Optimizing Artificial Neural Network for Beacon Based Indoor Localization

Filip Mazan, Alena Kovarova

Abstract: *In this paper, we study the problem of indoor localization with emphasis on precision. There are already various technologies that can be used to gather data and more or less precisely estimate the user's location. In our work, we use Bluetooth Low Energy beacons. When these transmitters are properly placed in the environment, their signal can serve as a data input. We designed a feed-forward artificial neural network that processes this data and produces estimated coordinates that denote the position of the user. Experiments show, that our approach achieves the best average precision of 1.21 meters which is comparable to results reported by other known approaches.*

Key words: *Indoor Localization, Neural Networks, Bluetooth Beacons, Localization Methods, Received Signal Strength.*

INTRODUCTION

A common feature of human and machine localization remains the same - in either way, it is necessary to know the position of reference points, which can be either fixed or at least calculable. For example, the global positioning system (GPS) uses earth-orbiting satellites as reference points. Satellite's positions (more exactly, distances from them) are precisely calculated based on the radio signal travel time. The GPS can operate almost in any location on earth as long as there is an unobstructed line of sight to at least three orbiting satellites [12]. This poses a problem for indoor localization, where the buildings themselves shield the satellite signal and the receivers cannot receive it.

Even in indoor localization the (semi-)static reference points are used to estimate the user's position. Usually, these reference points are some kind of transmitting devices with static position. The position of reference points and parameters of their signal are fundamental and indispensable data that the localization module uses to calculate the user's position.

These devices can operate with different types of signal. Recently, the Wi-Fi signal is being used [1, 2, 8, 13], but also Bluetooth [11, 13], GSM [9] or other types of signal [3]. Since the properties of the signal is very similar, similar methods can be used to process it. Researchers have devised many different approaches on how to effectively and precisely localize objects [3, 5, 13].

RELATED WORK

In our previous publication [10] we studied the basic properties of Bluetooth beacons and their signal transmission. We found out that the received signal strength (RSSI) falloff varies between beacon types and manufacturers, the environment they are set up in and, of course, the distance. Based on the observations, we cannot tell precisely how far the beacon is from the receiver after approximately 9-10 meters. We also concluded two simple experiments to show that our approach of artificial feed-forward neural networks is suitable for this problem by achieving the average error rate of 1.21 meters which is compared to other solution in the Table 1. We have decided to further continue in our work to improve our solution and define the whole localization method.

CompSysTech'16, 23-24 June 2016, Palermo, Italy
 ISBN 978-1-4503-4182-0/16/06...$15.00
http://dx.doi.org/10.1145/2983468.2983515

Amongst all the papers on the topic of indoor localization we mention three, dealing with the possibility of combination of more than one sources of signal, fingerprinting algorithm of Wi-Fi and Bluetooth signal and modular neural network approach. At the time of the study we did not find any papers with pure Bluetooth LE beacons based approach using machine learning.

LaMarca et al. [9] show the possibilities of combining information about GSM, Wi-Fi and Bluetooth transmitters into one database. By combination of these three sources of data, they could improve the overall precision by more than 50% as opposed to pure Wi-Fi based solution.

Wang et al. [13] describe the use of particle filtering [5] and fingerprinting [2] algorithm to combine data from Wi-Fi and Bluetooth transmitters inside of a building. They could achieve an average error of 2.9 meters with maximum error of 8.9 meters. By using solely Wi-Fi data, the average error was 3 meters with maximum of 9.4 meters.

Ahmad et al. in their work [1] on indoor localization employed Modular Multi-Layer Perceptron (MMLP) technique to provide better location estimates than other approaches. The authors collected 300 samples of Wi-Fi signal strengths for each of the reference points in their building, which were approximately 2-3 meters apart. Then the data was divided into training and testing datasets and used to train a classification neural network in various configurations. The best result they could achieve was by using a 3-8-8-1 structure, by using logsig and tan transfer functions and Levenberg-Marquardt training algorithm. Average error in this configuration was only 0.12 meters with maximum error of 2.16 meters. Although these results are acceptable for Wi-Fi signal, we cannot assume the same for Bluetooth beacon signal. Due to some inferior properties - mainly much lower transmitting power, we expect to get similar or worse results.

LOCALIZATION METHOD DESIGN

The core principle of our approach is to use measured beacon signal strengths as an input for a multi-layered feed-forward neural network. We chose this type of neural network because feedforward networks are well-suited for approximation of unknown continuous functions such as signal propagation, whereas other types are suitable for other kinds of problems, e.g. recurrent networks for modelling temporal behaviour, or convolutional neural network for image recognition. Simplified diagram of our designed method is in the Figure 1.

First step is to perform fingerprinting [2, 7, 10] of the surveyed area, in which we perform localization. We chose this method as a data input because other methods based on precise distance estimates from the beacons would not perform well due to the ununiformed signal radiation as we found out in our previous work [10].

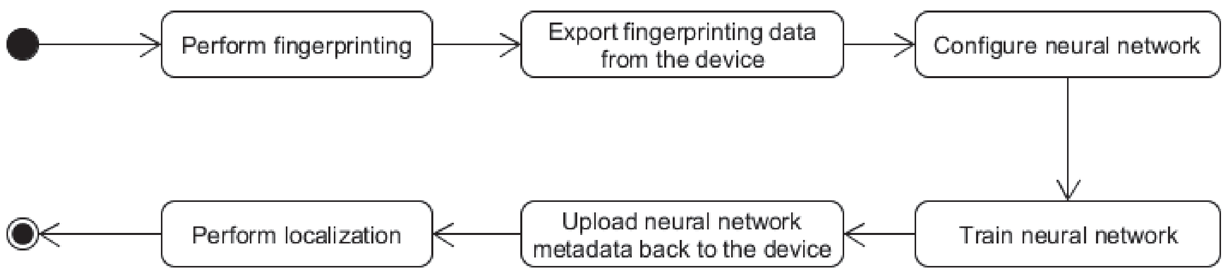

Figure 1. Simplified activity diagram of the workflow.

The next step of neural network configuration starts with determining its structure - number of neurons in each layer, transfer functions, learning algorithm, etc. The number of input neurons is set by the number of beacons we possess in our dataset. For each beacon there is one input neuron with its value set as normalized signal strength from that beacon to the range of 0 to 1. The number of output neurons is always two - x and y coordinate in Cartesian space. The interesting part is choosing number of hidden layers and number of neurons in these layers. This has impact on how "powerful" the network becomes in finding patterns and generalization. The next step after determining the neuron counts is to decide what transfer and activation functions the neuron should use to produce outputs. We decided to use mainly two functions - tanh and log functions as in the Ahmad's work [1]. Also for comparison, we added the basic sigmoid transfer function. Then, the training phase is applied - a resilient backpropagation learning algorithm continues to train the neural network until the training error rate reaches a set threshold. Different thresholds have impact on the ANN genericity - lower thresholds tend to overspecialize, and sometimes may even not be reached. The dataset was split into two parts - training and testing subset, in the ratio of 3:1.

As the application starts to gather RSSI values of surrounding transmitters, in real-time it feeds these values after normalizing to the neural network. The artificial neural network then produces output on its two output neurons, which after denormalization yield x and y coordinate respectively. These coordinates are then fed into the refinement algorithm which produces the final result and displays it.

EVALUATION

The first experiment [10] was held on the south wing of the second floor of our university building with four Bluetooth beacons. Three beacons were USB-powered beacons and one was battery-powered. We designed a 4x4 meters grid (it divided our space into 14 squared cells) on which we performed fingerprinting of RSSI from all four beacons using a handheld smartphone device. This way we gathered 10 samples from each of 14 cells – their centers. Each sample consisted of 10 measurements from which the maximum value of RSSI was taken for each beacon. We chose 10 measurements because of the similarity to the real user scenario. Ten measurements take about 1-2 seconds to collect and process, which means we can use this approach to localize semi-static target in a real environment (quickly moving target would get lower accuracy).

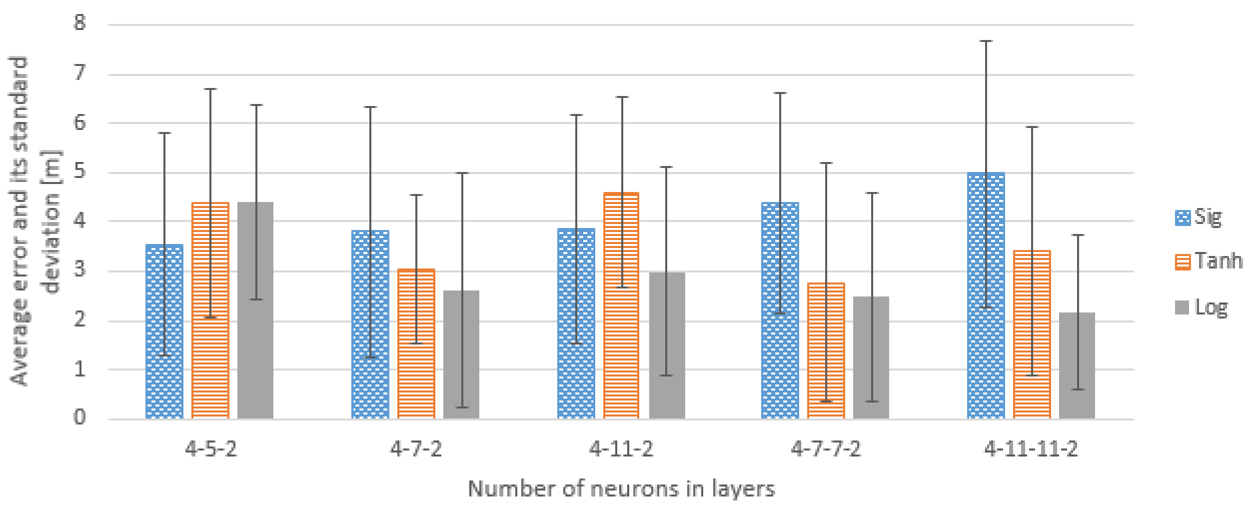

Figure 2. Comparison of the average error and its standard deviation in the first experiment.

The input data consisted of four measured RSSI values from all four beacons, and the output data represented x and y coordinates on the building floor. Point zero was set in the middle of the hall opening. All values were linearly normalized to the interval from 0 to 1, which means that upon receiving the results from output neurons, we will have to denormalize them to find out the actual x and y coordinates. The whole dataset was divided into the training set (75%) and the testing set (25%). We experimented with different number of neurons in the hidden layer and the number of hidden layers – 5, 7 and 11 neurons for one hidden layer and 7-7 and 11-11 for two hidden layers as well as with different transfer function – sigmoid (sig), hyperbolic tangent (tanh) and logarithmic (log). The average errors and their standard deviation calculated from testing set are shown in chart in Figure 2. The lowest achieved average error was 2.16 m.

In the second experiment [10] we use the same space, but with different beacons in different locations. There were 9 kontakt.io beacons in a row (set up transmission power = 4 dBm, TxPower in open space= -69 dBm, advertising interval = 500 ms), the space was divided in 36 cells one by other in a row, each 1 m x 1 m. This time we gathered 20 samples from each cell (from its center). Each sample, as in the previous experiment, consisted of 10 measurements of RSSI of all 9 beacons, from which only the maximum RSSI value of each beacon was noted. As in the previous experiment, the data was pre-processed - normalized and segregated. The training algorithm was resilient backpropagation in all the cases and target error goal of 1 % which was reached. We experimented with tanh and log functions and with 15 neurons in one or both two hidden layers. The lowest achieved average error was 1.21 m for 9-15-15-2 Log neural network. We also tried to reduce the dataset by one half - we selected only those even coordinated to see whether dense dataset is needed to satisfy the neural network. For some neural networks, the error increased and declined elsewhere. The lowest achieved average error was 1.24 m for 9-15-2 Log neural network.

The third experiment was very similar as the second, but there were used 12 Gimbal beacons in a little bit longer area. The beacons were approximately 3.6 m apart one from each other. We gathered the data from 13 points spaced 3 meters apart. We experimented with Tanh and Log function, 19 neurons in one and two hidden layers (alternatively 10 for halved dataset). The results are shown in the Figure 3. The lowest achieved average error was 2.93 m for 12-19-2 Tanh and the same error for 6-10-2 Log reduced.

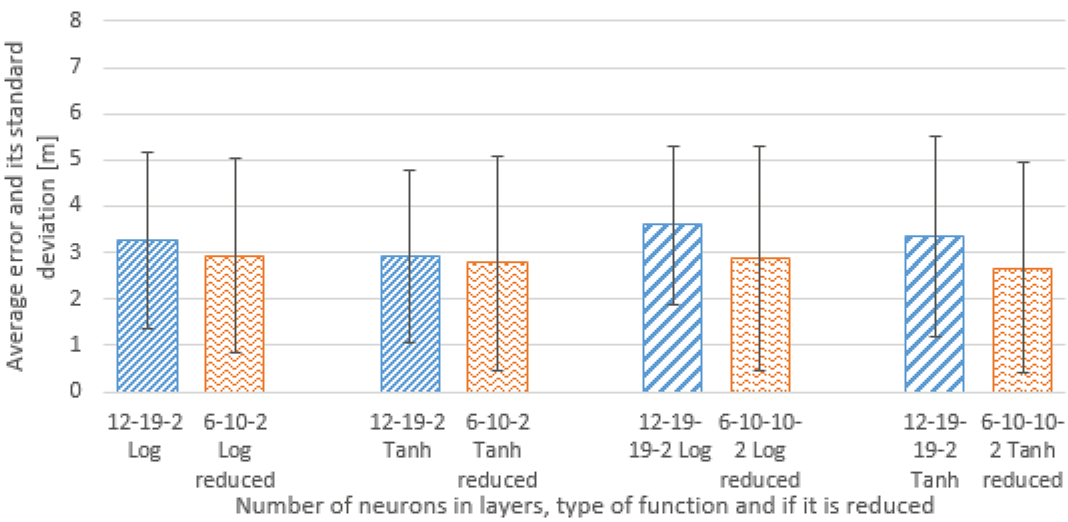

Figure 3. Results of the comparison of full dataset and reduced dataset for training.

Moreover, we tried to keep only a specified number of strongest signals (str. s.) in the dataset - the others were set to zero. We will call this feature the weak signal stripping. As we can see, the reduced dataset performed in a very similar fashion. This means, that it is not necessary to have a dense reference point grid, but for future reference it is sufficient to have the points placed at least 2 meters apart. As we can see in the Figure 4, keeping only 5 strongest signals in each sample had a significant effect in improving both the average and minimum errors. However, keeping only 3 strongest signals has in some cases increased the error, most notably the maximum error by 3 meters in comparison to keeping 5 strongest signals. Our weak signal stripping feature reduced the error to 1.93 m (12-19-2 Tanh, 5 str. s), which yields 34 % improvement.

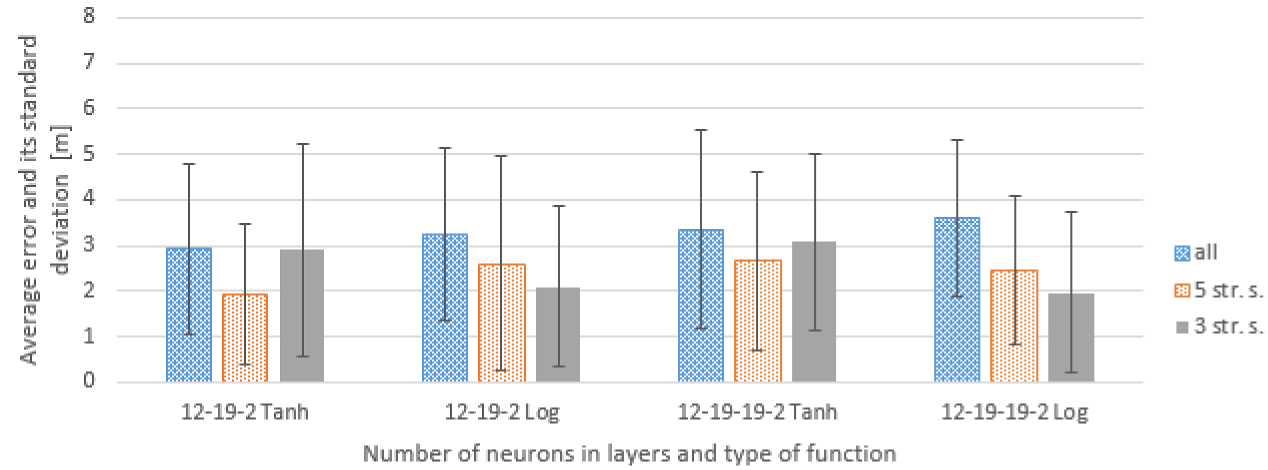

Figure 4. Comparison of the average error and its standard deviation of the third experiment.

The final experiment was held in a 2D space of the faculty building, where both x and y coordinates were used. We placed 21 Gimbal beacons (set up transmission power = 0 dBm, advertising interval = 100 ms, TxPower in open space = -62 dBm) on the ceiling 3.6 meters apart as seen in the Figure 5.

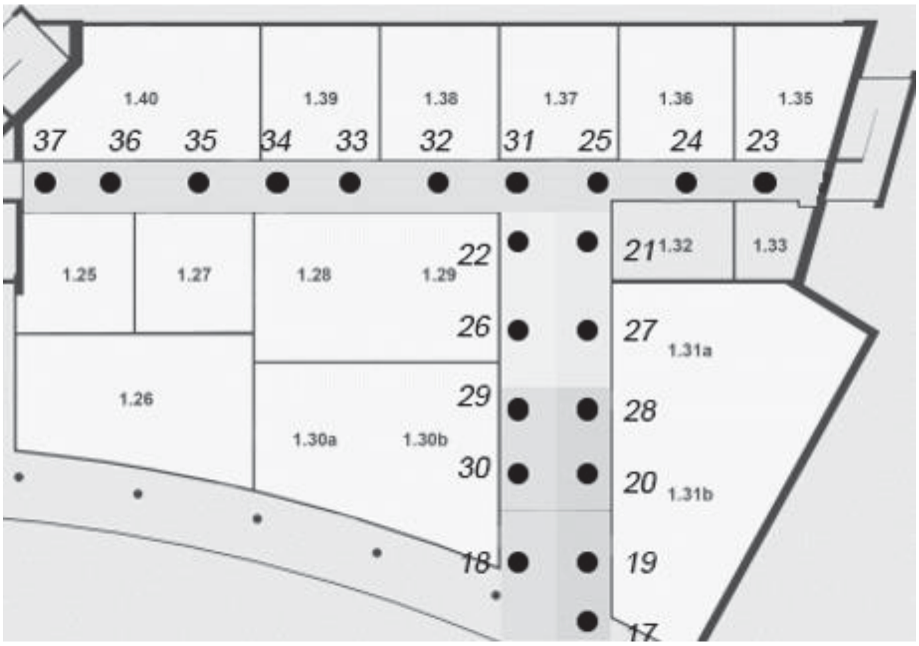

Figure 5. Positioning of beacons marked by their ID on a part of the first floor.

In this experiment we tried altering target error values from 1% down to 0.01% in one set configuration of the neural network 21-33-33-2 with logarithmic transfer function. Of course, the lower the threshold is, the longer the training phase will take while the threshold must not be even reached. This configuration was set according to the recommendation of the Encog framework with one more hidden layer of neurons, which was proved to perform slightly better than a network with one hidden layer. The logarithmic transfer function was chosen based on our experiments, where it outperformed other types of functions. As in previous experiments, we gathered 20 samples (~500 ms) from each of the 28 reference points (centres of cells of 3 m x 3 m grid). The results of the training in the Figure 6 show that the average error was lowering with the lower error threshold values, and started to level out at the threshold of 0.1% and average error of 1.3 meters. This value can be used in later experiments as a good ratio of average error and the time needed for the actual training.

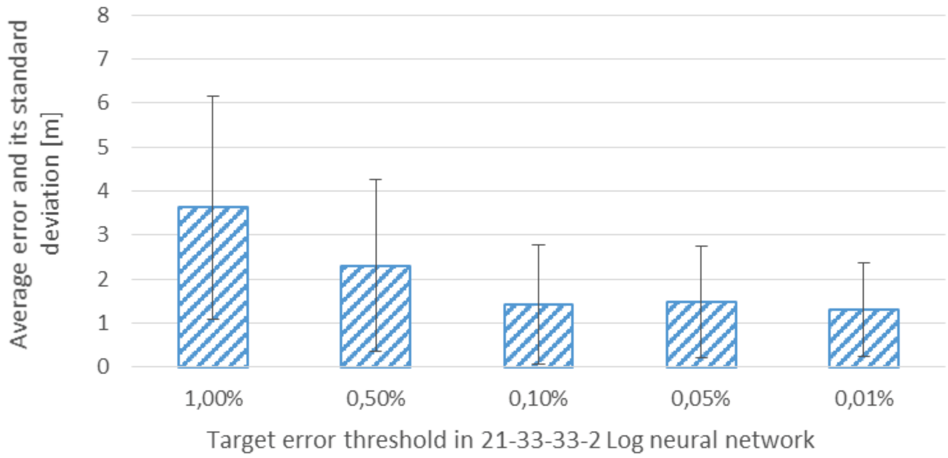

Figure 6. Comparison of the average error and its standard deviation of the fourth experiment.

DISCUSSION

Our experiments have shown, that there are too many variables, that influence the final accuracy. It is the shape and material of measured space, count, type and position of beacons within this space, the neural network itself with different number of hidden neurons and layers, different transfer functions, different threshold values for training phase and many others we have not even yet studied. According to our results we can say that logarithmic transfer function works the best, two hidden layers do not bring remarkable improvements, but on the other side, the signal stripping feature to five strongest signals can improve the results, e.g. by 34 %. Dataset reduction shows, that we can place beacons less dense by a factor of two. We believe, that the increase of beacon density at the beginnings and the ends of hallways would further lower the errors, since there is lower signal coverage.. The learning threshold can be reduced to 0.1% what can bring us even 60 % error reduction (from 3.63 m to 1.42 m).

The results in the Table 1 show that our approach has an acceptable localization precision compared to the other solutions. Exact comparison cannot be evaluated since different authors had different experiment setup and did not described it in their papers sufficiently – usually the shape and size of used area and the set-up of transmitters is missing.

Table 1. Comparison of our solution to other approaches.

Solution	Transmitter type	Number of transmitters	Algorithm	Samples per location	Average error
RADAR [5]	Wi-Fi	3	k-nearest neighbors	40	2.65 m
Rice University [12]	Wi-Fi	9	Bayesian inference localization	100	1.50 m
Kyung Hee University [9]	Wi-Fi	3	Classification neural network	300	0.13 m
Fusion [8]	Wi-Fi	unknown	Bayesian filtering	700	3.03 m
Fusion [8]	Wi-Fi + Bluetooth	unknown	Bayesian filtering	700	2.91 m
ASELSAN [11]	Bluetooth	6	RMSE	unknown	2.31 m
our attempt [10] (in 62 m^2 I-shaped area)	Bluetooth	9	Regression neural network	20	1.21 m
our best attempt (in 76 m^2 I-shaped area)	Bluetooth	12	Improved regression neural network	20	0.68 m
our best attempt (in 136 m^2 T-shaped area)	Bluetooth	21	Improved regression neural network	20	1.42 m

CONCLUSION

We approached the problem of indoor localization as a machine learning task and analysed the possibilities of using Bluetooth beacons. We performed basic signal measurements and compared it to the theoretical model. Then, we designed a localization method based on fingerprinting and an artificial neural network. As a part of our design methodology, we performed more experiments to determine suitable parameters for the solution of this problem – the logarithmic transfer function often works the best, two hidden layers do not bring remarkable improvements, signal stripping feature to five strongest signals improve the results, reduction to half increased the error only a slightly and the learning threshold of 0.1 % improve the results. We will continue with further research of this topic and try to achieve even more precise solution.

As the next step, we would like to group all the experiment's results and design a well-performing configuration of a neural network and try and apply the Kalman filter to its output – i.e., the estimated 2D position. According to Eliasson's paper on GPS position refinement using Kalman filter [4], we might expect significant improvement in position estimation in real-world scenarios. We would like to test this ability in a scenario where a real person moves with the device and the application saves the current estimated position in time. Then, we compare the real user's position with the estimated ones - raw output from the neural network, output smoothed out by moving average and finally by the Kalman filter.

Acknowledgement

This work was partially supported by the Scientific Grant Agency of Slovak Republic, grant No. VG 1/0752/14 and by Tatra Banka Foundation NTB 2015et009.

REFERENCES

[1] U. Ahmad, A. Gavrilov, U. Nasir, M. Iqbal, Seong Jin Cho and Sungyoung Lee, "In-building Localization using Neural Networks," *2006 IEEE International Conference on Engineering of Intelligent Systems*, Islamabad, 2006, pp. 1-6.

[2] P. Bahl and V. N. Padmanabhan, "RADAR: an in-building RF-based user location and tracking system," *INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, Tel Aviv, 2000, pp. 775-784 vol.2.

[3] K. Curran, E. Furey, T. Lunney, J. Santos, D. Woods and A. Mc Caughey, "An Evaluation of Indoor Location Determination Technologies," *Journal of Location Based Services*, Vol. 5, No. 2, pp. 61-78, June 2011.

[4] M. Eliasson. (spring 2014) "A Kalman filter approach to reduce position error for pedestrian applications in areas of bad GPS reception." [Online]. Available: http://www8.cs.umu.se/education/examina/Rapporter/MattiasEliasson.pdf

[5] J. Hightower and G. Borriello, "Location Systems for Ubiquitous Computing, " *Computer*, Vol. 34, No. 8, pp. 57-66, August 2001.

[6] B. Hofmann-Wellenhof, H. Lichtenegger and J. Collins. *Global positioning system: Theory and Practice, 5*th *rev. ed*. Springer-Verlag Wien, Austria, 2001.

[7] K. Kaemarungsi and P. Krishnamurthy, "Properties of indoor received signal strength for WLAN location fingerprinting," *Mobile and Ubiquitous Systems: Networking and Services, 2004. MOBIQUITOUS 2004. The First Annual International Conference on*, 2004, pp. 14-23.

[8] A. M. Ladd, K. E. Bekris, G. Marceau, A. Rudys, D. S. Wallach and L. E. Kavraki, "Using wireless Ethernet for localization," *Intelligent Robots and Systems, 2002. IEEE/RSJ International Conference on*, Lausanne, Switzerland, 2002, pp. 402-408 vol.1.

[9] A. LaMarca et al. "Place Lab: Device Positioning Using Radio Beacons in the Wild," *Pervasive Computing* (PERVASIVE'05) *Proceedings of the Third international conference on*, Springer-Verlag, Berlin, Heidelberg, Germany, 2005, pp. 116-133.

[10] F. Mazan and A. Kovarova, "A Study of Devising Neural Network Based Indoor Localization Using Beacons: First Results," *Computing and Information Systems Journal. University of the West of Scotland*. Vol. 19, No. 1, pp. 15-20. 2015.

[11] İ. Okşar, "A Bluetooth signal strength based indoor localization method," *IWSSIP 2014 Proceedings*, Dubrovnik, 2014, pp. 251-254.

[12] J. M. Samper, J. M. Lagunilla and R. B. Perez, "GPS and Galileo: Dual RF Front-end receiver and Design, Fabrication, & Test (Communication Engineering)," 1st ed. McGraw-Hill Education, 2009.

[13] R. Wang, F. Zhao, H. Luo, B. Lu and T. Lu, "Fusion of Wi-Fi and bluetooth for indoor localization," *Mobile location-based service* (MLBS '11) *Proceedings of the 1st international workshop on*. ACM, New York, NY, USA, 2011, pp. 63-66.

ABOUT THE AUTHORS

Ing. Filip Mazán, Dr. Alena Kovárová, Institute of Informatics, Information Systems and Software Engineering, Faculty of Informatics and Information Technologies, Slovak University of Technology in Bratislava, Slovakia, E-mails: filip.mazan@gmail.com, alena.kovarova@stuba.sk.