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Confidence-interval Fuzzy Model-based Indoor Localization

Simon Tomažič, Dejan Dovžan and Igor Škrjanc

***Abstract*—In this paper an efficient indoor localization algorithm based on confidence-interval fuzzy model (INFUMO) is presented. The width of the confidence interval is essential within the proposed fingerprinting method for calculating weights, which are then taken into account while searching for the K nearest neighbours in the database of fingerprints. For each beacon in the test room a new confidence-interval fuzzy path-loss model composed of several local linear models is constructed. The map of fingerprints is then constructed of a set of confidence-interval fuzzy models. By their consideration the localization accuracy is significantly improved in comparison with other commonly used path-loss models. The most important novelty of this paper is the introduction of the confidence interval within the fingerprinting method, which additionally improves localization results. The platform of the localization system is developed on the basis of a smartphone and Bluetooth beacons. Therefore the localization algorithm has to be optimized in order to be computationally efficient, which is essential for real-time processing and low energy consumption on a smartphone.**

***Index Terms*—fuzzy model, confidence interval, indoor localization, fingerprints, nearest neighbours.**

I. INTRODUCTION

In recent years, the rapid developments in mobile and communication technologies have encouraged many studies in the field of localization and navigation in indoor environments. Smartphones are becoming almost indispensable accessories of people, not least because of the possibility to use them as a personal navigation system (PNS). While outdoor localization is, to a large extent, a solved problem, for indoor environments it is still not clear as to which localization approach and technology will dominate. An accurate localization system that can also operate in an indoor environment has a lot of practical value, since it can be built into a personal navigation system for guiding people through shopping malls, museums, airports, public institutions, etc. Such a system would be particularly useful for blind people.

Since modern mobile devices can receive various radio signals, different approaches to localization using cellular networks (GSM, LTE) [1], Wi-Fi networks [2], Bluetooth [3], FM signals [4], NFC connections [5] etc., have been established. For radio-based localization systems a crucial step is to measure the various parameters of the radio signals (e.g., the signal strength – RSSI, the MAC address of the transmitter, the packet transmission frequency) traveling between a mobile device and a group of base-stations [6].

Due to signal reflection and absorption, the signal-strength measurements contain a lot of noise. Therefore, to achieve a high localization accuracy, great emphasis needs to be placed on the construction of models that describe the signal's attenuation. The propagation of Wi-Fi or Bluetooth signals can be described using the Log Distance Path Loss (LDPL) model [7]. The latter represents a simple way of modeling the signal's spreading, without taking into account influencing factors such as time changes, the presence of people and other obstacles in the area, and dynamic changes to the signal coverage. Often, the description of the measurement using LDPL models is not accurate enough, which means it is necessary to use a more sophisticated approach to modeling, e.g., Gaussian processes [8], neural networks or the fuzzy identification of nonlinear models [9]. The identification of nonlinear static and dynamic processes is a well-established scientific field, which has already been covered by many authors [10]–[16]. Hartmann and others [17], [18] showed with numerous examples that the SUHICLUST (Supervised, Hierarchical CLUSTtering) algorithm, which is based on an iterative identification approach, has enormous potential for solving the problem of the identification of nonlinear models. The algorithm partitions a data set into many clusters and determines the corresponding local linear models. Some authors [19], [20] have also suggested the use of interval type-2 fuzzy logic in the learning phase of RSSI-based indoor localization, but they have achieved only a few meters' accuracy. A type-2 fuzzy model includes information about the confidence interval which could be exploited for the purpose of improving the localization results, but this still has not been done in existing solutions.

The SUHICLUST algorithm has been chosen in our case for the construction of interval fuzzy models of signal strengths, since it is very efficient and easier to implement than interval type-2 fuzzy logic [17], [18]. In path-loss modeling, great emphasis was placed on the corresponding confidence interval, which gives very useful information, since it allows us to determine the level of confidence in the model for a selected input (i.e. distance to the transmitter) and to verify the adequacy of the model. The fuzzy confidence-interval identification was discussed by many authors [21], [22] but its practical use is still not widespread. In our case, the efficient use of the confidence interval is the most important idea that results in a

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very promising outcome. To obtain the desired localization results, the selection of localization method (Section II) is also very important, since it needs to take advantage of the confidence interval.

The paper is organized as follows. In Section II. an introduction to indoor localization is given. Section III. provides the summary of the interval fuzzy modeling with the SUHICLUST algorithm. Section IV. describes the fuzzy confidence-interval model's identification. In Section V. the fingerprinting method is described, where the use of the fuzzy confidence interval is proposed. Section VI. presents the results of the path-loss model's construction and pedestrian localization using a smartphone. Concluding remarks are presented in Section VII.

II. Introduction to Indoor Localization

In previous studies, it was shown that the most accurate form of radio localization can be performed using a Wi-Fi or Bluetooth network [2]. The Bluetooth network (based on Bluetooth Low Energy (BLE) [23]) has many advantages over Wi-Fi [2], [24]: the lower energy consumption of the receivers (smartphones) and transmitters (a button-cell battery can supply transmitters for several months or even years), the low price of the transmitters, the greater robustness (signals contain less noise), and the smaller dimensions of the integrated circuits. In addition, a Bluetooth receiver can refresh the parameters of the network at a higher frequency (up to 50 Hz).

The location of the mobile device can be easily determined by measuring the strengths of radio signals (the reduction in the signal strength is proportional to the distance from the transmitter) emitted by base-stations and the use of trilateration [25].

In the field of localization three approaches based on an analysis of Wi-Fi or Bluetooth signal strengths have been established: the methods that consider the strongest base-station, the methods that require constructing path-loss models, i.e., models of signal strengths (and use trilateration) and the methods based on the principle of "fingerprints". The first approach is represented by the proximity-based methods [26], which are trivial, since the user's position can be determined from signal-strength measurements. These define which transmitter is the nearest to the receiver (since it emits the strongest signal) and since the positions of the transmitters are known, the receiver's position is also approximately known. The advantage of this approach is computational simplicity, while the disadvantage is low accuracy, which is dependent on the number of transmitters (density) [25].

In the second approach, which involves the building of signal-strength models (which describe the signal path loss for each transmitter), the position of the user's mobile device is determined by using these models that define the distances to the transmitters according to the measured signal strengths on the mobile device. In this way a circle on which the receiver can be located is obtained for each transmitter. The point at which the receiver is located is then determined with a geometrical technique – trilateration [27], [28]. This localization approach is relatively effective and easy to implement, but the achieved accuracy is not very high (accuracy to a few meters [29]), since signal reflections, noise, absorption and interference due to the presence of obstacles, such as doors, walls, ceiling, people, etc., affect the measurements of signal strengths (the signal strengths vary continuously). Therefore, the models of signal strengths need to be designed in such a way that they take into consideration the changes in the area.

The third approach is represented by the fingerprint-based methods [30], [31], which are easy to implement and less sensitive to the noise of radio signals than trilateration [32]. With this method a more accurate position can be achieved [33] (the accuracy is between 1 m and 5 m on average). A localization system based on the use of fingerprints usually consists of two phases, i.e., the offline learning phase and online positioning phase [34]. In the learning phase, the aim is to build a database that contains measurements of the signal strengths from all the transmitters (i.e., fingerprints) for each grid point of the area [35], [36]. During the stage of online positioning, the currently measured signal strengths are compared with the measurements in a database, and according to which fingerprint best matches the current vector of signal strengths, the receiver's position is determined. So at this point it is recommended to use the method of searching for the K-nearest neighbours - KNN or K most likely neighbours [37] or consider the Bayesian rule [38]. When the nearest neighbours (fingerprints) are known, the current position of the receiver is determined as the average of the coordinates that belong to them.

Mirowski et al. [39] proposed an algorithm that takes into account the probability distribution (described by histograms instead of a Gaussian curve) instead of individual signal strengths at the reference point. They used Kullback-Leiber divergence for determining the similarities between the fingerprints, and kernel regression to carry out the localization. The authors showed that their approach is superior to solutions based on the use of the KNN method, the Kalman filter or a particle filter, since they achieved an average positioning accuracy of $\sim$1 m.

In Fig. 1 the schematic representation of the proposed indoor localization system is shown. It consists of offline and online procedures which are performed either on the server or on a smartphone. All the key elements of the system are described below.

III. Construction of fuzzy models

The SUHICLUST algorithm [17], [18] makes it possible to identify nonlinear systems. The resulting model is composed of several local linear sub-models. SUHICLUST combines the advantages of supervised learning, since it includes a hierarchical algorithm (which takes into account model errors during further data partitioning), which is based on heuristic tree construction, and the advantages of fuzzy clustering (unsupervised learning). The contributions of the linear models are determined by the weights (membership functions), obtained in the process of fuzzy clustering. During the algorithm's initialization step the maximum number of local models (this is equal to the number of clusters) or maximum permissible global error must be defined, since they determine the

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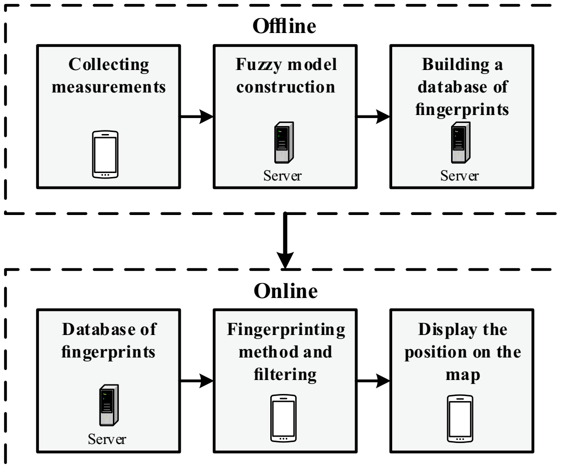

Fig. 1. Schematic representation of the indoor localization system

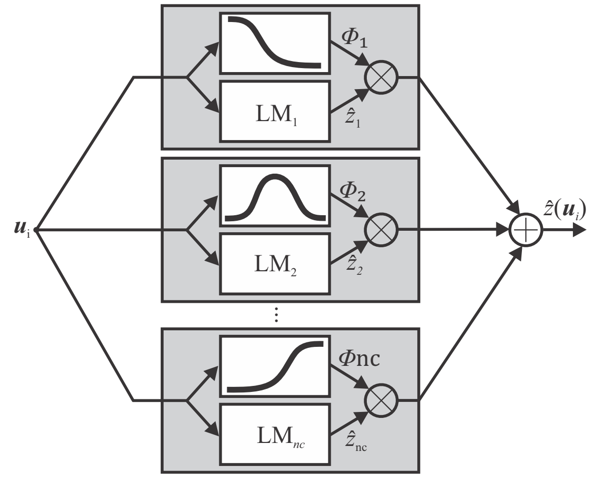

Fig. 2. Fuzzy model consists of several linear models

maximum number of iterations. The input space is incrementally subdivided according to the membership functions (obtained with the clustering algorithm), which, at the same time, determine the contributions of individual local models. The parameters of the local linear models can be easily and efficiently estimated by local or global least-squares (LS) methods. The model's complexity increases incrementally, and the algorithm is terminated when the error is small enough, or the maximum number of local linear models is generated.

The structure of the SUHICLUST model is in the form of a Takagi-Sugeno (T-S) fuzzy model. The latter can be used as a nonlinear approximator for a nonlinear static function or a nonlinear dynamic model approximation [40]–[42]. In the algorithm the membership functions have the form of Gaussian functions.

The output $\hat{z}(\boldsymbol{u}_i)$ (T-S) of the fuzzy model with nu inputs $\boldsymbol{u}_i$ is defined as the interpolation of nc outputs of linear models (Fig. 2) $\hat{z}_k(\boldsymbol{u}_i) = \hat{\boldsymbol{\theta}}_k^T \boldsymbol{u}_i + \hat{\theta}_{k0}$, where $k = 1, \ldots, nc$ and $i = 1, \ldots, N$ ($\hat{\boldsymbol{\theta}}_k = [\hat{\theta}_{k,1}, \ldots, \hat{\theta}_{k,nu}]^T$ are the parameters of the local linear model and N is number of all the input-output measurements):

$$\hat{z}(\boldsymbol{u}_i) = \sum_{k=1}^{nc} \hat{z}_k(\boldsymbol{u}_i)\phi_k(\boldsymbol{u}_i), \tag{1}$$

where $\boldsymbol{u}_i = [u_{i,1}, \ldots, u_{i,nu}]^T$. The ϕ_k represents normalized membership functions (or weighting functions), which describe the regions and contributions of the local linear models to the final global model or its output.

The weighting functions, which determine the contribution of the local models, can take a value between 0 and 1. Thus, the sum of the contributions of all the local models is equal to 1 everywhere in the input space:

$$\sum_{k=1}^{nc} \phi_k(\boldsymbol{u}_i) = 1, \phi_k(\boldsymbol{u}_i) > 0. \tag{2}$$

The SUHICLUST uses the Gustafson-Kessel (GK) algorithm [43] in the process of fuzzy clustering. Each cluster is determined by the position of its center $\boldsymbol{c}_k = [c_{k,1}, c_{k,2}, \ldots, c_{k,nu}, c_{kz}]^T$ and the fuzzy covariance matrix $\boldsymbol{P}_k$.

The fuzzy covariance matrix $\boldsymbol{P}_k$ of the k-th fuzzy cluster $\boldsymbol{P}_k \in \mathbb{R}^{(nu+1)\times(nu+1)}$ is defined as:

$$\boldsymbol{P}_k = \sum_{i=1}^{N} \phi_k^2(\boldsymbol{d}_i)(\boldsymbol{d}_i - \boldsymbol{c}_k)(\boldsymbol{d}_i - \boldsymbol{c}_k)^T, \tag{3}$$

where $\boldsymbol{d}_i = [\boldsymbol{u}_i^T z_i]^T$ $(i = 1, \ldots, N)$ is a data vector with length $(nu + 1)$ and ϕ_k is normalized membership degree of data vector $\boldsymbol{d}_i$ to the k-th cluster.

The fuzzy covariance matrix determines the directions and the variability of the data in the I/O (input-output) space. It can be decomposed with Singular Value Decomposition (SVD).

The algorithm 1 summarizes the path-loss model identification by using SUHICLUST algorithm (the details have been described in [17]).

IV. Fuzzy confidence interval identification

Let the confidence interval [22] be defined for a new dataset, given by the same function $g \in G$ as in the case of the model identification. The validation dataset is defined with the set of measured output values $\boldsymbol{Z}^* = \{z_1^*, ..., z_M^*\}$ over the set of input values $\boldsymbol{U}^* = \{\boldsymbol{u}_1^*, ..., \boldsymbol{u}_M^*\}$: $z_i^* = g(\boldsymbol{u}_i^*)$, where $\boldsymbol{u}_i^* \in \boldsymbol{S}$ $(i = 1, ..., M)$.

In order to define a confidence interval during the fuzzy identification, firstly the lower fuzzy function $\underline{f}$ and the upper fuzzy function $\overline{f}$ need to be determined in such a way that:

$$\underline{f}(\boldsymbol{u}_i^*) \le g(\boldsymbol{u}_i^*) \le \overline{f}(\boldsymbol{u}_i^*), \ \forall \boldsymbol{u}_i^* \in \boldsymbol{S}. \tag{4}$$

Thus, the function g is located with a certain confidence in the band defined by the lower and the upper fuzzy functions.

The measured output values of the k-th local linear model (the number of local models is nc) are determined as:

$$\boldsymbol{z}_k^* = [z_1^*, ..., z_M^*]^T = \boldsymbol{\Psi}_k^{*T}\boldsymbol{\theta}_{v_k} + \boldsymbol{e}_k^* \quad (k = 1, \ldots, nc), \tag{5}$$

where $\boldsymbol{\Psi}_k^* = [\boldsymbol{\psi}_{k,1}^*, ..., \boldsymbol{\psi}_{k,M}^*]$ stands for the regression matrix of the k-th local linear model and $\boldsymbol{\theta}_{v_k} = [\theta_{k0}\ \boldsymbol{\theta}_k^T]^T$ are the

Algorithm 1 Path-loss model identification

```
Transformation (centring and normalizing) of the process data.
Initialization of parameters (number of clusters, etc.).
Computation of covariance matrix.
Definition of initial cluster prototypes.
GK clustering using all the data.
while (End criteria is not met) do
    Computation of normalized membership functions.
    Computation of parameters of local linear models using local LS.
    Quality evaluation of each local linear model.
    Definition of initial prototypes for the cluster with the largest local error.
    GK clustering using only the splitting-cluster's data.
    Determination of new initial cluster centres.
    GK clustering using all the data.
    Re-transformation of centres and fuzzy covariance matrices.
    Computation of normalized membership functions for re-transformed data.
    Computation of parameters of local linear models using global LS.
    Computation of the output of the fuzzy model (1).
end while
```

model parameters. $\boldsymbol{\psi}_{k,i}^{*T}(\boldsymbol{u}_i^*) = \phi_k(\boldsymbol{u}_i^*)[1\ \boldsymbol{u}_i^{*T}]$ represents the regression vector.

The output of the k-th local linear model is in the case of the validation dataset is defined as follows:

$$\hat{\boldsymbol{z}}_k^* = \boldsymbol{\Psi}_k^{*T}\hat{\boldsymbol{\theta}}_{v_k}, \tag{6}$$

where $\hat{\boldsymbol{\theta}}_{v_k} = [\hat{\theta}_{k0}\ \hat{\boldsymbol{\theta}}_k^T]^T$ are the parameters of the k-th model, determined with the least-squares method (considering the vector of the output measurements $\boldsymbol{z}_k = [z_{k,1}, ..., z_{k,N_k}]^T$ and the regression matrix $\boldsymbol{\Psi}_k = [\boldsymbol{\psi}_{k,1}, ..., \boldsymbol{\psi}_{k,N_k}]$) in the phase of the fuzzy identification.

To determine the confidence interval, the expected covariance of the residual between the model output and the new set of data needs to be calculated in each local domain:

$$\begin{aligned} cov(\boldsymbol{z}_k^* - \hat{\boldsymbol{z}}_k^*) &= E\{(\boldsymbol{z}_k^* - \hat{\boldsymbol{z}}_k^* - E\{\boldsymbol{z}_k^* - \hat{\boldsymbol{z}}_k^*\}) \\ &\cdot (\boldsymbol{z}_k^* - \hat{\boldsymbol{z}}_k^* - E\{\boldsymbol{z}_k^* - \hat{\boldsymbol{z}}_k^*\})^T\}. \end{aligned} \tag{7}$$

Considering the same statistical properties of the noise for the data in the validation dataset ($E\{\boldsymbol{e}_k^*\} = 0$) and for the identification set ($E\{\boldsymbol{e}_k\} = 0$), the expected value of the error between the measured output and the estimated output becomes $E\{\boldsymbol{z}_k^* - \hat{\boldsymbol{z}}_k^*\} = 0$. Therefore, the covariance matrix (7) can be written as:

$$cov(\boldsymbol{z}_k^* - \hat{\boldsymbol{z}}_k^*) = E\{(\boldsymbol{e}_k^* - \boldsymbol{\Psi}_k^{*T}\tilde{\boldsymbol{\theta}}_{v_k})(\boldsymbol{e}_k^* - \boldsymbol{\Psi}_k^{*T}\tilde{\boldsymbol{\theta}}_{v_k})^T\} \tag{8}$$

and further as:

$$\begin{aligned} cov(\boldsymbol{z}_k^* - \hat{\boldsymbol{z}}_k^*) &= E\{\boldsymbol{e}_k^*\boldsymbol{e}_k^{*T}\} - E\{\boldsymbol{\Psi}_k^{*T}\tilde{\boldsymbol{\theta}}_{v_k}\boldsymbol{e}_k^{*T}\} \\ &- E\{\boldsymbol{e}_k^*\tilde{\boldsymbol{\theta}}_{v_k}^T\boldsymbol{\Psi}_k^*\} + E\{\boldsymbol{\Psi}_k^{*T}\tilde{\boldsymbol{\theta}}_{v_k}\tilde{\boldsymbol{\theta}}_{v_k}^T\boldsymbol{\Psi}_k^*\}, \end{aligned} \tag{9}$$

where $\tilde{\boldsymbol{\theta}}_{v_k} = [\tilde{\theta}_{k0}\ \tilde{\boldsymbol{\theta}}_k^T]^T$. In the next step, the equation for the least-square optimization is taken into account:

$$\tilde{\boldsymbol{\theta}}_{v_k} = (\boldsymbol{\Psi}_k\boldsymbol{\Psi}_k^T)^{-1}\boldsymbol{\Psi}_k\boldsymbol{e}_k, \tag{10}$$

where $\hat{\boldsymbol{\theta}}_{v_k} = \boldsymbol{\theta}_{v_k} + \tilde{\boldsymbol{\theta}}_{v_k}$. Assuming that both noise signals (from the identification and validation phases) have the same statistical properties $E\{\boldsymbol{e}_k\boldsymbol{e}_k^T\} = E\{\boldsymbol{e}_k^*\boldsymbol{e}_k^{*T}\} = \hat{\sigma}_k^2$ (i.e., the variance of $\boldsymbol{e}_k$) and they are mutually uncorrelated $E\{\boldsymbol{e}_k\boldsymbol{e}_k^{*T}\} = E\{\boldsymbol{e}_k^*\boldsymbol{e}_k^T\} = 0$, the covariance matrix (7) can be written as follows:

$$cov(\boldsymbol{z}_k^* - \hat{\boldsymbol{z}}_k^*) = \hat{\sigma}_k^2\boldsymbol{I} + \hat{\sigma}_k^2\boldsymbol{\Psi}_k^{*T}(\boldsymbol{\Psi}_k\boldsymbol{\Psi}_k^T)^{-1}\boldsymbol{\Psi}_k^*. \tag{11}$$

On the basis of the latter covariance, the lower and upper bounds of the confidence interval [22] for the k-th local linear model can be defined as:

$$\begin{aligned} \underline{f}_k(\boldsymbol{u}_i^*) &= \boldsymbol{\psi}_{k,i}^{*T}\hat{\boldsymbol{\theta}}_{v_k} \\ &- t_{\alpha,M-n_u}\hat{\sigma}_k(1 + \boldsymbol{\psi}_{k,i}^{*T}(\boldsymbol{\Psi}_k\boldsymbol{\Psi}_k^T)^{-1}\boldsymbol{\Psi}_{k,i}^*)^{1/2}, \\ & i = 1, \ldots, M, \end{aligned} \tag{12}$$

$$\begin{aligned} \overline{f}_k(\boldsymbol{u}_i^*) &= \boldsymbol{\psi}_{k,i}^{*T}\hat{\boldsymbol{\theta}}_{v_k} \\ &+ t_{\alpha,M-n_u}\hat{\sigma}_k(1 + \boldsymbol{\psi}_{k,i}^{*T}(\boldsymbol{\Psi}_k\boldsymbol{\Psi}_k^T)^{-1}\boldsymbol{\Psi}_{k,i}^*)^{1/2}, \\ & i = 1, \ldots, M, \end{aligned} \tag{13}$$

where $t_{\alpha,M-n_u}$ is a constant that is obtained from the Student's t-distribution at $100(1-2\alpha)$ percent confidence interval or $100(1-\alpha)$ percentile, which is defined with the upper bound (e.g., for $100(1-0.1) = 90$ % confidence interval where $\alpha = 0.05$, the upper bound represents the $100(1-0.05) = 95$th percentile of the probability distribution). The number of degrees of freedom is equal to $M - n_u$, where n_u is the length of the vector $\boldsymbol{u}$. In the equations for the lower (12) and upper (13) bounds, $\boldsymbol{\psi}_{k,i}^{*T}\hat{\boldsymbol{\theta}}_{v_k}$ represents the output of the k-th local linear model for the i-th point.

V. Fingerprinting method based on interval fuzzy model

The localization system addressed in this section is based on searching the vector of signal strengths, i.e., the fingerprint $\boldsymbol{R_B}$ (within the database or map of fingerprints) that is the most similar to the current vector of the measured signal strengths $\boldsymbol{R_M}$ from the nearby transmitters.

The localization system based on the use of fingerprints usually consists of two phases, i.e., the offline learning phase and the online positioning phase. In the learning phase, the aim is to construct the map of fingerprints (database) that contains the measurements of the signal strengths (from all the transmitters) for all the reference (grid) points in the area [35]. In the online positioning phase the current vector of the measured signal strengths $\boldsymbol{R_M}$ is compared to the values in the database, and depending on which reference point best fits the current vector, the receiver's position (x, y) is determined. In many studies the problem of searching for the nearest neighbour (the most similar vector) was discussed [44].

The map of fingerprints consists of uniformly distributed points around the area, to which the vectors of the signal strengths

$$\boldsymbol{R_B} = [R_1, ..., R_m] \tag{14}$$

from all the available transmitters (the total number of available transmitters is m) belong. In addition to the information about the signal strengths the map of fingerprints also contains the coordinates for each reference (grid) point and the IDs of the transmitters from which the signals are received.

In the offline learning phase the map of fingerprints is usually constructed in such a way that a receiver is placed at all the reference points where the measurements of the signal strengths from all the available transmitters are taken [45]. A large number of reference points means a time-consuming process of collecting the measurements in the database [46].

In our case the construction of the map of fingerprints is somewhat simplified in terms of collecting the measurements, since the fingerprints are generated by using the models of the signal strengths $R = f_R(d)$. All the necessary data for obtaining the models are properly gathered while walking along a path. In this case the receiver's position is tracked with a relative localization system that is based on visual odometry and an inertial navigation system [47].

At the stage of online positioning, the goal is to find the fingerprint $\boldsymbol{R_B}$ within the database (using one of the methods of searching for the nearest neighbour), which is the most similar (according to the criterion) to the current vector of measurements of the signal strengths $\boldsymbol{R_M}$ [48].

When calculating the similarity between the vectors from the database $\boldsymbol{R_B}$ and the vector of measurements $\boldsymbol{R_M}$ some of the K most similar vectors are closer to the vector $\boldsymbol{R_M}$ than the others. Therefore, in determining the position the reciprocal interpolation of the K nearest neighbours is preferred. The contribution of each vector can be determined by using the method of weighted K-nearest neighbours. The weight β of each fingerprint is calculated as: $\beta_k = 1/l_k$ $(k = 1, ..., K)$, where l_k is the distance between the vector from the database $\boldsymbol{R_{B_k}}$ and the vector of the measurements $\boldsymbol{R_M}$. In this way, a contribution (to the position estimation) of more distant fingerprints is smaller than the contribution of fingerprints that are close to the vector of the measurements. If $\boldsymbol{x_{B_k}}$ is the location of the fingerprint $\boldsymbol{R_{B_k}}$, then the estimated position of the receiver is defined as:

$$\boldsymbol{x_M} = \frac{\sum_{k=1}^{K} \beta_k \boldsymbol{x_{B_k}}}{\sum_{k=1}^{K} \beta_k}. \tag{15}$$

A. The use of the fuzzy confidence interval

For all the fingerprints $\boldsymbol{R_B}$ or the corresponding signal strengths R_{B_i} (for $i = 1, ..., m$ where m is the total number of available transmitters) that are obtained with the fuzzy models, the confidence intervals can be determined depending on the lower/upper confidence bounds of the fuzzy models. For each value $R_{B_i} = f_i(d_i)$ $(i = 1, \ldots, m)$ within a particular fingerprint $\boldsymbol{R_B}$, the width of the confidence interval is defined as:

$$\delta_{pi} = \overline{f}_i(d_i) - \underline{f}_i(d_i) \tag{16}$$

at the selected input d_i (i.e., the distance between the position of the i-th transmitter and the position of the fingerprint) where

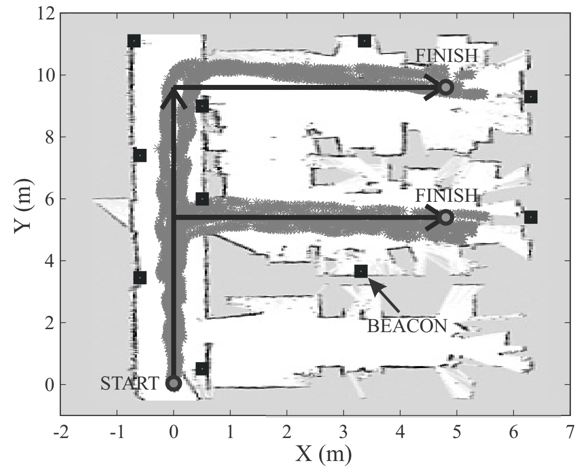

Fig. 3. Positions of BLE beacons and all positions in which the measurements of the signal strengths were made.

$\underline{f}_i(d_i)$ is the lower bound and $\overline{f}_i(d_i)$ is the upper bound of the i-th fuzzy model. In this way, an additional vector

$$\boldsymbol{\delta_p} = [\delta_{p1}, \ldots, \delta_{pm}]^T \tag{17}$$

is assigned to each fingerprint $\boldsymbol{R_B}$ saved in the database. Based on the width of the confidence interval δ_{pi} the weights of all the elements R_{B_i} within each fingerprint are determined as:

$$\boldsymbol{w} = [w_1, \ldots, w_m]^T, \tag{18}$$

where $w_i = 1/\delta_{pi}$ $(i = 1, \ldots, m)$. The weights can be considered when calculating the distance l_w (in the process of searching for the K nearest neighbours) between a fingerprint $\boldsymbol{R_B}$ and the vector of the current measurements of the signal strengths $\boldsymbol{R_M}$:

$$l_w = \sqrt{\sum_{i=1}^{n} w_i (R_{B_i} - R_{M_i})^2} \tag{19}$$

Equation (19) represents the weighted Euclidean distance, where n is the number of beacon IDs that are present in both vectors. The difference $(R_{B_i} - R_{M_i})$ has a greater contribution to the distance l_w if the confidence interval δ_{pi} is narrower, which means that the weight w_i is larger (the measurement R_{M_i} has a larger impact).

VI. Results

A. Results of model construction

In the $\sim$ 85 m^2 laboratory ten Bluetooth beacons (transmitters) from the company Kontakt.io were installed for the purpose of testing the localization algorithms, which are based on measuring the signal strengths. The beacons were distributed throughout the room, as can be seen in Fig. 3. In order to reduce the impact of the presence of the human body on the measurements of the signal strengths the transmitters were mounted at a height of 2 m above the ground.

The measurements of the signal strengths from all ten stations were acquired in such a way that a pedestrian walked the routes that are shown in Fig. 3 (from the START point to

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the FINISH point) ten times while the smartphone recorded the data. The current position of the smartphone was tracked by the algorithm, which combines the visual odometry and the inertial navigation system with the extended Kalman filter [47]. All the positions in which the measurements of the signal strengths were made can be seen in Fig. 3. This figure shows that the obtained points slightly deviate from the plotted route (the lines were marked on the ground), i.e., about 0.5 m. A part of these errors can be attributed to the localization algorithm [47], which determines the position relative to the starting point, and a part to the inaccurate pedestrian walk along the line.

A path loss (or path attenuation, which is a reduction in strength that a signal experiences as it travels through the air or through objects between the transmitter and receiver) can be described by a mathematical model that takes a general form of nonlinear equation and has three parameters for distances $d \geq 1$ m:

$$\begin{aligned} &if\ ratio < 1 : d = ratio^{10} \\ &else:\ d = K_1 \cdot ratio^{K_2} + K_3, \end{aligned} \tag{20}$$

where $ratio = R/TXP = R/{-59}$ ($TXP = -59$ dBm represents a signal strength at the distance of 1 m).

Fig. 4 (dashed line) shows the fit of the model (20) to the measurements of the signal strengths from the transmitter with the MAC address D9:50:3B:F6:AA:46 and position $(3.30, 3.65)$. While collecting the measurements of the signal strengths for this transmitter along the paths shown in Fig. 3, many obstacles (walls, pillars, wooden barriers), which cause the reflection and absorption of radio waves, were present between the transmitters and the receiver. Consequently, in Fig. 4 it is clear that the signal strengths are very scattered (they contain a lot of noise) at the same distance from the transmitter. In the path-loss model (20) the parameters K_1, K_2 and K_3 are only present in the case when the distance from the transmitter to the receiver is greater than or equal to 1 m. The model fit (20) was carried out with a constrained nonlinear optimization (where a trust-region method was used), with which the parameters K_1, K_2 and K_3 were obtained.

In this case the signal strengths do not monotonically decrease with distance from the transmitter and, consequently, the model (20) cannot fit the data very well. This means that in one part of the room the signal strengths are well described by the model, and in the other part (e.g., behind the wall) they are very poorly described.

By using the SUHICLUST algorithm, the fuzzy identification model that describes the signal strength as a function of the distance from the transmitter was constructed for each beacon in the room. Fig. 4 shows that a better fit of the model over the entire range of the distances d can be achieved by using the SUHICLUST algorithm. Since in this case the entire model consists of ten local models, a better compromise can be reached in the sense that the model equally well describes the signal strengths over the entire circumference around the transmitter (at a certain distance d), even if the measurements are very scattered.

In Fig. 4 the upper and lower bounds of the confidence interval with a confidence level of 95 % are also shown.

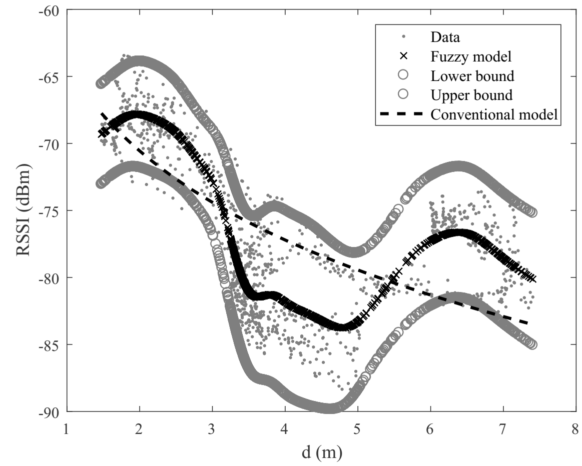

Fig. 4. The fit of the fuzzy model to the measurements of the signal strengths for the BLE beacon with the MAC address D9:50:3B:F6:AA:46.

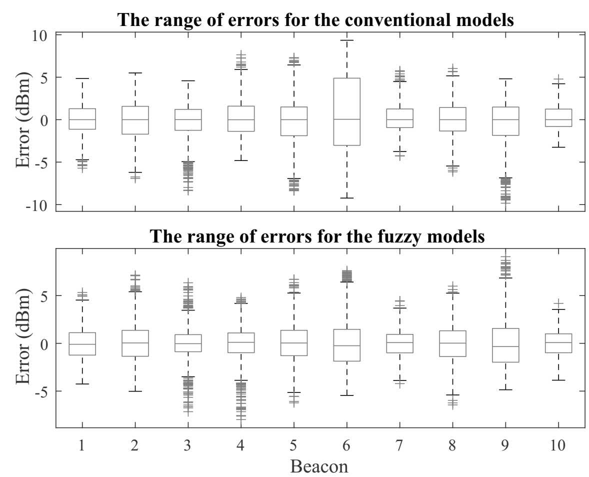

Fig. 5. The range of errors for all the identified models.

The degree of fit of the model to the measurements of the signal strength can be evaluated by calculating the root-mean-square error ($RMSE$). This is equal to 2.57 for the fuzzy model (constructed with the SUHICLUST algorithm), which is shown in Fig. 4. If the model (20) and nonlinear optimization were used, a much worse result would be obtained, i.e. $RMSE = 4.66$.

In Fig. 5 two box plots that show the range of errors for all the conventional nonlinear models (20) and fuzzy models can be seen. Rectangular frames, which can be seen in Fig. 5, include 50 % of all the errors for each model. In the figure the crosses denote the divergent errors, i.e. outliers, which are higher than $Q3 + 1.5 \cdot IQR$ or lower than $Q1 - 1.5 \cdot IQR$ (between these two limits 99.3 % of all errors are placed), where $Q1$ stands for the first quartile (25th the percentile), $Q3$ is the third quartile (75th percentile) and $IQR = Q3 - Q1$. Fig. 5 shows that the range of errors is smaller for the fuzzy models, especially for model 6, which belongs to the beacon, the measurements of which are shown in Fig. 4.

By the use of other algorithms for nonlinear identification, e.g., LOLIMOT [17], the results of model fitting could be

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as good as those obtained with algorithm SUHICLUST. But the major contribution represents the introduction of the confidence interval to the interval fuzzy models and its intuitive usage in the fingerprinting method.

B. Localization results

In order to evaluate the developed localization algorithm, which is based on the proposed fingerprinting method, the measurements of the signal strengths were acquired with an Android smartphone along the path shown in Fig. 3. A vector of signal strengths $\boldsymbol{R_M}$ from which the current position was determined was created each time the receiver measured at least one new signal strength that was greater than -90 dBm. In our example, this occurs on average every 30 ms. In order to determine the accuracy of the localization algorithms, a real receiver's (smartphone) position where the vector $\boldsymbol{R_M}$ was created, was also recorded.

In order to obtain a unique solution for determining the current position, the vector of signal strengths $\boldsymbol{R_M}$ must include the measurements from at least three transmitters. It turned out that the greatest positioning accuracy was achieved when the vector $\boldsymbol{R_M}$ contained five measurements from different beacons. By increasing the number (over five) of measurements from different transmitters in each vector, $\boldsymbol{R_M}$ the localization accuracy was no longer improved.

To determine the current receiver's position with the fingerprinting method, only one nearest neighbour ($K = 1$) to the vector $\boldsymbol{R_M}$ needs to be found within the database of fingerprints. But since the positions of the fingerprints within the map are sparse, it is recommended to use several nearest neighbours to achieve greater accuracy in the online positioning. The simulation results showed that the localization accuracy was the highest when 23 of the nearest neighbours were taken into account (the sum of the position errors decreased by 18 %).

In order to compare the fingerprinting method with the well-established trilateration [29] and experimental method, which is based on particle-swarm optimization (PSO) [49], [50], Fig. 6 was generated. The latter shows the results of the indoor positioning with three different methods, where the path-loss models were constructed with conventional nonlinear models (20). In all the mentioned methods, the measurements of the signal strengths from five different beacons were used when determining the current receiver's position. Fig. 6 shows that the best localization results can be obtained with the fingerprinting method, where in 92 % of position estimates the error is smaller than 1 m or in 42 % of estimates it is smaller than 0.5 m. In this case the maximum error is 2.3 m. When using the trilateration method the maximum error is substantially smaller (about 1.7 m), but the overall results are poorer, since in 78 % of position estimates the error is smaller than 1 m or in 23 % of estimates it is smaller than 0.5 m. When using the PSO method the maximum error is less than 1.4 m, which is a considerably better result than when the positions are determined with the trilateration or fingerprinting method. However, the overall results are not as good as with the fingerprinting method, since the error is smaller than 1 m in 91 % of the position estimates or it is smaller than 0.5 m in 31 % of estimates.

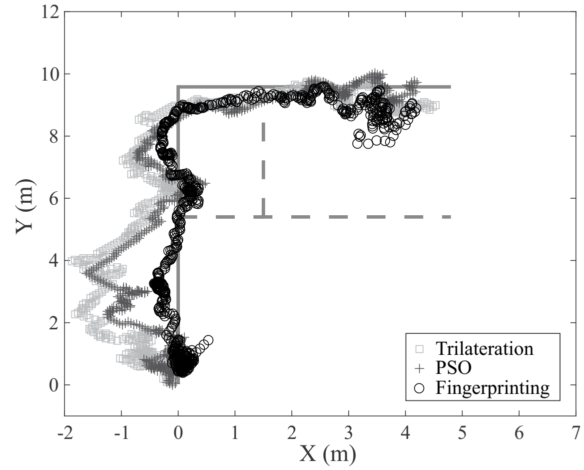

Fig. 6. The results of indoor positioning obtained by using the fingerprinting method, trilateration and PSO respectively. The path-loss models were constructed with conventional nonlinear models (20).

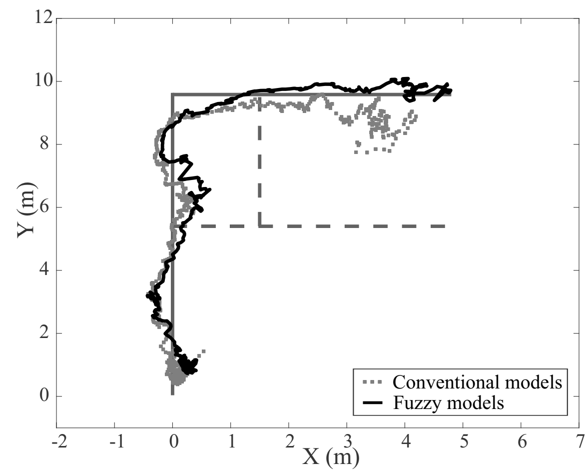

Fig. 7. The results of indoor positioning using the map of fingerprints that was constructed with the nonlinear models (20) or the fuzzy models.

According to the obtained results (Fig. 6), it can be concluded that the fingerprinting method is the most appropriate for indoor localization based on Bluetooth signal strengths, since it is accurate and fast, which is important for real-time processing on less powerful devices. When testing the localization algorithm in the Matlab environment, the fingerprinting method spends only 2 ms to calculate a position, while the trilateration method spends 60 ms. The fingerprinting method also provides the most intuitive way of using fuzzy models and the corresponding confidence intervals as it is explained in subsection V-A. Therefore, the fingerprinting method was selected to be used in combination with the interval fuzzy models and conventional nonlinear models (20) in the final evaluation of the localization algorithm (Fig. 7).

In the first case when the map of fingerprints was constructed using the nonlinear models (20), the receiver positions were less accurately determined, especially in the last part of the path (Fig. 7). In the second case the fuzzy models were

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TABLE I
SUMMARY OF LOCALIZATION RESULTS

Approach	**Errors < 0.5 m**	**Errors < 1 m**
Trilateration	23 %	78 %
PSO	31 %	91 %
Fingerprinting	42 %	92 %
Fing. and Fuzzy mod.	43 %	97 %
Fing. and INFUMO	53 %	99 %

used for creating the map, and as can be seen in Fig. 7 the localization results were significantly improved. In this case the average error was 0.51 m (or 0.68 m without low-pass filter), and when the nonlinear models (20) were used, the average error was slightly higher, i.e., 0.57 m (or 1.25 m without low-pass filter).

By considering the weights (18) in the calculation of the Euclidean distances (in the process of searching the K nearest neighbours within the database of fingerprints) the positioning errors were further reduced. In determining the positions along the path that is shown in Fig. 7 the average error was reduced by 6 % (from 0.51 m to 0.48 m) which represents a significant improvement.

A more detailed comparison of the localization results can be performed with the graph of the cumulative distribution function, which is shown in Fig. 8. It can be seen that the solid curve (obtained on the basis of the positioning errors when interval fuzzy models with confidence intervals are used) has a greater slope than the dashed curve (obtained on the basis of positioning errors when nonlinear models (20) are used), which means that the greater part of the errors is concentrated at lower values than with the dashed curve. The solid curve also has a greater slope than dash-dot curve, which is obtained with fuzzy models but without considering the confidence intervals and proposed fingerprinting method. Fig. 8 shows that the error is smaller than 1 m in 99 % of position estimates or it is smaller than 0.5 m in 53 % of estimates if the interval fuzzy models with confidence intervals are used. When using the nonlinear models (20), the error is smaller than 1 m in 92 % of the position estimates or smaller than 0.5 m in 42 % of the position estimates. In Fig. 8 it can be seen that the usage of the confidence intervals within fingerprinting method significantly improves localization results, since the number of localization errors which are smaller than 0.5 m is increased by 10 % and the number of localization errors which are smaller than 1 m is increased by 2 %. Table I summarizes the localization results, where the first three results were obtained with conventional nonlinear models (20) and the last two results were obtained with fuzzy models. From those results it can be concluded that the combination of confidence-interval fuzzy models (INFUMO) and improved fingerprinting method is the most promising low-cost indoor localization solution which, due to high accuracy, has a great potential.

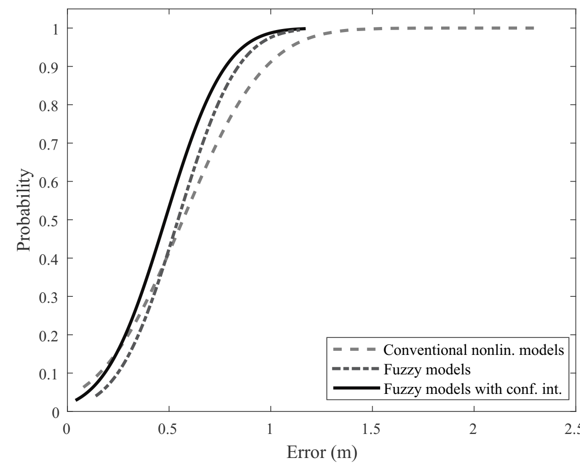

Fig. 8. Cumulative distribution functions for the positioning errors in determining the positions by the use of fingerprints that were generated by the nonlinear models (20) or fuzzy models.

VII. CONCLUSION

In this paper a sophisticated approach to indoor localization using the interval fuzzy model and the improved fingerprinting method, based on the confidence interval, is presented. The developed indoor localization system, which is based on the use of Bluetooth beacons and a smartphone, can operate in real time and consumes very little energy. The fuzzy models, which consist of a set of local linear models, more accurately describe the changing of the signal strengths with increasing distance from the transmitters than conventional nonlinear, path-loss models, even when the measurements are very scattered due to the presence of obstacles. With the use of fuzzy models the localization accuracy is improved by around 45 %. To construct accurate path-loss models, in addition to the efficient SUHICLUST algorithm, a suitable collection of measurements of the signal strengths is required. In our case the measurements are obtained quickly and easily using the visual odometry and inertial navigation system. Consequently, with the path-loss models taken into consideration, the map with the selected density of fingerprints is quickly built. By determining the confidence interval for each fuzzy model and by using the proposed fingerprinting method the localization accuracy is improved by 6 %. This improvement presents an important contribution to indoor localization since the developed localization system outperforms the existing low-cost localization systems. Namely, with an average error of 0.48 m it is way ahead of the rest. With such excellent results many doors will open for the developed localization system, as it can be used for guiding autonomous mobile systems or people inside buildings.

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