Future Generation Computer Systems 89 (2018) 335–348

Contents lists available at ScienceDirect

Future Generation Computer Systems

journal homepage: www.elsevier.com/locate/fgcs

Smartphone based intelligent indoor positioning using fuzzy logic

F. Orujov [a], R. Maskeliūnas [a], R. Damaševičius [a], Wei Wei [b,c,d,*], Ye Li [c,d]

[a] Centre of Real Time Computer Systems, Kaunas University of Technology, Kaunas, Lithuania
[b] School of Computer Science and Engineering, Xi'an University of Technology, Xi'an 710048, China
[c] Qilu University of Technology (Shandong Academy of Sciences), China
[d] Shandong provincial Key Laboratory of Computer Network, China

H I G H L I G H T S

- An experimental investigation of indoor positioning algorithms.
- A fuzzy logic based scheme to select the best localization algorithm depending upon the size of the room, the number of beacons available and the strength of the RSSI signal.
- Evaluation of indoor positioning in real world conditions (office building).

A R T I C L E I N F O

Article history:
Received 9 March 2018
Received in revised form 8 May 2018
Accepted 18 June 2018
Available online 5 July 2018

Keywords:
Indoor positioning
Bluetooth Low Energy (BLE) beacons
Fuzzy logic

A B S T R A C T

Smartphones are indispensable helpers of people in their daily routine, including functions that serve the disabled or aged people finding their outdoor location. This paper presents an experimental investigation of the indoor positioning algorithms based on the signal strength received from the Bluetooth Low Energy (BLE) beacons. We have implemented and compared several positioning algorithms (Proximity Localization, Centroid Localization, Weighted Centroid Localization, Weight-Compensated Weighted Centroid Localization Based on RSSI, Fingerprinting and Trilateration Localization). We also proposed and implemented a fuzzy logic based scheme to select the most fitting algorithm depending upon the size of the room, the number of beacons available and the strength of the signal. We have evaluated our scheme in real-world conditions (office building). The experimental results show that the algorithm of fingerprinting localization is the most suitable one. Finally, we propose a fuzzy logic system for the selection of an indoor localization algorithm based on the size of the room, the number of available beacons, and the strength of RSSI signal.

1. Introduction

Accurate positioning of people in public indoor environments using low cost solutions such as Wi-Fi and Bluetooth Low Energy (BLE) technologies or smartphone-based solutions is difficult due to surrounding conditions that affect the spreading of the signal making the determination of location prone to both noise and crowdedness of the environment. The problem is especially relevant to people with special needs such as aged, impaired or disabled, which may need special care and attention when moving around in large public buildings. United Nations reports that about 15% of the global population has some form of disability [1]. Therefore, the development of public use infrastructure and technologies that support accessibility, active and assisted living is important, especially in the context of developing Smart Cities [2]. Indoor Positioning Systems (IPS) have been previously applied in different environments such as transportation hubs [3], stores and supermarkets [4], libraries [5], museums [6], car parking lots [7], underground construction sites [8], and hospitals [9]. The business potential for such system is growing, and the predicted value of IPS services for 2020 is USD 10 billion [10], therefore, the research in the development of practical and affordable IPS systems is relevant, as has been emphasized by several recent reviews on the latest development in this domain [11,12].

Specifically designed traditional indoor location systems naturally allow achieving a high accuracy of localization, but also requiring a high cost of deployment [13]. The use of Wi-Fi technology for indoor positioning is challenging primarily due to removal or change of position of the access points (AP), other devices working in the same signal band, variations in internet traffic, signal availability and propagation effects, variability and noise of received strength signal (RSS) [14].

* Corresponding author at: School of Computer Science and Engineering, Xi'an University of Technology, Xi'an 710048, China.
E-mail address: weiwei@xaut.edu.cn (W. Wei).

https://doi.org/10.1016/j.future.2018.06.030
0167-739X/

Solutions involving the use of RGB-D sensors from the Kinect platform, in combination with WiFi-based positioning systems (WPSs) allow tracking people in indoor environments, but require a large number of devices to avoid occlusions [15]. Other solutions such as based on ultrasound sensors [16] have low precision due to noise interference. Smartphones with an addition of internal and external sensors, so called Beacons, often running on low powered Bluetooth protocol [17], or even over WiFi [18], allow doing this affordably and with an acceptable error rates. BLE technology [19] has emerged as one of leading choices in the field, as it ensures fine positioning. This technology is supported by contemporary mobile devices such as smartphones and tablets [20], and allows for providing additional services [21], ensures low power consumption [22], and the costs are reasonable.

The utilization of phone internal sensors, which is shown in [23], allows to achieve and effective indoor localization [24], moderating the drift in data estimations with a particle filter [25], in addition to Kalman filter [26], extended Kalman filter [27] and Least Square-Support Vector Machines (LS-SVM) for detecting indoor movement states [28]. Fusion of smartphone sensor measurement with those of wireless signals can provide reliability and robustness for different positioning scenarios [29,30]. Ma et al. [31] uses an improved Euclidean distance and joint probability to calculate intermediate results from several fingerprints, and then weighted fusion is applied to calculate the final value by weighting the Euclidean distances by their variances. Chen et al. [32] proposes a smartphone based localization method based on sensor fusion problem, but uses a Kalman filter instead of a particle filter. Liu [33] offers a similar method based on fine graining of features. Practical implementation usually suffers from inherent localization errors introduced by low-cost sensors and the complexity of human movements in real-world scenarios [34]. However, by using a location estimation model, an error can be reduced to around 2 m [35]. Camera and image processing can be utilized as well by the combination of an image recognition system with a distance estimation algorithm [36]. Lin et al. [37] use the proximity localization beforehand dividing the room into areas. The proposed method uses time-based Received Signal Strength Indication (RSSI) filtering to find the nearest beacon. Er Rida et al. [38] used the trilateration localization to determine the location. They suggest to install beacons on the ceiling as a grid. Zhu et al. [39] used the fusion method of trilateration and centroid. They suggested to establish the Beacons as an equilateral triangle. Bai et al. [40] used the fingerprint localization to determine the indoor location, suggesting to use with RSSI data from Wi-Fi and Bluetooth. Ma et al. [41] offered the RSSI ranking based fingerprinting method that uses Kendall Tau Correlation Coefficient (KTCC) to correlate a new signal position with the signal strength ranking of multiple iBeacon devices. Zou et al. [42] proposed the iBeacon technology based BlueDetect scheme for indoor–outdoor location detection and provision of seamless location based services (LBS) running on Android mobile devices. The scheme is supported by Wi-Fi and Global Positioning System (GPS) technologies in semi-indoor environments. Alshami et al. [43] proposed WLAN fingerprinting enhanced with RSS certainty, and used K-Nearest Neighbor (KNN) and Artificial Neural Network (ANN) classification for dynamic and multi-floor environments that account for people presence. Pei et al. [44] proposed training the fingerprint database for mobile indoor localization via crowd sensing. Xu et al. [45] proposed the Bayesian inference based KNN (BKNN) algorithm for improved localization robust to signal multipath propagation and environmental interference.

As indoor localization has to deal with noisy and uncertain Wi-Fi or Bluetooth signals, the fuzzy logic based approaches are often employed to address the uncertainty of the position measurements. Specifically, known methods such as formal concept analysis [46], symbolic signatures [47], vector quantization [48], or c-means clustering [49] can be fuzzified to address uncertainty, imprecise data or incomplete information.

The aim of this paper is to investigate the indoor positioning algorithms using BLE beacons. The objectives of the research are the following:

1. Investigate the broadcasting range of BLE beacon in a real world environment. What is the effect of the distance between the mobile device and the beacon on the signal strength? How does the orientation of mobile devices affect the signal strength?
2. Investigate, which indoor positioning algorithms using Bluetooth Smart Beacons show the highest accuracy.
3. Propose the fuzzy logic based scheme for the selection of most suitable indoor positioning algorithms based on room size, beacon number and signal strength factors.

The proposed approach is motivated by the ambiguity and uncertainety of the conditions in which BLE beacons are used, which provides a reason for the introduction and use of the fuzzy logic system.

2. Methods and algorithms

This section describes the model of the environment in which the indoor positioning algorithms are used. A positioned facility that receives the BLE signals is called agent. In this case, the "agent" means a smartphone. The model of environment includes several beacons and an agent. Without loss of generality, the space is regarded as a flat environment in which there may be interferences from walls — floors, diverse signals, etc. Fig. 1 illustrates an example of arrangement of the agent and the beacons in the plane, where B_i is ith beacon, (X_i, Y_i) is the Cartesian coordinates of ith beacon, P_i is the RSS from the ith beacon, A is the agent, (X_A, Y_A) is the Cartesian coordinates of the agent, and N is the number of beacons.

We describe the algorithms used to detect location of an agent using the power signals emitted by a few beacons in the room below.

The proximity algorithm [50] assigns to the agent the coordinates of the beacon, which emits the signal with greatest power. The algorithm is the simplest from a computational point of view. For instance, if four beacons are located in the room and the highest power signal $P1$ has been received from $B1$, then the agent is assigned the coordinates of $B1$ beacon. The advantages of this algorithm include the ease of implementation due to the low computational complexity and the necessity to know only the location of the beacons. The obvious disadvantage is very low accuracy. This algorithm is useful as an initial approximation, the result of which can be used for a different algorithm.

The Centroid algorithm [51] calculates the geometric center of the plane figure formed by multiple beacons. In this case, the coordinates of the agent are calculated as a linear combination of the coordinates of the beacons. Location of the agent is determined by the following formulas:

$$\begin{cases} X_A = \dfrac{1}{N}\displaystyle\sum_{i=1}^{N} X_i \\ Y_A = \dfrac{1}{N}\displaystyle\sum_{i=1}^{N} Y_i \end{cases} \tag{1}$$

here X_A, Y_A are Cartesian coordinates of agent; X_i, Y_i are the Cartesian coordinates of ith beacon; and N is the number of beacons.

The advantages of this algorithm include the ease of implementation, the complexity of computing is low and one needs to know only the location of the beacons. The obvious disadvantage is low accuracy. As information about the power of the signal is not taken into account, consequently, the error may reach the range of the signal broadcast by the beacon.

Weighted Centroid algorithm [52] is an improved version of the Centroid algorithm. The coordinates of the agent are calculated as a linear combination of the coordinates of the beacons based on signal power as a weight factor.

$$\begin{cases} X_A = \dfrac{\sum_{i=1}^{N} w_i \cdot x_i}{\sum_{j=1}^{N} w_j} \\ Y_A = \dfrac{\sum_{i=1}^{N} w_i \cdot y_i}{\sum_{j=1}^{N} w_j} \end{cases} \quad w_i = \frac{1}{d_i^g} \tag{2}$$

where X_A, Y_A Cartesian coordinates of agent; X_i, Y_i is the Cartesian coordinates of ith beacon; w_i - weight characteristics; d_i - refers to the distance between agent and ith beacon and g to the degree which determines the contribution of beacon; N is the number of beacons.

The advantages of this algorithm include the ease of implementation and the need to know only the location of the beacons. The disadvantage is the dependence on the number of beacons simultaneously available to the agent. The more signals of known beacons the agent receives, the higher accuracy of calculation of his location will be.

The major improvement of Weighted Centroid Localization algorithm based on calculation of RSSI (WCWCL-RSSI) is presented in [53]. The method needs no calculation of distance, which makes it faster and more accurate than an original WCL method. The characteristic of weight is calculated as follows:

$$W_i = \frac{w_i}{\sum_{j=1}^{N} w_j} = \frac{\sqrt{\left(10^{\frac{P_i}{10}}\right)^g}}{\sum_{j=1}^{N} \sqrt{\left(10^{\frac{P_j}{10}}\right)^g}} \tag{3}$$

here X_A, Y_A are Cartesian coordinates of agent; X_i, Yi are the Cartesian coordinates of ith beacon; w_i-weight characteristics; P_i is the RSS from the ith beacon, g is the degree that defines contribution of beacon; and N is the number of beacons.

Furthermore, the authors suggested to improve the weight characteristic by increasing the weight of the closest transmitter:

$$w_i' = w_i \cdot N^{2 \cdot w_i} \tag{4}$$

here w_i - weight characteristics;P_i is the RSS from the ith beacon and g is the degree that defines contribution of the beacon.

Determination of the agent's position is calculated using the formula:

$$\begin{cases} X_A = \sum_{i=1}^{N} W_i X_i \\ Y_A = \sum_{i=1}^{N} W_i Y_i \end{cases} \tag{5}$$

The Trilateration algorithm [54] is based on a comparison of the distances from three (3) beacons to calculate the agent's location. The signal strengths of the beacons are decreasing exponentially, depending on the distance between the transmitter and the receiver. Thus, this dependency can be considered as a function of distance. The distance estimated by signal strength is presented as a circle with a radius around the beacon. The intersection of the broadcasting radiuses created by the three beacons provides a location of a receiver. The advantages of this algorithm are low computational complexity and the necessity to know only the location of the beacons. The algorithm is very reliable, and its application include GPS and cellular networks.

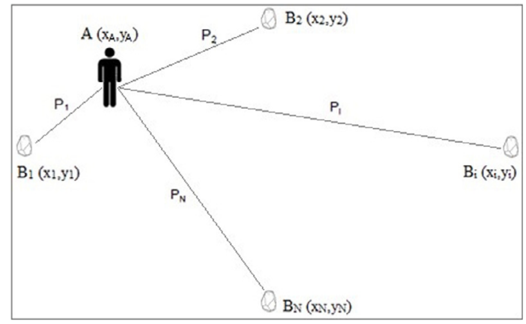

Fig. 1. Model of the environment.

The Fingerprinting algorithm [55–58] (see Fig. 2) has two stages: data acquisition and location positioning. The data acquisition process acquires the signals, and forms a database of fingerprints. Determination of the position is required to find the nearest pre-planned location point, which is recorded in the database. For this purpose, the data incoming in real time from beacons has to be compared with the data stored in the database by calculating distance metrics. The algorithms of Nearest Neighbors (NN) and k—Nearest Neighbors (KNN) are used in the [24,25]. NN is a special case of k—NN, when $k = 1$, where k is the number of nearest pre-planned location points. To achieve good accuracy, a larger number of pre-planned location points is needed, e.g., Chi et al. [59] suggested using 4-NN. This implies a number of drawbacks: the need for a large amount of time for the configuration database; permanent reconfiguration due to changes in the environment; and high computational complexity of $O(k \times M)$, where M is the number of records in the database.

3. Experiment 1: Measurement of signal strength

In this section, we perform the experimental comparison of the indoor positioning algorithms presented in Section 2 in real-world (office building) conditions in terms of their accuracy. We describe hardware and software used, the experimental setting, calibration of beacons, and the results in more detail below.

Hardware and software. The smartphones starting with iPhone 4 (or newer) and running on iOS 7 operating system (or newer) support the iBeacon technology. The Apple iPhone 5 was used in the development and testing of software and in the execution of experiments (see Fig. 3).

For signal transmission, we use the Estimote beacons. At least four (4) beacons should be used in the experiments. Apple smartphones and tablets have to be updated to iOS 7 or later versions of iOS as the iBeacon technology is available from the 7th version of the operating system. The configuration of beacons is stored in RAM and the device's file system. The data are stored in the file system are in text and uses the comma-separated values (CSV) format [60–62].

Experimental setting. The testing was conducted in a variety of areas such as office rooms (see Fig. 4) and corridors in office buildings. Initially, all Bluetooth devices, which could affect the test results have been removed from the rooms. No measurable variation in positioning accuracy was detected. All measurements were performed in the realistic scenario without removing any present electronic devices [63–65].

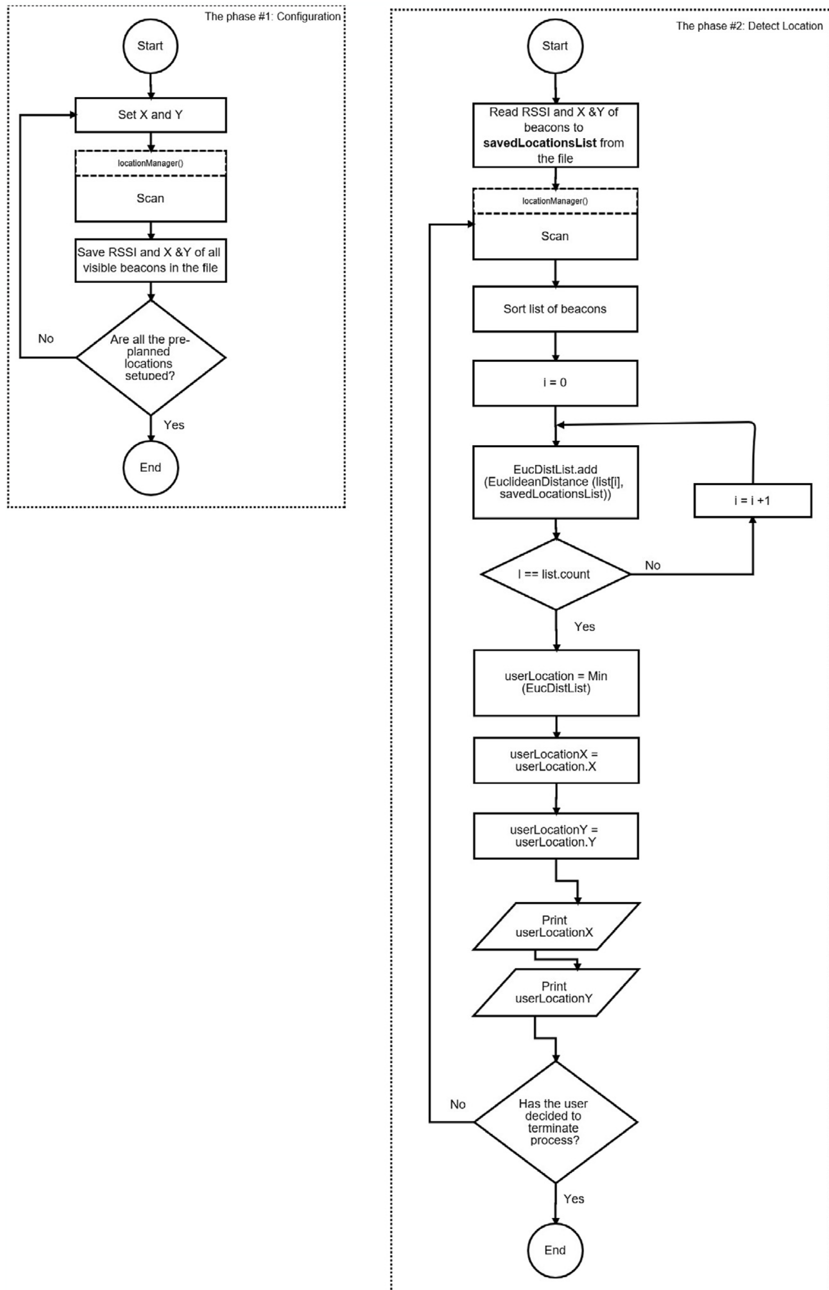

Fig. 2. The Fingerprinting algorithm.

Calibration of the estimotes. The strength of the signal transmitted from the Estimote beacon was measured experimentally using the Estimote beacon and the non-metallic measuring tape were set on a plastic surface (see Fig. 5). In the experiment, we used the Proximity Location Algorithm. The values of RSSI and Accuracy are collected. The initial distance between the smartphone and the beacon was taken no more than a few millimeters. Further measurements were carried by increasing the distance from the beacon for every half a meter with rotation of the smartphone on its axis. The data collection lasted no more than 2 min. For more accurate results, the experiment was repeated using another Estimote beacon [66–68].

Upon completion of these experiments, we have obtained the following results. Fig. 6 depicts the relationships between the distance and the strength of the signal transmitted from the beacon. The data are average values of the results that have been obtained from the series of experiments conducted in different rooms [69]. The graph shows the dependence of the signal strength on the distance of the smartphone with the corresponding settings:

1. Transmit power (Tx) is 4 dBm (Strong)
2. Transmit power (Tx) is −12 dBm (Weak)

With a distance of 0–1.5 m, indications of signals on a smartphone, with different settings of transmit power, differ considerably, almost by 20 dB. If the distance exceeds 1.5 m, the difference in indications of signals start disappearing. With a distance of more than 3 m, indications of signals tend to fluctuate from −77 to −80 dBm. Therefore, when aiming at efficient performance of positioning algorithms, the data obtained from beacons should only be used within a distance of 3 m because if the mentioned distance is exceeded, the differences in data will disappear and the data becomes useless. The manufacturer ensures that beacons can

Fig. 3. Smartphone used in the experiment.

Fig. 4. Photo of one of the rooms used for experiments.

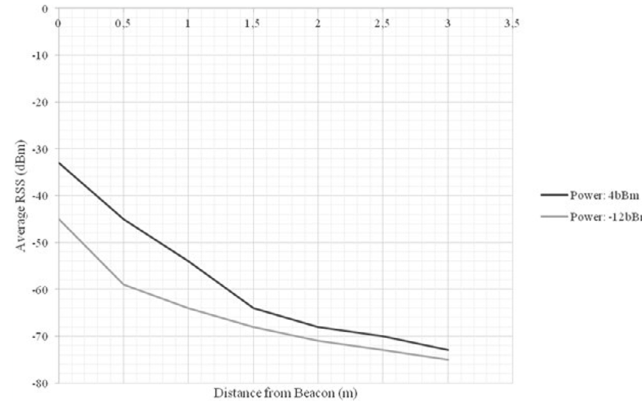

Fig. 6. Relationships between the distance and the strength of the signal.

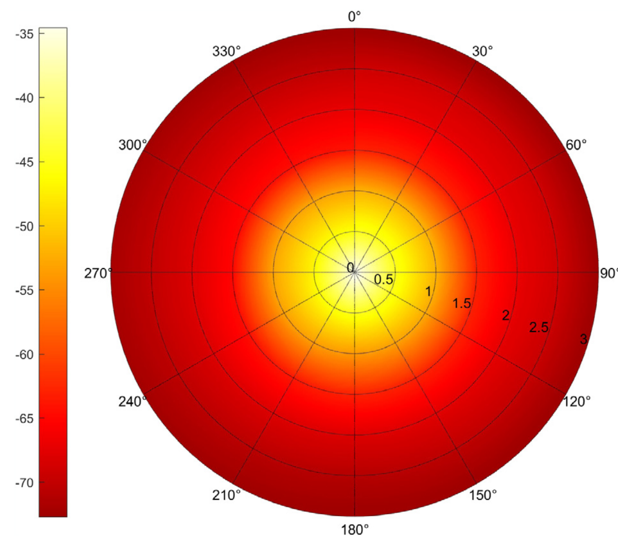

Fig. 7. The average dependence of the signal from the rotation of the smartphone.

broadcast signals within a distance of 50 m at their highest settings. However, the experiments have proved that under real conditions beacons can broadcast signals just within a distance of 10 m.

In the rotation experiment, we have established that the rotation of the smartphone does not affect the RSS that is shown in Fig. 7. The experiment was conducted in portrait mode with a fixed value of X and Z axes, and a smartphone rotated by 90°, 180° and 270°. The signal measurements taken within a distance of up to 3 m prove that rotation of the smartphone does not have a marked influence on the strength of a signal (std. deviation of signal strength values does not exceed 1°).

Fig. 8 shows the average error in calculating the distance between the smartphone and the Estimote beacon. The calculations of the distance are performed by the iOS operating system. However, the formula for computing the distance is not known (it is factory-set).

Within a distance of 0–1 m, the error of distance calculation is limited to the maximum of 0.3 m; however, within a distance of 1–2.5 m, the maximum error is 0.5 m. It should be noted that current indicators fluctuate over time. In general, an error in the calculation is small. However, if an obstacle is located between a smartphone and a beacon, an error value can grow significantly.

See the results of measurements under different conditions in Tables 1–5.

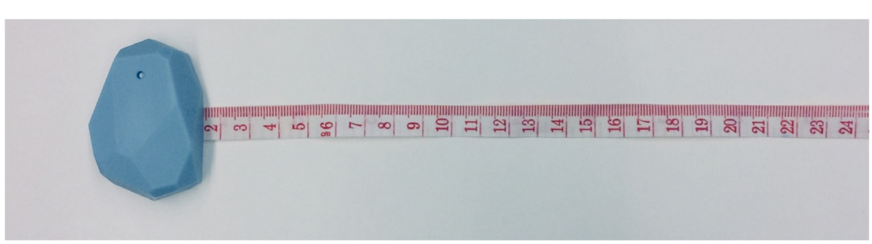

Fig. 5. The experiment measuring the strength of Bluetooth beacon signal.

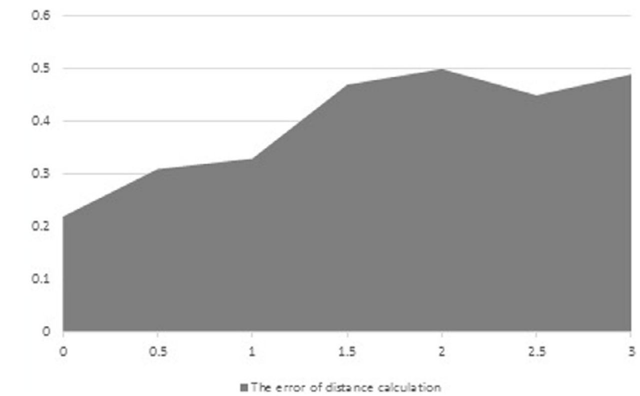

Fig. 8. The relationships between the distance and the strength of the signal.

Table 1
Results of experiment with non-covered beacon (signal strength, dB).

	0 m	0.5 m	1 m	1.5 m	2 m	2.5 m	3 m
0°	−34	−45	−52	−63	−67	−69	−73
90°	−33	−45	−54	−63	−68	−71	−73
180°	−35	−47	−53	−65	−68	−70	−72
270°	−34	−46	−53	−64	−67	−70	−73

Table 2
Results of experiment with beacon fully covered with a ceramic plate (signal strength, dB).

	0 m	0.5 m	1 m	1.5 m	2 m	2.5 m	3 m
0°	−45	−63	−71	−75	−81	−84	−87
90°	−44	−63	−70	−76	−80	−83	−86
180°	−45	−62	−72	−74	−82	−84	−88
270°	−44	−64	−69	−75	−81	−82	−87

Table 3
Results of experiment with beacon partially covered with a ceramic hood (inside a vase type chamber) (signal strength, dB).

	0 m	0.5 m	1 m	1.5 m	2 m	2.5 m	3 m
0°	−51	−62	−70	−74	−83	−87	−90
90°	−48	−61	−71	−75	−82	−86	−91
180°	−50	−63	−71	−74	−81	−87	−88
270°	−49	−62	−70	−75	−82	−88	−89

Table 4
Results of experiment with beacon partially covered with a metallic plate (non-faraday cage, covered from one side) (signal strength, dB).

	0 m	0.5 m	1 m	1.5 m	2 m	2.5 m	3 m
0°	–	−71	−76	−81	−88	−94	−96
90°	–	−73	−75	−80	−90	−93	−96
180°	–	−71	−78	−82	−89	−92	−97
270°	–	−70	−77	−82	−91	−93	−96

Table 5
Results of experiment with a human body as an obstacle between beacon and smartphone (signal strength, dB).

	0 m	0.5 m	1 m	1.5 m	2 m	2.5 m	3 m
0°	–	−73	−76	−82	−91	−93	−96
90°	–	−74	−75	−81	−90	−92	−97
180°	–	−71	−75	−81	−90	−93	−96
270°	–	−72	−74	−82	−91	−94	−95

4. Experiment 2: Measurement of indoor position

Research aims. The primary purpose of this experiment is to measure the signal strength of the Bluetooth beacon and the effect of their changes. The objectives of the experiment are clarifying the following questions:

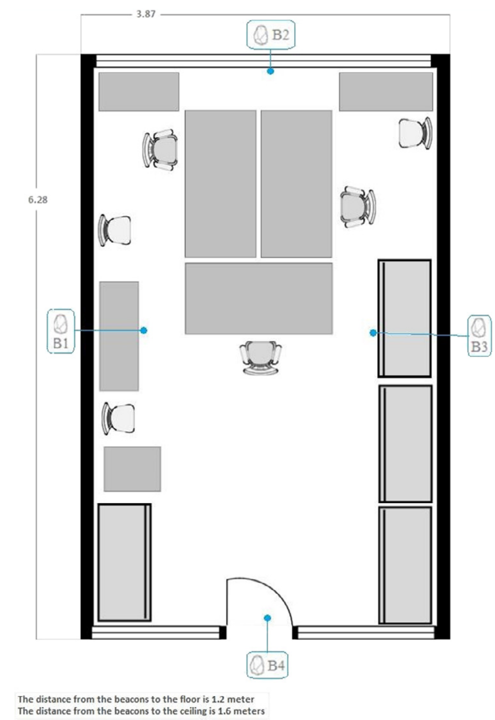

Fig. 9. Schematic representation of the room to test the algorithms.

Table 6
Coordinates of beacons.

Beacons	Coordinates (in meters)
B1	(0.00, 3.14)
B2	(1.93, 6.28)
B3	(3.87, 3.14)
B4	(1.93, 0.00)

Table 7
Coordinates of beacon groups.

Name of beacon groups	Real location coordinates (in meters)
Red	(1.93,3.14)
Green	(0.88, 5.20)
Blue	(0.88, 5.20)

- What types of indoor positioning algorithms are suitable for which types of rooms?
- What is the minimum amount of BLE beacons should be used depending on the type of algorithm?
- What is the optimal place for the installation beacons to minimize the impact of obstacles?

Experimental setting. The experiment was conducted in a variety of indoor areas. For clarity, we describe one of the tested rooms. Fig. 9 shows a schematic representation of the room. It uses four beacons for testing algorithms. There is a possibility of installing four or more beacons. The beacons are installed on each of the walls and at the same horizontal level. The smartphone was positioned in same plane as the beacons in the experiments.

By using the software provided by the manufacturer, we have set the maximum power and frequency signal of the beacon, based on the results of the previous experimentation. The configuration parameters of the BLE beacon are as follows: Transmit power (Tx) is 4 dBm, and Advertising Interval is 200 ms. The beacons were installed according to Fig. 10 and set the corresponding coordinates in the Cartesian coordinate system (see Table 6).

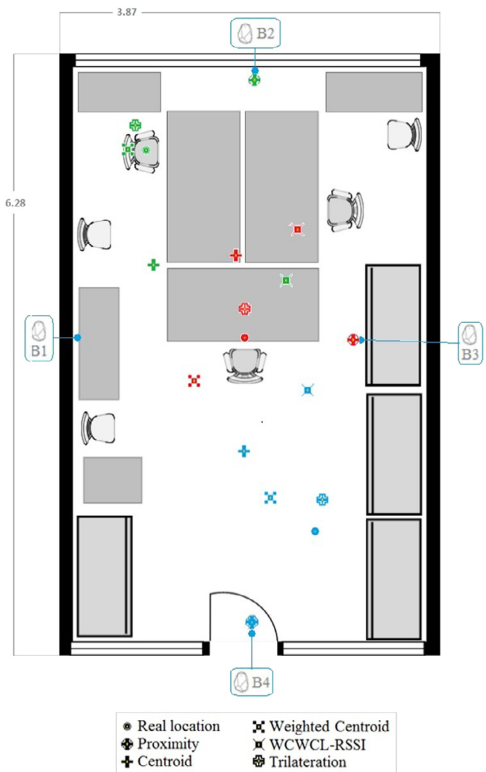

Fig. 10. The result of the algorithms.

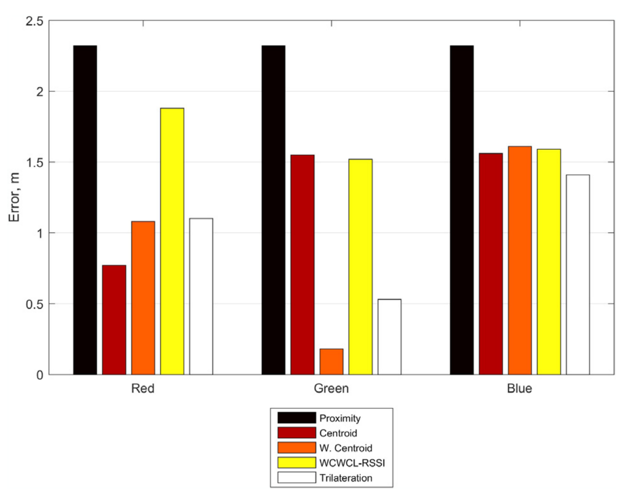

Fig. 11. Location calculation error for three beacons.

These points are divided to the three groups in Table 7.

Results. Fig. 11 shows the result of the analyzed indoor localization algorithms.

Fig. 12 shows calculation error for each algorithm in meters for three beacons.

The nearest three of four beacons have been used in the experiment for Weighted Centroid and WCWCL-RSSI. The Proximity Localization shows the highest value of error, which is equal to 2.32 m. The Trilateration localization shows the smallest error value (a mean value of 1 m). Fig. 13 shows the error of calculation in meters using four beacons. Fig. 14 shows a calculation error in meters for the fingerprinting algorithm.

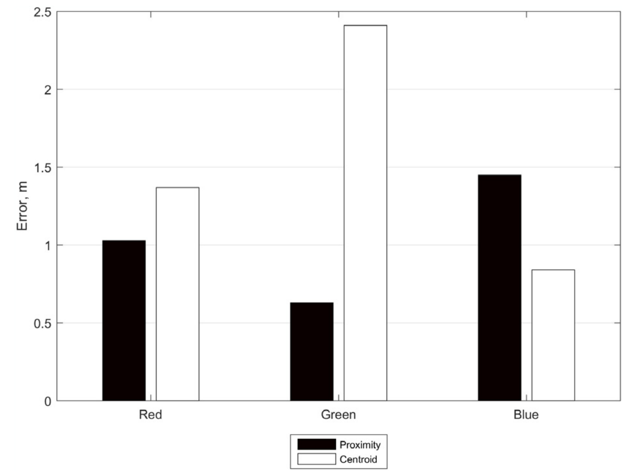

Fig. 12. Location calculation errors for 4 beacons.

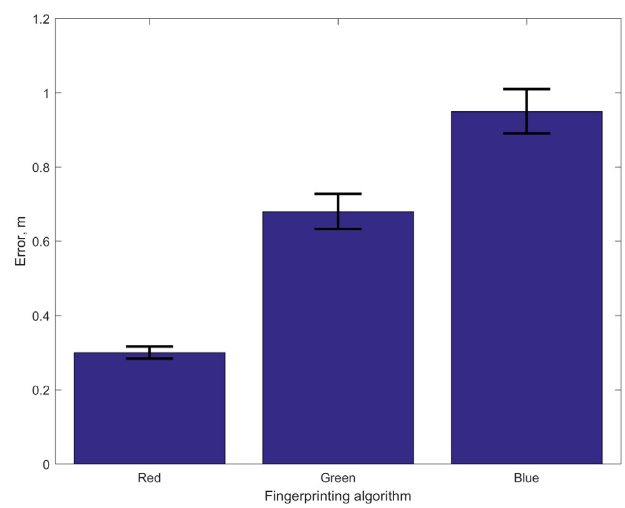

Fig. 13. Calculation errors for the fingerprinting algorithm.

Upon the completion of these experiments, the results were obtained as described in Fig. 15 below. The duration of the testing conducted was 5 min for each algorithm and the average value of the error for each algorithm has been recorded. The fingerprinting algorithm showed the highest accuracy in determining the indoor location, an error, which was 0.65 m whereas the Proximity algorithm showed the worst result and the error was 2.5 m. The results of this algorithm can be improved by reducing the parameter k (the number of neighbors) in the k−NN algorithm, the error increased due to the fact that the distance from the beacon, which had the greatest signal strength, was not taken into account. The algorithm also has shown good results not only in a room, but also in the corridors (passageways) of the office building. Considering the specifications, the algorithms should not reduce the number of required beacons, otherwise, it leads to errors in the approximation. During experiments, the beacons were installed on the walls as well as on the ceiling, the result in both cases can be specified as satisfactory, as the error is less than 1 m. Fig. 15 presents the results of an experiment conducted in the corridors of the building.

The algorithms of the Proximity Localization and Centroid Localization showed the worst result with any number of beacons. Moreover, none of the algorithms have shown the expected result in long and narrow premises like office building corridors. The

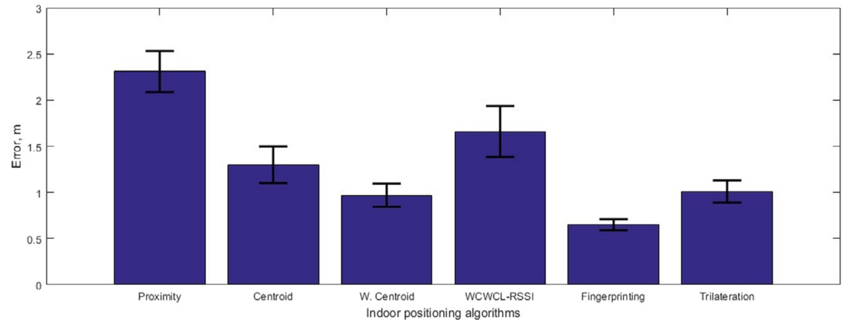

Fig. 14. Comparison of the error of indoor positioning algorithms.

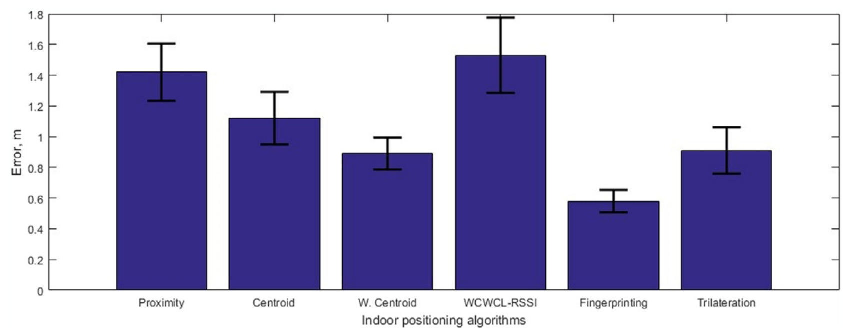

Fig. 15. Comparison of the error of indoor positioning algorithms (in a corridor).

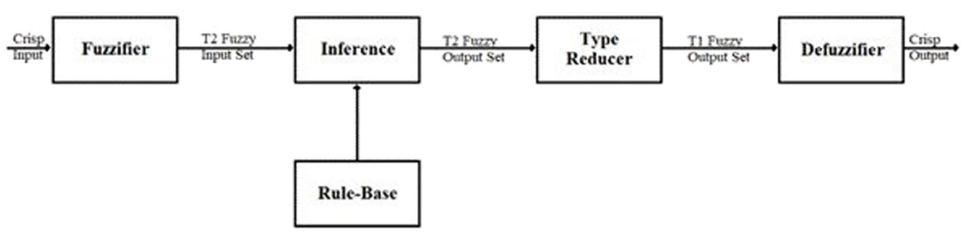

Fig. 16. Type-2 fuzzy logic system.

beacons have been fixed vertically on the walls at the level of 1.5 m from the floor. Given the specificity of these algorithms, the installation of beacons on the ceiling is an unreasonable step.

The experiments conducted in the corridors also showed the best result when using the Fingerprinting algorithm. Although the Weighted Centroid and Trilateration algorithms also have shown good results. Other algorithms have returned the coordinates outside of the room, when an agent has been moving. To avoid errors of this type, we propose to create a map of the room and use room boundaries in computing. However, the fingerprinting algorithm also has its own limitations: it requires manual collection of data for setting up a database before positioning could be performed, which has also been noted by Wang et al. [70].

The increase in the number of beacons does not affect the accuracy of determining the position in the experimental room, in contrast to the corridors. Probably, the reason is that the signals from the beacons have not fully covered the room. Therefore, an increase in the number of beacons will make a slight improvement of the positioning accuracy.

5. Measurement of indoor position using fuzzy selection

Considering the ambiguity and uncertainty of the conditions in which BLE beacons are used, the fuzzy logic system (FLS) can be adopted to address this problem. Originally, fuzzy logic was introduced by Zadeh [71] to solve problems which can be represented only vaguely. In a universe of discourse X a fuzzy subset A of X is a set defined by a membership function $f_A(x)$ representing a mapping which maps each element x in X to a real number in the closed interval [0, 1]. The triangular fuzzy numbers are often used to characterize the fuzzy values of data and linguistic terms used in fuzzy reasoning. Let $B = (a, b, c), \quad a < b < c$, be a fuzzy set on $R = (-\infty, \infty)$ is called a triangular fuzzy number, if its membership function is:

$$\mu_B(x) = \begin{cases} \dfrac{x-a}{b-a}, & if \quad a \le x \le b \\ \dfrac{c-x}{c-b}, & if \quad b \le x \le c \\ 0, & otherwise \end{cases} \tag{6}$$

Fuzzy logic rules are defined by fuzzy variables, fuzzy operators and fuzzy inference. Such rules may be key when representing an expert knowledge and experience in decision support systems. We have chosen to implement the Mamdani (Type-2) fuzzy rules (fuzzy v2), due to flexibility. Fuzzy operation is realized as two Type-1 membership functions: Upper Membership Function (UMF) and Lower Membership Function (LMF) and as Footprint of Uncertainty (FOU) function between those two — the

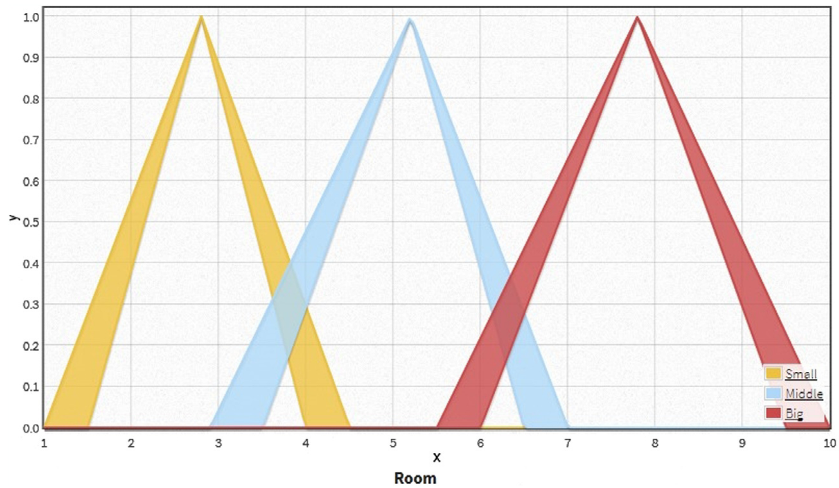

Fig. 17. Fuzzy variable for room size.

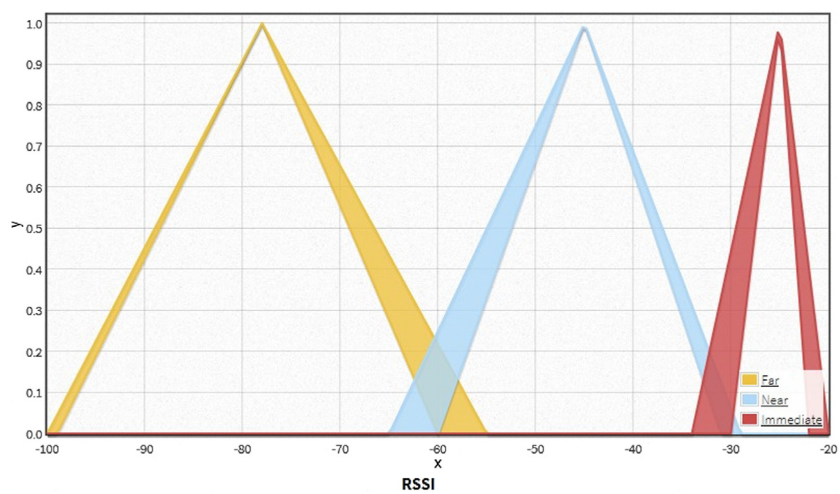

Fig. 18. Fuzzy variable for RSSI.

area of uncertainty, under which our algorithm selects the most appropriate parameter. In comparison to standard Type-1 fuzzy logic system, our implementation of Type-2 fuzzy logic have much in common, the difference is that after the "Inference" step we introduce an additional reducer set (based upon the algorithm of Centroid type-reduction for IT2 Fuzzy Logic Systems (FLSs) by Chen and Wang [72]). The FLS we use is depicted in Fig. 16. Fuzzy v2 was implemented using a Juzzy library [73]. We decided to use Fuzzy logic as a mechanism for choosing one of the indoor positioning algorithms, based on the following characteristics:

- The size of the room (room size)
- Signal Strength from Beacons (RSSI)
- Number of available beacons (Quantity of Beacons)

Thus, we have used 3 input parameters (crisp input). The Fuzzifier was set as a triangular membership functions for "room size". Rules had the following linguistic variables for "room size":

- Small (room size ≤ 5 m^2)
- Middle (room size ≤ 15 m^2)
- Big (room size ≥ 15 m^2)

Table 8
Fuzzy variable membership function values for room size.

Room size	UMF	LMF
Small	4.0 –18.0	6.0 –16.0
Middle	12.0 –28.0	14.0 –26.0
Big	22.0 –40.0	24.0 –38.0

The initial values for the UMF and LMF functions were determined experimentally. We have defined the fuzzy values for room size (small, middle, big) (see Table 8 and Fig. 17), and RSSI signal strength (far, near, immediate) (see Fig. 18), and the number of available beacons (not enough, enough) (see Fig. 19). The Fuzzifier has triangular membership functions for RSSI with the following parameters (see Table 9):

- Far (signal strength less than −60 dBm)
- Near (signal strength −30 to −60 dBm)
- Immediate (signal strength −30 dBm or more)

The Fuzzifier has Trapezoidal membership functions for Number of Beacons with the following parameters (see Table 10):

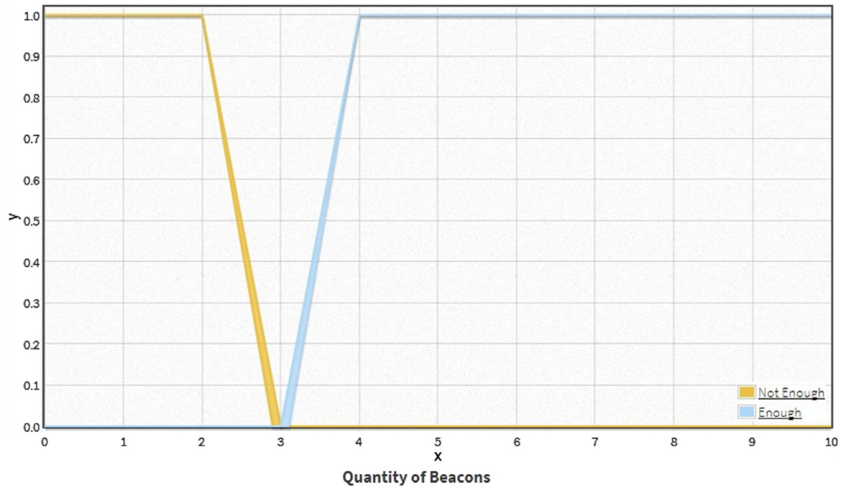

Fig. 19. Fuzzy variable for the number of available beacons.

1. If Room is Small and Quantity of Beacons is Not Enough and RSSI is Far **then** Localization is Proximity
2. If Room is Small and Quantity of Beacons is Not Enough and RSSI is Near **then** Localization is Proximity
3. If Room is Small and Quantity of Beacons is Not Enough and RSSI is Immediate **then** Localization is Proximity
4. If Room is Middle and Quantity of Beacons is Not Enough and RSSI is Far **then** Localization is Proximity
5. If Room is Middle and Quantity of Beacons is Not Enough and RSSI is Near **then** Localization is Proximity
6. If Room is Middle and Quantity of Beacons is Not Enough and RSSI is Immediate **then** Localization is Proximity
7. If Room is Big and Quantity of Beacons is Not Enough and RSSI is Far **then** Localization is Proximity
8. If Room is Big and Quantity of Beacons is Not Enough and RSSI is Near **then** Localization is Proximity
9. If Room is Big and Quantity of Beacons is Not Enough and RSSI is Immediate **then** Localization is Proximity
10. If Room is Small and Quantity of Beacons is Enough and RSSI is Far **then** Localization is Centroid
11. If Room is Small and Quantity of Beacons is Enough and RSSI is Near **then** Localization is Weighted Centroid
12. If Room is Small and Quantity of Beacons is Enough and RSSI is Immediate **then** Localization is Weighted Centroid
13. If Room is Middle and Quantity of Beacons is Enough and RSSI is Far **then** Localization is Centroid
14. If Room is Middle and Quantity of Beacons is Enough and RSSI is Near **then** Localization is Trilateration
15. If Room is Middle and Quantity of Beacons is Enough and RSSI is Immediate **then** Localization is Weight-Compensated Weighted Centroid
16. If Room is Big and Quantity of Beacons is Enough and RSSI is Far **then** Localization is Fingerprinting
17. If Room is Big and Quantity of Beacons is Enough and RSSI is Near **then** Localization is Trilateration
18. If Room is Big and Quantity of Beacons is Enough and RSSI is Immediate **then** Localization is Trilateration

Fig. 20. Fuzzy rules for algorithm selection.

Table 9
Fuzzy variable membership function values for RSSI.

RSSI value	UMF	LMF
Far	−100 to −55	−98 to −60
Near	−65 to −28	−60 to −30
Immediate	−35 to −20	−30 to −22

Table 10
Fuzzy variable membership function values for number of beacons.

Number of beacons	UMF	LMF
Enough	0-0-2-3	0-0-2-3
Not enough	3-4-10-10	3-4-10-10

- Not enough (less than 3 beacons, as 3 are not enough than for reliable localization)
- Enough (more than 3 beacons are considered as enough for localization task)

The Fuzzifier has the following Gaussian membership functions for Output with these parameters:

- Proximity
- Centroid Localization
- Weighted Centroid
- Weight-Compensated Weighted Centroid
- Trilateration
- Fingerprinting

To select the most suitable algorithm for indoor localization the following set of fuzzy rules was applied (see Fig. 20). The rules were derived by an expert upon the analysis of the results of experiments of indoor positioning described and presented in Section 4.

The implementation of the FLS is presented using Unified Modeling Language (UML) model in Fig. 21. The main

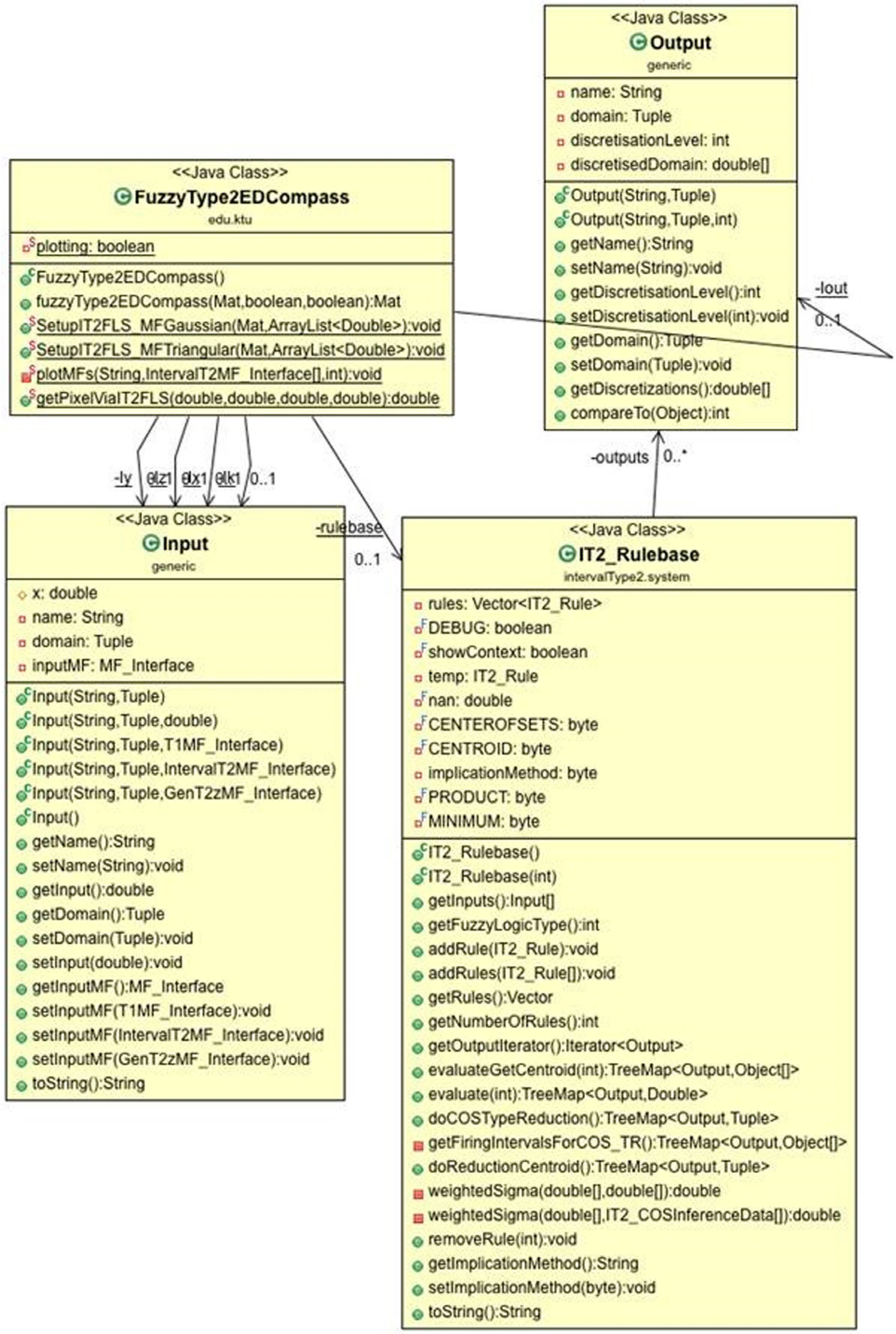

Fig. 21. UML model of the implementation of a FLS.

class is *fuzzyType2EDCompass*. To setup the FLS, we use the *SetupIT2FLS_MFGaussian* and *SetupIT2FLS_MFTriangular* functions. In these functions, the *Input* class is called to create the input parameters. There are two accessory functions (UMF and LMF), Gaussian, and triangular respectively, for each these methods. Next, the classes *IT2_Antecedent* and *IT2_Consequent* are initiated for communication between the input parameters and the access functions. Then we initiate the *IT2_Rulebase* class and create fuzzy rules. The *plotMFs* function defuzzifies and produces the result, which is then passed to select the most appropriate indoor positioning algorithm.

The result of the fuzzy algorithm is the variable for selection of the indoor positioning algorithm (see Fig. 22).

6. Conclusion

In this paper, we have presented an implementation and experimental research of indoor localization algorithms (Proximity Localization, Centroid Localization, Weighted Centroid Localization, Weight-Compensated Weighted Centroid Localization Based on RSSI (WCWCL-RSSI), Fingerprinting and Trilateration Localization) used for the indoor positioning task in real-world scenario. We

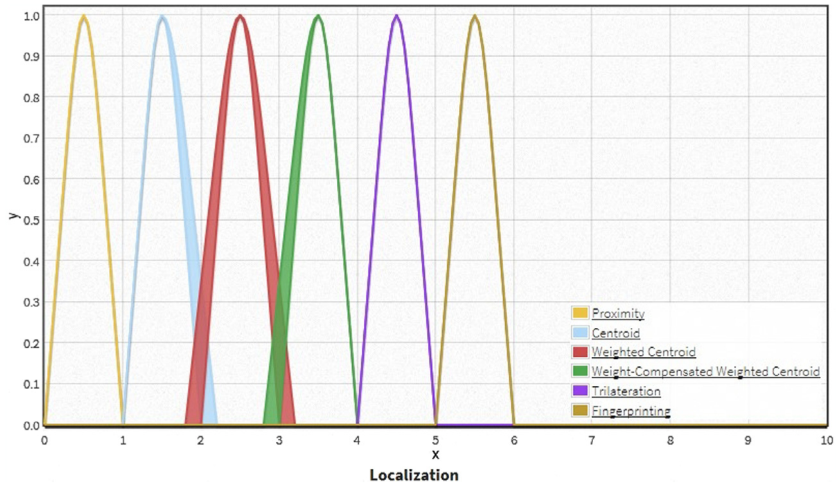

Fig. 22. Fuzzy selection of algorithm.

used the Estimote beacons based on Bluetooth Low Energy (BLE) technology. The number of beacons was set from 3 to 6, and during experiments we have found that the amount fully covers the room up to 5 m long. We can state that:

- The range of signal broadcast in the real world does not correspond to the range that has been declared by the manufacturer. The signal is practically damped by the walls of the room. For an efficient operation of indoor positioning algorithms, the data obtained from beacons has to be from within a 3 m range.
- The Fingerprinting algorithm can be used as an indoor positioning algorithm using the BLE beacons. The algorithm showed relatively high positioning accuracy that distinguishes it from others, however, the main disadvantage is the need for the pre-configuration stage. The error of calculation is 0.67 m.
- The greater is the number of beacons, the better is the result of the positioning. The longer is the room wall, the more the beacons is required for correct localization with consideration of the maximum range of broadcasting in real environment.

We have found that as the conditions differ greatly due to the size of rooms, number of BLE beacons used and strength of a signal, there is no a single best indoor positioning algorithm in terms of accuracy. Therefore, we also proposed a fuzzy logic based scheme for the selection of a fittest indoor localization algorithm based on the size of the room, the number of available beacons, and the strength of RSSI signal, which guarantees the accuracy of the results would be at least equal to the results achieved using the best performing algorithm.

Acknowledgments

This work is supported by the Key Research and Development Program of Shaanxi Province (No.2018ZDXM-GY-036), supported by the National key R&D Program of China under Grant No. 2018YFB0203900 and Open Research Fund from Shandong provincial Key Laboratory of Computer Network (Grant No. SDKLCN-2017-02), the Specialized Research Fund for the Doctoral Program of Higher Education of China (Grant No. 20136118120010) and Xi'an science and technology project (CXY1440(6)).

References

[1] United Nations, Good practices of accessible urban development, online Available. http://www.un.org/disabilities/documents/desa/good_practices_in_accessible_urban_development_october2016.pdf.
[2] V. Gutiérrez, E. Theodoridis, G. Mylonas, F. Shi, U. Adeel, L. Diez, D. Amaxilatis, J. Choque, G. Camprodom, J. McCann, L. Munoz, Co-creating the cities of the future, Sensors 16 (2016) 1971.
[3] S.A. Zekavat, H. Tong, J. Tan, A novel wireless local positioning system for airport (indoor) security, Proc. SPIE 5403 (2004) 522–533.
[4] P. Kourouthanassis, G. Roussos, Developing consumer- friendly pervasive retail systems, IEEE Pervasive Comput. 2 (2003) 32–39.
[5] M. Aittola, T. Ryhänen, T. Ojala, SmartLibraryLocation-Aware mobile library service, in: Proceedings of the Human-Computer Interaction with Mobile Devices and Services: 5th International Symposium, vol. 8–11, 2003, pp. 411–416.
[6] R.E. Grinter, P.M. Aoki, A. Hurst, M.H. Szymanski, J.D. Thornton, A. Woodruff, Revisiting the visit: Understanding how technology can shape the museum visit, in: Proceedings of the ACM 2002 Conference on Computer Supported Cooperative Work (CSCW 2002), vol. 16–20, 2002, pp. 146–155.
[7] D. Gusenbauer, C. Isert, J. Krösche, Self-contained indoor positioning on off-the-shelf mobile devices, in: 2010 International Conference on Indoor Positioning and Indoor Navigation, IPIN, 2010, pp. 15–17.
[8] A. Mossel, Robust 3D position estimation in wide and unconstrained indoor environments, Sensors 15 (2015) 31482–31524.
[9] L. Calderoni, M. Ferrara, A. Franco, D. Maio, Indoor localization in a hospital environment using random forest classifiers, Expert Syst. Appl. 42 (2015) 125–134.
[10] P. Connolly, D. Boone, Indoor Location in Retail: Where Is the Money? Business Models Analysis Report, 2003.
[11] A. Correa, M. Barcelo, A. Morell, J.L. Vicario, A review of pedestrian indoor positioning systems for mass market applications, Sensors 17 (2017) 1927.
[12] R.F. Brena, J.P. Garca-Vazquez, C.E. Galvan-Tejada, D. Munoz-Rodriguez, C. Vargas-Rosales, Jr. J. Fangmeyer, Evolution of indoor positioning technologies: A survey, Sensors (2017) 21. http://dx.doi.org/10.1155/2017/2630413.
[13] K.P. Subbu, C. Zhang, J. Luo, A.V. Vasilakos, Analysis and status quo of smartphone-based indoor localization systems, IEEE Wirel. Commun. 21 (4) (2014) 106–112.
[14] M. Castanon–Puga, A.S. Salazar, L. Aguilar, C. Gaxiola-Pacheco, G. Licea, A novel hybrid intelligent indoor location method for mobile devices by zones using Wi-Fi signals, Sensors 15 (2015) 30142–30164.
[15] J.Duque Domingo, C. Cerrada, E. Valero, J.A. Cerrada, An improved indoor positioning system using RGB-d cameras and wireless networks for use in complex environments, Sensors 17 (2017) 2391.
[16] J. Qi, G.P. Liu, A robust high-accuracy ultrasound indoor positioning system based on a wireless sensor network, Sensors 17 (2017) 2554.
[17] Y. Zhuang, J. Yang, Y. Li, L. Qi, N. El-Sheimy, Smartphone-based indoor localization with bluetooth low energy beacons, Sensors 16–5 (2016) 596. http://dx.doi.org/10.3390/s16050596.
[18] B.J. Shin, K.W. Lee, S.H. Choi, J.Y Kim, W.J. Lee, H.S. Kim, Indoor WiFi positioning system for Android-based smartphone, in: International Conference on Information and Communication Technology Convergence, ICTC, 2010, pp. 319–320.

[19] G.C. García, I.L. Ruiz, M.A. Gomez-Nieto, State of the art, trends and future of bluetooth low energy, near field communication and visible light communication in the development of smart cities, Sensors 16 (2016) 1968.
[20] P. Kriz, F. Maly, T. Kozel, Improving indoor localization using bluetooth low energy beacon, Mob. Inf. Syst. 2016 (2016) 11. http://dx.doi.org/10.1155/2016/2083094.
[21] G. de Blasio, A. Quesada-Arencibia, C.R. García, J.M. Molina-Gil, C. Caballero-Gil, Study on an indoor positioning system for harsh environments based on Wi-Fi and bluetooth low energy, Sensors 17 (2017) 1299.
[22] M. Castillo-Cara, J. Lovon-Melgarejo, G. Bravo-Rocca, L. Orozco-Barbosa, I. Garca-Varea, An analysis of multiple criteria and setups for bluetooth smartphone-based indoor localization mechanism, Sensors 17 (2017) 22. http://dx.doi.org/10.1155/2017/1928578.
[23] F. Li, A reliable and accurate indoor localization method using phone inertial sensors, in: UbiComp '12 Proceedings of the 2012 ACM Conference on Ubiquitous Computin, 2012, pp. 421–430.
[24] H. Wan, No need to war-drive: Unsupervised indoor localization, in: MobiSys '12 Proceedings of the 10th international conference on Mobile systems, applications, and services, 2012, pp. 197–210.
[25] J. Qian, J. Ma, R. Ying, P. Liu, L. Pei, An improved indoor localization method using smartphone inertial sensor, in: Proceedings of International Conference on Indoor Positioning and Indoor Navigation, IPIN, 2013, pp. 1–7.
[26] Z.A. Deng, Extended Kalman filter for real time indoor localization by fusing wifi and smartphone inertial sensors, Micromachines 6 (4) (2015) 523–543. http://dx.doi.org/10.3390/mi6040523.
[27] S.H. Lee, I.K. Lim, J.K. Lee, Method for improving indoor positioning accuracy using extended Kalman filter, Mob. Inf. Syst. 2016 (2016) 15. http://dx.doi.org/10.1155/2016/2369103.
[28] L. Pei, J. Liu, R. Guinness, Y. Chen, H. Kuusniemi, R. Chen, Using LS-SVM based motion recognition for smartphone indoor wireless positioning, Sensors 12 (5) (2012) 6155–6175. http://dx.doi.org/10.3390/s120506155.
[29] J. Liu, R. Chen, L. Pei, R. Guinness, H. Kuusniemi, A hybrid smartphone indoor positioning solution for mobile LBS, Sensors 12 (12) (2012) 17208–17233. http://dx.doi.org/10.3390/s121217208.
[30] E.S.P. Mohebbi, I. Nikolaidis, Sensor-data fusion for multi-person indoor location estimation, Sensors 17 (2017) 2377.
[31] R. Ma, Q. Guo, C. Hu, J. Xue, An improved wifi indoor positioning algorithm by weighted fusion, Sensors 15 (2015) 21824–21843.
[32] Z. Chen, H. Zou, H. Jiang, Q. Zhu, Y.C. Soh, L. Xie, Fusion of wifi, smartphone sensors and landmarks using the Kalman filter for indoor localization, Sensors 15 (1) (2015) 715–732. http://dx.doi.org/10.3390/s150100715.
[33] K. Liu, Guoguo: Enabling fine-grained indoor localization via smartphone, in: MobiSys '13 Proceeding of the 11th annual international conference on Mobile systems, applications, and service, 2013, pp. 235–248.
[34] W. Kang, Smartpdr: Smartphone-based pedestrian dead reckoning or indoor localization, IEEE Sens. J. 15 (5) (2015) 2906–2916.
[35] M.O. Gani, C. OBrien, S.I. Ahamed, R.O. Smith, Rssi based indoor localization for smartphone using fixed and mobile wireless node, in: 2013 IEEE 37th Annual Computer Software and Applications Conference, COMPSAC, 2013, pp. 110–117.
[36] M. Werner, M. Kessel, C. Marouane, Indoor positioning using smartphone camera, in: International Conference on Indoor Positioning and Indoor Navigation, IPIN, 2011, pp. 1–6.
[37] X.Y. Lin, T.W. Ho, C.C. Fang, Z.S. Yen, B.J. Yang, F. Lai, A mobile indoor positioning system based on ibeacon technology, in: 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC, 2015, pp. 4970–4973, http://dx.doi.org/10.1109/embc.2015.7319507.
[38] M.E. Rida, F. Liu, Y. Jadi, A.A. Algawhari, A. Askourih, Indoor location position based on bluetooth signal strength, in: 2nd International Conference on Information Science and Control Engineering, 2015, http://dx.doi.org/10.1109/icisce.2015.177.
[39] W. Zhu, S. Kim, J. Hong, C. Kim, Analysis of indoor positioning based on BLE, in: ACIIDS 2017, Studies in Computational Intelligence, vol. 710, 2017, pp. 421–430.
[40] S.Y. Bai, C.C. Chiu, J.C. Hsu, Campus-wide wireless indoor positioning with hybrid ibeacon and Wi-Fi system, in: 6th International Symposium on Next Generation Electronics, ISNE, 2017, pp. 1–2, http://dx.doi.org/10.1109/isne.2017.7968740.
[41] Z. Ma, S. Poslad, J. Bigham, X. Zhang, L. Men, A BLE RSSI ranking based indoor positioning system for generic smartphones, in: 2017 Wireless Telecommunications Symposium, WTS, 2017, pp. 1–8, http://dx.doi.org/10.1109/wts.2017.7943542.
[42] H. Zou, H. Jiang, Y. Luo, J. Zhu, X. Lu, L. Xie, Bluedetect: An ibeacon-enabled scheme for accurate and energy-efficient indoor-outdoor detection and seamless location-based service, Sensors 16 (268) (2016).
[43] I.H. Alshami, N.A. Ahmad, S. Sahibuddin, F. Firdaus, Adaptive indoor positioning model based on wlan-fingerprinting for dynamic and multi-floor environments, Sensors 17 (2017) 1789.
[44] L. Pei, M. Zhang, D. Zou, R. Chen, Y. Chen, A survey of crowd sensing opportunistic signals for indoor localization, Mob. Inf. Syst. 2016 (2016) 16. http://dx.doi.org/10.1155/2016/4041291.
[45] H. Xu, Y. Ding, P. Liv R. Wang, Y. Li, An RFID Indoor Positioning algorithm based on Bayesian probability and K-nearest neighbor, Sensors 17 (2017) 1806.
[46] J. Medina, M. Ojeda-Aciego, J. Ruiz-Calviño, On multi-adjoint concept lattices: Definition and representation theorem, in: Formal Concept Analysis, Springer Berlin Heidelberg, 2007, pp. 197–209. http://dx.doi.org/10.1007/978-3-540-70901-5_13.
[47] C. Pozna, N. Minculete, R.-E. Precup, L.T. Kóczy, Á. Ballagi, Signatures: Definitions, operators and applications to fuzzy modelling, Fuzzy Sets and Systems 201 (2012) 86–104. http://dx.doi.org/10.1016/j.fss.2011.12.016.
[48] J. Nowaková, M. Prílepok, V. Snášel, Medical image retrieval using vector quantization and fuzzy s-tree, J Med Syst 41 (2) (2016). http://dx.doi.org/10.1007/s10916-016-0659-2.
[49] D.K.A. Kumar, S.K. Jarial, A hybrid clustering method based on improved artificial bee colony and fuzzy c-means algorithm, Int. J. Artif. Intell. 15 (2) (2017) 40–60.
[50] A. Küpper, Location-Based Services: Fundamentals and Operation, Wiley, 2005, p. 365.
[51] K.W. Kolodziej, J. Hjelm, Local Positioning Systems: LBS Applications and Services, CRC Press, 2006, p. 445.
[52] S.C. Liang, L.H. Liao, Y.C. Lee, Localization algorithm based on improved weighted centroid in wireless sensor networks, J. Netw. 9 (1) (2014) 183–189.
[53] Q. Dong, X. Xu, A novel weighted centroid localization algorithm based on rssi for an outdoor environment, J. Commun. 9 (3) (2014) 279–285.
[54] M. Shchekotov, Indoor localization method based on Wi-Fi trilateration technique, in: Proc. of the 16th Conference of Open Innovations Association FRUCT, 2014, pp. 177–179.
[55] L. Chen, B. Li, K. Zhao, C. Rizos, Z. Zheng, An improved algorithm to generate a Wi-Fi fingerprint database for indoor positioning, Sensors 13 (2013) 11085–11096.
[56] J. Tang, Y. Chen, L. Chen, J. Liu, J. Hyyppä, A. Kukko, H. Kaartinen, H. Hyyppä, R. Chen, Fast fingerprint database maintenance for indoor positioning based on UGV SLAM, Sensors 15 (2015) 5311–5330.
[57] J. Luo, L. Fu, A smartphone indoor localization algorithm based on wlan location fingerprinting with feature extraction and clustering, Sensors 17 (2017) 1339.
[58] E.S. Lohan, J. Torres-Sospedra, H. Leppäkoski, P. Richter, Z. Peng, J. Huerta, Wi-Fi crowdsourced fingerprinting dataset for indoor positioning, Data 2 (2017) 32.
[59] W. Chi, Y. Tian, M. Al-Rodhaan, A. Al-Dhelaan, Y. Jin, A revised received signal strength based localization for healthcare, IEEE Trans. Consum. Electron. 55 (3) (2009) 1295–1299.
[60] X. Fan, H. Song, X. Fan, J. Yang, Imperfect information dynamic stackelberg game based resource allocation using hidden Markov for cloud computing, IEEE Trans. Serv. Comput. 11 (1) (1939) 78–89. http://dx.doi.org/10.1109/TSC.2016.2528246.
[61] X.L. Yang, B. Zhou, J. Feng, P.Y. Shen, Combined energy minimization for image reconstruction from few views, Math. Probl. Eng. 2012 (3) (2012) 1094–1099.
[62] X.L. Yang, P.Y. Shen, B. Zhou, Holes detection in anisotropic sensornets: Topological methods, Int. J. Distrib. Sens. Netw. 2012 (2012) (2012).
[63] Y. Qiang, J. Zhang, A bijection between lattice-valued filters and lattice-valued congruences in residuated lattices, Math. Probl. Eng. 2013 (2) (2013) 1437–1450.
[64] Q. Xu, L. Wang, X.H. Hei, P. Shen, W. Shi, L. Shan, Gi/geom/1 queue based on communication model for mesh networks, Int. J. Commun. Syst. 27 (11) (2014) 3013–3029.
[65] Z. Sun, H. Song, H. Wang, X. Fan, Energy balance-based steerable arguments coverage method in wsns, IEEE Access 6 (2017). http://dx.doi.org/10.1109/ACCESS.2017.2682845.
[66] H. Song, W. Li, P. Shen, A. Vasilakos, Gradient-driven parking navigation using a continuous information potential field based on wireless sensor network, Inform. Sci. 408 (C) (2017) 100–114.
[67] H. Song, H. Wang, X. Fan, Research and simulation of queue management algorithms in Ad Hoc network under DDoS attack, IEEE Access 5 (99) (2017) 27810–27817. http://dx.doi.org/10.1109/ACCESS.2017.2681684.
[68] X. Fan, H. Song, H. Wang, Video tamper detection based on multi-scale mutual information, Multimedia Tools Appl. (9) (2017) 1–18.
[69] Q. Ke, J. Zhang, H. Song, Y. Wan, Big data analytics enabled by feature extraction based on partial independence, Neurocomputing (2017).
[70] X. Wang, M. Jiang, Z. Guo, N. Hu, Z. Sun, J. Liu, An indoor positioning method for smartphones using landmarks and PDR, Sensors 16 (2016) 2135.
[71] L.A Zadeh, Fuzzy set, Inform. Control 8 (1965) 338–353.
[72] Y. Chen, D. Wang, Studies on centroid type-reduction algorithms for interval type-2 fuzzy logic systems, in: 2015 IEEE Fifth International Conference on Big Data and Cloud Computing, IEEE, 2015. http://dx.doi.org/10.1109/bdcloud.2015.14.

[73] C. Wagner, Juzzy - a java based toolkit for type-2 fuzzy logic, in: 2013 IEEE Symposium on Advances in Type-2 Fuzzy Logic Systems (T2FUZZ), IEEE, 2013. http://dx.doi.org/10.1109/t2fzz.2013.6613298.

Farid Orujov (received M.S. degree in Computer Science field, in 2016 from Kaunas University of Technology, Lithuania) currently is a Ph. D. student in Information Engineering field at Faculty of Informatics, Multimedia Engineering Department at Kaunas University of Technology. He worked as Software Research Developer at "SINAM" LTD, concentrating on developing various mobile solutions in GIS sphere. He was awarded "Best Author of Master Thesis Project" by the Multimedia Engineering Department of Kaunas University of Technology. His main areas of scientific research are: modeling, designing and development indoor positioning and navigation system, mainly targeted at people suffering from visual impairment.

Rytis Maskeliunas (received Dr. (Ph. D.) degree in Computer Science field, in 2009) is a professor at Faculty of Informatics, Department of Multimedia Engineering and a chief researcher at Centre of Real Time Computer Systems, at Kaunas University of Technology. He has won various awards/honors including the Best Young Scientist Award of 2012, National Science Academy Award for Young Scholars of Lithuania (2010) and others. He is author/co-author of over 80 refereed scientific articles and serves as Project evaluation expert for multiple scientific organizations, as a consultant for Eureka and Eurostars calls and as a reviewer/committee member for various refereed journals. His main areas of scientific research are: multimodal signal processing, modeling, development and analysis of associative, multimodal interfaces, mainly targeted at elderly and people with major disabilities, also technologies for the development of HCI techniques for patients of Huntington's disease. His main academic subjects are related to computer gaming, development, modeling of mechanics, design and gamification, application design for smart devices, development of user interfaces and usability, development of shaders for 3D graphics, signal processing and IT project management.

Robertas Damaševičius received his Ph.D. in Informatics Engineering from Kaunas University of Technology (KTU) in 2005. Currently, he is a Professor at Software Engineering Department, KTU and lectures software maintenance, human–computer interface and robot programming courses. His research interests include sustainable software engineering, human–computer interfaces, assisted living, data mining and machine learning. He is the author of over 130 papers as well as a monograph published by Springer. He is also the Editor-in-Chief of the Information Technology and Control journal and has been Guest Editor of several invited issues of international journals (Biomed Research International, Computational Intelligence and Neuroscience, Journal of Universal Computer Science).

Dr. Wei Wei is an associate professor of School of Computer Science and Engineering, Xi'an University of Technology, Xi'an 710048, China. He is a senior member of IEEE and CCF. He received his Ph.D. and M.S. degrees from Xian Jiaotong University in 2011 and 2005, respectively. He ran many funded research projects as principal investigator and technical members. His research interest is in the area of wireless networks, wireless sensor networks Application, Image Processing, Mobile Computing, Distributed Computing, and Pervasive Computing, Internet of Things, Sensor Data Clouds, etc. He has published around hundreds of research papers in international conferences and journals. He is an editorial board member of FGCS, AHSWN, IEICE, KSII, etc. He is a TPC member of many conferences and regular reviewer of IEEE TPDS, TIP, TMC, TWC, JNCA and many other Elsevier journals.