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-38050 Trento, Italy.
E-mail: andrea.massa@disi.unitn.it, Web-page: http://www.eledia.ing.unitn.it

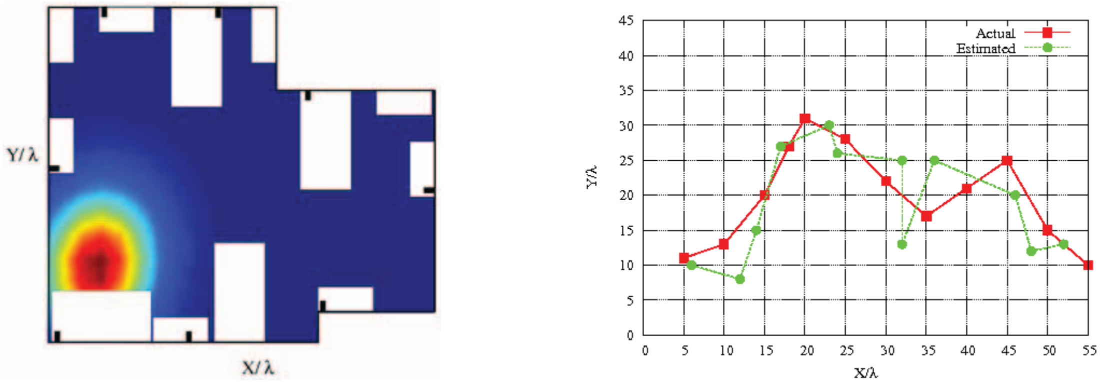
1. INTRODUCTION

Localization and tracking play a key role in several applications both civilian and military [1]. The growing needs of remote monitoring private and public areas caused 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 stimulated several studies in 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 the target equipped with a transmitting device [2]. In this work, an innovative approach based on a 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 (WSN) deployed in the environment and without any additional on board sensor.

2. PROBLEM FORMULATION

Without loss of generality, let us consider a WSN deployment in an indoor environment as shown in Fig. 1*(a)*. 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 $(x_k, y_k); k = 1,...,K$ 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 $(i = 1,...,K)$ node to the j-th $(j = 1,...,K-1)$ 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 $\psi_{ij} = \left\{\left(RSSI_{(j)}^{(i)}\right)^{void}; i = 1,...,K; j = 1,...,K-1\right\}$ without the targets is taken into account to filter out the environment contribution and acquire differential measurements $\Gamma_{ij} = \frac{\rho_{ij} - \psi_{ij}}{\psi_{ij}}; i = 1,...,K; j = 1,...,K-1$ where the term $\rho_{ij} = \left\{\left(RSSI_{(j)}^{(i)}\right)^{full}; i = 1,...,K; j = 1,...,K-1\right\}$ refers to the real-time data collected by the sensor nodes in the presence of the moving target.

Starting from the differential measures $\mathbf{\Gamma} = \{\Gamma_{ij}; i = 1,...,K; j = 1,...,K-1\}$, 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 a SVM-based procedure [3] is applied. By assuming the knowledge of a set of R training configurations $\Delta = \{[\mathbf{\Gamma}, (x_n, y_n)], s_n; n = 1,...,N\}_r$ $r = 1,...,R$, being (x_n, y_n) a randomly-chosen position whose status



(a) (b)

Figure 1 – Probability risk-map of the final object position in the indoor environment (a) and real/estimated paths (b).

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 [4]. Afterwards, the SVM classifier labels whatever input data test $\mathbf{\Gamma}$ by evaluating the a posteriori probability $\Pr\{\mathbf{s} = 1 \mid \mathbf{\Gamma}\}$ [5], where $\mathbf{s} = \{s_c; c = 1,...,C\}$, C being the number of the test points lying in D_I.

3. EXPERIMENTAL RESULTS

The feasibility and the effectiveness of the proposed approach have been assessed through a preliminary experimental validation. A set of $K = 8$ Corex nodes [6], indicated by the black rectangles in Fig. 1*(a)*, have been deployed in a realistic indoor environment of dimension $X_I = 55\lambda$ and $Y_I = 45\lambda$, λ being the wavelength at $f = 2.4GHz$. It is a standard office room, where some desks and closets are present. The training set is composed by $R = 250$ samples and the test data are concerned with object positions not belonging to those of the training set. 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 1*(b)* shows the actual path and the estimated one. For completeness, the probability map related to the last position of the target is displayed in Fig. 1*(a)*. As it can be observed, the moving target is quite carefully tracked with a maximum value of the localization error of about some wavelengths.

4. REFERENCES

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