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Artificial Intelligence Techniques for Mobile Station Location Estimation

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ABSTRACT Modern wireless communication systems require positioning functions, which provide are automatic location estimation of stations within a network. However, when new networks are implemented, much higher accuracy is required when determining geographical coordinates of a mobile station to develop of services related to the station location. To solve the problem of mobile station positioning, its geographical coordinates are calculated, coordinates of the closest base stations being known. The paper proposes to use a genetic neuro-fuzzy controller for improving the effectiveness of positioning a mobile station. Positioning methods providing usage of artificial intelligence methods are based on measurements of levels for signals from the closets access points or base stations, their coordinates are known. The proposed localization method is based on values of received signal strength indicator – RSSI. At the same time, the RSSI method has a disadvantage – low accuracy, which is proposed to be increased by applying methods of artificial intelligence – fuzzy logic, neural networks, genetic algorithms. Therefore, the objective of this paper is to elaborate an optimized method for determining location of a mobile station. In compliance with the suggested method, RSSI values and ToA values enter the genetic neuro-fuzzy controller, after corresponding processing, the distance from the mobile station to the base station appears at its output.

KEYWORDS mobile station, positioning, fuzzy controller.

I. INTRODUCTION

Nowadays, with the fast development of wireless and mobile communication technologies, the demand for new and more efficient positioning algorithms is becoming more and more urgent [1]. In mobile networks, localization refers to determination of exact coordinates or location of mobile stations. In case of appropriate positioning, location-based services will be able to efficiently provide corresponding services to the users according to their current locations. Such location-based services play an important role in many fields and require the high accuracy of positioning. To ensure the reliable estimation of mobile stations location, some studies propose cellular-based positioning methods, which analyze the signals of cellular networks.

One of the most effective cellular-based positioning methods of the mobile station localization is RSSI. It is a signal intensity metric that estimates the intensity of a signal received by a receiver. Its strength is used to estimate the distance between the transmitter and receiver [2]. The relationship between distance and RSSI is as follows

$$RSSI = -10n \cdot \log d + A \,.$$

However, the RSSI method has a drawback – instability due to fading and multipath effect.

The simplest method is Time of Arrival. It is based on the exact time when a signal was sent, the exact time the signal arrives, and the speed of the signal (usually the speed of light). So, the distance from a base station to a mobile station can be calculated as:

$$d = c \times (t_{arrival} - t_{sent}) \,.$$

The possible locations of the mobile station can be determined by using this distance.

Such popular solution as Global Positioning System requires a high power consumption and its data may be inaccurate due to obstacles, multi-path propagation, and indoor environment [3].

So, to reduce the drawbacks of existing positioning methods, novel methods considering ultimate achievements of science and technology are being developed [4].

Positioning methods using artificial intelligence techniques are based on measuring signal levels from all nearby access points or base stations, and their coordinates are known [5]. Neural networks are employed to optimize the RSSI method [6-7]. Also, for this purpose, a fuzzy-controller software or hardware solution may be created [8]. To enhance accuracy of the fuzzy controller, it can be combined with a neural network and a genetic algorithm. The neural network updates the fuzzy set parameters and the genetic algorithm can tune its rule base properly. So, it is necessary to create a mathematical positioning model and to perform a network training and updating. Such approach combines the merits of fuzzy logic, neural networks and genetic algorithms.

Many mathematical models are known that can describe the dependence between the distance to the object and the signal level, and it is also possible to develop a new model for a specific case.

Therefore, it can be concluded that methods of positioning a mobile station using artificial neural networks can provide sufficiently high accuracy.

In order to provide a higher efficiency, we propose to combine both RSSI and ToA methods and to elaborate them with artificial intelligence techniques.

The aim of this paper is developing a genetic neuro-fuzzy controller to be used for mobile station positioning.

II. FUZZY-CONTROLLER

For developing a fuzzy-controller, its linguistic variables should be defined, their terms and membership functions should be specified. Input variables of the fuzzy-controller represent all possible states of a controlled process. Its output variable represents all possible controlling actions. Further, a rule base should be determined. It is a set of IF-THEN rules each of them describing a controlled state.

Input linguistic variables of the positioning fuzzy controller are the received strength signal indication (R) and the time of arrival (T), its output variable is the distance between the mobile station and a base station (or an access point) (D). Fig.1 presents the architecture of the fuzzy-controller.

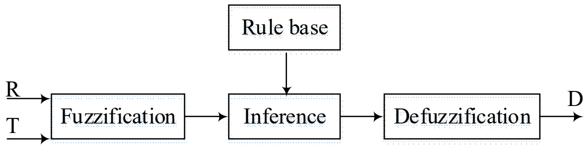

FIG. 1. Architecture of the proposed fuzzy-controller.

The fuzzy controller converts all input variables to membership function values, then evaluates a fuzzy output according to a rule base, eventually converts the fuzzy output to a crisp value.

The developed fuzzy-controller can be converted into an adaptive neuro-fuzzy inference system (ANFIS), which suits well for operating under uncertain and altering conditions. Moreover, to update the rule base, a genetic algorithm will be applied. Fig.2. illustrates the architecture of the genetic neuro-fuzzy controller.

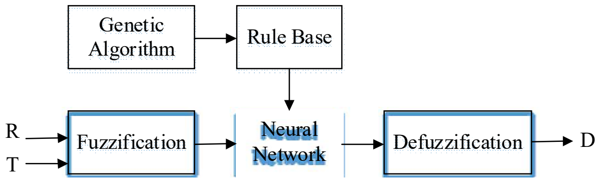

FIG. 2. Architecture of the genetic neuro-fuzzy controller.

The linguistic variable of the received strength signal indication RSSI is defined with terms “very weak”, “weak”, “medium weak”, “strong” and “very strong” (Fig.3):

$$T(R) = \{VW, V, MW, S, VS\}.$$

Its membership functions are shown in Fig.3.

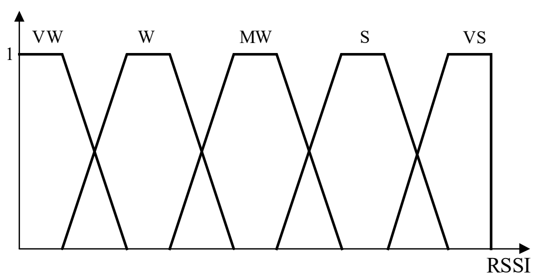

FIG. 3. Membership functions for RSSI.

The linguistic variable of the time of arrival ToA is defined with terms “very small”, “small”, “medium”, “large” and “very large”:

$$T(T) = \{VS, S, M, L, VL\}.$$

Its membership functions are shown in Fig.4.

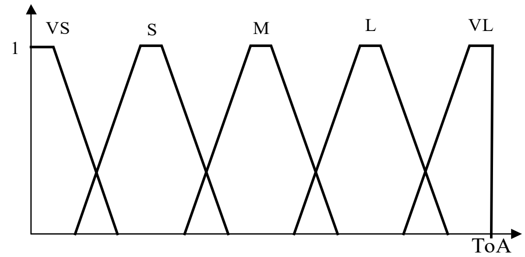

FIG. 4. Membership functions for time of arrival.

The linguistic variable of the distance D is defined with terms “very near”, “near”, “not near”, “not far”, “far”, and “very far”:

$$T(D) = \{VN, N, NN, NF, F, VF\}.$$

Its membership functions are shown in Fig.5.

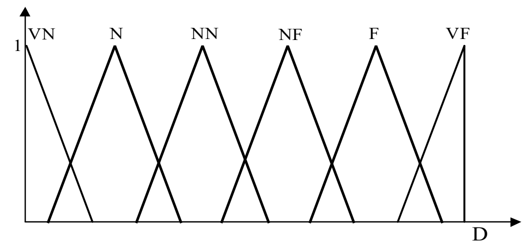

FIG. 5. Membership functions for the distance.

The proposed positioning fuzzy-controller operates according to a rule base consisting of 25 rules:

$$if\ \ R = VW\ \ and\ \ T = VL,\ then\ \ D = VF;$$
$$if\ \ R = VW\ \ and\ \ T = L,\ then\ \ D = VF;$$
$$if\ \ R = VW\ \ and\ \ T = M,\ then\ \ D = VF;$$
$$if\ \ R = VW\ \ and\ \ T = S,\ then\ \ D = F;$$
$$if\ \ R = VW\ \ and\ \ T = VS,\ then\ \ D = F;$$
$$if\ \ R = W\ \ and\ \ T = VL,\ then\ \ D = F;$$
$$if\ \ R = W\ \ and\ \ T = L,\ then\ \ D = F;$$
$$if\ \ R = W\ \ and\ \ T = M,\ then\ \ D = F;$$
$$if\ \ R = W\ \ and\ \ T = S,\ then\ \ D = NF;$$
$$if\ \ R = W\ \ and\ \ T = VS,\ then\ \ D = NF;$$
$$if\ \ R = MW\ \ and\ \ T = VL,\ then\ \ D = NF;$$
$$if\ \ R = MW\ \ and\ \ T = L,\ then\ \ D = NF;$$
$$if\ \ R = MW\ \ and\ \ T = M,\ then\ \ D = NN;$$
$$if\ \ R = MW\ \ and\ \ T = S,\ then\ \ D = NN;$$
$$if\ \ R = S\ \ and\ \ T = VS,\ then\ \ D = NN;$$
$$if\ \ R = S\ \ and\ \ T = VL,\ then\ \ D = NN;$$
$$if\ \ R = S\ \ and\ \ T = L,\ then\ \ D = NN;$$
$$if\ \ R = S\ \ and\ \ T = M,\ then\ \ D = N;$$
$$if\ \ R = S\ \ and\ \ T = S,\ then\ \ D = N;$$
$$if\ \ R = S\ \ and\ \ T = VS,\ then\ \ D = N;$$

$$if \;\; R = VS \;\; and \;\; T = VL, \;\; then \;\; D = N \, ;$$

$$if \;\; R = VS \;\; and \;\; T = L, \;\; then \;\; D = N \, ;$$

$$if \;\; R = VS \;\; and \;\; T = M, \;\; then \;\; D = VN \, ;$$

$$if \;\; R = VS \;\; and \;\; T = S, \;\; then \;\; D = VN \, ;$$

$$if \;\; R = VS \;\; and \;\; T = VS, \;\; then \;\; D = VN \, .$$

The location estimation algorithm is as follows:

1. Calculate the Received Signal Strength of the signal sent from a base station to a mobile station.
2. Calculate the Time of Arrival of the signal sent from the mobile station to the base station.
3. Define the fuzzy input and output linguistic variables.
4. Perform the fuzzification of the input values.
5. Perform the fuzzy rule evaluation.
6. Perform the defuzzification. This gives the distance of the mobile station from the base station node.

III. NEURAL NETWORK

Neural Networks are composed of interconnected artificial neurons. They are able to acquire, store, utilize expert knowledge, and to learn new patterns. Neural networks can be used for solving problems of optimization, identification, classification, prediction, pattern matching and recognition, function approximation, data clustering.

To enhance the operability of the developed fuzzy controller, it was converted into a neuro-fuzzy controller. The Adaptive Neuro-Fuzzy Inference System (ANFIS) was chosen for this aim. ANFIS is an artificial neural network, however it operates like a fuzzy system under uncertain conditions, thus combining both fuzzy logic and neural network main principles. therefore, it can process nonlinear and complex systems [9]. ANFIS is capable to approximate non-linear functions. Its main advantage is ability to combine fuzzy reasoning with learning capabilities when solving a problem.

Fig. 6 presents a block diagram of the neuro-fuzzy controller.

Layer 1: each node's output is the membership degree of input R_0, T_0:

$$R_0 \Rightarrow R_{VW}, \, R_W, \, R_{MW}, \, R_S, \, R_{VS} \, ,$$

$$T_0 \Rightarrow T_{VS}, \, T_S, \, T_M, \, T_L, \, T_{VL} \, .$$

Layer 2: each node's output is the weighting factor of the fuzzy rule:

$$w_1 = \min[R_{VW}, \; T_{VL}], \qquad w_2 = \min[R_{VW}, \; T_L],$$

$$w_3 = \min[R_{VW}, \; T_M], \qquad w_4 = \min[R_{VW}, \; T_S],$$

$$w_5 = \min[R_{VW}, \; T_{VS}], \qquad w_6 = \min[R_W, \; T_{VL}],$$

$$w_7 = \min[R_W, \; T_L], \qquad w_8 = \min[R_W, \; T_M],$$

$$w_9 = \min[R_W, \; T_S], \qquad w_{10} = \min[R_W, \; T_{VS}],$$

$$w_{11} = \min[R_{MW}, \; T_{VL}], \qquad w_{12} = \min[R_{MW}, \; T_L],$$

$$w_{13} = \min[R_{MW}, \; T_M], \qquad w_{14} = \min[R_{MW}, \; T_S],$$

$$w_{15} = \min[R_{MW}, \; T_{VS}], \qquad w_{16} = \min[R_S, \; T_{VL}],$$

$$w_{17} = \min[R_S, \; T_L], \qquad w_{18} = \min[R_S, \; T_M],$$

$$w_{19} = \min[R_S, \; T_S], \qquad w_{20} = \min[R_S, \; T_{VS}],$$

$$w_{21} = \min[R_{VS}, \; T_{VL}], \qquad w_{22} = \min[R_{VS}, \; T_L],$$

$$w_{23} = \min[R_{VS}, \; T_M], \qquad w_{24} = \min[R_{VS}, \; T_S],$$

$$w_{25} = \min[R_{VS}, \; T_{VS}] \, .$$

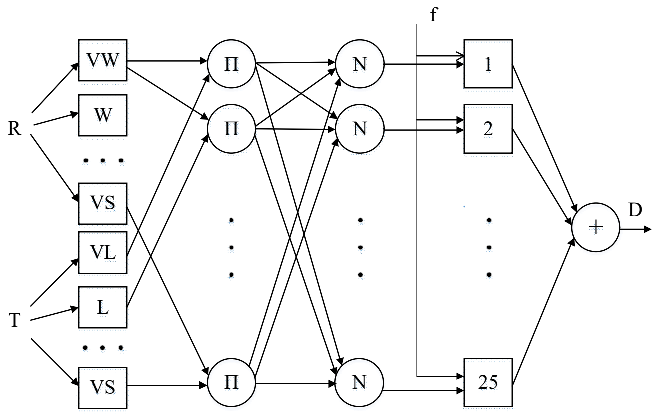

FIG. 6. Block diagram of the neuro-fuzzy controller.

Layer 3: each node's output is the ratio of the firing strength of the fuzzy rule to the total value of all firing strengths:

$$w_i^n = \frac{w_i}{w_1 + w_2 + \ldots + w_{25}} \, .$$

Layer 4: each node's output is multiplication of the normalized output with the node function:

$$D_1 = w_1^n \cdot D_{VF}, \qquad D_2 = w_2^n \cdot D_{VF}, \qquad D_3 = w_3^n \cdot D_{VF},$$

$$D_4 = w_4^n \cdot D_F, \qquad D_5 = w_5^n \cdot D_F, \qquad D_6 = w_6^n \cdot D_F,$$

$$D_7 = w_7^n \cdot D_F, \qquad D_8 = w_8^n \cdot D_F, \qquad D_9 = w_9^n \cdot D_{NF},$$

$$D_{10} = w_{10}^n \cdot D_{NF}, \qquad D_{11} = w_{11}^n \cdot D_{NF}, \qquad D_{12} = w_{12}^n \cdot D_{NF},$$

$$D_{13} = w_{13}^n \cdot D_{NN}, \qquad D_{14} = w_{14}^n \cdot D_{NN}, \qquad D_{15} = w_{15}^n \cdot D_{NN}$$

$$D_{16} = w_{16}^n \cdot D_{NN}, \qquad D_{17} = w_{17}^n \cdot D_{NN}, \qquad D_{18} = w_{18}^n \cdot D_N,$$

$$D_{19} = w_{19}^n \cdot D_N, \qquad D_{20} = w_{20}^n \cdot D_N, \qquad D_{21} = w_{21}^n \cdot D_N,$$

$$D_{22} = w_{22}^n \cdot D_N, \qquad D_{23} = w_{23}^n \cdot D_{VN}, \qquad D_{24} = w_{24}^n \cdot D_N,$$

$$D_{25} = w_{25}^n \cdot D_N \, .$$

Layer 5: the node's output yields the output of the neuro-fuzzy controller:

$$D_0 = \sum_{i=1}^{25} D_i \, .$$

Membership functions and fuzzy control rules are two key parameters of a fuzzy logic controller, which determine its accuracy. In contradistinction to a simple fuzzy-controller, the neuro-fuzzy controller possesses a learning ability that allows adapting and improving membership functions. To adjust the fuzzy control rules, we apply a genetic algorithm, that promotes the genetic fuzzy-controller to behave as closely as possible to the expert behavior.

IV. GENETIC ALGORITHM

Genetic algorithms are suitable for solving parameter optimization problems [10]. Such processes as selection, crossover, mutation, and reproduction are simulated in the genetic algorithms. They provide optimization of both continuous and discrete variables. Thus, one can employ a genetic algorithm to update a fuzzy rule base.

A chromosome corresponds a solution encoded into genes. In this study, a gene represents to a linguistic variable value. Ehe proposed encoding of the fuzzy rule premises into chromosomes is shown in Table 1. The term "Very Weak" of the input linguistic variable RSSI is specified as "000". The term "Very Small" of the input linguistic variable ToA is also specified as "000". The term "Medium" of both input linguistic variables is proposed to be specified as "01". Next, The term "High" of both input linguistic variables is proposed to be specified as "11".

Here, table 2 shows the proposed encoding of the fuzzy rule consequent into chromosomes. The term "Very Near" of the output variable is specified as "000". The term "Very Far" of the output variable is specified as "101".

TABLE 1. Encoding the input values.

R	VW 000	W 001	MW 010	S 011	VS 100
T	VS 000	S 001	M 010	L 011	VL 100

TABLE 2. Encoding the output value.

D	VN 000	N 001	NN 010	NF 011	F 100	VF 101

In this study, each fuzzy rule is defined by a set of genes, which represent fuzzy sets for two input and one output variables.

A chromosome for the 1-th fuzzy rule looks so: 000100101.

A chromosome for the 25-th fuzzy rule looks so: 10000000.

In this case, we propose to apply the classic genetic algorithm.

V. CONCLUSION

The paper proposes a method for positioning mobile stations of wireless communication systems, which involves the use of a genetic neuro-fuzzy controller to establish the correspondence between the obtained values of the received signal levels from the base stations and time of arrival for these signals and the distances from them to the mobile station. Hybrid systems combining fuzzy logic, neural networks, and genetic algorithms have proved their effectiveness in a wide variety of problems. Combining these intelligent technologies, it is possible to get a hybrid system that can process uncertain values and can be learned and optimized. The proposed fuzzy controller was converted into the neuro-fuzzy system. Moreover, the genetic algorithm was proposed for improving the rule base. Thus, the proposed approach can increase the accuracy on mobile station location estimation.

AUTHOR CONTRIBUTIONS

Author O.S – the conceptual idea; A. S. – mathematical modeling of the fuzzy-controller; A. L. – mathematical modeling of the neuro-fuzzy system; V. D. – chromosome encoding.

COMPETING INTERESTS

The authors declare no competing interests.

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Застосування методів штучного інтелекту для визначення місцеположення мобільної станції

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АНОТАЦІЯ Для сучасних систем безпровідного зв'язку важливими є функції позиціонування, тобто автоматичне визначення місцеположення станції у межах мережі. Наразі все більшої популярності набувають різні способи позиціонування об'єктів як на відкритому просторі, так і усередині приміщення. Процедура позиціонування включає в себе визначення координат і параметрів руху мобільного абонента. Проте, при впровадженні більш нових мереж, для розвитку послуг, пов'язаних з місцеположенням станції, необхідна значно вища точність визначення географічних координат мобільної станції. Для розв'язання задачі позиціонування мобільної станції обчислюються її географічні координати при відомих координатах найближчих базових станцій. У роботі запропоновано використовувати генетичний нейро-нечіткий контролер для підвищення ефективності визначення місцезнаходження мобільної станції. Методи позиціонування, що передбачають використання методів штучного інтелекту, базуються на вимірюваннях рівнів сигналів від найближчих точок доступу або базових стацій, а їх координати є відомими. Пропонований метод визначення місцеположення базується на значеннях величини рівня прийнятого сигналу – RSSI. В той же час, недоліком методу RSSI є його недостатня точність, підвищити яку пропонується за рахунок використання методів штучного інтелекту – нечіткої логіки, нейронних мереж, генетичних алгоритмів. Таким чином, метою даної роботи є розроблення оптимізованого методу визначення місцеположення мобільної станції. Згідно запропонованого методу, значення RSSI та ToA надходять у генетичний нейро-нечіткий контролер, що функціонує за базою з 25 правил, на його виході після відповідного оброблення з'являється значення відстані від мобільної станції до однієї із базових станцій. Застосовано гібридний підхід, де нейромережева структура передбачає адаптивне налаштування бази нечітких правил, а генетичний алгоритм забезпечує вибір оптимального варіанту.

КЛЮЧОВІ СЛОВА мобільна станція, позиціонування, нечіткий контролер.