Fuzzy Inference with Parameter Identification for Indoor WLAN Positioning

M. Alakhras Member IAENG, M. Oussalah, M.I. Hussein

***Abstract*— This paper considers the fuzzy inference as position estimator for WLAN indoor environments, based on received signal strength measurements RSS. The proposal algorithm includes a fuzzy inference which uses the k-nearest neighbor classification in signal space, where the position of target node is calculated as a weighted combination of nearest fingerprints, where the weights are estimated using enhanced Takagi–Sugeno fuzzy controller with multivariable inputs and parameter identification with constrained optimization. The new developed technique is proposed to enhance the accuracy of position estimation in WLAN indoor environments;**

Index Terms*— Clustering, Fuzzy logic, RSS, WLAN indoor positioning;

I. Introduction

Position estimation techniques gained potential attention from various disciplines ranging from pure engineering to social and/or psycho- logical domain. Moreover, the emergence and proliferation of the wireless communication industry and the popularity of mobile and handheld devices with billions of users has also prompted the interest in the position estimation task to a higher level where the location of the data is as important as the data itself. This is referred to as Location Based Services (LBS), where the quality of service (QoS) received is highly dependent on the accuracy of the location estimation [1]. Positioning is also a key in ubiquitous computing architectures as sensors/access points are distributed across the whole environment such as intelligent cities and health monitoring. Mobile services such as user's tracking, location specific advertising, finding the nearest points of interest, route planner etc. In this respect, the LBS makes use of technologies involving Global Positioning System (GPS), GSM for outdoor environments, and local range technologies, e.g., Bluetooth, WiFi, Radio Frequency Identification (RFID) [2]. Although it is acknowledged that the Global Positioning Systems (GPS) technology becomes effective and affordable in open and flat outdoor environments, its use in WLAN indoor environments as well as in Non-Line-Of-Sight (NLOS) scenarios is not effective. This triggers the need for alternative positioning techniques in wireless systems. Besides, the constraints imposed by regulator bodies to force the operators to achieve minimal positioning accuracy regardless of availability of GPS data for emergency purpose, together with the need to accommodate local network constraints, e.g., communication cost and nature of outcome, pushed towards the development of wireless-like solution as a pre-requisite to the success of the underlying application(s). The variety of applications in wireless systems as well as the growing challenges has led to a range of positioning techniques developed to meet various constraints [2,3]. Many measurements can be employed for positioning purpose, such as time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA) and received signal strength (RSS) [4]. The latter is usually the cheapest preferred option when one excludes the possibility of adding an extra hardware support to the system. Fingerprinting approach [5], which makes use of a training phase where RSS data are collected from different survey points, yielding a radio map of the deployment area. While in the online stage, the current RSS measurement set is mapped to its best match in the radio map according to the underlying mapping strategy where various machine learning based methods [6] have been put forward for this purpose. But still the problem is very challenging because of the *uncertainty pervading* the RSS data due to *signal fading*, *signal attenuation* as well as the *radio propagation model* and the *non-uniformity of data* in radio.

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To tackle the above challenges, in continuation of work carried out in [7] and as part of the positioning project for WLAN, this paper presents an RSS based algorithm combining fuzzy methodology yielding a Multiple Variable Fuzzy Localization (MVFL) algorithm. Especially, a multivariable Takagi–Sugeno (TS) fuzzy inference system [8] was designed to estimate the weight of the target position relative to its surrounding neighbors, and use, in turn, such information to estimate its location. Unlike work in [7], different input variables have been employed and a new procedure for *identification of parameters of fuzzy* system using *gradient descent approach together with a set of rational constraints has been introduced*. The performances of the algorithm have been evaluated and compared to some state of art algorithms. The rest of the paper is organized as follow. Section 2 presents some related work. Section 3 explains the methodology with highlighting the fingerprint approach, localization algorithms and fuzzy parameter identification. Section 4 presents the implementation results and discussion. Section 5 presents the conclusion.

II. Related Work

Since the introduction of IEEE 802.11 standard for implementing WLAN, various methods and technologies have been proposed to address the indoor position estimation problem using the RSS measurements. The Microsoft Radar system [9] was probably one of the pioneer works in integrating the RSS measurements with a local area map, which, using k-Nearest Neighbor (kNN) approach, achieved a localization accuracy of up to 5 m. This ultimately assumes that the strength of the signal from an IEEE 802.11 access point does not vary significantly at a given location. Improvements to RADAR's fingerprint matching algorithm

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have been suggested in [10] for the purpose of improving its accuracy. Support vector machine approach to wireless localization has been advocated in [11] and a comparable performance to kNN approach was reported. In [12] histogram and Kernel based approach was investigated for the same purpose. In [13] the use of WLAN RSS signals for indoor positioning was considered for a university buildings and labs using empirical models. The original Active Badge System proposed in [14] used infrared emitters and detectors to achieve 5–10 m accuracy. The Daedalus project [15] developed a system for coarse- grained user location, which coincides with that of the base station to which it is attached to, so that the accuracy is restricted by the radius of the base station. This obviously corresponds to the easiest and simplest fingerprinting-like approach. On the commercial market, Ekahau [16] has taken a leading role in indoor positioning through a combination of signal strength pattern recognition with an attempt to recover user's history.

Strictly speaking, in order for the aforementioned methods to perform well, a large number of labeled samples need to be collected at each survey point, which is rather context dependent. Indeed, the target environment is critical for the accuracy of WLAN fingerprinting-like approach. Besides, radio characteristics in an open environment are *never static*, and there is no universally fine methodology to tune the data to accommodate environmental change, although, one acknowledges a growing interest in post-deployment adaptation in recent years from telecom industry [17]. Even the commercial products like that provided by Ekahau fall victim to environmental change post-deployment adaptation problems [17]. Consequently, the issue of handling uncertainty pervading the signal strength measurements as well as environmental layout is of paramount importance. This opened the way to alternative uncertainty models like fuzzy logic [19] in wireless indoor position. In this course, one distinguishes two broad classes of solutions. One makes use of fuzzy inference system and the other one advocates a fuzzy clustering related approach, especially fuzzy c-means algorithm. The former is based on the idea that the positioning of the (unknown) target node is determined as a weighted combination of fingerprint nodes, where the weights are determined using some fuzzy inference system [20]. While the latter strategy employs a fuzzy c-means-like algorithm to cluster the fingerprint in the RSS space into a certain number of classes. Next, those fingerprints that belong to the same class of the target were selected, and the target position is estimated by taking the average of fingerprints [3].

A combination of fingerprint based on fuzzy inference system with multi-nearest neighbor algorithm to locate objects in wireless sensor networks was reported in [21]. This work showed that fuzzy logic can significantly enhance the accuracy and keep the cost of computation as low as possible. However, given that the fuzzy inference system only makes use of one single input consisting of the RSS distance measurements, renders the approach very limited to handle dynamic environmental changes. This partly motivates our choice to advocate a fuzzy logic approach for developing our indoor positioning algorithm. On the other hand, the choice of fuzzy c-means-like approach was discarded mainly because of its computational cost due to its iterative behavior and its sensibility to initialization. Overall, this work differs from the aforementioned related works in different perspectives. First, the suggested fuzzy inference makes use of several input variables in order to enhance the robustness of the outcomes (weight parameters). Second, a nonlinear optimization approach based on gradient descent and resilient propagation together with a set of rational constraints that ensure easy interpretability as well as agreement with radio propagation model have been used to estimate the parameters of the fuzzy systems (antecedents and consequents parts of fuzzy "If … then" rules). Third, the dynamic change of environment is accounted for through the integration of empirical radio propagation model.

III. METHODOLOGY

A. Fingerprint based on RSS

Fingerprinting is a positioning technique that involves a two-stage process: an offline phase and an online phase as shown in (Fig. 1). In the offline phase, the goal is to build a database for each reference location (fingerprint), say, FP_i by sampling the RSS from several wireless Access Points (APs) yielding vectors (RSS_{i1}, RSS_{i2}, ..., RSS_{in}), i = 1 to m, where RSS_{ik} is the signal strength from the i^{th} reference location (fingerprint FP_i (x, y)) to the k^{th} AP, n is the total number of access points and m is the total number of fingerprints [22]. While in the online phase, the location of the target (or target node) T with a measured RSS vector is estimated using some pattern matching algorithm by comparing the current observed signal (RSS vector) with pre-recorded values in database.

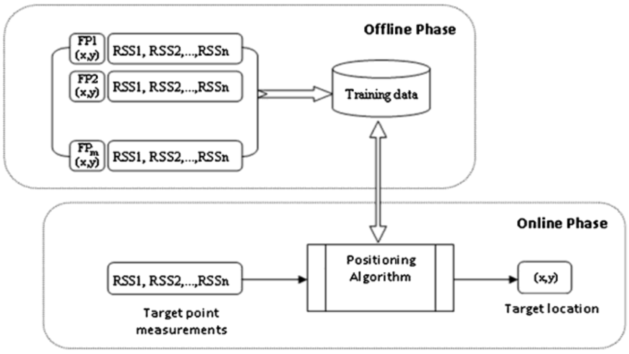

Fig 1 General bloack diagram of fingerprinting technique

Then the similarity between the i^{th} fingerprint and the target can be calculated using some form of (Euclidean) distance [23]. Moreover, several possibilities could be considered for obtaining the location of the target T. Machine learning related approaches [6], including neural network, support vector machine, support vector regressions, histogram and kernel methods as well as fuzzy approaches [12,19,20,21] have also been suggested to handle the positioning aspect.

Strictly speaking, most of these techniques rely on the generalization power of the underlying method. Nevertheless, it should be noted that, fingerprinting for indoor WLAN environment performance still is limited by some growing challenges. First, most of the indoor WLAN are implemented using the 2.4 GHz public band WLAN frequency proposed by IEEE 802.11 which is also used by

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GSM, microwave and other wireless devices. This may cause irregular RSS patterns to the collected data in offline stage. Second, the availability of blocking bodies in the indoor environment could weaken the signal and could hide the LOS between AP and receivers. Third, the accuracy of fingerprinting methods heavily relies on the density of fingerprints collected during the offline phase, where, on long term run, any change in the environment such as Access Point (AP) replacement, facilities upgrade, etc., can lead to poor system performance. Indeed, if for any reason one of the reference nodes vanished from the map, the algorithm will end selecting a point with larger Euclidean distance, and this will negatively impact the accuracy of estimation. This motivates the need to account for physical signal properties when using the RSS data. More specifically, the use of appropriate radio propagation model that accounts for such irregularities contributes significantly to the performance of the underlying fingerprinting application. Our approach for such issue is detailed in next section.

B. Multivariable fuzzy localization (MVFL) architecture

Similarly to work carried out in [7], a fuzzy inference system is applied to find out weights attached to the kNN fingerprints. Then, the location of the target node is determined as the weighted combination of these K fingerprints:

$$x_T=\frac{1}{K}\sum_{i=1}^{K} w_i x_{FP_{\sigma(i)}} \quad , \quad y_T=\frac{1}{K}\sum_{i=1}^{K} w_i y_{FP_{\sigma(i)}} \qquad (1)$$

where w_i is the weight for every fingerprint and $\sum_{i=1}^{K} w_i = 1$. $(x_{FP_{\sigma(i)}}, y_{FP_{\sigma(i)}})$ stands for x-y coordinates for fingerprints. σ corresponds to a permutation of the indices of K fingerprints.

Therefore, the first phase consists of determining the k-nearest neighbors. This is performed by calculating the distances in RSS space from each fingerprint to the target node, and then selecting the fingerprints yielding the k-smallest distances.

In order to determine the weights in (1), a fuzzy inference system has been put forward. The proposal makes use of two input variables:

i. The *distance D(j) (j = 1 to K)* in RSS space from the target node to the j^{th} nearest neighbor fingerprint.

ii. The *difference of the signal variations V(j)* between target node and j^{th} nearest neighbor with respect to different APs.

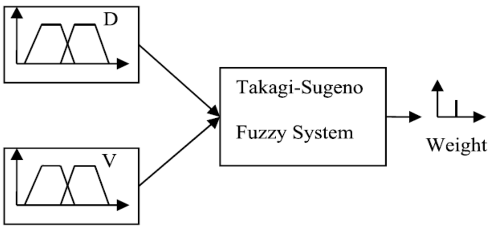

Fig 2 General bloack diagram of MVFL

The output of the fuzzy system consists of the weight attached to each fingerprint belonging to the set of kNNs. A Takagi–Sugeno (TS) fuzzy system was adapted as the main fuzzy inference. The main feature of T–S fuzzy models is that they characterize the local dynamics of each fuzzy rule by a linear model. In our system, as it will be detailed later on, the outcome is constant. The generic system is shown in Fig. 2. More formally, the input variables are expressed as

$$D(j)=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(RSS_{ij}-RSS_{Tj})^2} \qquad (2)$$

$$V(j)=\left|(\max_i RSS_{ji}-\min_i RSS_{ji})-(\max_i RSS_{Ti}-\max_i RSS_{Ti})\right| \qquad (3)$$

$$j\in\{\sigma(1),\sigma(2),....,\sigma(K)\}$$

Strictly speaking, the input variable *V(j)* allows us to control the extent to which both the target and the underlying fingerprint agree in terms of the total variations caused by the use of distinct access points. Indeed, it is trivial that the distance is not a sufficient indicator to discriminate between distinct scenarios. For instance, geometrically speaking, points located on the same circle have equal distance to the center of this circle even if they may be very disparate from each other. Consequently, adding an extra discrimination parameter sounds intuitively useful. In the same spirit, authors in [20] have employed standard deviation statistics as an extra discriminating variable. Therefore, the more a given fingerprint agrees with the target node in terms of both distance D and variation V, the more important is the weight associated to the underlying fingerprint. In order to quantify this statement in fuzzy logic, a set of “if… then...” rules are elaborated. For instance,

$If\ D(j)\ is\ VSmall\ AND\ V(j)\ is\ VSmall\ THEN\ w_j\ is\ VHigh$

$If\ D(j)\ is\ high\ AND\ V(j)\ is\ high\ THEN\ w_j\ is\ Vlow$

$If\ D(j)\ is\ high\ AND\ V(j)\ is\ Small\ THEN\ w_j\ is\ low$

The above linguistic qualifications are obtained through fuzzification process where the (crisp) inputs are transformed into fuzzy sets. The latter are characterized by their membership functions, which describe the shapes. Typically, simple parameterized models, e.g., Gaussian, triangular, S-shape, were used in the literature. In our model, trapezoid membership functions were employed as shown in Fig. 3.

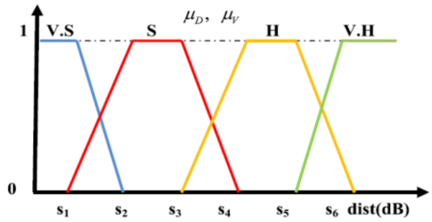

Fig 3 Fuzification of input variable D (or V)

According to Fig. 3, the assignment of a specific (fuzzy) linguistic quantifier to the distance *d* (in signal space) output depends on its numerical value. More formally, we have for instance

$If\ d\le s2,\ then\ d\ (in\,dB)\ is\ classified\ as\ VerySmall(VS)$

$If\ s1\le d\le s4,\ then\ d\ is\ classified\ as\ Small(S)$

$If\ s3\le d\le s6,\ then\ d\ is\ classified\ as\ High(H)$

$If\ d\ge s5,\ then\ d\ is\ classified\ as\ VeryHigh(VH)$

On the other hand, the determination of the boundary of the membership functions in Fig. 3 obeys some rational criteria [25]. This includes:

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i. easy interpretability.
ii. respect of physical and statistical characteristics of the RSS.
iii. agreement with one of membership function interpretations.
iv. existence of sufficient number of (fuzzy) rules could be activated.
v. minimization of predicted output and ground truth.

Especially, requirement (ii) imposed some constraints on the simulation and experiment setup. Indeed, given that the RSS values fail sharply in the first meter or so (~40 dB) as opposed to smooth transition in the range 1m – 50m, therefore, we deliberately chosen situations in which the APs and fingerprints/target were at least one meter distant in order to ensure smooth coverage of the whole RSS range. More detailed handling of the above constraints is highlighted in next section.

C. Fuzzy system parameter identification

First in order to ease the comparison with previous work, we consider the output of the fuzzy system to be a numerical constant value. This makes the underlying fuzzy system coincide with zero-order Takagi–Sugeno fuzzy system [8]. The i^{th} rule can be formulated as:

$$R^i : If\ D\ is\ F_D^i\ AND\ V\ is\ F_V^i\ then\ W\ is\ \theta_{VD}^i$$

where F_D^i and F_V^i are fuzzy sets associated to variables D and V, respectively, while θ_{VD}^i stands for a constant value associated to weight W , for the rule R^i . In accordance to fuzzy operators where the fuzzy connective AND is implemented using the product operator [25], then assuming the center of area-like defuzzification, the output associated to M fuzzy rules is provided by [18]:

$$\hat{w}(V,D) = \frac{\sum_{i=1}^{M} \theta_{VD}^i \mu_{F_V^i}(V).\mu_{F_D^i}(D)}{\sum_{i=1}^{M} \mu_{F_V^i}(V).\mu_{F_D^i}(D)} \tag{4}$$

where the membership functions $\mu_{F_V^i}$ and $\mu_{F_D^i}$ are defined as trapezoidal function as pointed out previously, Through their associated four parameters defining the support and core of the membership function as in (5).

$$\mu_{F_V^i}(V) = \begin{cases} 0 & if\ V < v_1^i or\ V > v_4^i \\ \dfrac{V - v_1^i}{v_2^i - v_1^i} & if\ v_1^i \le V \le v_2^i \\ 1 & if\ v_2^i \le V \le v_3^i \\ \dfrac{v_4^i - V}{v_4^i - v_3^i} & if\ v_3^i \le V \le v_4^i \end{cases} \tag{5a}$$

$$\mu_{F_D^i}(D) = \begin{cases} 0 & if\ D < \rho_1^i or\ D > \rho_4^i \\ \dfrac{D - \rho_1^i}{\rho_2^i - \rho_1^i} & if\ \rho_1^i \le D \le \rho_2^i \\ 1 & if\ \rho_2^i \le D \le \rho_3^i \\ \dfrac{\rho_4^i - D}{\rho_4^i - \rho_3^i} & if\ \rho_3^i \le D \le \rho_4^i \end{cases} \tag{5b}$$

From (5), the problem of fuzzy system identification boils down to estimating the parameters of the fuzzy system; namely, v^i and ρ^i, which correspond to antecedents parts of rule R^i and the consequent part θ^i.

From a set of observation *(V_i , D_i , w_i) i=1…N*, the estimation of the parameter vector should also minimize the estimation error:

$$J(v,\rho,\theta) = \sum_{i-1}^{m} [w_i - \hat{w}_i(v_i, \rho^i, \theta_{VD}^i)]^2 \tag{6}$$

Notice that the weights w_i issued from the observation are quantified according to the distance of the underlying fingerprint to the known target so that the more the location of the fingerprint is close to the (true) target, the higher is the associated weight. More formally, given a target T in *x–y* coordinates and a fingerprint P_i yielding (V_i , D_i) measurement, then weight is given as

$$w_i = \begin{cases} 1 & if\ dist(P_i,T) < \tau_1 \\ 1 - \dfrac{dist(P_i,T)}{\tau_2} & if\ \tau_1 \le dist(P_i,T) < \tau_2 \\ 0 & if\ dist(P_i,T) > \tau_2 \end{cases} \tag{7}$$

where *dist* stands for distance in Euclidean space, and τ_1 and τ_2 are thresholds on distance delimiting the full coincidence with target node and full separation, respectively.

Strictly speaking, at least two streams of research in the estimation of the fuzzy system parameters could be distinguished. The first one advocates the use of a two stage strategy where the antecedent parts v^i and ρ^i (*i*=1 to *M)* of the membership functions were identified through clustering or neural network/genetic algorithm-like approaches [26]. Next, the consequent parts were determined, usually using least square algorithm. The second stream involves the use of optimization-like approach such as gradient descent where all parameters are learned through iterating with constant adjustment factor until a satisfactory level of performance metric, usually estimation error, is reached [27]. Hybrid approaches employing both gradient descent and clustering and/or least squares can also be envisioned. Besides, the number of partition of the input space *V* and *D*, which controls the number of total fuzzy rules *M,* can also be used as part of system identification. For this purpose, usually inter-class validity criteria is used in case of clustering based approach, while it can also be part of parameters to be identified in case of gradient descent-like approach. On the other hand, it is also worth pointing that both clustering and gradient descent-like approaches may lead to non-appealing result where there is less or full absence between fuzzy sets, which, in turn, result in weakly activated or not activated at all fuzzy rule(s) for some combination of input space, see for instance [26] and references therein. This yields into relaxation of optimality criteria governing either the clustering or the gradient descent-like approaches. Even early work of Sugeno and Yasukawa [28] fits into this category. This motivates our approach to employ the gradient descent approach in order to estimate both the antecedent and the consequent parts of the rule in conjunction with a set of rational constraints that ensure full comply with desirable requirements set in earlier section. Especially, in order to ensure requirements (i) and (iv), we consider that, for a given input variable, for any fuzzy set,

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there is always one fuzzy rule for which the overlapping part has a membership grade of 0.5 as it can be seen in the example of Fig. 3. Besides, in order to ensure requirements (ii) and (iii), the range of the values that can be assigned to the input variable is determined by the physical and statistical characteristics of RSS. The latter are simulated using the simulated environment as well as the radio propagation model (14) as will be detailed later. In this context, the core and support of the membership function can be interpreted as the extent of the interval where the true boundary of the distance in signal space will possibly and certainly lie in, respectively. This agrees with the random set view interpretation, where the membership function is viewed as a nested family of level-cuts [25].

More formally, the determination of the fuzzy system parameters boils down to the following optimization problem:

$$\underset{v,\rho,\theta}{\text{Minimize}} \quad \mathrm{J}(v,\rho,\theta)=\sum_{i-1}^{m}[w_i-\hat{w}_i(v_i,\rho^i,\theta_{VD}^i)]^2 \tag{8}$$

Such that

$$\forall V_i \in U_V, \quad \sum_{i=1}^{M_1}\mu_{F_V^i}(V_i)=1, \quad i=1,m \tag{9}$$

$$\forall D_i \in U_D, \quad \sum_{i=1}^{M_2}\mu_{F_D^i}(D_i)=1, \quad i=1,m \tag{10}$$

$$[\inf(V)\ \ \sup(V)]=f(RSS) \tag{11}$$

$$[\inf(D)\ \ \sup(D)]=g(RSS) \tag{12}$$

Expression (8) is in agreement with requirement (v) where the estimated parameters constituting of rule premise antecedents part v and ρ as well as consequent parts θ are the unknown variables.

Expressions (9) and (10) state that for each value of the input variables V and D belonging to the corresponding universe of discourse U_D and U_V , the sum of membership grades associated to all fuzzy sets of the partition (M_1 partition for input variable V and M_2 partition for variable D) is equal to unity. This insures that for each value of the input variable, there is at least one rule which is activated. If there is an overlapping between two fuzzy sets, then the maximum membership grade of the overlapping area is equal to 0.5. This guarantees the interpretability requirement stated earlier.

Finally, expressions (11) and (12) indicate that the range of values associated to universe of discourse of the two input variables is function of the signal strength values.

In order to implement the above optimization problem a gradient descent method is applied, similar to work in [27]. Besides, in order to strengthen its computational complexity, we used resilient propagation RPROP [29], initially developed for neural network training, and employed a gradient descent algorithm with a resilient parameter update step. A link of RPROP with Matlab FIS system environment is also established in order to ease the solution of the above constrained optimization problem. Besides, the fact that the trapezoidal functions are piecewise derivable makes the use of the RPROP appropriate. On the other hand, the number of partition is taken constant $M_1=M_2=4$, yielding a total of $M=4\times4=16$ rules. This is mainly motivated on one hand, by the desire of simplification of the above optimization problem, and the ease of comparison with alternative approaches on the other hand. Strictly speaking, an alternative implementation would be to work out the augmented Lagrangian operator from (8)–(9) as:

$$\underset{v,\rho,\theta,\lambda,\chi}{\text{Minimize}} \quad \mathrm{J}(v,\rho,\theta,\lambda,\chi) = \sum_{i-1}^{m}\left[w_i-\frac{\sum_{j=1}^{M}\theta_{VD}^j\mu_{F_V^j}(V_i).\mu_{F_D^j}(D_i)}{\sum_{i=1}^{M}\mu_{F_V^i}(V).\mu_{F_D^i}(D)}\hat{w}_i(v_i,\rho^i,\theta_{VD}^i)\right]^2 + \sum_{i=1}^{m}\lambda_i\sum_{j=1}^{M_1}\left(1-\mu_{F_V^j}(V_i)\right)+\sum_{i=1}^{m}\chi_i\sum_{j=1}^{M_2}\left(1-\mu_{F_D^j}(D_i)\right) \tag{13}$$

and then set the derivatives with respect to antecedent, consequent rule parameters as well as Lagrange multipliers λ, χ to zero, yielding a solution close to clustering-like fuzzy identification approach. Nevertheless such solution has not been pursued due to already proven efficiency of RPROP and less sensitivity to initial guess-this can be part of the future investigation-. Alternative studies have shown that even applying much more exhaustive search strategies i.e., Johansen and Foss [28] only marginally outperform RPROP.

D. Properties of MVFL

Interestingly, MVFL induces the same result as standard kNN when either both input variables were evaluated Very Small or High. Particularly, based on the values of input variables V and D, some useful cases regarding the performance of the MVFL algorithm can be distinguished.

Proposition 1. If the fingerprints outputted by the kNN are such that

$max(Di,Vi) \leq s_1$ for some nearest neighbor i, and

$min(Dj,Vj \geq s_6, \forall j = 1, K, j \neq i$,

then, the outcome of MVFL coincides with the i^{th} nearest fingerprint.

The proof of the above proposition follows straightforwardly from the fact that the condition $max(D_i,V_i) \leq s_1$ entails that both D_i and V_i are evaluated *VerySmall* and there is only one single fuzzy rule activated. This yields according to (7) a maximum weight of 1 attached to i^{th} nearest neighbor, while the statement $min(D_j,V_j) \geq s_6$, $\forall j=1,k$, $j\neq i$ ensures that all other nearest neighbors were evaluated to *High* for both input variables D and V, which again, according to (7) and uniqueness of fuzzy rule activated, yields a zero weight attached to those fingerprints. Therefore applying (7) yields straightforwardly result pointed out in Proposition 1.

Proposition 2. If the fingerprints outputted by the kNN are such that $min(Dj, Vj) \geq s_6$, $\forall j = 1,K$

then, the outcome of MVFL almost coincides with that of the standard kNN using (1).

The proof of Proposition 2 follows the same spirit as that of Proposition 1. That is, the condition stated in the body of the proposition entails that all nearest neighbors were evaluated to High for both V and D inputs, which, together with uniqueness of activated fuzzy rule(s), yields almost a zero-valued weight attached to each nearest neighbor.

Proposition 3. If the fingerprints outputted by the *k*NN are such that $max(D_i, V_i) \leq s_1$ for all nearest neighbor i (i = 1, K), then, the outcome of MVFL coincides with that of standard kNN using (1). Again this follows from the fact that the condition in Proposition 3 entails that all nearest neighbors were evaluated to Very Small for both input variables yielding maximum weight value 1.

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IV. Implementation and Discussion

To evaluate the proposal a testbed was constructed using 4 APs mounted in the corners of 20×20 meters area with coordinates AP1(0, 0), AP2(20,0), AP3(20,20) and AP4(0,20). 64 fingerprints were specified in symmetric way with approximately 2.2 meter space, and 16 random testing targets to be localized were generated with known coordinates, as shown in Fig. 4. The simulation setup was chosen for its similarity with experiment layout that is carried out at later stages of the project, and will be described in the future works.

The radio propagation model (14), which describes the signal attenuation with respect to the distance between emitter (access point) and receiver. In this experiment the used radio propagation model was is adapted from [24], which has been tested in indoor environment close to that experienced in this paper. Interestingly, the model includes an uncertainty element constituting of ± 8, which describes an upper and lower bounds to the path loss. This would be especially interesting when eliciting the fuzzy membership functions.

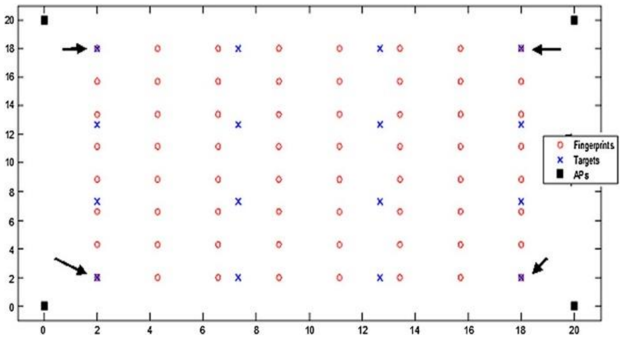

Fig 4 Testbed layout

The radio propagation model pointed out in (14) is used to construct the RSS map for the fingerprints and targets.

$$RSS_{ij} = -40 - 31\,log_{10}(d_{ij}) + \varepsilon \qquad (14)$$

where d_{ij} stands for the distance from the j^{th} fingerprint to the i^{th} access point, while ε stands for the Gaussian random noise of zero mean and standard deviation 2 dB. The latter was introduced to account for a bounded uncertainty of 8 dB as proposed in [24]. Indeed, using the fact that, for a zero-mean Gaussian signal of standard deviation σ, the range of the underlying random variable is approximately bounded by [−3σ , 3σ], therefore, to account for a bounded uncertainty of 8 dB, a random Gaussian zero mean and standard deviation 2 dB sounds rational.

In the offline phase the radio map is created by calculating the physical distance from every fingerprint to each AP, using the initial (known) x–y coordinates. Then, the propagation model (14) is used to generate fingerprint's RSS values. For each fingerprint *j*, one therefore generates a vector of *RSS* values where each component corresponds to the associated signal strength from a given AP to the j^{th} fingerprint. The dimension of such vector is equal to the total number of access points. The set of all such vectors pertaining to all fingerprints constitutes the offline stage of the fingerprinting localization approach. It should be noted that in case where all APs were visible to all fingerprints, the dataset of the offline phase boils down to standard m×n matrix (where m and n stand for the number of fingerprints and AP, respectively).

In the online phase, the kNN algorithm is first used to identify the K closest neighbors for a given target according to the Euclidean distance in as defined in the equation (2). Then the distances *D* and *V* (in signal space) for each closest neighbor, are used as inputs to the multivariable Takagi–Sugeno fuzzy inference system, which, in turn, determines the weight associated to each fingerprint of the kNN. Finally, the positioning of each target is estimated using: (15). Note that (15) is induced from (1) when the weights are not normalized. And the symbols are defined similarly.

$$x_T = \begin{cases} \dfrac{\sum_{i=1}^{K} w_i x_{FP_{\sigma(i)}}}{\sum_{i=1}^{K} w_i} \\ \dfrac{1}{K}\sum_{i=1}^{K} x_{FP_{\sigma(i)}} \end{cases} \quad and \quad y_T = \begin{cases} \dfrac{\sum_{i=1}^{K} w_i y_{FP_{\sigma(i)}}}{\sum_{i=1}^{K} w_i}, & if \sum_{i=1}^{K} w_i \neq 0 \\ \dfrac{1}{K}\sum_{i=1}^{K} y_{FP_{\sigma(i)}}, & otherwise \end{cases} \qquad (15)$$

Pseudo-code of the overall methodology is summarized as follow:

```
OFFLINE stage
   For each access point i
      For each fingerprint j
           Compute euclidean distance d(i, j )
           Compute rss(i, j ) using (7)
           Store rss(i, j )
      End
   End
ONLINE stage
For each target t
     Calculate k-nearest neighbours fingerprints to t
     For each nearest fingerprint i (i = 1 to k )
           Calculate v (i)t using (10)
           Calculate d(i)t using (9)
           Input v (i)t and d(i)t to t–s fuzzy inference system
           Collect the weight wi of fingerprint i
      End
      Estimate the location of target t using (23)–(24)
 End
```

Given the knowledge of the true position of the target from the user's perspective, the performance of the developed fuzzy positioning system can be evaluated using standard root mean square error (RMSE) metric; namely:

$$Error = \sqrt{(X_T - X_{TAct})^2 + (Y_T - Y_{TAct})^2} \qquad (16)$$

where X_{TAct} , and Y_{TAct} are the actual coordinates of target T. The results of this technique are compared to kNN combined with single variable fuzzy localization (SVFL) proposed in [21], as well as the standard kNN, weighted kNN and triangulation approach. First, in Fig. 5 is shown the positioning of the target within the environmental layout.

It is also shown the true (actual) positions of the targets as well as their estimations using alternative (average) kNN approach. A total of sixteen test points (target nodes) randomly generated in the environment layout, were employed. The graph illustrates the good performance of the developed MVFL algorithm as demonstrated by the closeness of the estimated target position to the actual (true)

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position. Besides given the randomness inherent in parameter ε of expression (14), the calculus of the estimation is averaged over 100 Monte Carlo simulations. This process is repeated for both offline and online phases. Although, for the offline stage, the process is only performed once in order to build the radio map. The dataset issued from the radio map are then called upon by each fingerprinting algorithm to calculate the position of the target.

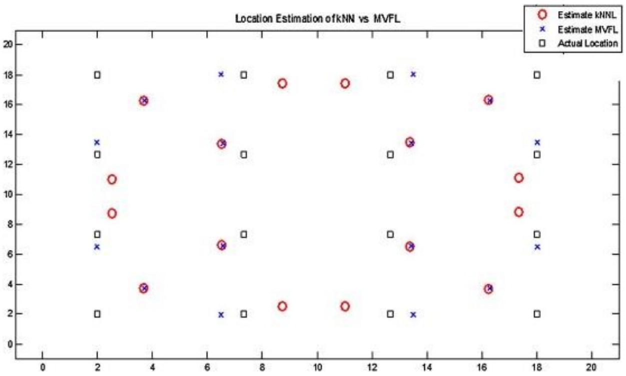

Fig 5 Positions estimated via MVFL (x) and SVFL$_{kNN}$ (o)

Fig. 6 illustrates the performance of the MVFL algorithm with respect to root mean square error metric for each target. Namely, the x-coordinate in Fig. 6 corresponds to the target label (first target, second target, etc.) and not to the number of targets as it may sound like.

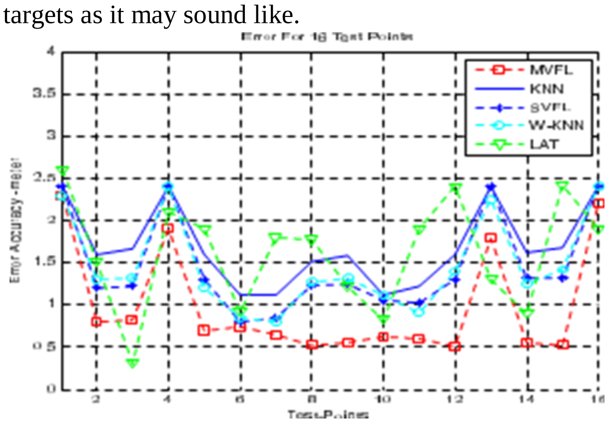

Fig 6 Error in estimations MVFL (□)

The plot also displays the performance of alternative positioning algorithms (average kNN, Weighted kNN, SVFL and triangulation or lateration—LAT).

It is worth pointing out from Figs. 5 and 6 that the MVFL outperforms the kNN localization algorithm, as well as other alternative approaches. However, in case where the target node coincides with a given fingerprint as those symbolized by an arrow in testbed of Fig. 4, one notices that MVFL evaluation degrades slightly to almost coincide sometimes with that of kNN in Fig. 6. This can be explained through several arguments. First, the fact that target is generated at same location as a given fingerprint does not mean necessarily that the associated RSS value also coincides with that of fingerprint due to effect of randomness. Otherwise, if conditions of Proposition 1 were met, the algorithm would provide as stated in Proposition 1 a fully accurate result consisting of the position of the underlying fingerprint. Second, given the nature of RSS space and the fuzzification of the distance parameters D and V, it is not fully excluded that both input variables will be evaluated to very small, yielding according to Proposition 3 a result which coincides with kNN result. Third, the number of nearest neighbors k plays also a non-negligible role. Indeed, for our case, with k = 3, which was found to perform well, the algorithm (both kNN and MVFL) tends in such situation to locate the target within a triangle constituted of the three nearest neighbors. Roughly speaking to handle such scenario, a trivial solution consists of reducing substantially the value of k to a singleton. However, although, such solution seems to be appropriate for this special case, provided that signal strength of the target was very close to that of the underlying fingerprint, it will cope poorly with the vast majority of cases in which the testdata do not coincide with any fingerprint.

Next, in order to compare more efficiently the performance of the developed algorithm, one considers situations of various noise intensities, and one evaluates the RMSE value of each positioning algorithm. For this purpose, the RSS value corresponding to the target (node) is modified to account for the noise intensity. This boils down to rewriting expression (14) as

$$RSS_{iT} = -40 - 31\, log_{10}(d_{iT}) + \varepsilon_{\sigma} \qquad (17)$$

where ε_{σ} is now zero-mean Gaussian noise with (variable) standard deviation σ . Notice that (14) is only applied to the generated RSS value of the target T to each access point, while the RSS values of fingerprints remain unchanged with respect to that already stored in the radio map. The result provided in Table 1 corresponds to the average across all testdata (the sixteen targets) of the RMSE quantification.

The results pointed out in Fig. 6 and Table 1 clearly show that MVFL outperforms SVFL as well as other standard indoor localization algorithms, which justifies of the robustness and the feasibility of the proposal.

Table 1 Noise intensity for different algorithms

Noise level SdB	Average accuracy error				
	kNN	MVFL	SVFL	W-kNN	LAT
1	1.32	0.61	0.88	0.86	0.51
2	1.69	0.82	1.41	1.47	1.6
3	1.94	0.81	1.42	1.48	1.65
4	1.98	0.94	1.43	1.53	1.71
5	2.11	0.88	1.44	1.56	1.88
6	2.14	0.93	1.47	1.61	1.93
7	2.16	0.92	1.48	1.62	1.9
8	2.21	0.98	1.48	1.66	1.91
9	2.22	0.98	1.51	1.68	2.13
10	2.27	0.99	1.52	1.71	2.42
11	2.3	1.01	1.53	1.73	2.53
12	2.37	1.01	1.57	1.74	2.52
13	2.41	1.03	1.58	1.75	2.71
14	2.44	1.04	1.62	1.78	2.77
15	2.51	1.05	1.63	1.82	2.69

Nevertheless, the results also show that for one testdata, the triangulation technique outperforms the rest of the algorithms. Strictly speaking, such result cannot be fully discarded. This is mainly due to the fact that triangulation approach does not rely on the fingerprints but only on access points. On the other hand, it is almost unanimously acknowledged that any fingerprinting-like approach is ultimately restricted by the density and homogeneity of the radio map created at the offline stage in the sense that the denser the radio map, the higher is the accuracy of the estimation.

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Table 1 also shows a constant increase of the accuracy of all localization algorithms with respect to noise intensity, which is also trivially expected. On the other hand, it is worth pointing out that the variation of both MVFL and SVFL is relatively smaller than the variations of other algorithms, which demonstrates, to some extent, the robustness of the fuzzy inference system to noise. To see it, a graphical illustration is presented in Fig. 7. The graph restricts the plot to MVFL and kNN only for clarity of illustration.

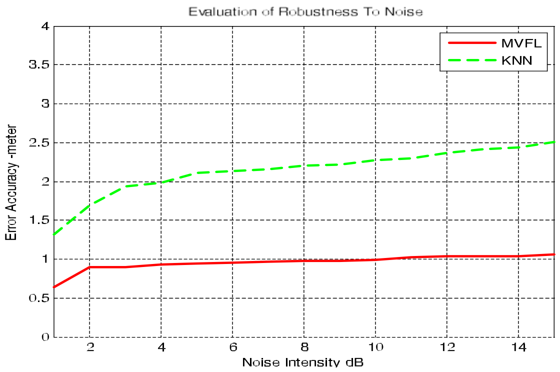

Fig 7 MVFL vs kNN robustness against noise

V. CONCLUSION

This paper investigates a new approach for wireless indoor localization using fuzzy logic. The performances of the proposal have been evaluated and compared to several alternative approaches, including, triangulation, standard kNN, weighted kNN and single input variable fuzzy-based positioning already proposed in literature. The results demonstrated the feasibility of the proposal. Some refinements of the proposal have also been put forward in order to handle the uncertainty pervading the RSS values. Also, the choice of the membership functions has been refined to accommodate the radio propagation model and the observed fluctuations in terms of standard deviations of the RSS signals at various conditions, e.g., the range of RSS values between −65 dB and −80 dB are much more dominant than other ranges, it will be interesting to design a metric that enhances such discrimination power.

Similarly, enforcing some flexibility and adaptivity on the choice of k would reduce the amount of the associated uncertainty. On the other hand, the current fuzzy system calculates the weight associated to each nearest neighbor from the two inputs involving only the target node and the associated nearest fingerprint. This implicitly assumes full independence among the fingerprint measurements. However such assumption is not always valid. Indeed, for instance, all measurements do share the same target node. This makes the conditional independence a more plausible assumption rather than of full independence.

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