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PERFORMANCE ANALYSIS OF AN RFID-BASED 3D INDOOR POSITIONING SYSTEM COMBINING SCENE ANALYSIS AND NEURAL NETWORK METHODS

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Abstract: The main purpose of this research is to improve localization accuracy of an active Radio Frequency Identification, RFID tag, in 3D indoor space. The paper presents a new RFID based 3D Indoor Positioning System which shows performance improvement. The proposed positioning system combines two methods: the Scene Analysis technique and Artificial Neural Network. The results of both simulation using Log-Distance Path Loss Model and physical experiments validate that the proposed positioning system improves the localization accuracy of an RFID tag compared with well-known Scene Analysis technique solutions.

Index Terms: Indoor Positioning System, Neural Network, Radio Frequency Identification, Scene Analysis

1. INTRODUCTION

For many years, short range wireless technologies have been used in various industrial and home applications including Indoor Positioning System, IPS, used to localize or track objects or people inside buildings. Many solutions have been based on Radio Frequency IDentification, RFID, technology. However, most of the RFID-based IPSs do not satisfy the target localization reliability and accuracy in 3D space.

A design of robust and accurate system for 3D target localization is needful.

Scene Analysis, SA, which is one of fingerprinting techniques [1][2] is based on comparison of actual measurements of Received Signal Strength, RSS, or Time of Arrival, ToA, with a pattern called a radio map, which is a set of measurements performed beforehand with tags placed at the points of given coordinates. Nevertheless, RFID transmitters and receivers which are able to measure ToA need to be precisely synchronized, which makes this application relatively expensive. Besides the fact that the *RSS* measurements are exposed to indoor environment interferences, this type of measurement is commonly used.

This paper proposes a new hybrid IPS combining SA with Artificial Neural Network, ANN. The hybrid system using *RSS* measurements affected by interferences in an indoor environment, may improve robustness and accuracy of target localization.

The presented results of simulations and physical experiments confirm the considerable advantages of the proposed solution compared with other reported solutions.

2. SURVEY OF RELATED WORKS

Nowadays, indoor localization systems based on WIFI, Bluetooth, ultrasound, infrared or RFID standards are widely used [3] for the following purposes such as tracking [4], smart packaging [5], automated parking [6][7] or biomedical monitoring [8][9]. Especially due to its advantages, the RFID technology using different algorithms has been widely applied for target localization [4][6][7][10].

Common algorithms used for 3D positioning in an indoor environment are triangulation and SA methods [3]. They apply RSS or ToA for distance measurement 11. The widespread proximity algorithm is used for 2D positioning in robotics and tracking applications [4].

One of the popular SA-based techniques of target localization is the RADAR method, which is a deterministic approach, and in addition to signal strength, uses a radio propagation model [12]. The Horus method applying a probabilistic technique, exploits the correlation among the collected RSS measurements to improve localization accuracy [13].

In [14], Miao et al. propose a hybrid Genetic Algorithm-Back Propagation Neural Network, GA-BP NN, algorithm for 2D RFID-based indoor positioning. Their results confirm that using the ANN can reduce problems caused by complexity and variation in the radio signal propagation in an indoor environment.

It was shown that the integration of the fingerprinting algorithm with Neural Network can enhance localization accuracy in an indoor environment [15]. The authors propose the ANN based pattern matching algorithm to estimate the positioning error, which is used to adjust primarily computed target coordinates.

3. PROBLEM STATEMENT AND MAIN CONTRIBUTION

From the review of related works one can observe that RFID systems based on triangulation or SA techniques are used to localize a target in a 3D space. Taking into consideration the fact that triangulation has some drawbacks, e.g. missing an intersection, the alternative SA method may be worth further development. Applying the Scene Analysis can improve a target localization when the used *RSS* measurements are contaminated by indoor environment interferences.

Considering the stated performance problem of 3D IPS, the well-founded research inquiry leads to a question if the localization quality can be improved by a RFID system using the algorithm combining the Scene Analysis technique with Artificial Neural Network?

It seems to be justifiable to hypothesize that using a positioning system based on the RFID Scene Analysis technique combined with the Artificial Neural Network, improves accuracy of the 3D target localization in an indoor environment compared with reported Scene Analysis algorithms.

The main contribution of this paper is modeling of the RFID system combining the Scene Analysis with the NN technique and then implementing the model in Matlab to verify its performance. To validate the simulated results, the physical system is used and suitable experiments are performed. Furthermore, the proposed system performance is referred to performance of reported solutions.

4. MODELING

A radio propagation model which defines the signal path loss in an indoor environment is needed to model a virtual positioning system. The SA-NN IPS is modeled and analyzed using a suitable block diagram.

4.1. Radio wave propagation model

The Friis transmission equation is useful to represent radio waves propagation between RFID readers and tags. In case of free space, the received signal power for a given transmitter-receiver distance *d* is defined by the Friis Free Space Propagation Model as:

$$\frac{P_r(d)}{P_t(d)} = \frac{G_t G_r}{L}\left(\frac{\lambda}{4\pi d}\right)^2 \qquad (1)$$

where P_r, P_t represent the received power and the transmit power, respectively. G_r, G_t refer to a gain of the received antenna and transmitted antenna, respectively, λ is the wavelength, *d* is the distance between receiver and transmitter and *L* depicts the system losses.

For an isotropic antennas in (1) G_r,$=G_t$,$=L=1$, thus the path loss *A* defined as a dB ratio can be expressed by:

$$A(d) = 10\log\left(\frac{P_r(d)}{P_t(d)}\right) = 20\log\left(\frac{\lambda}{4\pi d}\right) \qquad (2)$$

A surrounding environment, interferences and noise affect the quality of the used *RSS*. Therefore, the widely used Log-Distance Path Loss Model, LDPLM, defines a mean signal loss over an indoor distance *d* as [16]:

$$PL(d) = A(d_0) + 10n\log_{10}\left(\frac{d}{d_0}\right) + X_\delta \qquad (3)$$

where *PL(d)* is a path loss at transmitter-receiver distance *d*, $A(d_0)$ refers to the path loss (2) for reference distance d_0, *n* represents a propagation factor which for a free space environment equals n=2. The inferences are represented by X_δ, which depicts a log-normal Additive White Gaussian Noise (AWGN), a random variable with zero mean and standard deviation σ.

4.2 Positioning system model

The system consists of a set of *N* RFID readers located in reference points and a tag in a specified position. The tag position is defined by a vector of tag's RSSs received by the readers, where RSS depends on the distance between the tag and a reader.

The principle of the RFID based Scene Analysis technique is a comparison of the actual *RSS* measure with *RSS* pattern called also *RSS* map [1][2]. The proposed model is divided into two stages: offline and online. During the first, offline stage, the map is established from *RSS*s measurements at points of given 3D coordinates. The map precision is limited by a number of points and by interferences of *RSS* measurements caused by the indoor environment. During the second, estimation online stage, the identified target coordinates are found by referring the actual *RSS* measurements to the previously created map.

The SA paradigm is similar to the ANN principle and therefore a possible hybrid SA-NN solution may gain from advantages of both methods. The block diagram of the proposed hybrid positioning system is shown in Fig. 1. The system algorithm begins with the offline phase, when *RSS* map and NN structure are established. Firstly, tag's *RSS*s at *k* different known points are measured by each of *N* readers. A set of the sampling points creates a sampling grid in an indoor environment. The measurements create *RSS* sampling matrix $\mathbf{RSS_S}$ of the size $k \times N$. The sampling matrix $\mathbf{RSS_S}$ along with a matrix of *k* corresponding tag's coordinates (x_{si}, y_{si}, z_{si}), create the database called *RSS Map*. The composed *RSS Map* is used as an input data of ANN training process determining the appropriate values of NN weights and biases.

The online estimation phase begins with measurements of *N RSS* values of an identified tag placed at unknown position (x_t, y_t, z_t). The *RSS* measurements from all *N* readers create matrix $\mathbf{RSS_t}$ which is used in the estimation process resulting in the estimate of target tag coordinates (x_e, y_e, z_e).

5. SOLUTION IMPLEMENTATION

The implemented model includes software and hardware parts. The system consists of eight readers located in a test cubic room of the size 5.13 m×4.50 m×2 m presented in Fig. 2.

5.1 Software Implementation

The proposed positioning system is implemented in MATLAB. The ANN system consists of three layers: the input layer, the hidden layer and the output layer. The input layer includes eight inputs corresponding to tag's *RSS* received by each reader. The size of the second hidden layer was determined empirically by starting from a small number of neurons, gradually increasing up to the number of 23, at which the network performance did not show improvement anymore. The network output layer includes three neurons corresponding to the estimated tag's 3D positioning coordinates. Activation functions used in the hidden layer

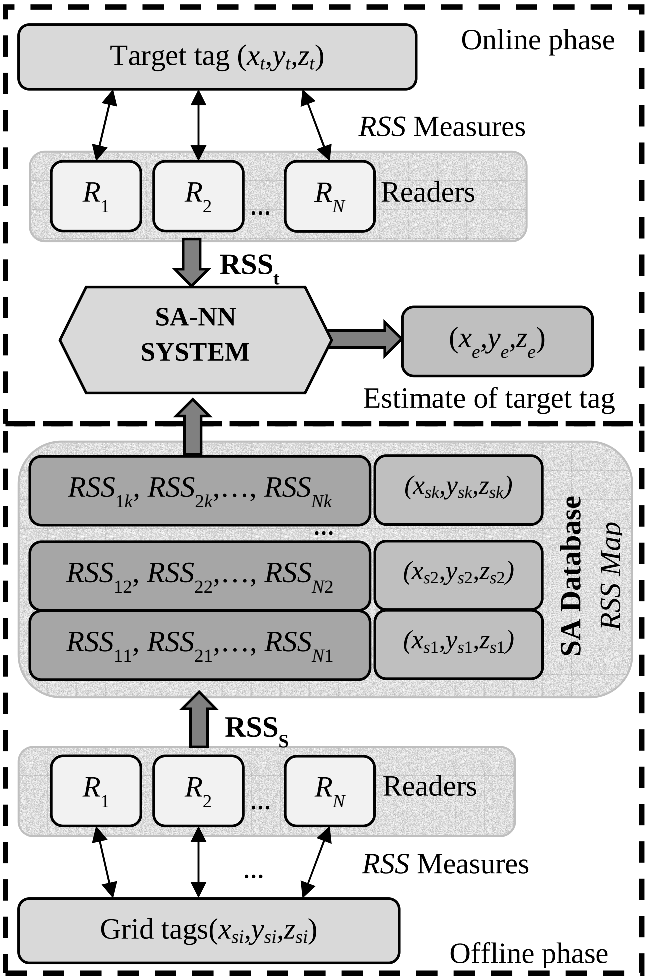

Fig. 1. Block diagram SA-NN positioning system

are hyperbolic tangent sigmoid functions. Moreover, the linear function is used in the output layer.

The Neural Network training process is based on the back propagation function. To determine the best back propagation method, various functions were examined and the function that updates weight and bias values was chosen accordingly to the gradient descent momentum and adaptive learning rate. Mean Square Error, MSE, was used as the best performance function.

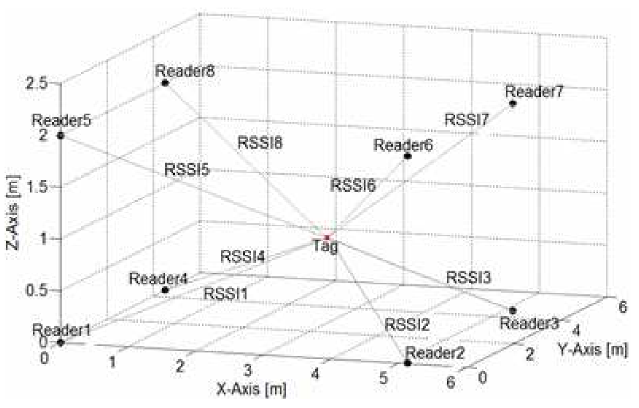

Fig. 2. Room model with placement of readers and a tag.

5.2 Hardware Implementation

The tested real positioning system consists of eight RFID readers connected to a PC and one active tag. The Wavetrend L-RX-900 with AN100 linear polarized whip antenna served as a reader. The active tag was L-TG 501. The system carrier frequency was 433.92 MHz. The tag was mounted vertically to the tripod with adjustable height. All readers were arranged based on the heuristic knowledge.

5.3 Model Integrity

The hardware implementation process began with the formation of a Received Signal Strength Indicator, *RSSI map*. The *RSSI* is a numeric parameter defined by the manufacturer, which indicates the power of a signal and is commonly used as a signal strength parameter in RFID or WIFI receivers [14]. However, the used RFID equipment does not provide a direct relationship between the relative *RSSI* and the corresponding absolute power of a signal. Since the virtual IPS model is based on *RSS* expressed in dBm, therefore the comparison of simulation and physical experiment performance uses different SA maps, which nevertheless does not limit the analysis generality.

6. VALIDATION

The validation of the proposed solution is based on the comparison of the simulation results with the results from the physical system measurement. Moreover, performance of both the virtual and physical systems is collated with data from other reported Scene Analysis applications.

6.1 Physical Experiment Results

Our validation was performed in the cubic room of the size 5.13 m × 4.5 m × 2 m. The eight readers were installed in room corners, as presented in Fig. 2.

The offline learning phase of the experiment started with the placement of target tag at coordinates (0.5, 0.5, 0.5) m. The room was sampled with a 0.5 m step in all directions, and ended up at the coordinate (4.5, 4, 1.5) m, which resulted in 216 sample *RSSI Map*, used in SA-NN training process.

The online estimation phase was performed for 20 randomly selected positions of the target tag. The uncertainty histogram of estimated positioning shown in Fig. 3, allows us to conclude about its normal distribution. The results presented in Table 1 indicate that the mean positioning uncertainty of hybrid SA-NN IPS system is 5.0 cm and the standard deviation is 20 cm.

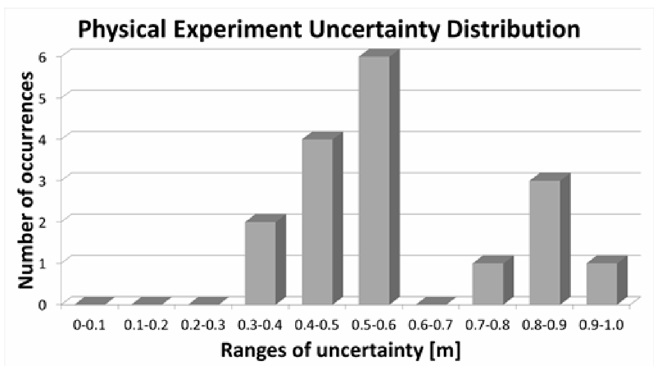

Fig. 3. Histogram of tag position estimation uncertainty of physical experiment.

6.2 Virtual Experiment Results

In all simulations, we used the value of propagation factor n=2.79. The standard deviation σ=2.7 of the log-normal AWGN X_δ (3) was applied in the virtual experiment offline phase. The used values are based on measurements reported in [16] for a similar indoor environment.

Our tested virtual system was based on the LDPLM (3) used to create a virtual *RSS Map* based on a grid of 0.5 m mesh with 550 samples.

The virtual experiment was performed for randomly generated 100 tag positions using the same LDPLM (3). To examine system robustness to noise, the simulations were performed for three AWGN levels with zero mean value and variance of σ_1=1.7, σ_2=2.7 and σ_3=3.7. The uncertainty histograms of estimated virtual positioning shown in Fig. 4, allows us to conclude about their normal distribution. The simulation results shown in Table 1 indicate that the system's mean positioning uncertainty is within the range of 2.8 cm for the lowest noise level up to 7.3 cm for the noisiest case. The standard deviation is quite consistent in the range between 20 cm and 23 cm.

6.3 Result Analysis

To uniquely judge the quality of our solution, we apply the detection efficiency factor, treated as a ratio of a number of target localized with accuracy better than required 1 m to a number of all measures. The results presented in Table 1 show that the simulation localization efficiency varies just a little, between 86% and 90%. Then, the physical experiment detection rate is just slightly worse at the level of 85%.

The applied various levels of AWGN corresponding to different types of environment, are used to verify, if the assumed value of standard deviation σ for log-normal random variable X_δ (3) is appropriate for the tested physical experiment. The figures in Table 1 show that results from simulations with the primarily assumed standard deviation σ=2.7 match the physical experiment results. For this noise level, the mean uncertainties are 3.3 cm and 5.0 cm for virtual and real experiments respectively, and standard deviation of 21 cm and 20 cm for simulation and physical experiment, respectively.

From the results in Table 1, we can also judge that the proposed system is robust for increasing noise level. Both the standard deviation of the position estimate uncertainty and the efficiency, almost do not change with an increasing noise level. It indicates high precision of the measurement method.

To further verify our proposal we compared its performance with reported results from other Scene Analysis applications, see Table 2. The Horus system designed for detection on the whole floor of the building, achieves positioning uncertainty of about 42 cm with standard deviation of 28 cm [13]. For similar detection area, as for Horus, the RADAR method average uncertainty was 400 cm with standard deviation of 326 cm [12]. Both, Horus and RADAR methods concern 2D positioning using the WLAN standard. Another RFID based Scene Analysis technique of 2D target localization is a method based on GA-BP Neural Network [14]. Its reported distance mean uncertainty was 8.1 cm with standard deviation of 210 cm. As compared to these reported results, the proposed SA-NN method designed for 3D single room localization, achieves the distance estimation mean uncertainty of 5.0 cm and standard deviation of 20 cm and shows the best positioning accuracy.

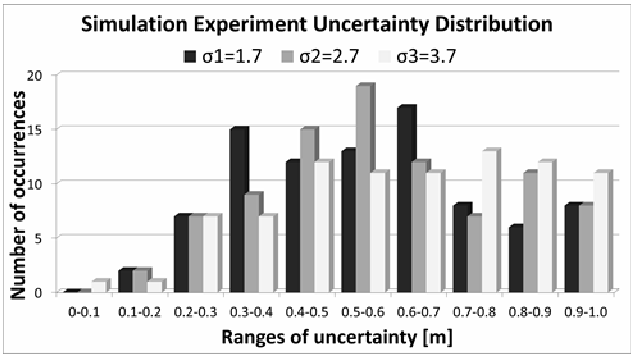

Fig. 4. Histogram of tag position estimation uncertainty from simulation

7. CONCLUSION

The aim of this paper was to prove that a combination of Scene Analysis with NN technique improves performance of target indoor localization compared with other fingerprinting techniques. To confirm this, the simulation model and the physical experiment stand were designed, implemented and suitable tests were carried out in the indoor environment. The obtained results show that for a physical experiment, the mean of positioning uncertainty was 5.0 cm with standard deviation of 20 cm. Whereas, the accuracy achieved from virtual experiments was 3.3 cm with standard deviation of 21 cm.

The experimental results summarized in Table 1 also show that the standard deviation σ=2.7 of AWGN used in the LDPLM, matches the noise standard deviation level used for indoor applications. Moreover, the validation experiment proves that the LDPLM is a suitable representation of radio wave propagation phenomena useful for modeling *RSS* based distance measurement. The estimated system's offset vector can be introduced to the system to correct the result and increase the positioning accuracy.

The performance of the proposed virtual and physical systems was collated with data from others reported positioning systems applying SA approach. The result

Table 1. Experimental results of virtual and physical systems performance.

SNR (simulations)	Mean uncertainty [cm]				STD [cm]	Effi-ciency
	x	*y*	*z*	*d*		
σ =1.7	-0.2	2.5	-1.3	2.8	23	88%
σ =2.7	-2.9	1.4	0.8	3.3	21	90%
σ =3.7	-5.0	4.0	3.0	7.3	20	86%
Experiment	-1.6	-4.7	0.5	5.0	20	85%

Table 2. Performance comparison of different Scene Analysis applications.

Method	Technology	Area	Mean [cm]	STD [cm]
SA-NN	RFID	3D room	5.0	21
Horus	WLAN	2D floor	42	28
RADAR	WLAN	2D floor	400	326
GA-BP NN	RFID	2D room	8.1	210

analysis confirms the advantage of the proposed method over the others SA based solutions.

Further research on the Scene Analysis technique may concern ToA-based distance measurement. However, this approach would need a consideration of tradeoff between a cost and accuracy.

Complementary research may concern improvement of *RSS* map by optimizing a sampling procedure. The optimized sampling step should increase an accuracy of target tag positioning.

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ANALIZA SYSTEMU LOKALIZACJI 3D W POMIESZCZENIU OPARTEGO NA TECHNOLOGI RFID I ŁĄCZĄCEGO METODĘ ANALIZY SCENY ZE SZTUCZNYMI SIECIAMI NEURONOWYMI

Głównym celem tej pracy badawczej jest poprawa dokładności systemu lokalizacji 3D w przestrzeni zamkniętej, aktywnego identyfikatora RFID. Proponowany system lokalizacji stanowi hybrydę dwóch metod: Analizy Sceny oraz Sztucznych Sieci Neuronowych. W pracy tej przedstawiono model proponowanego rozwiązania, a w celu walidacji systemu wykonano badania symulacyjne modelu komputerowego wykorzystującego m.in. Logarytmiczny Model Propagacji Fali Radiowych. Przeprowadzono również badania na modelu rzeczywistym w pomieszczeniu zamkniętym o rozmiarach geometrycznych 5,13 m×4,50 m×2 m, które potwierdziły poprawność wybranego parametru propagacji sygnału radiowego. Uzyskane wyniki potwierdzają a, że proponowany system lokalizacji 3D, charakteryzuje się wysoką dokładnością pozycjonowania aktywnego identyfikatora RFID. Uzyskana dokładność pozycjonowania, jest lepsza niż 0,5 m. Badania potwierdzają założoną hipotezę, że proponowany system lokalizacji 3D w przestrzeni zamkniętej charakteryzuje się lepszą dokładnością niż znane rozwiązania oparte na technice Analizy Sceny.

Słowa kluczowe: analiza sceny, identyfikacja radiowa, system pozycjonowania wewnątrz pomieszczeń, sztuczne sieci neuronowe.