid resolutions compared to MCL with various sample sizes, respectively.

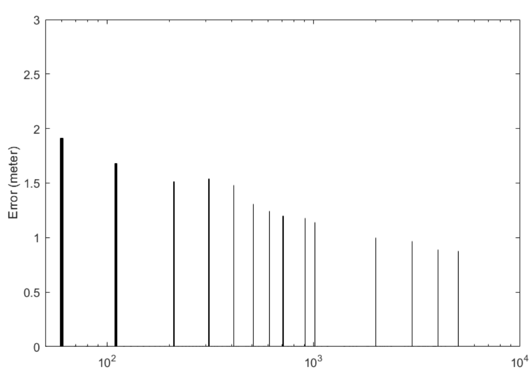

Fig. 6. Average estimation error for MCL with different particles (meter).

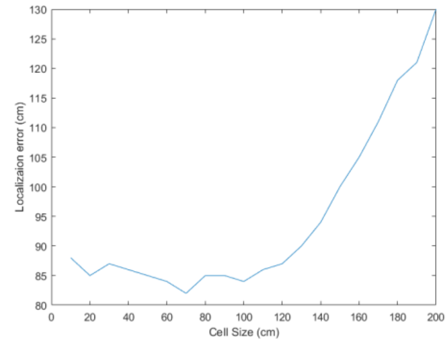

Fig. 7. Average estimation error for Markov localization with different grid resolution.

From Fig. 7, the accuracy of the Markov localization-based algorithm increases with the resolution of the grid. However, as the key factor in determining the accuracy is related to the stability of the RSSI value, a grid resolution of less than 100 cm would not decrease the localization error dramatically. Meanwhile, Markov localization that applies high resolution may not permit updating in real time, even under optimized conditions or when selective update schemes are utilized [2].

Fig. 6 illustrates that the accuracy of MCL increases with the number of applied particles, where the number of particles is less than 1,000. According to the experimental results, the optimal number of particles was between 500 and 3,000. In this situation, the computation of MCL was far less than the grid-based Markov localization algorithm, as the latter requires a large amount of memory (normally millions of grids), whereas obtaining MCL accuracy merely requires thousands of particles, which requires much less memory and computation.

In the second experiment, two methods: a trilateration based positioning algorithm proposed in [11] and the nearest beacon (NB) algorithm [12] were compared with MCL in the same location. A set of results for the estimation error for each test point (TP1-TP11 in Fig. 4) is shown in Table I.

Table I. AVERAGE ERROR OF MCL AND PROPOSED ALGORITHM

Test Point	Average error(Triangulation)	Average error(MCL)	Average error(NB)
1	1.13	0.75	1.68
2	1.02	0.88	1.46
3	1.89	1.61	2.58
4	1.08	1.19	1.81
5	0.99	0.97	1.51
6	1.43	1.39	1.55
7	1.31	1.22	1.75
8	4.38	3.59	5.31
9	3.68	3.01	2.89
10	2.98	2.57	3.01
11	3.59	3.12	2.85

As can be seen in Table I, the localization errors for MCL, NB, and the triangulation algorithm for Test Point 1 to Test Point

6 were lower than those for Test Point 7 to Test Point 11. This is because the transmission path in Test Path 1 is better than Test Path 2 (two BLE beacons are deployed in the next room with a non-LOS propagation path). This result indicates that obstacles such as walls in a non-LOS environment still play a major negative factor in indoor localization systems. However, as the MCL could 'recall' the previous location information, the inaccurate results can be corrected to some degree. Thus, the error of the MCL under a non-LOS environment is also lower than the triangulation algorithm and the NB method.

In addition, the accuracy of MCL is better than the triangulation algorithm, especially in Test Points 3 and 6. In a LOS environment, the average error of MCL is at least 20 cm lower than that of the triangulation algorithm. Meanwhile, the fluctuation of MCL is also lower than the proposed triangulation algorithm. The NB method shows better performance than the triangulation algorithm. However, this method demands a high deployment condition and density of BLE beacons, which means the potential of NB is limited. In addition, the NB-based indoor positioning algorithm is not stable due to the high average value of standard deviation (STD-DIV). The standard deviation of RSSI in different environments is analyzed in [8].

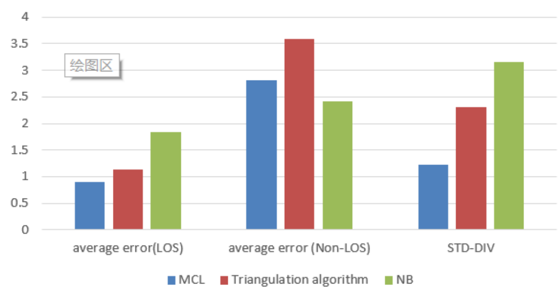

Fig. 8. Comparison between triangulation algorithm and Monte Carlo localization (MCL) algorithm in a line-of-sight (LOS) environment.(Unit: Meter)

In summary, according to the experimental results shown in Fig. 8 in a LOS environment (Path 1), the average error of the MCL is lower than that of the MCL and NB algorithms. Because of the limitation of the proposed triangulation algorithm in [11] and the NB algorithm, the minimum error was difficult to optimize to less than 1 m, while this value for MCL was 80 cm. The second advantage of MCL, compared with other algorithms, was that the requirement of the BLE beacon deployment condition was lower because the user's position could be located more accurately in complex environmental conditions. Moreover, the standard deviation of MCL was small because the fluctuation error caused by fading was reduced by randomly distributed particles. In this case, MCL was more stable than the previously proposed triangulation and NB-based localization system.

V. Conclusion

In this paper, we have presented a technique that utilizes MCL that exploits two sensors, namely, the accelerometer and compass, with commonly deployed BLE beacons to locate people with mobile devices indoors. Two experiments have been conducted in an indoor environment that included both LOS and non-LOS cases to compare the performance of MCL and other indoor positioning algorithms.

The first experiment was to undertake a comparison between the two methods, MCL and Markov localization. Experimental results indicated that the computation of MCL was far less than the grid-based Markov localization algorithm when the same accuracy level was achieved.

In the second experiment, two methods: a trilateration based positioning algorithm proposed in [11] and the NB algorithm [12] were compared with MCL in the same location. Experimental results illustrated that, first, the accuracy of MCL is higher than the proposed triangulation algorithm and NB algorithm in the non-LOS environment. This is because inaccurate results can be corrected by recalling the previous location information. Secondly, in the LOS environment, the standard deviation value of MCL is lower than the proposed triangulation and NB algorithms, which implies that the stability of MCL is better than both the proposed triangulation and NB algorithms.

In future studies, the BLE-based MCL will be used with hybrid sensor readings including Wi-Fi and geomagnetic fields. Different filters will also be applied to de-noise the RSSI value to increase the stability and accuracy of MCL, especially in non LOS environments.

VI. References

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