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**Real-time Indoor Localization and Tracking of Passive Targets by means of Wireless Sensor Networks**

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## Introduction

Recently, the growing need of monitoring private or public areas for security purposes in civilian and military applications is driving the research community to design non-invasive systems based on tiny sensing devices [1]. The tracking of a vehicle in a restricted area, the detection of animals in a dynamic environment, or the analysis of people behavior from movements are few examples of applications where the employment of systems for the localization and tracking of targets is mandatory. In the framework of wireless communications and technologies, the development of low-power and low-cost devices, such as Wireless Sensor Networks (WSN) [2], integrating on-board processing and radio interface has favored the development of efficient cooperative signal processing algorithm for tracking purposes. Most of these systems are based on the processing of data acquired by dedicated sensor, or they assume to localize an active target, namely provided with some transmitting devices [3]. Unfortunately, in many applications the targets can not be equipped with wireless modules and the use of a complex system based on specific sensors is often not affordable.

In this work, the localization problem is addressed by considering only the information provided by the quality indexes of the wireless links between the nodes of the WSN as in [4]. Consequently, unlike state-of-the-art approaches, the infrastructure needed by the tracking procedure is limited to the nodes of the WSN, without the need of additional sensors. As a matter of fact, the target moving inside the scenario under test interacts with the electromagnetic signals transmitted by the wireless devices, thus modifying the values of the quality indexes measured at each node of the network. By reformulating such a problem in terms of a simplified electromagnetic inverse scattering problem, the localization and tracking of a passive target is carried out by means of a learning-by-example (LBE) strategy [5]. With respect to [4], the novelty of this paper lies in the application of the proposed approach to realistic indoor scenarios and in the use of differential measurements in order to remove the background contribution.

## Mathematical Formulation

Let us consider a WSN infrastructure composed by $K$ nodes arranged in a realistic environment. An unknown target is moving inside such a non-homogeneous region, called investigation domain $D_I = \{0 \le x \le X_I, 0 \le y \le Y_I\}$. Each node $N_k$, $k = 1,...,K$, lies in the known position $(x_k, y_k)$ and can behave as a transmitting and receiving device at different time instants. Under the assumption that each node is able to communicate with all the remaining $K-1$ nodes, a total amount of $Z = K(K-1)$ wireless links can be defined. In order to define a quality index of the z-th wireless link, let us define the quantity $RSSI_{(j)}^{(i)}$ as the received signal strength indicator evaluated by the *j*-th, $j = 1,...,K-1$, node when only the *i*-th, $i = 1,...,K$, node is transmitting. Such a quantity depends on the interactions between the transmitted signals and the objects located in $D_I$, as well as on the presence and the position of the target to be localized.
In order to evaluate the footprint of the reference scenario, the set of quality indexes $\psi_{ij} = \left\{\left(RSSI_{(j)}^{(i)}\right)^{void}; i = 1,...,K; j = 1,...,K-1\right\}$ is measured in absence of the target. Then, starting from the differential measurements

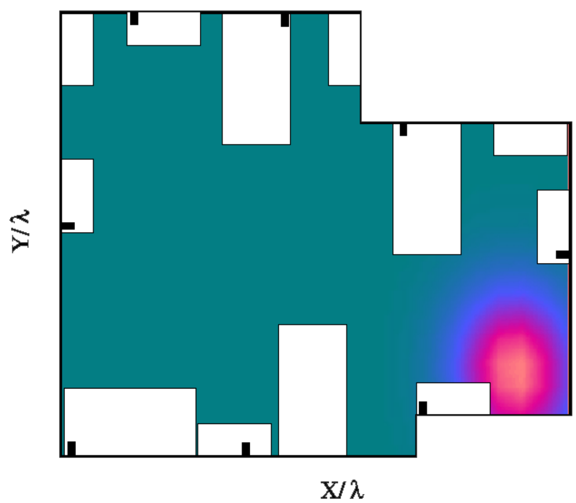
$$\Gamma_{ij} = \left\{\frac{\rho_{ij} - \psi_{ij}}{\psi_{ij}}; i = 1,...,K; j = 1,...,K-1\right\} \tag{1}$$

$\rho_{ij} = \left\{\left(RSSI_{(j)}^{(i)}\right)^{full}; i = 1,...,K; j = 1,...,K-1\right\}$ being measured in presence of the moving target, the problem of determining at each time instant the position of the target inside $D_I$ is recast as a classification problem solved by means of a procedure based on a Support Vector Machine (SVM) [5]-[7].
In order to define suitable decision function $\Phi$, the SVM classifier starts from a set of *R* known training configurations $\Delta = \left\{\left[\boldsymbol{\Gamma}, (x_n, y_n)\right], s_n; n = 1,...,N\right\}_r$, $r = 1,...,R$, being $(x_n, y_n)$ a randomly-chosen position where the respective state $s_n$ ($s_n = 1$ if the position coincides with the barycenter of the object, $s_n = -1$ otherwise) is defined. Then, the SVM classifier labels whatever input data $\boldsymbol{\Gamma}$ by evaluating the a posteriori probability $\Pr\{\mathbf{s} = 1 \mid \boldsymbol{\Gamma}\}$ [5], being $\mathbf{s} = \{s_c; c = 1,...,C\}$ and $C$ the number of the test points (typically the barycenters of a uniform two-dimensional lattice).

## Numerical Validation

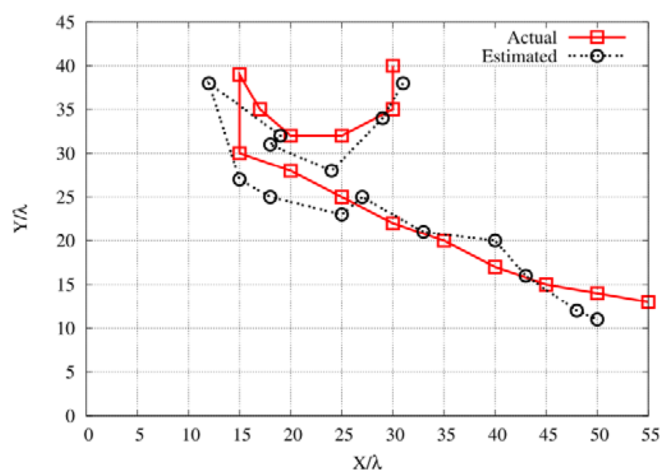
The effectiveness and the reliability of the proposed approach have been assessed by carrying out a preliminary experimental validation. As shown in Fig.

1, a set of $K = 8$ WSN nodes, represented by the black rectangles, have been deployed on desktops, depicted by the white rectangles, inside a realistic indoor environment of size $X_I = 55\lambda$ and $Y_I = 45\lambda$, $\lambda$ being the wavelength at the frequency $f = 2.4GHz$. The training set is composed by $R = 250$ samples and the test data are collected with object positions not belonging to the training set. The considered test case refers to a single target that moves inside $D_I$ from the position ($x_{start} = 55\lambda$, $y_{start} = 13\lambda$) to ($x_{stop} = 30\lambda$, $y_{stop} = 40\lambda$). The probability map related to the initial target position is reported in Fig. 1, while Figure 2 shows the comparison between real and estimated paths of the target. The latter can be estimated by evaluating at each time step the peaks of the probability map.




(*a*)

**Figure 1** – Probability risk-map of the initial target position.




(*b*)

**Figure 2** – Real and estimated path of the target.

## Conclusions

In this paper, an innovative approach for the localization and tracking of a passive target in an indoor non-infrastructured environment has been presented. The proposed strategy is based on a LBE approach in order to define at each time step a map of risk of the presence of the target. Unlike other state-of-the-art methods, the proposed strategy does not require neither the use of specific sensors nor the equipment of radio devices for the object to be tracked, since only the interactions between the target and the wireless links are exploited. The numerical validation performed in a realistic noisy environment has pointed out the effectiveness and reliability of the proposed tracking methodology.

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