 ISBN: 978-989-95618-4-7

Using Multi-Layer Perceptrons to Enhance the Performance of Indoor RTLS

Dante I. Tapia, Javier Bajo, Juan F. De Paz, Ricardo S. Alonso, Sara Rodríguez and Juan M. Corchado

Department of Computer Science and Automation, University of Salamanca
Plaza de la Merced s/n, 37008, Salamanca, Spain
{dantetapia, jbajope, fcofds, ralorin, srg, corchado}@usal.es

Abstract. Accuracy in indoor Real-Time Locating Systems (RTLS) is still a problem requiring novel solutions. Wireless Sensor Networks are an alternative to develop RTLS aimed at indoor environments. However, there are some effects associated to the propagation of radio frequency waves, such as attenuation, diffraction, reflection and scattering that depends on the materials and the objects in the environment, especially indoors. These effects can lead to other undesired problems, such as multipath. When the ground is the main responsible for waves reflections, multipath can be modeled as the ground reflection effect. This paper presents a model for improving the accuracy of RTLS, focusing on the mitigation of the ground reflection effect and the estimation of the final position by using Neural Networks.

Keywords. Applications of sensor and actuator networks, wireless sensor networks, real-time location systems, ground reflection effect.

1. Introduction

Indoor Real-Time Location Systems (RTLS) are gaining relevance during the recent years and represent a currently growing market. The most important factors in the locating process are the kinds of sensors used and the techniques applied for the calculation of the position based on the information recovered by these sensors. Indoor locating (*e.g.*, inside buildings or tunnels) needs still more development, especially with respect to accuracy and low-cost and efficient infrastructures [12; 15]. One of the main challenges is to deal with the problems that arise from the effects of the propagation of radio frequency waves, such as attenuation, diffraction, reflection and scattering. These effects can lead to other undesired problems, such as multipath. When the ground is the main responsible for waves reflections, multipath can be modeled as the ground reflection effect. Due to these effects, the energy of the transmitted electromagnetic waves is substantially modified between transmitter and receiver antennas in these systems. Therefore, it is necessary to develop Real-Time Locating Systems that allow performing efficient indoor locating in terms of precision and optimization of resources.

 ISBN: 978-989-95618-4-7

Amongst the technologies that are most currently used in the development of RTLS we have RFID (Radio Frequency IDentification), Wi-Fi and ZigBee [7]. However, in addition to the technology used, it is necessary to establish mathematic models that allow us to determine the position from the recovered signals. For this reason, different algorithms exist, such as *triangulation*, *fingerprinting* and *multilateration* [7; 8]. However, these models present important disadvantages when developing a precise locating system, especially indoors. Therefore, it is necessary to define new models that allow the improvement of precision in this type of system. Reflection, diffraction, scattering, reflection effect can provoke which is known as multipath effect, and, more specifically to indoor RTLS based on WSNs, the ground reflection effect [6]. Therefore, it is necessary to define new models and techniques that allow the improvement of accuracy in these kinds of systems.

In this paper, a new model is presented in order to improve the precision of RTLS based on wireless sensor networks. This model uses Artificial Neural Networks (ANNs) [13] as a new component to mitigate the ground reflection effect and calculate the position of the elements. The basic functioning of the system is as follows. Firstly, it is necessary to place a network of fixed nodes within the space where location will be carried out. In addition, there are a set of mobile nodes, generally called "tags", which periodically transmit a signal that contains their identifier in the network. That signal is detected by the fixed nodes within their coverage area, containing power (RSSI – *Received Signal Strength Indication*) and quality (LQI – *Link Quality Indicator*) measurements of the received signal. A central node collects all the reference measurements from all of the fixed nodes in the network and sends them to a computer to be processed.

The paper is structured as follows: Section 2 explains the problems that the ground reflection effect introduces in RTLS and describes a new proposal for reducing the ground reflection effect by using ANNs. Section 3 describes the case study. Finally, Section 4 describes a set of tests evaluating our proposal.

2. The RTLS Model

The infrastructure of a Real-Time Locating System contains a network of reference nodes called *readers* [7] and mobile nodes, known as *tags* [15; 7]. Tags send a broadcast signal which includes a unique identifier associated to each tag. Then, readers obtain the identifier, as well as specific measurements of the signal. These measurements give information about the power of the received signal (*e.g.*, RSSI), its quality (*e.g.*, LQI), the Signal to Noise Ratio (SNR) or the Angle of Arrival (AoA) to the reader, amongst many others. These signals are gathered and processed in order to calculate the position of each tag.

RTLS can be categorized by the kind of its wireless sensor infrastructure and by the locating techniques used to calculate the position of the tags. This way, there is a range of several wireless technologies, such as RFID, Wi-Fi, UWB, Bluetooth and ZigBee, and also a wide range of locating techniques that can be used for determining the position of the tags. Amongst the most widely used locating techniques we have signpost, fingerprinting, triangulation, trilateration and multilateration [7; 8]. The set of the locating techniques that a RTLS integrates is known as the *locating engine* [7].

This way, the position of each tag is estimated no matter the position of the readers in the environment. However, two main aspects have to be taken into account when calculating the position of the tags. On the one hand, it is necessary to establish a relationship between the RSSI levels of the signals sent by the tags and the distance between such a tag and a set of readers. In order to do this, it is necessary to model the ground reflection effect, which distorts considerably the relationship between a certain range of RSSI levels and distances. On the other hand, it is necessary to apply an algorithm that allows estimating the final position of each tag basing on the distances calculated according to the measured RSSI levels.

2.1. Modeling of the Ground Reflection Effect

In ideal conditions, the modeling of the relationship between RSSI levels and distances between antennas has a decaying exponential shape. Nevertheless, as shown in Figure 1, when ground reflection effect is taken into account, the process of approximation of the relationship between the RSSI levels and the distances between antennas is complex and problematic. Therefore, it is necessary to use other models that allow considering the ground reflection effect in order to obtain a reliable estimation of the distances between tags and readers.

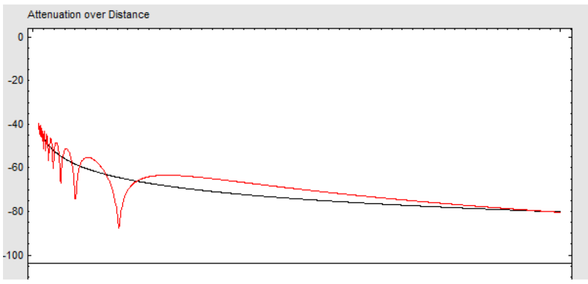

Fig. 1. The X axis represents the distance and the Y axis represents the RSSI at the receiver antenna. The black line shows the values of the signal in an ideal situation, with no ground reflection effect. The red line shows the signal affected by the ground reflection effect.

Currently there is a wide range of models for function approximation. Amongst the most widely used, we have the *regression models*. Some alternatives to these regression models are the *Support Vector Regression* (SVR) [16; 14], and *Polynomial interpolation* methods [2; 17]. These methods allow approximating values from a certain tabbed data set. Other regression methods applied when the distribution of data and their relationships are unknown are *supervised learning neural networks*. In the work of Kalogirou [9] it is presented a complete review of case studies where these artificial neural networks have been applied. Amongst supervised learning networks we have the *Multi-Layer Perceptron* (MLP) or the *radial basis function*

ISBN: 978-989-95618-4-7

(RBF) networks [1]. Artificial Neural Networks are applied to a wide range of function approximation problems.

Artificial Neural Networks allow working with time series. The use of time series facilitates the forecast if it is not possible to make estimations of non-independent values with consecutive samples. This way, it is provided a more realistic forecast of values. Indeed, this is a fundamental feature for the forecast of distances from the RSSI levels, thus mitigating the ground reflection effect. This is because the ground reflection effect mainly occurs inside certain ranges of the distances.

There are fluctuations in the distance values regarding the RSSI levels for a certain range of RSSI values. Thus, a certain RSSI value can mean distinct distances. In order to model the ground reflection effect we utilize time series applied to Artificial Neural Networks. Artificial Neural Networks allow forecasting a value according to the received historical values. Therefore, in this work the neural network is provided as inputs with both the current detected RSSI value and the RSSI values detected in previous time instants. This is the way we intend to mitigate the ground reflection effect. In order to improve the forecast of the time series it was opted to incorporate the RSSI levels provided by other readers into the neural network. This way, the distances forecasting is done using a subset of the deployed readers in the system simultaneously. The architecture of the neural network is depicted in the Figure 2. This neural network has *k* input groups with *n* neurons each of them. These *n* neurons correspond with the *n* values of the time series. Likewise, the *k* groups correspond with number of readers that are considered for the distance estimation. This number of readers is set in advance, thus selecting the readers with highest measured RSSI levels from the tag. The intermediate layer is made up of $2(k + n) + 1$ neurons, whereas output layer is formed by *k* neurons (*i.e.*, a neuron per each reader).

The groups of input neurons are ordered according to the current RSSI level from highest to lowest. Therefore, the first output of the neurons is associated to the reader that received the highest RSSI level and so on.

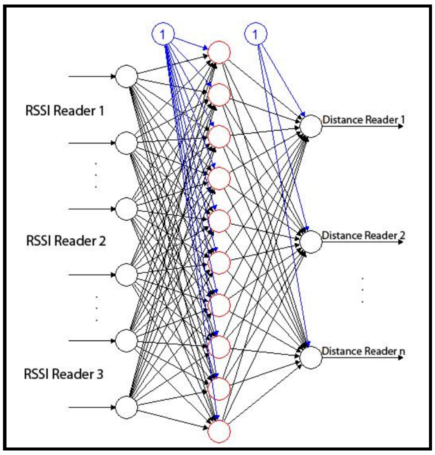

Fig. 2. Structure of the Multi-Layer Perceptron used in the training stage for the mitigation of the ground reflection effect using multiple readers. The ANN contains *n* inputs for each of the *k* readers and *k* outputs.

 ISBN: 978-989-95618-4-7

2.2. Locating Techniques

As mentioned before, there are several locating techniques that can set up the *locating engine* of a Real-Time Locating System. In our research, we are centered on three of them: *signpost*, *fingerprinting* and *trilateration*.

The *signpost* technique is the simplest one and its computational complexity is relatively low [7]. In signpost, the location of each tag is estimated from the strongest signal received from each reader. *Fingerprinting* technique is based on the study of the characteristics of each area of locations (*e.g.*, buildings), performing measurements of distinct radio frequency characteristics and estimating in which area of influence each tag is found [8]. *Trilateration* [7], sometimes wrongly confused to *triangulation*, is a technique that calculates the position of each tag from the distance to several readers. Graphically, it is performed an intersection of several spheres in a three-dimensional space.

Our proposed model captures data from the estimation of the positions by the trilateration algorithm. It stores these in a memory to subsequently use to carry out the training of an MLP (Multi-Layer Perceptron). This way, the neural network allows us to make the fastest estimations and is more responsive to variations in the distances resulting from the reflections of the emitted waves. Input data in the neural network correspond with the distances calculated by means of the MLP described in Section 2.1 from a pre-fixed number of readers and the position of the readers. These readers are selected according to the lowest distances they have to the tag. Output has two coordinates, one for each coordinate in a plane. The number of neurons in the hidden layer is $2n + 1$, where n is the number of neurons in the input layer. Finally, there is one neuron in the output layer. The activation function selected for the different layers has been the *sigmoid*. Furthermore, the neurons exiting from the hidden layer of the neural network contain *sigmoidal* neurons. Network training is carried out through the *error backpropagation algorithm* [10].

3. Case Study

In order to test the performance of this model into an indoor environment, we proceeded to deploy a WSN infrastructure made up of several ZigBee nodes (*i.e.*, readers and tags). As mentioned before, the ZigBee standard is specially intended to implement WSNs and allows operating in the frequency range belonging to the radio band known as *Industrial, Scientific and Medical* (ISM), specifically in the 868MHz band in Europe, the 915MHz in the USA and the 2.4GHz in almost all over the world. The underlying IEEE 802.15.4 standard is designed to work with low-power and limited computational resources. The ZigBee standard allows more than 65,000 nodes to be connected in a star, tree or mesh topologies. Therefore, RTLS can be implemented by means of ZigBee and different locating techniques can be used.

Each ZigBee node in our case study included an 8-bit RISC (Atmel ATmega 1281) microcontroller with 8KB RAM, 4KB EEPROM and 128KB Flash memory, as well as an IEEE 802.15.4/ZigBee transceiver (Atmel AT86RF230) [11]. The ZigBee network was formed by 15 fixed nodes acting as readers and distributed throughout

 ISBN: 978-989-95618-4-7

three rooms. The total size of the monitored area was 19m per 19m with 3 different rooms. The distribution of the readers was done in this way in order to each tag could be identified by several readers simultaneously. Therefore, the selected locating techniques (*i.e.*, *signpost*, *fingerprinting* and *trilateration*) could be applied using several simultaneous measurements.

4. Results and Conclusions

Several tests were performed in order to validate the mitigation of the ground reflection effect and the estimation of the final position. Firstly, as a previous step before the estimation of the tags positions, it was carried out the training of the neural network built to estimate the distances between nodes from the RSSI levels. A test tag was successively moved through different predefined location sequences (*i.e.*, zones inside the laboratory). This way, it was calculated the relationship of the measured RSSI levels with the real distances between the tag and the readers. For doing this, it was measured the detected RSSI levels between the tag and each of the 15 readers. Thus, the RSSI–distances measurements were used to make predictions in the time series. In total, 200 cases were generated for the training of the neural network according to the structure previously shown in Figure 2. In addition, it was randomly chosen different positions throughout the zones to generate 100 new cases and estimate each position by means of both the neural network and other approximation methods to compare them. These other methods were *SVR*, a *linear regression model* and a *logarithmic regression model*. The calculation of these relationships is necessary because the characteristics of the existing materials affect considerably to the detected distances.

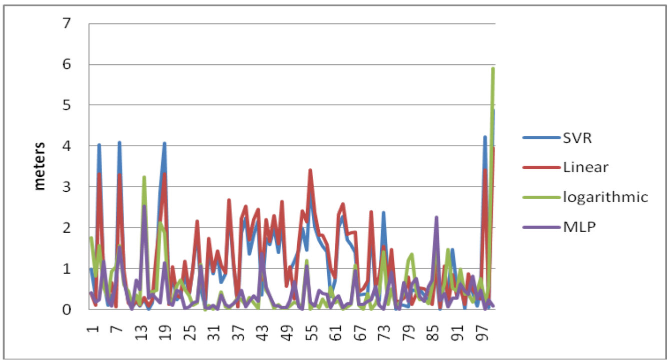

Fig. 3. Errors in the estimations of the distances from the RSSI levels for the different compared models: SVR, linear regression model, logarithmic model and the MLP.

For the training of the neural network it was carried out both the proper training and a crossed validation. The neural network followed the architecture described in the Section 2.1, being the number of groups $k = 4$. The number of measurements for each group was *15*. This way, the number of inputs was *60*. Likewise, the number of

 ISBN: 978-989-95618-4-7

outputs was *4*, one per each group. In order to generate the distinct compared models (SVR, linear, and logarithmic), only the information of the group with highest RSSI levels was used. Thus, it was only utilized 15 input values and 1 output value in these models. Both in the neural network and the other models it was used 200 cases of the training stage and 100 cases to make predictions.

Figure 3 shows the absolute errors obtained for the SVR, the linear regression model, the logarithmic model and the neural network. As can be seen on this figure, the neural network obtained better results that the other methods because it presents a lower error for the distances estimation.

The information of mean error and standard deviation in the estimation for each of the compared models is shown in Table 1. As can be seen, the typical error and the deviation of the neural network are lower than SVR and regression models.

Table 1. Mean error and standard deviation of the distances estimation for each of the compared models.

Model	Average	Deviation
SVR	1.09	1.04
Linear	1.16	0.98
Logarithmic	0.55	0.78
MLP	0.36	0.43

In order to analyze the significance of the differences and to determine if we can state that the neural network is statistically better than both the SVR and the regression models, we applied the *t-test*. This test determines two values: H_0 and H_1. H_0 shows if the data in both groups presents the same average error, whereas H_1 determines if there is difference. Table 2 shows the p-value obtained for the comparison method of the row and the corresponding column. Considering a significance $\alpha = 0.05$ we have that the p-value corresponding to linear–SVR and logarithmic–MLP is greater than α. Therefore, we cannot discard H_0, while it is discarded for the equality comparisons of distributions of SVR–MLP and linear–MLP. Nevertheless, even though it cannot be discarded H_0 for the logarithmic–MLP case and a significance $\alpha = 0.05$, the value that it presents, *0.0758*, is low. This way, taking a significance value $\alpha = 0.1$, H_0 would be discarded. Observing the information presented in the Table 2, we can state that the MLP improves the results obtained by the logarithmic model.

Table 2. T-Test data distribution equality test for the distances error.

	SVR	Linear	Logarithmic	MLP
SVR				
Linear	0.627			
Logarithmic	4.546e-5	1.911e-6		
MLP	5.957e-9	2.915e-11	0.0758	

In order to determine the position of each tag, it was carried out a forecast of the final positions by means of the application of *signpost* and *trilateration* to obtain the RSSI levels. For the training of the neural network it was utilized 200 positions initially realized and 300 of the carried out with *trilateration*. The 100 remaining

 ISBN: 978-989-95618-4-7

measurements were used to make predictions. Figure 4 shows the absolute error (in meters) obtained for the calculation of 100 positions by the different compared methods. As can be seen, forecasting based on the neural network improves the results of the other methods, reducing the error in the predictions.

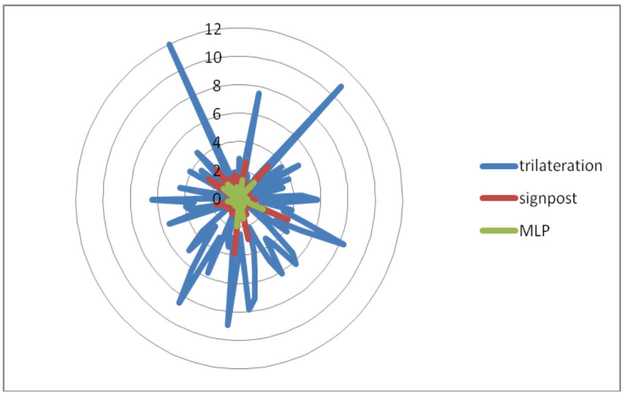

Fig. 4. Comparison of mean absolute prediction error for 100 values using signpost, trilateration and MLP.

Amongst the wide range of Wireless Sensor Networks applications, *Real-Time Locating Systems* are emerging as one of the most exciting research areas. There also are different wireless technologies that can be used on these systems. The ZigBee standard offers interesting features over the rest technologies, as it allows the use of large mesh networks of low-power devices and the integration with many other applications as it is an international standard using unlicensed frequency bands.

The operation of Real-Time Locating Systems can be affected by undesired phenomena as the multipath effect, and more specifically, the *ground reflection effect*. As demonstrated in this study, the use of Artificial Neural Networks to forecast distances from RSSI levels allows improving the estimation of distances when using SVR or regression models. In addition, focusing the forecast according to time series allows reducing the ground reflection effect that occurs when considering only the last RSSI measurement. The results presented in this article demonstrate that the use of artificial neural networks allows improving the approximations provided by the locating techniques. Nevertheless, it is required a previous data gathering stage. In this article, this stage was carried out in a both manual and automatic way by means of the *trilateration* technique.

Acknowledgements. This work has been supported by the Spanish JCyL project JCRU / 463AC03.

ISBN: 978-989-95618-4-7

References

1. Anand, P., Siva Prasad, B.V., and Venkateswarlu, Ch. 2009. Modeling and optimization of a pharmaceutical formulation system using radial basis function network. International Journal of Neural Systems. 19, 2 (Abr. 2009), 127-136.
2. Carnicer, J.M., and García-Esnaola, M. 2002. Lagrange interpolation on conics and cubics. Comput. Aided Geom. Design. 19, 313-326.
3. Ducatel, K., Bogdanowicz, M., Scapolo, F., Leijten, J. & Burgelman, J. C. (2001). That's what friends are for. Ambient Intelligence (AmI) and the IS in 2010. Innovations for an e-Society. Congress Pre-prints, "Innovations for an e-Society. Challenges for Technology Assessment". Berlin, Germany.
4. Eui Seok Kim, Jin Ik Kim, Ik-Seon Kang, Chan Gook Park, and Jang Gyu Lee. 2008. Simulation results of ranging performance in two-ray multipath model. Control, Automation and Systems, 2008. ICCAS 2008. International Conference on (2008), 734-737.
5. Giunchiglia, F., Mylopoulos, J., Perini, A.: The tropos software development methodology: Processes, models and diagrams. In: AAMAS'02 Workshop on Agent Oriented Software Engineering (AOSE-2002) (2002) 63–74.
6. Goldsmith, A. Wireless communications. Cambridge University Press (2005).
7. Hui Liu, Darabi, H., Banerjee, P., and Jing Liu. 2007. Survey of Wireless Indoor Positioning Techniques and Systems. Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on, 37, 6 (2007), 1067-1080.
8. Kaemarungsi, K. and Krishnamurthy, P. 2004. Modeling of indoor positioning systems based on location fingerprinting. INFOCOM 2004. Twenty-third Annual Joint Conference of the IEEE Computer and Communications Societies (2004), 1012-1022 vol.2.
9. Kalogirou, S.A. 1999. Applications of artificial neural networks in energy systems: A review. Energy Conversion and Management. 40, 10 (Jul. 1999), 1073-1087.
10. Lecun, Y., Bottou, L., Orr, G.B, and Müller, K.R. 1998. Efficient BackProp. Lecture Notes in Computer Science. Springer Verlag. 5-50.
11. n-Core. 2011. n-Core: A Faster and Easier Way to Create Wireless Sensor Networks. Retrieved April 20, 2011, from http://www.n-core.info
12. Nerguizian, C., Despins, C., and Affès, S. 2004. Indoor Geolocation with Received Signal Strength Fingerprinting Technique and Neural Networks. Telecommunications and Networking - ICT 2004. Springer Berlin / Heidelberg. 866-875.
13. Nguyen, H. and Chan, C. 2004. Multiple neural networks for a long term time series forecast. Neural Computing & Applications, 13, 1 (Apr. 2004), 90-98.
14. Smola, A.J., and Schölkopf, B. 2004. A tutorial on support vector regression. Statistics and Computing. 14, 3 (2004), 199-222.
15. Tapia, D.I., De Paz, J.F., Rodríguez, S., Bajo, J., and Corchado, J.M. 2008. Multi-Agent System for Security Control on Industrial Environments. International Transactions on System Science and Applications Journal, 4 (3) (2008) 222-226.
16. Vapnik, V.N. 1998. Statistical Learning Theory. Wiley-Interscience.
17. Xue-Zhang Liang, Ren-Hong Wang, Li-Hong Cui, Jie-Lin Zhang, and Ming Zhang. 2006. Some researches on trivariate Lagrange interpolation. Journal of Computational and Applied Mathematics. 195, 1-2 (2006), 192-205.16 Razavi, R., Perrot, J., & Guelfi, N. (2005). Adaptive modeling: an approach and a method for implementing adaptive agents. Lecture Notes in Artificial INTELLIGENCE, 3446, 136-148.