PASSIVE REAL-TIME LOCALIZATION THROUGH WIRELESS SENSOR NETWORKS

F. Viani, M. Martinelli, L. Ioriatti, M. Benedetti, and A. Massa

ELEDIA Group – Department of Information Engineering and Computer Science,
University of Trento, Via Sommarive 14, I-38123 Trento, Italy.

ABSTRACT

The rapid progress of wireless communication and embedded systems has made wireless sensor networks a valuable backbone for numerous applications, mainly with monitoring purposes. In this field, the need for location aware systems has growth rapidly in the last few years. Most research efforts have been done in node localization but less attention has been paid on the localization and tracking of passive (that do not belong to the network infrastructure) objects. In this paper, the problem of passive object localization is dealt with an innovative methodology based on support vector machine exploiting the received signal strength indicator measured by the nodes. Some preliminary results chosen from the assessment of the proposed approach are presented.

***Index Terms*—** Wireless sensor network, support vector machine, received signal strength indicator, target localization, tracking.

1. INTRODUCTION

Localization and tracking play a key role in several applications both civilian and military [1]. The growing needs of monitoring private and public areas has fostered a fast development of wireless and pervasive systems. In such a framework, the availability of low-power devices integrating on-board processing and wireless communication allowed the development of efficient collaborative signal processing algorithms for tracking purposes. Most of them are based on the exploitation of data collected by dedicated sensor or they assume that the target is equipped with a transmitting device [2]. Assuming an active target, different properties of the received signal, like the time of arrival (TOA) and the direction of arrival (DOA) could be exploited to solve the localization problem [3]. However, these kinds of solutions are strongly related to the synchronization among the nodes and to the hardware quality. Wireless sensor network (WSN) architectures are characterized by low-cost sensor nodes with limited computational resources and in case of severe multipath

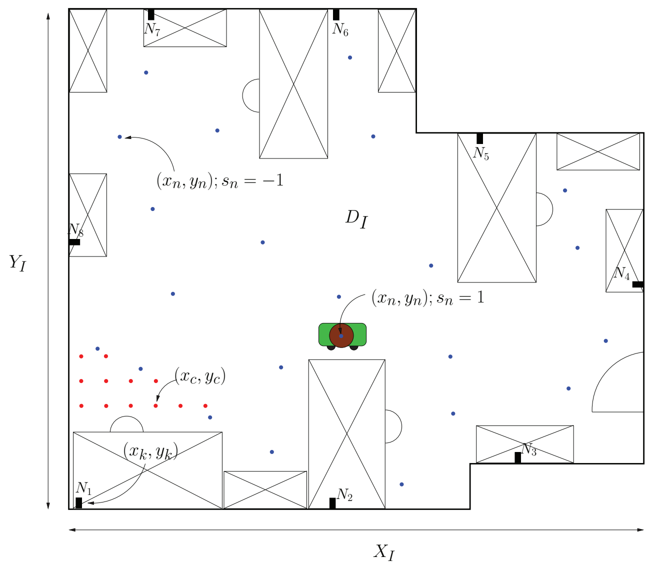

Fig. 1. Geometry of the localization problem.

propagation and shadow fading the DOA and TOA estimations become inaccurate, thus requiring complex signal processing technique for large errors correction.

Other modalities to locate active targets are based on the received signal strength (RSS) as a measure of distance between two nodes [4]. This easily measurable quantity has been exploited to localize a transmitting node that is linked with at least other three reference nodes. The distance between nodes is estimated through classic radio propagation models and the position is computed by means of some triangulation strategies.

In case of transceiver-free targets, state of the art approaches are based on Doppler radar as common microwave sensor to estimate the distance between the target and the sensor [5]. Moving target can be tracked exploiting the Doppler signature induced by the object motion [6]. Unfortunately, drawbacks like the high instability in real environments and the invisibility of slow-moving target [7] affect the measure provided by the radar. Even if widely employed, this methodology leads to a lot of false alarms.

In this work, an innovative approach based on a learning by

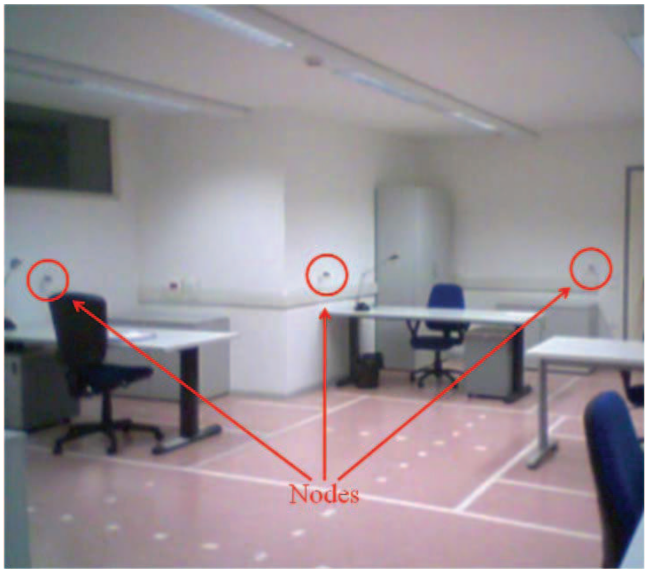

Fig. 2. Nodes deployment in real environment.

example (LBE) strategy to localize and track passive objects is presented. The localization problem is addressed only by considering the available received signal strength indicator (RSSI) at the nodes of a wireless sensor network deployed in the environment and without any additional on board sensor.

2. MATHEMATICAL FORMULATION

Without loss of generality, let us consider a WSN deployment in an indoor environment as shown in Fig. 1. Let the network be composed by K nodes. A set of unknown targets move throughout the two-dimensional investigation domain $D_I = \{0 \le x \le X_I, 0 \le y \le Y_I\}$. Each node N_k, located in a known position $(x_k, y_k); k = 1,\ldots,K$ both transmits and measures a signal at different time instants. Under the assumption that each node communicates with all the remaining $K-1$ nodes, a total amount of $Z = K \times (K-1)$ wireless links exists. The received signal strength indicator $RSSI_{(j)}^{(i)}$ of the z-th link, related to the transmitted power from the i-th $(i = 1,\ldots,K)$ node to the j-th $(j = 1,\ldots,K-1)$ receiving node, also depends on the interactions among the electromagnetic signal radiated by the i-th source, the scenario in D_I, and the targets to be localized. In order to quantify the impact of the scenario where the targets move, a reference measurement

$$\psi_{ij} = \left\{\left(RSSI_{(j)}^{(i)}\right)^{void}; i = 1,\ldots,K; j = 1,\ldots,K-1\right\} \quad (1)$$

without the targets is taken into account to filter out the environment contribution by the calculation of differential measurements

$$\Gamma_{ij} = \frac{\rho_{ij} - \psi_{ij}}{\psi_{ij}}; i = 1,\ldots,K; j = 1,\ldots,K-1 \quad (2)$$

where the term

$$\rho_{ij} = \left\{\left(RSSI_{(j)}^{(i)}\right)^{full}; i = 1,\ldots,K; j = 1,\ldots,K-1\right\} \quad (3)$$

refers to the real-time data collected by the sensor nodes in the presence of the moving target.

Starting from the differential measurements $\mathbf{\Gamma} = \left\{\Gamma_{ij}; i = 1,\ldots,K; j = 1,\ldots,K-1\right\}$, the problem at hand is recast as the definition of the probability that the targets are lied in a position inside D_I. Towards this end, a classification approach based on support vector machines (SVM) is applied [8]. By assuming the knowledge of a set of R training configurations

$$\Delta = \left\{\left[\mathbf{\Gamma}, (x_n, y_n)\right], s_n; n = 1,\ldots,N\right\}_r \; r = 1,\ldots,R \quad (4)$$

being (x_n, y_n) a randomly-chosen position whose status s_n is known ($s_n = 1$ if the target is present, $s_n = -1$ otherwise), a suitable decision function Φ is determined during a training phase by means of a SVM strategy [9]. In order to find the best decision function, the SVM model selection has been done to choose good hyperparameters so that the classifier can accurately predict unknown data during the test phase. Since the localization problem has been recast to a binary classification problem, the sign of the unthresholded output of the decision function gives the binary states $\mathbf{s} = sign\{\Phi(\mathbf{\Gamma})\}$, where $\mathbf{\Gamma}$ is whatever input data test and $\mathbf{s} = \{s_c; c = 1,\ldots,C\}$ the class indexes of the C test points lying in D_I. Instead of the sign of the decision function, let us consider the a-posteriori probability $\Pr\{\mathbf{s} = 1 \mid \mathbf{\Gamma}\}$ [10] to construct a location-probability map of the monitored area. The a-posteriori probability gives information about the degree of membership of test data to a particular class even if $sign\{\Phi(\mathbf{\Gamma})\}$ does not correctly classify the input pattern. This behavior is mainly due to the

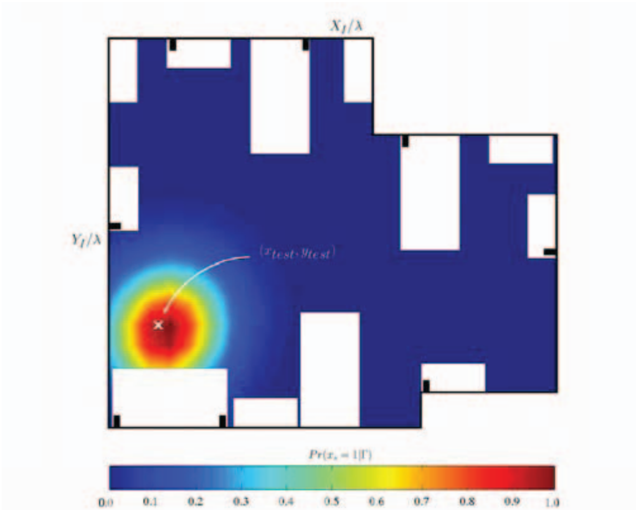

Fig. 3. Probability map of target presence.

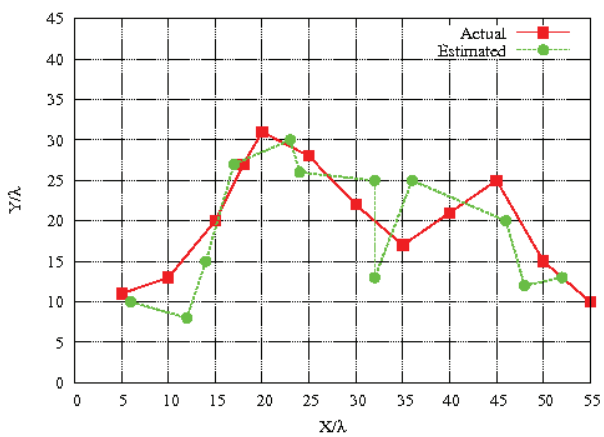

Fig. 4. Actual and estimated path of moving target.

generalization capabilities of the SVM approach that, in presence of highly non-separable data, constructs the best separating hyperplane even if the optimal solution to the optimization problem [9] does not exists. In this way, the input test data could belong to the wrong half-plane identified by the decision function, but taking into consideration the a-posteriori probability it is still possible to compute the distance of that example to each class means [11].

3. EXPERIMENTAL RESULTS

The feasibility and the effectiveness of the proposed approach have been assessed through a preliminary experimental validation carried out in an indoor environment. A set of $K = 8$ Corex nodes [12], indicated by the black rectangles in Fig. 1, has been installed as

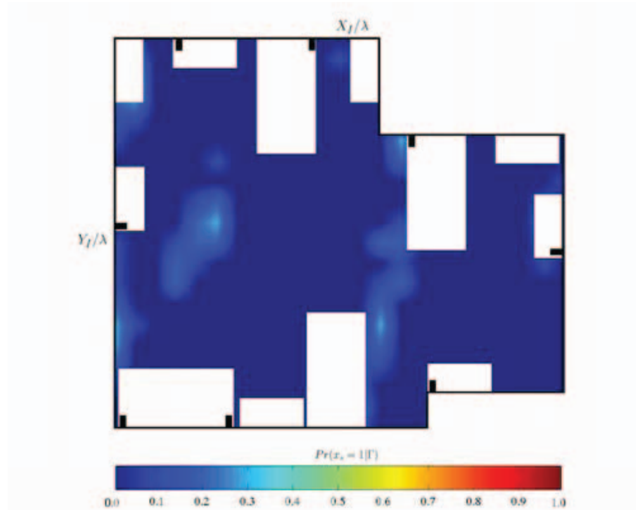

Fig. 5. Probability map retrieved when no objects are located in D_I.

shown in Fig. 2 on the walls of a office room with size $X_I = 55\lambda$ and $Y_I = 45\lambda$, λ being the wavelength at a working frequency $f = 2.4GHz$. The training set is composed by $R = 250$ randomly chosen samples and the test data are concerned with object positions not belonging to those of the training set. The reference measurements $\psi_{ij}, i = 1,...,K, j = 1,...,K-1$ have been performed without any target inside the room before starting the training acquisitions. For illustrative purposes, let us consider the case of a single target traveling in D_I from the position $x_{start} = 55\lambda$, $y_{start} = 10\lambda$ to $x_{stop} = 5\lambda$, $y_{stop} = 11\lambda$. Figure 4 shows the actual path and the estimated one. The estimated position of the target has been calculated starting from the evaluated probability map as follows

$$\tilde{x}_{\text{target}} = \frac{\sum_{c=1}^{C} x_c \Pr(s_c = 1|\mathbf{\Gamma})}{\sum_{c=1}^{C} \Pr(s_c = 1|\mathbf{\Gamma})} \quad (5)$$

$$\tilde{y}_{\text{target}} = \frac{\sum_{c=1}^{C} y_c \Pr(s_c = 1|\mathbf{\Gamma})}{\sum_{c=1}^{C} \Pr(s_c = 1|\mathbf{\Gamma})} \quad (6).$$

To quantify the localization accuracy, let us define the localization error

$$\varsigma = \sqrt{\left(x_{target} - \tilde{x}_{target}\right)^2 + \left(y_{target} - \tilde{y}_{target}\right)^2} \quad (7)$$

as the geometrical distance between the actual and the

$\min_s\{\varsigma_s\}$	$\max_s\{\varsigma_s\}$	$mean_s\{\varsigma_s\}$	$\text{var}_s\{\varsigma_s\}$
0.92λ	24.31λ	2.76λ	5.44λ

Tab. I. Statistical analysis of localization error.

estimated position. As a representative result, the probability map related to the last position (x_{stop}, y_{stop}) of the target is displayed in Fig. 3. As it can be observed, the moving target is quite carefully localized with a maximum value of the localization error ς of about some wavelengths. In order to further analyze the precision of the proposed approach, a set of $S = 50$ tests has been successively executed and a statistical analysis of $\varsigma_s; s = 1,...,S$ has been performed and reported in Tab. I. Beyond the information on the position and on the trajectory of the target inside the area, the knowledge of presence/absence of objects also plays a relevant role. The capability of the proposed method to identify the reference configuration (i.e. the absence of moving targets) has been verified by testing the algorithm with input pattern $\mathbf{\Gamma}$ when no objects are present. The obtained probability map is shown in Fig. 5. As it can be seen, only some low-probability clutters randomly distributed and without a significant distribution have been obtained, showing a good behavior of the methodology in detecting the presence of targets.

4. CONCLUSIONS

In this work, the localization of transceiver-free targets by means of a SVM-based strategy has been considered. The localization problem has been recast as a binary classification problem for determining an occupation probability map of the considered area. A suitable classifier has been trained exploiting the easily measurable RSSI parameter available on the nodes of a wireless sensor network. Differential quantities have been considered in order to filter out the environment contribution and to estimate in real-time the position of the object moving inside the monitored area. Some experimental results obtained in an indoor environment showed the effectiveness of the proposed approach in dealing with the tracking of a human being moving in an area of interest.

5. REFERENCES

[1] C.-Y. Chong and S. P. Kumar, "Sensor networks: evolution, opportunities, and challenges," *Proc. IEEE*, vol. 91, no. 8, pp. 1247–1256, Aug. 2003.

[2] G. Latsoudas and N. D. Sidiropoulos, "A fast and effective multidimensional scaling approach for node localization in wireless sensor networks," *IEEE Trans. Geosci. Remote Sens.*, vol. 55, no. 10, pp. 5121–5127, Oct. 2007.

[3] K. Pahlavan, X. Li, and J. Makela, "Indoor geolocation science and technology," *IEEE Commun. Mag.*, vol. 40, no. 2, pp. 112-118, Feb. 2002.

[4] X. Li, "Collaborative localization with received-signal strength in wireless sensor networks," *IEEE Trans. Veh. Technol.*, vol. 56, no. 6, pp. 3807-3817, Nov. 2007.

[5] W. Butler, "Design considerations for intrusion detection wide area surveillance radars for perimeters and borders," *IEEE Conf. Tech. Homeland Security*, pp. 47-50, May 2008.

[6] A. S. Bugaev, V. V. Chapurski, S. I. Ivashov, V. V. Razevig, A. P. Sheiko, I. A. Vasilyev, "Through wall sensing of human breathing and heart beating by monochromatic radar," *Proc. Tenth Int. Conf. on Ground Penetrating Radar*, vol. 1, pp. 291-294, Jun. 2004.

[7] P. Withington, H. Fluhler, and S. Nag, "Enhancing homeland security with advanced uwb sensors," *IEEE Microw. Mag.*, pp. 51-58, Sept. 2003.

[8] A. Massa, A. Boni, and M. Donelli, "A classification approach based on SVM for electromagnetic subsurface sensing," *IEEE Trans. Geosci. Remote Sens.*, vol. 43, no. 9, pp. 2084-2093, Sept. 2005.

[9] V. Vapnik, *Statistical Learning Theory*. New York: Wiley, 1998.

[10] J. Platt, "Probabilistic outputs for support vector machines and comparison to regularized likelihood methods," in "Advances in large margin Classifiers", (MIT Press, Cambridge, MA, 1999), Eds. A. J. Smola, P. Bartlett, B. Scholkopf, and D. Schuurmans.

[11] B. Scholkopf and A. J. Smola, *Learning with kernels*. MIT Press. Cambridge, MA. 2002.

[12] ArsLogica Corex Datasheet. http://www.arslogica.it/projects/vigilia/vigilia.html.