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A KEY POINT ALGORITHM IMPROVING INDOOR POSITIONING ACCURACY BASED ON BEACONS

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ABSTRACT

The indoor positioning technology in this paper identifies real-time positions of the crew in ships. It can be used to get the regional personnel distribution and find timely locations of accidents. Therefore, the accuracy is very important when estimating positions in ships. This research considers the nearest reference point and beacon in ships as key points for improving the accuracy. We look for three key points to predict a user position. Firstly, KNN algorithm is used to get the first point P1. Secondly, the nearest reference point to the nearest beacon is the second point P2. Finally, the weighted centroid point of nearest beacons is the third point P3. The centroid position of these three key points is the predicted user position. Experimental results show the accuracy has been improved by at most 54%.

Keywords: *Indoor Positioning, Key Point, Reference Point, In-ship Position, Crew Safety*

1. INTRODUCTION

Indoor positioning technology can help ship management personnel check the real-time location distribution of the crew. Once they are in danger, then the technology can also locate the accident location in time, and they can be quickly rescued.

The beacon is an IoT device for short distance communications based on BLE (Bluetooth Low Energy). Its advantages are low power consumption, miniaturization, wide signal range and low cost. Although BLE beacons have the advantages, their performance is not sufficiently good in terms of the indoor positioning accuracy when used in ships such as passenger ships. Larger error ranges of the existing indoor positioning algorithms may cause a serious problem in narrow and complex areas inside of passenger ships. Therefore, it is necessary to develop a novel indoor positioning algorithm with beacons to use in-ship environments.

Most indoor positioning algorithms using infrastructure have two-phase processes: offline and online. In offline phase, a fingerprint map is made with peak or average RSSI values gathered at RPs (Reference Points). In online phase, a user position is actually estimated. The nearest K RPs are looked up in the fingerprint map using the peak or average RSSI values of beacon signals received by a user device. Euclidean distance among the K RPs is calculated to estimate the user position.

Our key point algorithm proposed in this research uses the KNN's estimated position as one of three key points to predict the user position more accurately. It also considers not only the nearest RP but also the nearest beacons and their weighted centroid position. The nearest beacons are selected based on the beacon's distance. The performance of our key point algorithm shows more accurate predicted position than the KNN and the cut-off algorithm [1],[2]. The proposed algorithm can substantially reduce positioning errors because the proposed algorithms is improved by the distance information measured from multiple beacon nodes. The proposed algorithm is suitable for the environment inside the ship.

2. RELATED WORKS

Beacons use BLE technologies. BLE version 5.2 will be announced in the near future. Then the signal condition will be much improved than before and that will lead to the better application to the indoor positioning. Beacons are expected to be mostly used in indoor positioning purpose in the future [2],[3].

[4] presents iBeacon based positioning system, which built as an application running on iOS

platform. A machine learning algorithm called k-Nearest Neighbor (KNN) is applied to extract the most probable user location. [5] considers a typical 802.11ad indoor network with multiple access points (APs). Each AP collects the coarse signal-to-noise ratio of the directional beacons that clients transmit periodically. [6] proposes dynamical and optimal beacon selection method to minimize affections of wireless signal shielding by the static and movable obstructions. However, KNN does not have always the high accuracy of indoor positioning. We need a model to get more accurate position than KNN with smoothing the effects of fluctuation of wireless signals.

D. J. Kim et al. propose the cut-off scheme based on the fingerprint. The cut-off scheme improves the performance in terms of the time complexity and accuracy of the KNN algorithm. The application of the cut-off algorithm in the area of the ship positioning is introduced in detail, and the experimental results are given by simulation [7].

The fingerprint map has the following information: the RSSI (Received Signal Strength Index) of beacons received at each reference point (RP) whose location in the vessel is precisely decided, UUID, and coordinates of the RP. The cut-off scheme eliminates the beacons and RPs from the fingerprint map just before looking up the map to estimate user location. This elimination makes the map smaller, resulting in faster and nicely more accurate estimation possibly done by user device in online phase.

The BLE beacons send signals periodically with the constantly same strength. However, the RSSI values of the signals received by user device are not constant because the signal receiving times are random even though the distances between the beacons and the user device are fixed. Therefore, only one RSSI value is insufficient data for estimating the location.

To overcome this problem, the signals are usually scanned multiple times over a specific period of time. The cut-off scheme uses peak RSSI values of the scanned signals because they are relatively easier to get. Moreover, in the cut-off scheme, relative ranks of the peaks are used as meaningful features when not only making the fingerprint map but also estimating locations.

D. J. Kim et al. also proposed a preliminary indoor positioning cut-off scheme with considering the RPs of the same signal similarity [8]. In the original cut-off scheme, the relative ranks of the peak signal strengths of beacons around the user device are used to estimate the user position. However, when there are several closest RPs with the same signal similarity, the scheme has a weakness of low accuracy. To solve this problem, the paper proposed a weighted cut-off indoor positioning scheme. The weighted cut-off scheme is based on similarity between RSSI peaks of each RP and it improves the estimation accuracy.

However, the KNN and the cut-off algorithms only consider the center of K nearest RPs as the user position. The accuracy of predicted position is not sufficient to apply to the complex indoor environment like ships yet. Specifically, it is difficult to properly apply them to areas of various shapes in passenger ships which consist of narrow aisles, complex steel structures, engine rooms, etc (Figure 1).

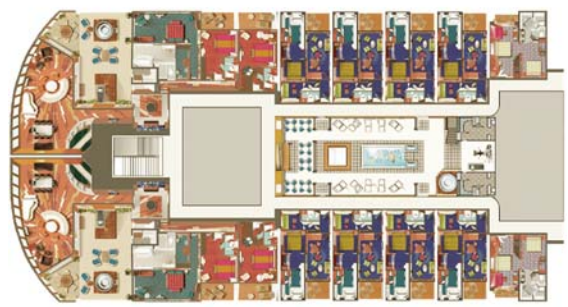

Figure 1: A Floor Plan Of A Passenger Ship ([9])

This requires more precise accuracy of position estimation. To achieve this goal, we have derived a key point algorithm to get better accuracy than the previously proposed ones have got. The key point algorithm considers the nearest RP and the weighted centroid position of the nearest beacons.

We have conducted experiments to compare the accuracy of our key point algorithm proposed in this paper with the previous algorithms. The experimental results show the key point algorithm is much more accurate than the previous algorithms.

3. THE KEY POINT ALGORITHM

Most indoor positioning algorithms using infrastructure are two-step processes: offline and online. In offline phase, a fingerprint map of peak or average RSSI values gathered at RPs is made in advance. In online stage, the nearest K RPs are looked up in the fingerprint map using the peak or

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average RSSI values of beacon signals received by a user device. Euclidean distance among the K RPs is calculated to estimate the user position.

However, the KNN and the cut-off algorithms only consider the center of K nearest RPs as the user position. The accuracy of predicted position is not sufficient to apply to the complicated indoor environments like ships yet.

The number N used in this key point algorithm is different from the number K that is used in the previous KNN and cut-off algorithms. N is the number of beacons whose signals are received by user device. N is not chosen roughly by the algorithm before running as the KNN and the cut-off do.

We propose the key point algorithm in order to improve the KNN and the cut-off algorithms. The algorithm considers the nearest RP and the weighted centroid position of the beacons whose signals are received by user device in the online phase. The distances between beacons and user device are calculated. The strength values of the received signals and other information in signals are also used to get the distance.

```
1. Receive RSSI from nearby beacons
2. Find the peak RSSI received from each beacon
3. Look up fingerprint map to find the RPs storing the same data
   as the beacon data received by user device
4. Find K nearest RPs in the fingerprint map
5. Estimate the center of RPs as user's position
```

Figure 2: KNN Algorithm

```
1. Receive peak RSSI from nearby beacons
2. Apply the KNN to get the key point P1
3. Look up the nearest beacon to the user device based on distance
   and the nearest RP (P2) to the nearest beacon
4. Calculate the weighted centroid position (P3) of the beacons whose
   signals are received
5. Get the centroid position of P1, P2, and P3 as the estimated user
   position
```

Figure 3: The Key Point Algorithm

N is defined in this key point algorithm as the number of beacons whose signals are received by a user device. N is different from K of the previous KNN and cut-off algorithms. K is the number of RPs whose beacons signal patterns are mostly similar to that received by the user device. K is chosen before the algorithms run, for example, K=3.

Firstly, KNN algorithm is executed to get the result of the algorithm that is the estimated user position and the N beacons as well. The N beacons are used in the following steps in the key point algorithm. The KNN's estimated user position is the first key point (P1) in this algorithm.

$$P3_x = \frac{\sum_{i=1}^{N} \frac{1}{\mathrm{distance}_i} \times \mathrm{beacon}_{ix}}{\sum_{i=1}^{N} \frac{1}{\mathrm{distance}_i}} \quad (1)$$

$$P3_y = \frac{\sum_{i=1}^{N} \frac{1}{\mathrm{distance}_i} \times \mathrm{beacon}_{iy}}{\sum_{i=1}^{N} \frac{1}{\mathrm{distance}_i}} \quad (2)$$

In the formulae, beacon_i is one of the N beacons. $\mathrm{distance}_i$ is the distance between beacon_i and the user device. The distance is calculated based on the power regression applied to a known table of distance / RSSI values for a particular device. The formula to get the $\mathrm{distance}_i$ is the follows:

$$\mathrm{distance}_i = A \times \left(\frac{r}{t}\right)^B + C \quad (3)$$

, where r is the peak RSSI of beacon_i measured by the user device. t is the reference RSSI measured one (1) meter away. t is usually given as a fixed value of beacon-specific one. A, B, and C are user device-specific constants. Those values can be found in the android-beacon-library when the user devices are

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android smart phones. In our experiment, the android-beacon-library shows the following values: A is 0.42093, B is 6.9476 and C is 0.54992 [10]

Next, the nearest beacon among the N beacons is calculated based on the peak RSSI values of N beacons. This algorithm considers the nearest RP to the nearest beacon as the second key point (P2). The nearest RP can be found easily using the fingerprint map.

Finally, the key point algorithm finds the third key point (P3) that is the weighted centroid position of the N beacons. The formulae to calculate the weighted centroid position are shown in (1) and (2) [11], where x and y are the horizontal and vertical coordinates, respectively.

Now, we show an example using Figure 4~8. The key point algorithm is now running in a user device. The algorithm runs KNN firstly where estimated user position P1 in Figure 4 is derived and N beacons information. In this example, three beacons' signals are assumed to be received. Then N is 3.

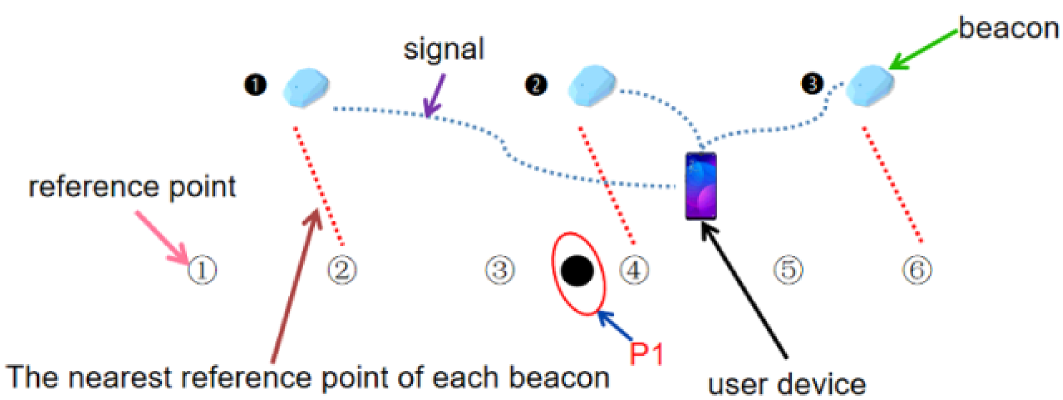

Figure 4: The Key Point Algorithm Processing (1)

Secondly, the key point algorithm finds the nearest beacon among N beacons. The algorithm calculates the distances between the user device and N beacons using the formula (3). Beacon ❷ in Figure 5 is the closest one in this example. The fingerprint map contains RP and beacon position information. So, it is very easy to identify the nearest RP to the nearest beacon. The nearest RP is the second key point in this algorithm. RP ④ is the nearest RP to the nearest beacon ❷ in this example that is used as the second key point P2 (Figure 5).

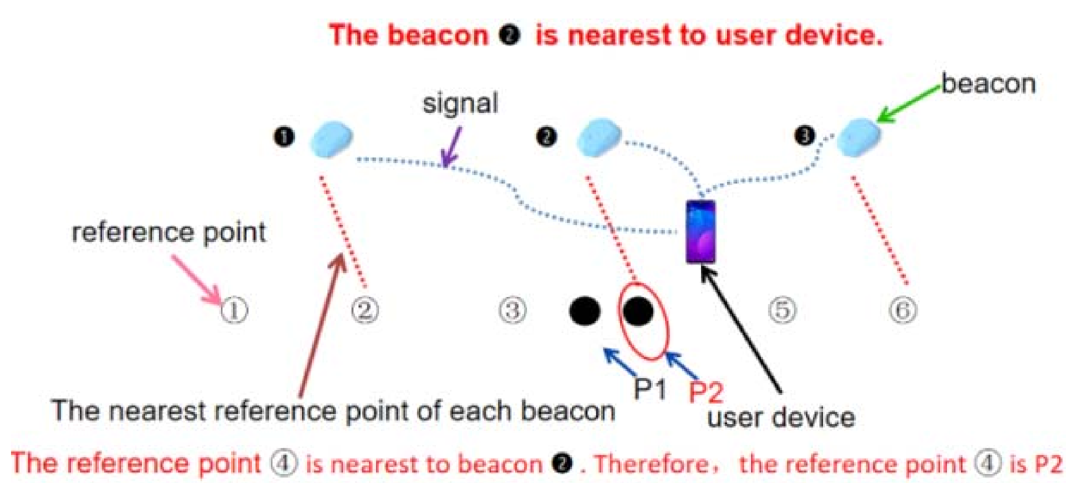

Figure 5: The Key Point Algorithm Processing (2)

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Thirdly, the distance between each beacon and user device is used as a weight for each beacon when the weighted centroid position of the N beacons is calculated. The weight is 1/distance [12]. The weighted centroid position of the N beacons is calculated using the formula (1) and (2). The position is the third key point P3. Figure 6 shows P3 for this example.

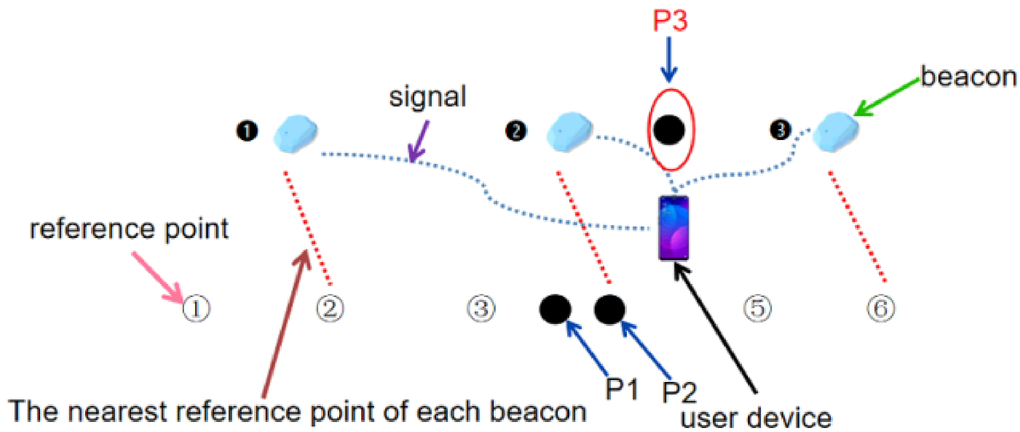

Figure 6: The Key Point Algorithm Processing (3)

Finally, the centroid position of the three key points P1, P2, and P3 is obtained as the estimated user position as in Figure 7.

4. PERFORMANCE EVALUATION

The environment is set up on the third floor of a building at our university. At first, the fingerprint map for this environment is built in the offline phase.

In Figure 8, the symbols Ⓐ ~Ⓜ stand for the positions of beacons, and the numbers 1~21 mean the RPs that are precisely determined and measured in advance. The marks (1) ~ (10) are arbitrarily chosen user locations at which the algorithm in this paper is applied to estimate the user position.

Figure 9 shows the experimental environment in which beacons and RPs are placed in the most proper way. The space between beacons is 10 m, and the space between RPs is 5 m. The distances between the beacons and the RPs are 3 m or 2 m (Figure 9). The test environment is 72 meters wide and 34 meters long. The environment is very similar to the ordinary corridor in ships.

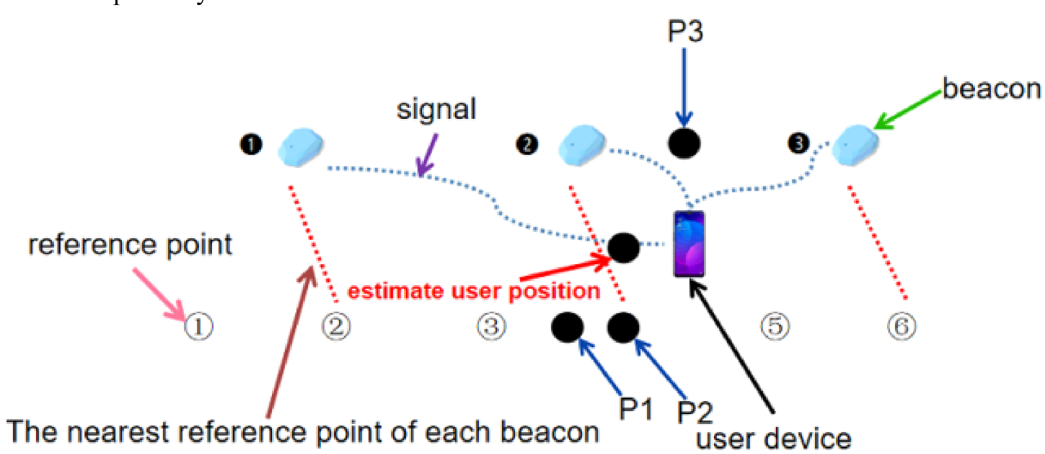

Figure 7: The Key Point Algorithm Processing (4)

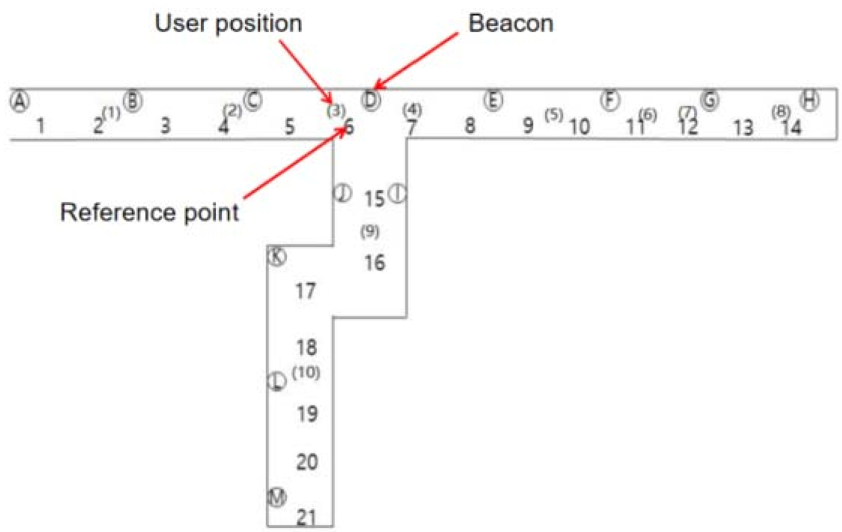

Figure 8: Experimental Environment

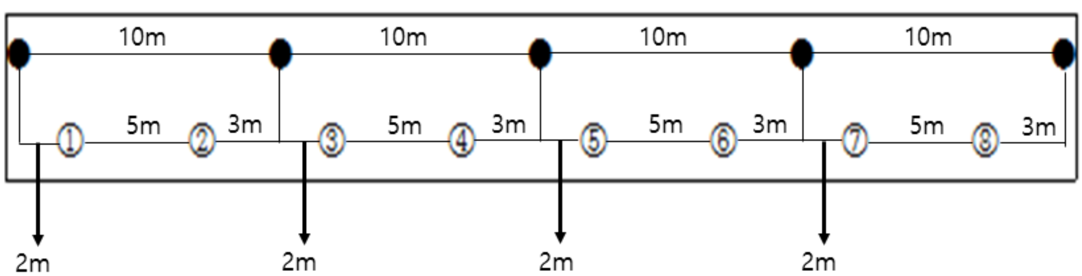

Figure 9: Placement Of Beacons And RPs

We made a table of (beacon, the nearest RP) as Table 1. A fingerprint map for each reference point in this environment is made. That is depicted at Table 2.

In this section, two cases are tested to show the outstanding results of our key point algorithm in terms of accuracy.

Table 1: The Nearest Reference Point Of Each Beacon

Ⓐ	Ⓑ	Ⓒ	Ⓓ	Ⓔ	Ⓕ	Ⓖ	Ⓗ	Ⓘ	Ⓙ	Ⓚ	Ⓛ	Ⓜ
1	2	4	6	8	11	12	14	15	15	17	18	21

Table 2. A Fingerprint Map Constructed At The Testing Environment

Beacon \ RP	Ⓐ	Ⓑ	Ⓒ	Ⓓ	Ⓔ	Ⓕ	Ⓖ	Ⓗ	Ⓘ	Ⓙ	Ⓚ	Ⓛ	Ⓜ
1	-74	-80	-95	100	100	100	100	100	100	100	100	100	100
2	-77	-73	-92	-97	100	100	100	100	100	100	100	100	100
3	-87	-76	-79	-95	100	100	100	100	100	100	100	100	100
4	100	-84	-74	-92	100	100	100	100	100	100	100	100	100

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5	-98	-96	-75	-83	100	100	100	100	-96	100	100	100	100
6	100	100	-78	-73	-96	100	100	100	-79	100	100	100	-85
7	100	100	-87	-74	-82	100	100	100	-85	100	100	100	-87
8	100	100	100	-84	-74	-92	100	-97	100	100	100	100	-93
9	100	100	100	-94	-79	-81	-91	-92	100	100	100	100	100
10	100	100	100	-97	-84	-74	-91	-90	100	100	100	100	100
11	100	100	100	100	-93	-76	-82	-91	100	100	100	100	100
12	100	100	100	100	-95	-83	-71	-86	100	100	100	100	100
13	100	100	100	100	-97	-90	-75	-81	100	100	100	100	100
14	100	100	100	100	100	-92	-83	-73	100	100	100	100	100
15	100	100	100	-83	100	100	100	100	-68	-97	-97	100	-77
16	100	100	100	-92	100	100	100	100	-82	-98	100	-91	-83
17	100	100	100	100	100	100	100	100	-96	-82	-88	-76	-97
18	100	100	100	100	100	100	100	100	-92	-75	-90	-84	100
19	100	100	100	100	100	100	100	100	-98	-76	-80	-93	100
20	100	100	100	100	100	100	100	100	100	-86	-73	-96	100
21	100	100	100	100	100	100	100	100	100	-90	-75	-98	100

1) The first case of estimating the user position (6)

As the first case of our testing, Table 3 shows the real-time peak RSSI values of beacons whose signals are received at the user position (6).

Table 3: Real-Time Peak RSSIs Received By The User Device At (6)

Beacon	Ⓕ	Ⓖ	Ⓗ
Peak RSSI	-78	-93	-84

In this example, N is three (3). The KNN algorithm is firstly applied to get the first key point P1. RP10, RP11 and RP14 are found as the most similar RPs to the real-time peak RSSIs in Table 3. Their fingerprint map is shown in Table 4. Therefore, the first key point P1 is derived by the centroid point of the three RPs like the follows:

Table 4: Part Of Fingerprint Map With Ⓕ, Ⓖ, Ⓗ Beacons Signals

RP / Beacon	Ⓕ	Ⓖ	Ⓗ
10	-84	-74	-91
11	-93	-76	-82
14	100	-92	-83

$$P1_x = \frac{RP10_x + RP11_x + RP14_x}{3} \quad (4)$$

$$P1_y = \frac{RP10_y + RP11_y + RP14_y}{3} \quad (5)$$

According to the peak RSSI values of signals from beacon Ⓕ, Ⓖ and Ⓗ in Table 3, beacon Ⓕ's distance, for instance, is calculated using the formula (3):

$$\text{distance} = 0.42093 \times \left(\frac{-78}{-66}\right)^{6.9476} + 0.54992 = 1.87 \quad (6)$$

Table 5: Distances Between Beacons And The User Device at (6)

Beacon	Ⓕ	Ⓖ	Ⓗ
Distance	1.87 m	4.43 m	5.57 m

Table 5 shows results of the calculation of beacon Ⓕ, Ⓖ and Ⓗ's distances. Due to the instability of the RSSI, KNN does not always find the nearest K RPs. It may make some errors. To reduce the error from the KNN, the key point algorithm finds the nearest beacon to user device

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using the distances. Then, in this example, beacon Ⓕ is found as the nearest beacon.

Now, Table 1 is searched to get the closest RP to beacon Ⓕ, and RP11 is the closest RP to beacon Ⓕ. The nearest RP11 is used as the second key point P2 in this example:

$$P2 = RP11 \tag{7}$$

The reciprocal numbers of the distances in Table 5 are used as weights when calculating the third key point P3. The weighted centroid position of N (=3) beacons is calculated as follows:

$$P3_x = \frac{\frac{1}{1.87} \times F_x + \frac{1}{4.43} \times G_x + \frac{1}{5.57} \times H_x}{\frac{1}{1.87} + \frac{1}{4.43} + \frac{1}{5.57}} \tag{8}$$

$$P3_y = \frac{\frac{1}{1.87} \times F_y + \frac{1}{4.43} \times G_y + \frac{1}{5.57} \times H_y}{\frac{1}{1.87} + \frac{1}{4.43} + \frac{1}{5.57}} \tag{9}$$

This position is the third key point P3.

We have obtained all of the three key points P1, P2 and P3 by the above steps so far. Now, as the final step, we calculate the center position of P1, P2 and P3 like the follows:

$$\text{user position}_x = \frac{P1_x + P2_x + P3_x}{3} = 53.52 \tag{10}$$

$$\text{user position}_y = \frac{P1_y + P2_y + P3_y}{3} = 1.00 \tag{11}$$

The position is the estimated user position (6).

2) The second case of estimating the user position (4)

As the second case, we estimate user position (4) through exactly the same processing procedure as the previous example.

Table 6: Real-Time Peak RSSIs Received By The User Device At (4)

Beacon	Ⓒ	Ⓓ	Ⓘ
Peak RSSI	-93	-79	-88

Table 6 is real-time peak RSSI values of beacons whose signals are received by the user device at user position (4). In this case, N is also three (3) just like the first example. Reference points RP5, RP6 and RP7 are found as the most similar RPs to the peak RSSIs in Table 6.

The part of the fingerprint map with the same beacons is shown in Table 7.

Table 7: Part Of Fingerprint Map With Ⓒ, Ⓓ, Ⓘ Beacons Signals

Beacon \ RP	Ⓒ	Ⓓ	Ⓘ
5	-75	-83	-96
6	-78	-73	-79
7	-87	-74	-85

It is also the same processing as the first case, the first key point P1 is derived by the centroid point of the three RPs like the follows:

$$P1_x = \frac{RP5_x + RP6_x + RP7_x}{3} \tag{12}$$

$$P1_y = \frac{RP5_y + RP6_y + RP7_y}{3} \tag{13}$$

According to the RSSI values of beacon Ⓒ, Ⓓ and Ⓘ in Table 6, the distance between the user device and each beacon is calculated. Beacon Ⓓ's distance, for instance, is calculated according to formula (3) like the follows:

$$\text{distance} = 0.42093 \times \left(\frac{-79}{-66}\right)^{6.9476} + 0.54992 = 2.03 \tag{14}$$

Table 8: Distances Between Beacons And User Device At (4)

Beacon	Ⓒ	Ⓓ	Ⓘ
Distance	6.31 m	2.03 m	5.04 m

Table 8 shows the results of calculation of beacon Ⓒ, Ⓓ and Ⓘ's distances. Then, we can find the RP6 as the nearest RP around the nearest beacon Ⓓ from the Table 1. The nearest RP6 is used as the key point P2 in this example:

$$P2 = RP6 \tag{15}$$

Then, the reciprocal numbers of the distances in Table 8 are used as weights when calculating the third key point P3. The weighted centroid position of N (=3) beacons is calculated as follows:

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$$P3_x = \frac{\frac{1}{6.31} \times F_x + \frac{1}{2.03} \times G_x + \frac{1}{5.04} \times H_x}{\frac{1}{6.31} + \frac{1}{2.03} + \frac{1}{5.04}} \quad (16)$$

$$P3_y = \frac{\frac{1}{6.31} \times F_y + \frac{1}{2.03} \times G_y + \frac{1}{5.04} \times H_y}{\frac{1}{6.31} + \frac{1}{2.03} + \frac{1}{5.04}} \quad (17)$$

We have successfully obtained three key points P1, P2 and P3 by the above steps. As the final step, we calculate the center position of P1, P2, and P3 as the estimated user position (4) as follows:

$$\text{user position}_x = \frac{P1_x + P2_x + P3_x}{3} = 29.12 \quad (18)$$

$$\text{user position}_y = \frac{P1_y + P2_y + P3_y}{3} = 1.77 \quad (19)$$

Three KNN, the cut-off, and the key point algorithms are compared in terms of the accuracy. Figure 10 shows the results. In the figure, the horizontal line shows the actual user positions where the tests are performed. The vertical line shows errors between the estimated user positions and actual positions in meter.

The KNN algorithm shows the average error of 3.05 m. The weighted preliminary cut-off scheme based on similarity between peaks of RSSI algorithm shows the average error of 3.8 m. The key point algorithm shows the average error of 1.74 m. The key point algorithm improves the estimation accuracy by 54% over the weighted preliminary cut-off and 43% over the KNN approximately.

Due to the instability of RSSI, the nearest RPs found by KNN is not accurate. The key point algorithm can reduce the error of KNN by more steps. The key point algorithm shows the average errors of all locations are reduced or the same as the previous algorithms except user position (4).

The maximum error of the key point algorithm is happened at position (4). The reason is mainly from the positions of the beacons that cannot be arranged linearly in this test environment. Beacon Ⓓ is the actual nearest beacon to user position (4). But the nearest RP to beacon Ⓓ is RP6. That means, even though the key point algorithm finds the nearest beacon correctly, that may not be the actual nearest RP to user device.

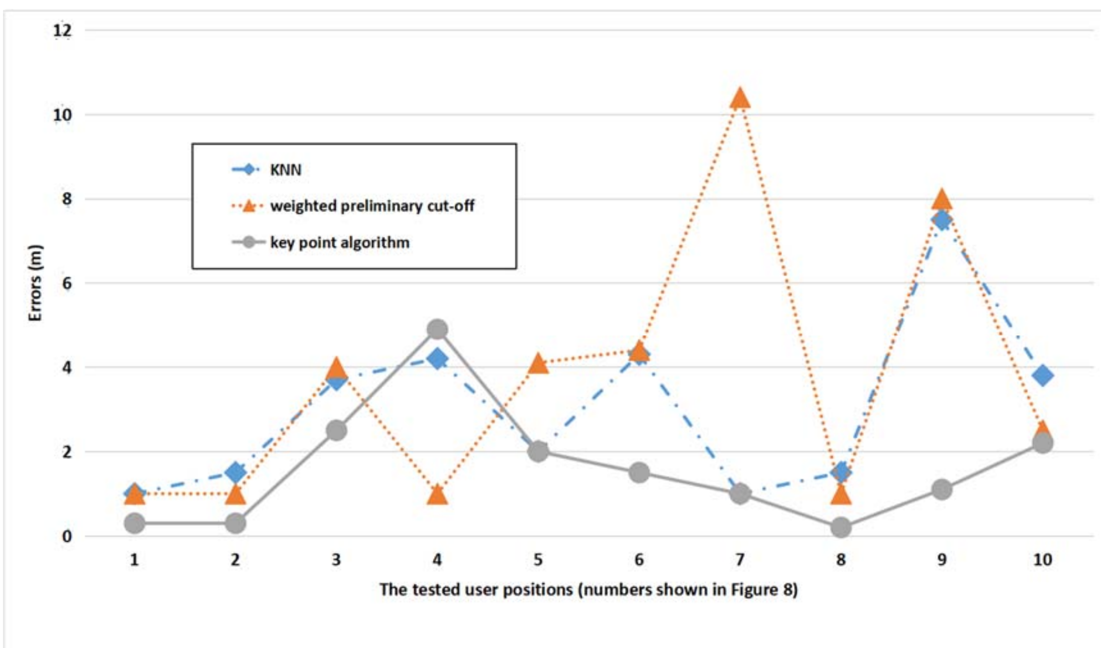

Figure 10: Comparing Key Point Algorithm With The Previous Schemes

That may cause the worse estimation. One more beacon needs to be installed around RP7 in this case. We have found the placement of beacons is very important to get the more accurate results. Other reasons are the space at the position (4) is relatively narrow-shaped, and the signals are easily interfered. Those causes result in the relatively higher errors in distances of beacons.

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5. CONCLUSION

The higher indoor positioning accuracy derived from the key point algorithm proposed in this research may help ship management personnel arrange crew work plan reasonably, locate the accident location precisely, and reduce the difficulty of prompt rescue.

The beacon has many advantages, but its performance is not sufficiently good when it is used for the indoor positioning in terms of accuracy. Specifically, most previous techniques are hard to apply appropriately to in-ship environments such as passenger ships which consist of narrow aisle, complex steel structure, engine room, etc. The only way to use beacons with indoor positioning algorithm properly in such a specific environment is that the algorithm should be improved to get more precise accuracy. We have derived a key point algorithm to get better accuracy than the previously proposed ones. The key point algorithm considers the nearest RP and the weighted centroid position of the nearest beacons.

The key point algorithm identifies three key points P1, P2, and P3 using the KNN, the nearest RP and weighted centroid position of N beacons whose signals are received, respectively. The centroid position of the three key points is the estimated user position. The second and third steps leads to a big improvement of the accuracy dramatically.

The experimental results show the proposed algorithm improves the estimation accuracy by at most 54% approximately. We have found the placement of beacons is very important to get the more accurate results. Other reasons are the space at the position (4) is relatively narrow-shaped, and the signals are easily interfered. Those causes result in the relatively higher errors in distances of beacons.

Future study on the more precise beacon placement is needed to get the higher accuracy evenly at any user position. The novel Bluetooth version 5 technology should be adapted to get the accuracy of less than 1 meter [3].

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