Research Journal of Information Technology, 2012
ISSN 1815-7432 / DOI: 10.3923/rjit.2012.


# Combined K-Nearest Neighbors and Fuzzy Logic Indoor Localization Technique for Wireless Sensor Network

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## ABSTRACT

The use of Wireless Sensor Network (WSN) has been growing each year. One of the more popular uses of WSN is object tracking. There are many localization techniques available for WSN. Some techniques have high accuracy, while the complexity is higher than others as well. K-Nearest Neighbors (KNN) has high accuracy in indoor environment. The accuracy of KNN could be improved by combining it with fuzzy logic. Fuzzy logic will allow the algorithm complexity to stay low. This study presents the results of experiment where the combined KNN and fuzzy logic localization technique (fuzzy KNN) improved the accuracy of KNN. When compared to other localization techniques from the literature with high accuracy, Multilateration and fuzzy logic indoor positioning system fuzzy KNN performed better in terms of accuracy and algorithm complexity.

**Key words:** Indoor localization, fuzzy logic, wireless sensor network, k nearest neighbors

## INTRODUCTION

Wireless Sensor Network (WSN) has been developing very rapidly in recent times. The functionalities of the sensors increase, while the cost and the power consumption decrease (Wu, 2005). These changes led to WSN being used in various applications (Sabri *et al.*, 2011; Wang *et al.*, 2011). One of the areas of the development of WSN is object tracking. There are many components that need to be designed and developed to create a tracking system. The main component of each tracking application is localization. Without good localization algorithm, the tracking application will not be of good use.

There are many localization techniques available in literature for WSN (Hightower *et al.*, 2000; Fukuju *et al.*, 2003; Ni *et al.*, 2003; Priyantha, 2005; Kuang and Shao, 2006; Chen *et al.*, 2010). But every technique was designed for a specific type of application to be used in (Li *et al.*, 2010; Xu and Zi-Shu, 2011). Some techniques have very good accuracy, some consume energy efficiently, some use fast performance algorithms, which requires less time to execute. Accuracy is the most important performance metric for localization (Liu *et al.*, 2007). However, there are other metrics, which also play high role in localization, complexity is one of them. Sometimes improving the real-time accuracy of localization involves using complex mathematical formulas and computations, which increases the complexity. Complexity can be the hardware complexity or the algorithm complexity. In this study, we consider only the complexity of the algorithm. We measure it by calculating the CPU time. CPU time is a measure of how fast a processor executes the algorithm. If the algorithm is very complex, it will take processor longer time to execute it which will result in higher energy consumption and shorter battery life. The accuracy is measured by calculating the Root Mean Square Deviation (RMSD) (Wang *et al*., 2009; Das *et al*., 2011).

Fingerprinting is one of the famous methods of indoor localization (Yim *et al*., 2008). K-Nearest Neighbors (KNN) (Bahl and Padmanabhan, 2000) is one of the fingerprinting-based algorithms, which has high accuracy indoors (Subhan *et al*., 2011). Fuzzy logic, first introduced by (Akpolat, 2005), is also one of the developing techniques that are used for localization. Fuzzy logic not only helps to reduce the complexity of the algorithm (Teuber *et al*., 2006), it also increases the accuracy of localization, which (Chen *et al*., 2010) claim their Fuzzy Logic Indoor Positioning System (FLIPS) does. FLIPS has a good indoor accuracy (Rozyyev *et al*., 2011). In the same study they compare FLIPS with Multilateration. Multilateration is the signal propagation model based technique which has high accuracy (Wang *et al*., 2009).

The objectives of this paper is to design a combined localization technique, by combining KNN algorithm with fuzzy logic to improve the accuracy of KNN, to compare the accuracy and the complexity of the combined technique (Fuzzy KNN) with Multilateration and FLIPS through experiment.

**K-nearest neighbors:** The process of localization is divided into two stages, offline and online. During the offline stage the fingerprints at different locations are taken. Fingerprints represent the Received Signal Strength Indicator (RSSI) values measured from each reference node or Access Point (AP). Based on these measurements the lookup table is constructed.

During the online stage, the fingerprints of the k nodes which have the closest RSSI values to the ones measured for the target node, are found. These k nodes are the k Nearest Neighbors (NNs). NNs are determined by comparing the Euclidean distance between the RSSI values.

The Euclidean Distance can be calculated according to Eq. 1 (Xiangyang and Zhang, 2009):

$$d = \sqrt{\sum_{i=1}^{n} (RSSI_{Ti} - RSSI_i)^2} \tag{1}$$

where, d is the Euclidean distance, $RSSI_{Ti}$ is the RSSI value from online stage, $RSSI_i$ is the RSSI value from offline stage.

The location of the target is calculated by averaging the coordinates of NNs. Since the range of the RSSI does not vary much for the same position and does not change with time, KNN is highly accurate method for localization. However, the accuracy depends on the offline stage readings. If the fingerprints are taken at about 1 $m^2$ area per point, the accuracy is high (Yim *et al*., 2008).

**Fuzzy logic indoor positioning system:** FLIPS is an indoor positioning system that uses Fuzzy Inference Engine (FIS) to estimate the location of the target. In their experiment, the authors prove that it gives more accuracy than commonly used triangulation method. RSSI is used to calculate the distance of the target from the reference nodes, or APs. The distance is used by FIS to calculate the weight which is used in the calculation of the target coordinates. The weight values vary from 0 to 1. The further the reference node is from the target, the smaller the weight.

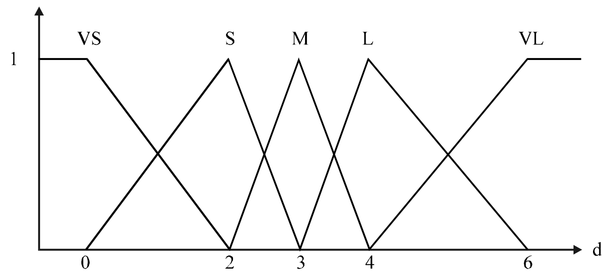


Fig. 1: Input membership function of FLIPS

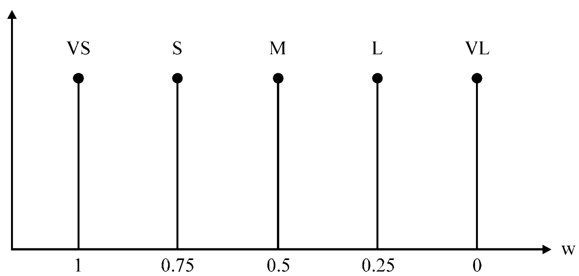


Fig. 2: Output membership function of FLIPS

The input membership function which accepts distance between AP and target, is illustrated in Fig. 1.

The output membership function which determines the weight for the distance input, is shown in Fig. 2.

The final coordinates, ($x_e$, $y_e$), of the target are calculated by Eq. 2 and 3, respectively:

$$x_e = \frac{x_1.w_1 + \ldots + x_N.w_N}{\sum_{i=1}^{N} w_i} \quad (2)$$

$$y_e = \frac{y_1.w_1 + \ldots + y_N.w_N}{\sum_{i=1}^{N} w_i} \quad (3)$$

where, $w_i$ is the weight for the ith reference node and N is the number of APs.

**Multilateration:** Multilateration is one of the variations of lateration techniques. The difference between trilateration (Motlagh *et al*., 2009) is that Multilateration uses more than three APs to locate the target. Given that ($x_1$, $y_1$), ($x_2$, $y_2$), ($x_3$, $y_3$) and ($x_4$, $y_4$) are the coordinates of reference points A, B, C and D, respectively. $R_1$, $R_2$, $R_3$ and $R_4$ are the distances between the target node T and APs A, B, C and D, respectively. $R_1$, $R_2$, $R_3$ and $R_4$ are also the radiuses of the three circles with origins at A, B, C and D, respectively. With these known, Eq. 4 can be used to calculate the coordinates of T, ($x_T$, $y_T$) using Multilateration with 4 APs:

$$\begin{cases}(x_1 - x_T)^2 + (y_1 - y_T)^2 = R_1^2 \\ (x_2 - x_T)^2 + (y_2 - y_T)^2 = R_2^2 \\ (x_3 - x_T)^2 + (y_3 - y_T)^2 = R_3^2 \\ (x_4 - x_T)^2 + (y_4 - y_T)^2 = R_4^2\end{cases} \tag{4}$$

The system of equations in Eq. 4 can be rewritten for n APs as shown in Eq. 5:

$$\begin{cases}(x_1 - x_T)^2 + (y_1 - y_T)^2 = R_1^2 \\ (x_2 - x_T)^2 + (y_2 - y_T)^2 = R_2^2 \\ \vdots \\ (x_n - x_T)^2 + (y_n - y_T)^2 = R_n^2\end{cases} \tag{5}$$

## SYSTEM MODEL

The localization technique using KNN algorithm calculates the location of the target by averaging the coordinates of the NNs. When averaging the coordinates of NNs, the coordinates of the target are calculated to be somewhere in the middle of the NNs. The distance between the target and NNs would not matter. However, if the target is very close to one of the NNs, its coordinates should be calculated accordingly. The coordinates of the closest NNs should have more weight in the calculation of the target location. Another technique that was described is FLIPS, which calculates the weight according to the distance between the target node and the AP using fuzzy logic. This weight is then used to estimate the location of the target. The weight calculation technique of FLIPS can be used with KNN to improve the accuracy. The Euclidean distance between the target and NNs will determine the weight which will be used to calculate the final coordinates of the target. The weight calculation formula was adopted from FLIPS.

The system model for fuzzy KNN is divided into two stages, offline stage and online stage. The objective of the offline stage is to measure the fingerprints with RSSI values at various positions across the experiment area. The online stage is for the real-time localization experiment. System model for indoor localization using fuzzy KNN is illustrated in Fig. 3.

**Euclidean distance:** The Euclidean distance is calculated between all fingerprints in the lookup table and RSSI values of the target measured in online stage.

Lookup table shows the mean RSSI values at each fingerprint position for each AP. This table serves as a database during the online stage. If there are 25 fingerprints across the area, the lookup table will be as shown in Table 1.

RSSI values of the target will be stored as shown in Table 2.

The Euclidean distance, d, between the readings from the APs in online stage and offline stage can be calculated from Eq. 6:

$$d = \sqrt{\sum_{i=1}^{n} (RSSI_{Ti} - RSSI_i)^2} \tag{6}$$

where, $RSSI_{Ti}$ is the RSSI value measured during the online stage, $RSSI_i$ is the RSSI value of the fingerprint in the lookup table, i is the index of APs, n is the total number of APs which is equal to 4.

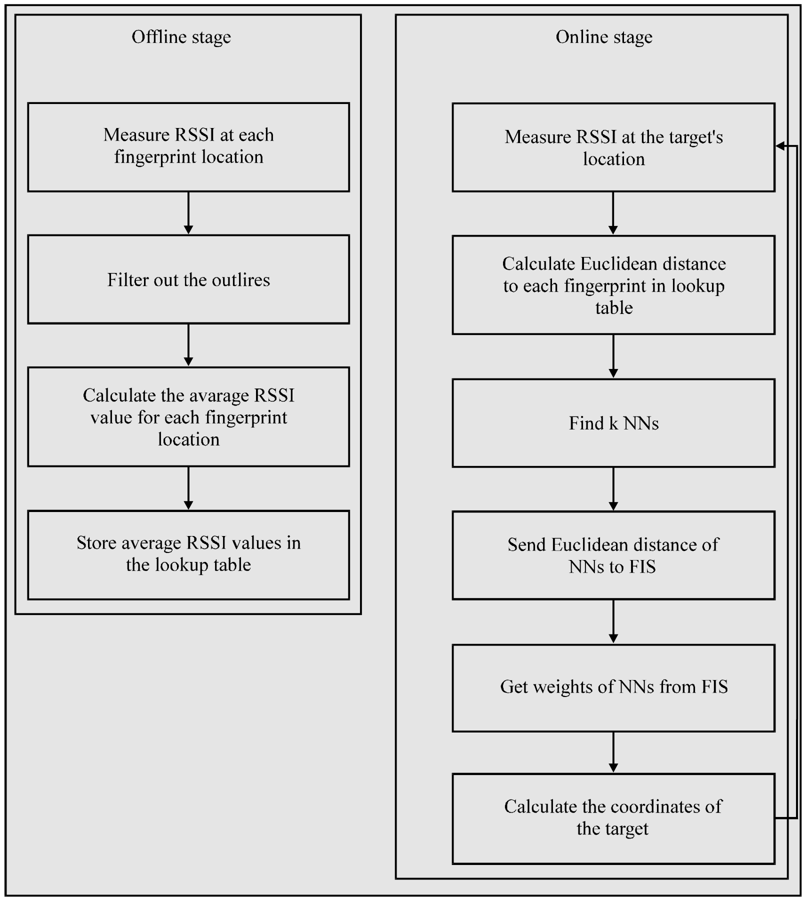


Fig. 3: System model

Table 1: Lookup Table

| | Coordinates | | | | | |
|---|---|---|---|---|---|---|
| Fingerprint | X | Y | AP1 | AP2 | AP3 | AP4 |
| A | $x_A$ | $y_A$ | $RSSI_{A1}$ | $RSSI_{A2}$ | $RSSI_{A3}$ | $RSSI_{A4}$ |
| B | $x_B$ | $y_B$ | $RSSI_{B1}$ | $RSSI_{B2}$ | $RSSI_{B3}$ | $RSSI_{B4}$ |
| C | $x_C$ | $y_C$ | $RSSI_{C1}$ | $RSSI_{C2}$ | $RSSI_{C3}$ | $RSSI_{C4}$ |
| ... | ... | ... | ... | ... | ... | ... |
| Y | $x_Y$ | $y_Y$ | $RSSI_{Y1}$ | $RSSI_{Y2}$ | $RSSI_{Y3}$ | $RSSI_{Y4}$ |

Table 2: RSSI measured during online stage

| $AP_1$ | $AP_2$ | $AP_3$ | $AP_4$ |
|---|---|---|---|
| $RSSI_{T1}$ | $RSSI_{T2}$ | $RSSI_{T3}$ | $RSSI_{T4}$ |

**Fuzzy inference system:** The membership functions for fuzzy KNN were adopted from FLIPS. In fuzzy KNN, Sugeno-type inference is preferred to Mamdani-type inference used by authors in FLIPS. For the output membership function, instead of Mamdani-singletons, Sugeno-constants were used. There are five output constants with values 0, 0.25, 0.5, 0.75 and 1, which have the linguistic values of VerySmall, Small, Medium, Large and VeryLarge, respectively.

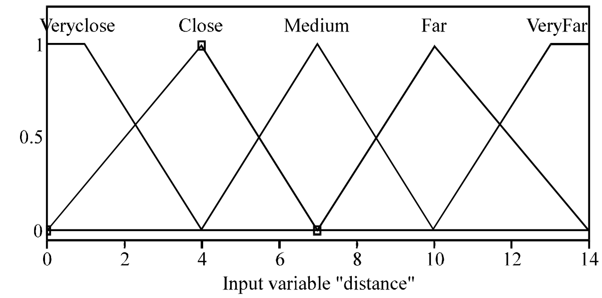


Fig. 4: Input membership function of fuzzy KNN

The input membership functions are shown in Fig. 4.
There are five rules in FIS which are:

- If (distance is VeryClose) then (weight is VeryLarge)
- If (distance is Close) then (weight is Large)
- If (distance is Medium) then (weight is Medium)
- If (distance is Far) then (weight is Small) and
- If (distance is VeryFar) then (weight is VerySmall)

The weight, calculated in FIS and the reference coordinates of k NNs will be used to calculate the coordinates of the target. The coordinates of the target, ($x_T$, $y_T$), are calculated using Eq. 7 and 8. These were adopted from FLIPS:

$$x_T = \frac{\sum_{i=1}^{k} w_i . x_i}{\sum_{i=1}^{k} w_i} \tag{7}$$

$$y_T = \frac{\sum_{i=1}^{k} w_i . y_i}{\sum_{i=1}^{k} w_i} \tag{8}$$

where, $w_i$ is the weight of ith NN, $x_i$ and $y_i$ are the x and y coordinates of ith NN, respectively and k is the number of NNs.

## Fuzzy KNN algorithm:

Algorithm: Localization using fuzzy KNN

**Initialization:**

| | |
|---|---|
| T[2]:double | //Coordinates of the Target T |
| rssi[4]:int | //RSS values from AP1, AP2, AP3, AP4 |
| RSS:int | //Measured RSS value |

```
F[25][4]:int                //RSS values of Fingerprints
FC[25][2]:double            //Coordinates of Fingerprints
NN[4][2]:double             //Coordinates of NNs
Nnd[4]:double               //Euclidean distances of RSS between T and NNs
w[4]:double                 //Weight from the distance between T and NNs, measured by FIS
d[25]:double                //Euclidean distances between T's and Fingerprints' RSS values
A=34                        //Initial signal strength at 1 m distance
n=2.375                     //Propagation coefficient
sumWC[4]:double             //Sum of weight * coordinate (x or y)
sumW[4]:double              //Sum of weights
BEGIN
1. for (i=1; i<= 4; i++)
Measure RSS value from APs to T: rssi[i] = RSS;
2. for (i=1; i<= 25; i++)
Calculate the Euclidean distance between RSS values of T and Fingerprints:
d[i] = sqrt( (rssi[1] – F[i][1])^2 + (rssi[2] – F[i][2])^2 + (rssi[3] – F[i][3])^2 + (rssi[4] – F[i][4])^2 );
3. Find 4 NNs:
for (i=1; i<= 25; i++) {
for (j =1; j<= 4; j++) {
IF(d[i] == min(4)) {
NN[j][1] = FC[i][1];
NN[j][2] = FC[i][2];
NNd[j] = d[i];
}
}
4. Send NNd[] to FIS
5. Calculate w[] from NNd[]: done by FIS
6. Get w[] from FIS
7. for (i=1;i<= 4; i++) {
    7.1. Calculate sum of (weight * X coordinate):sumWC[i] += w[i] * NN[i][1];
    7.2. Calculate sum of weights:sumW[i] += w[i];
}
8. T[1] = sumWC / sumW;
9. for (i=1;i<= 4; i++) {
    9.1. Calculate sum of (weight * Y coordinate):sumWC[i] += w[i] * NN[i][2];
    9.2. Calculate sum of weights:sumW[i] += w[i];
}
10. T[2] = sumWC / sumW;
END
```

**Experiment setup:** The experiment was conducted in the lab, in a 5×5 m area. To increase the accuracy of fingerprint measurements, the fingerprints were measured at 1×1 m grids per fingerprint. Figure 5 shows the locations of fingerprints in the experiment area.

As can be seen from Fig. 5, four 3Com Office Connect Wireless 11 g APs (3Com Corporation, 2003) were used to measure RSSI during the experiment. InSSIDer 2.0 (http://www.metageek.net/products/inssider/), an open-source software, which helps users to monitor the network activity and manage the network connections, was used to read the RSSI values.

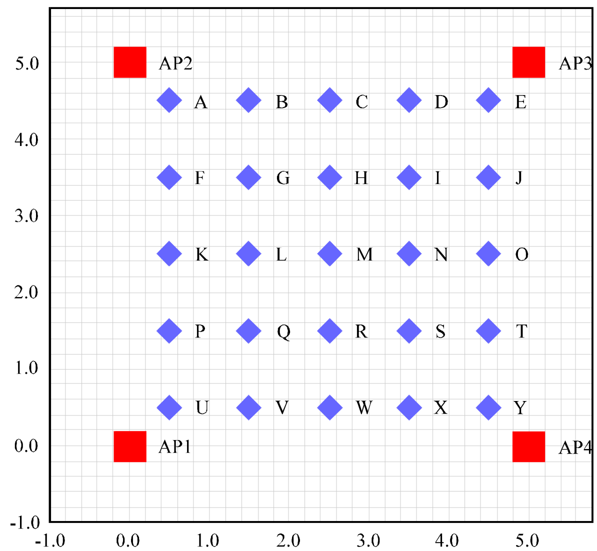


Fig. 5: Placement of fingerprints

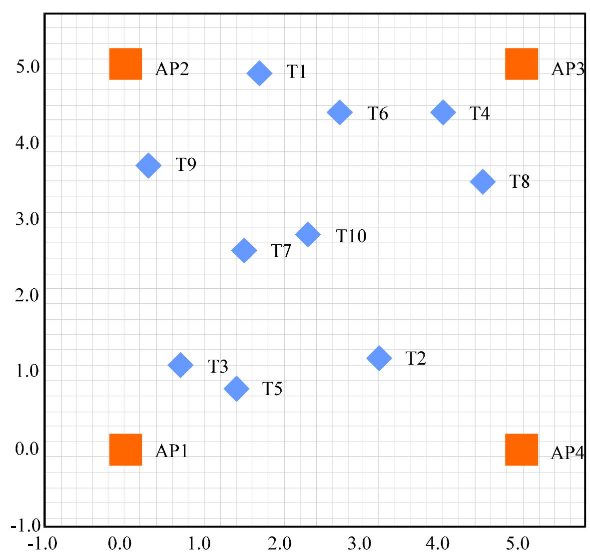


Fig. 6: Placement of target nodes

Figure 6 illustrates the locations of target nodes during the experiment.

## EXPERIMENT RESULTS

The accuracy of fuzzy KNN was compared to the accuracy of original KNN to see whether the combination with fuzzy logic improved the accuracy of KNN. Fig. 7 shows that the accuracy of fuzzy KNN for different number of NNs is better than the original KNN.

Fuzzy KNN was also compared to Multilateration and FLIPS based on accuracy and complexity. In both of the comparisons fuzzy KNN performs better than both Multilateration and FLIPS. This can be seen in Fig. 8 and 9.

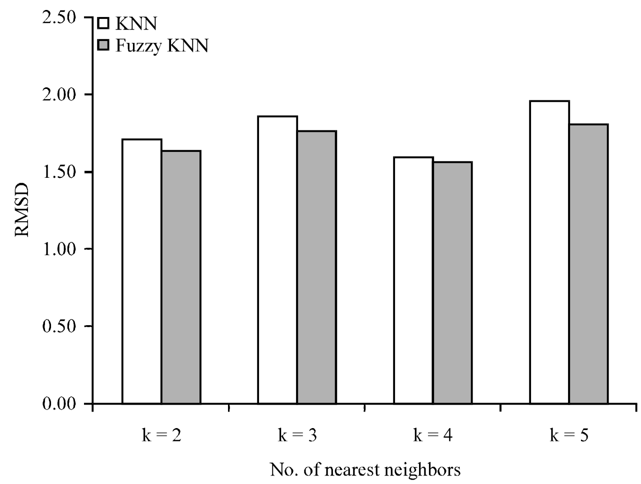


Fig. 7: Accuracy of KNN and fuzzy KNN

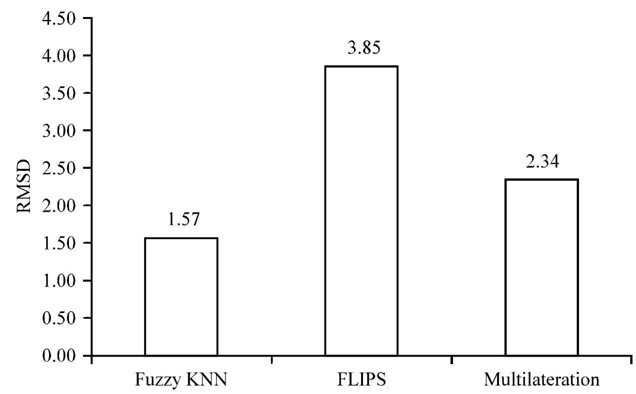


Fig. 8: The accuracy of localization techniques

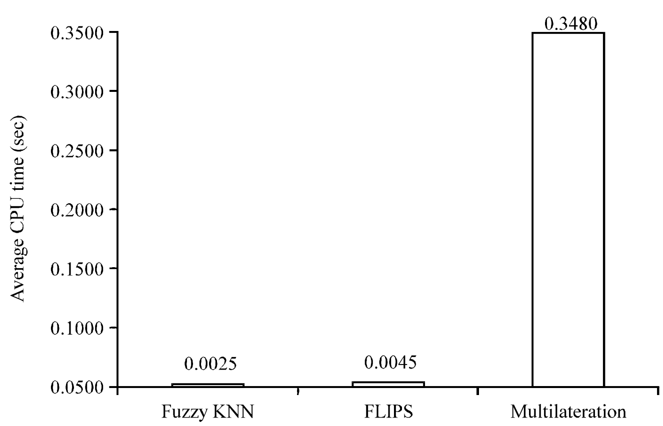


Fig. 9: Complexity of localization techniques

From Fig. 9 it can be seen than the complexity of Multilateration is much higher than the other two techniques. This could be due to the number of formulas used and the complexity of solving the system of quadratic formulas with two unknowns.

## CONCLUSION

This study presented localization technique, which is the combination of KNN algorithm and fuzzy Logic. The accuracy of KNN is very high indoors and Multilateration is very widely used method which also has high accuracy both indoors and outdoors. By weighting the Euclidean distance between the NNs, the NN which is nearest to the target gets higher value in the calculation of the target coordinates. And using fuzzy Logic to calculate the weight kept the complexity of the algorithm low. The experiment using Wi-Fi APs proved that fuzzy KNN is more accurate than both Multilateration and FLIPS, it also has lower complexity than both of these techniques.

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