Real-time Tracking of Transceiver-free Objects for Homeland Security

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***Abstract*— The increasing demand in homeland security speeds up the development of innovative and non-invasive systems to localize and track moving objects in complex environments. In this paper the real-time localization of transceiver-free targets is addressed by means of learning by example methodology that exploits the received signal strength indicator available at the nodes of a wireless sensor network as input data. This approach uses neither dedicated sensors nor active devices put on the target to localize both idle and moving objects. The definition of a customized classifier during an offline training procedure enables the real-time generation of a probability map of presence by processing the output of the support vector machine. Some selected experimental results validate the effectiveness of the proposed methodology applied in real scenarios.**

I. INTRODUCTION

Accurate localization and tracking is an essential part of many kind of applications based on the real-time determination of moving object position. General location discovery problem has recently attracted interest in civilian and military surveillance thanks to the growing advances in low-power, low-cost and highly integrated sensors. In certain civilian applications, human beings walking through a building, as schools or hospitals, can be located exactly at all times. In the framework of communication systems, wireless sensor networks (WSNs) appear as an ideal infrastructure for localization purposes providing clear interaction with the physical world. Sensors exploit the benefits of sensor data fusion by collaborating and sharing information. Tracking in WSN poses different challenges due to communication, processing and energy constraints.

Nowadays, most of the proposed approaches deal with the localization of targets that wear an active transmitting and receiving device [1-3]. Starting from this assumption, the mobile target could be localized exploiting different parameters of its transmitted signal such as the direction of arrival (DOA) or the time of arrival (TOA) [4]. Unfortunately, the indoor radio channel suffers from severe multipath propagation and shadow fading causing less accurate measurements. Moreover, in indoor areas, due to different kind of obstructions, dramatically large errors occur in the estimation of such parameters. To overcome these drawbacks, complex signal processing techniques have to be implemented although the limited resources available on the integrated and portable systems.

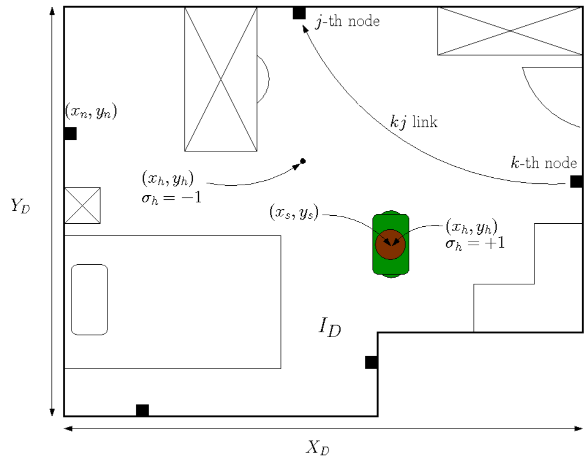


Fig. 1 Schematic geometry of a realistic indoor environment with WSN infrastructure for target localization.

Other location-sensing modalities based on received signal strength (RSS) have been studied to localize active targets exploiting the easily measurable RSS [5]. In such approaches, the localization problem is based on the known location coordinates of some reference nodes and on the RSS measurements among the other network elements. These measurements are related to the distance between the transmitting nodes through classic radio propagation pathloss models and, according to triangulation strategies, the localization of the active target is possible if it is connected to at least three reference nodes.

Alternative approaches are focused on the localization of unknown targets taking up the monitored area without any transmitting device. Conventionally, applications like perimeter monitoring for homeland security adopt Doppler radar as common microwave sensor to detect the distance and the velocity of the object [6]. Since the objective of life recognition for homeland security is the identification of human presence and the differentiation among the human activities, it could be intuitive the use of the Doppler signature induced by human motion [7]. This technology, although widely employed, leads to a lot of false alarm and requires clear environment for reliable operation. Moreover, slow-moving targets become invisible since the Doppler shift depends on the target motion [8].

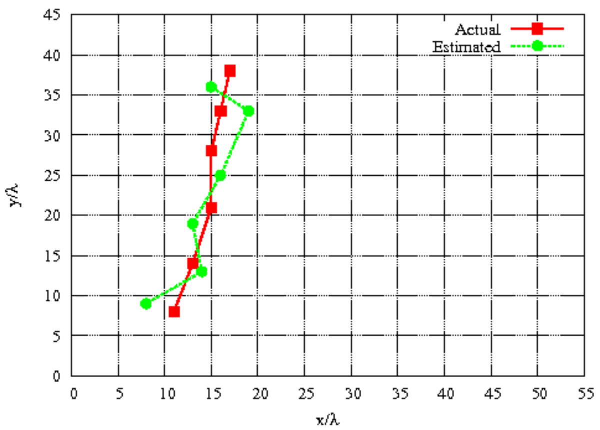


Fig. 2 Actual and estimated path of the moving target.

In this work, the localization problem is addressed by considering only the RSS provided by the nodes of a WSN, as in [9]. Unlike state-of-the-art approaches, the tracking procedure needs only the quality link information easily provided by the nodes of the WSN, without the need of additional sensors. As a matter of fact, the target moving inside the investigation domain interacts with the electromagnetic signals transmitted by the wireless devices, thus modifying the values of the measured quality indexes. Such a localization problem can be reformulated in terms of a simplified electromagnetic inverse scattering problem and solved in real-time by means of a learning-by-example (LBE) strategy [10]. A standard Support Vector Machine (SVM) classifier constructs a rule for discriminating between classes and just selecting the class with the most winning two-class decision [11]. However, in such an application the output binary classification map could provide a raw estimation of the object position since the reconstructed information is thresholded just considering the sign of the decision function. To overcome this drawback, the proposed procedure gives as output the probability that the target was located in a precise position inside the considered area. This posterior probability, when evaluated overall the investigation domain, produces a map of presence probability of the whole monitored area.

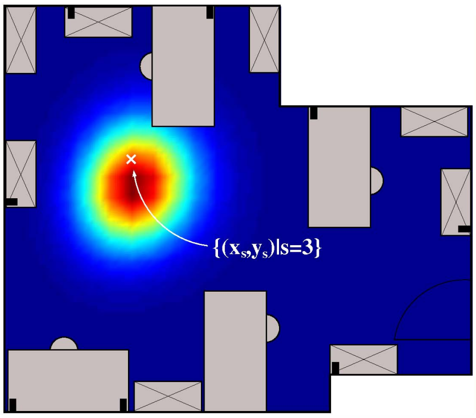
II. Mathematical Formulation

Let us assume that a two-dimensional indoor space I_D is monitored by a WSN infrastructure of N reference nodes. $I_D = \{0 \le x \le X_D; 0 \le y \le Y_D\}$ is a realistic homeland environment of whatever shape, where heterogeneous objects can be found in, as shown in Fig. 1. For the sake of reality, the nodes are installed on the walls of the room, that is the perimeter of I_D, in order to minimize the negative impact of the network. More in detail, each sensor node is located at known position $(x_n, y_n), n = 1,\dots,N$ and can take measurements at a sequence of time instants $\{t_j^{(n)}; j = 0,\dots,J-1; n = 1,\dots,N\}$, J being the maximum number of time samples needed to collect all the link quality indexes avoiding data loss due to transmission errors. The nodes are all connected via a multi-hop network strategy with the advantage that each one only has to be within the range of at least one other node to guarantee the transmission of the data also in case of temporary malfunctioning of some network elements. Assuming that each node can transmit and receive data with all the others, the maximum number of $M = N \times (N-1)$ wireless links exists in the network. The quality of each link can be quantified by the Received Signal Strength Indicator ($RSSI$) as an easily measurable parameter. Every time the k-th, $k = 1,\dots,N$, node receives the signal from another l-th, $l = 1,\dots,N-1$, node the quality index $RSSI_k^l\left(t_j^{(k)}\right)$ is available at the $t_j^{(k)}$ time instant, at the k-th node. The value of the signal strength depends, first of all, from the distance between transmitter and receiver, but it is also strictly related to the presence of obstacles the signal runs into. The consequent generation of the basic propagation effects like reflection, diffraction and scattering is responsible for the unknown perturbation of the signal strength. Moreover, the raw collected data are affected by fluctuations that could be attributed to different kind of fading as well as hardware instability. These multiple effects can be quickly removed by pre-processing the raw data with ad-hoc filtering techniques as the histogramic analysis proposed in [12]. The output of the filtering procedure can be seen as a stabilized value $\overline{RSSI}_k^l = \Omega\left(RSSI_k^l\left(t_j^{(k)}\right)\right)$ obtained after J time samples. Among the physical factors influencing the signal strength, the presence and the position (x_s, y_s) of the moving target object play a significant role, where $s = 1,..,S$ are the indexes of the timestamps when the changing object position is considered. This contribution is the quantity that carries the unknown relation with the target position and can be almost isolated by subtracting the environment footprint from the raw signal through differential measurements

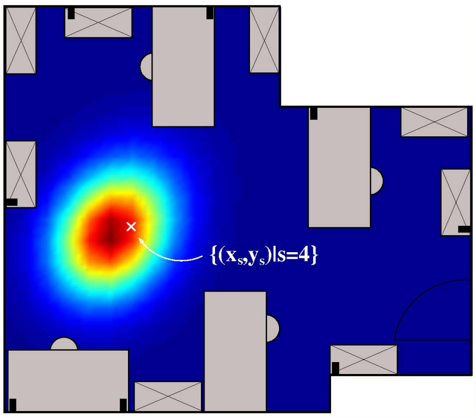
$$\Delta_{(k;l)} = \frac{\phi_{(k;l)} - \varphi_{(k;l)}}{\varphi_{(k;l)}}; k = 1,\dots,N; l = 1,\dots,N-1$$

$\phi_{(k;l)}$ and $\varphi_{(k;l)}$ being the $\overline{RSSI}_k^l$ measurements in presence and absence of the moving target, respectively.

Starting from the quantities $\Delta_{(k;l)}$, the problem of tracking the moving target inside I_D is reformulated as the definition of a location-probability map of the observation domain. Such a probability is derived from the unthresholded output of an ad-hoc SVM classifier $f(\omega)$ [13], where $\omega = \{\Delta_k^l, (x_t, y_t); t = 1,\dots,T\}$ is the input test data vector, T being the number of the test points (x_t, y_t) of I_D where the probability is evaluated.



(a)



(b)

Fig. 3 Probability maps of presence of moving object inside homeland environment at (a) s=3 and (b) s=4 time sample.

Test data are classified by the learning machine that constructs, only once and offline, the decision function $f(\bullet)$ on the base of the input-output vector pairs $(\mathbf{m}_r, \mathbf{n}_r), r = 1,\ldots,R$, representing the so-called training data set Ψ,

$\mathbf{m}_r = \{\Delta^l_k, (x_h, y_h); h = 1,\ldots,H\}_{(r)}$ and

$\mathbf{n}_r = \{\sigma_h; h = 1,\ldots,H\}_{(r)}; r = 1,\ldots,R$

being the input vector and the output vector, respectively. Every input-output pair carries the unknown relation between the measured data $\Delta_{(k;l)}$ and the corresponding class σ_h to which the position (x_h, y_h) belongs. Since the localization problem has been recast as a binary classification problem, the class index $\sigma_h \in \{-1,+1\}$. More in detail, $\sigma_h = +1$ if the h-th point of I_D corresponds to the position of the target object, $\sigma_h = -1$ otherwise, as shown in Fig. 1.

s	$x_s[\lambda]$	$y_s[\lambda]$	$\varepsilon_s[\lambda]$
1	17	38	2.8
2	16	33	3.0
3	15	28	3.2
4	15	21	2.8
5	13	14	1.4
6	11	8	3.1

Tab. I Localization errors of all the considered time instants.

III. Experimental Results

The effectiveness of the proposed methodology has been assessed by carrying out a set of preliminary experimental results.

The localization strategy has been applied to a realistic noisy environment monitored by a WSN infrastructure composed by $N = 8$ sensor nodes installed on the walls of the room. The size of the considered area has dimensions $X_D = 55\lambda$, $Y_D = 45\lambda$, where λ is the wavelength of the working frequency $f = 2.4GHz$. As shown in the maps of Fig. 3, some heterogeneous obstacles, like desks and closets, are present and they obscure the line of sight of many wireless links. In the optimal condition when each node communicates with all the others, a total of $M = 56$ wireless links exists. Even if some transmitted packets are corrupted because of transmission errors or collisions, the selected value $J = 10$ of subsequent time instants of RSSI measurements guarantees that all the links were acquired and the proper generation of the input vector ω.

The training set Ψ is composed by $R = 250$ samples, each one has been generated with a different randomly-chosen and uniformly distributed position of the target object inside I_D. Every training position is composed by $H = 100$ samples, still randomly-chosen, whose states are set according to the binary rule previously defined. More in detail, if the training data refers to a single object detection, $H-1$ class states are $\sigma_h = -1; h = 1,\ldots,H-1$.

The selected representative results deal with the tracking of a single human being moving inside the monitored area. Fig. 2 shows the actual path in comparison with the estimated positions obtained at $S = 6$ subsequent time instants. For each acquisition the probability map of presence is generated and in Fig. 3 two representative results obtained at $s = 3$ and $s = 4$ are shown. As can be seen, the proposed methodology detects the presence of the human being and the actual position, depicted by the white cross, is correctly estimated.

Localization errors $\varepsilon_s = \sqrt{\left(x_s - \overline{x_s}\right) + \left(y_s - \overline{y_s}\right)}$, where $\left(\overline{x_s}, \overline{y_s}\right)$ is the estimated position with higher probability, of all the timestamps are reported in Tab. I.

IV. CONCLUSIONS

In this work, the problem of localizing and tracking transceiver-free moving objects in WSN infrastructured environments has been dealt with. The applicability of such methodology to indoor scenarios makes it very attractive to the field of homeland security. The proposed strategy exploits the easily available signal strength measured by the nodes of the WSN in conjunction with a learning-by-example methodology based on SVM in order to obtain real-time probability maps of target presence inside the investigation domain. Some experimental results related to the tracking of a single moving human being inside a realistic indoor environment have been shown.

REFERENCES

[1] G. Latsoudas and N. D. Sidiropoulos, "A fast and effective multidimensional scaling approach for node localization in wireless sensor networks," IEEE Trans. on Signal Processing, vol. 55, no. 10, pp. 5121-5127, Oct. 2007.

[2] K. Yedavalli and B. Krishnamachari, "Sequence-based localization in wireless sensor networks," *IEEE Trans. Mobile Comput.*, vol. 7, no. 1, pp. 81-94, Jan. 2008.

[3] P. Biswas, T. Liang, K. Toh, Y. Ye, and T. Wang, "Semidefinite programming approaches for sensor network localization with noisy distance measurements," *IEEE Trans. Autom. Sci. Eng.*, vol. 3, no. 4, pp. 360-371, Oct. 2006.

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

[5] 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.

[6] 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.

[7] 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.

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

[9] F. Viani, L. Lizzi, P. Rocca, M. Benedetti, M. Donelli, and A. Massa, "Object Tracking through RSSI Measurements in Wireless Sensor Networks," *Electronic Letters*, vol. 44, no. 10, pp. 653-654, May 2008

[10] 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, Sept. 2005.

[11] T. Wu and R. C. Weng, "Probability estimates for multi-class classification by pairwise coupling," *Journal of Machine Learning Research 5*, pp. 975-1005, Oct. 2004.

[12] F. Cabrera-Mora and J. Xiao, "Preprocessing technique to signal strength data of wireless sensor network for real-time distance estimation," *IEEE Int. Conf. on Robotics and Automation*, Pasadena, CA USA, May 19-23, 2008.

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