Object tracking through RSSI measurements in wireless sensor networks

F. Viani, L. Lizzi, P. Rocca, M. Benedetti, M. Donelli and A. Massa

The localisation of moving and transceiver-free objects is addressed by processing the Received Signal Strength Indicator (RSSI) available at the nodes of a wireless sensor network. Starting from the RSSI measurements, the probability of the presence of unknown mobile objects is determined by means of a customised classification approach based on a support vector machine. Experimental results assess the feasibility of the proposed approach.

Introduction: The need to deal with real-time localisation in innovative civilian and military applications [1] has led to growing interest in suitable signal processing techniques and wireless communication systems. Low-cost and pervasive systems like wireless sensor networks (WSNs) are mostly used for monitoring, but they constitute an ideal infrastructure to be profitably exploited for localisation purposes, as well. Until now, some solutions have been proposed for node localisation [2, 3], but, to the best of our knowledge, few research efforts have been devoted to localise an unknown object not belonging to the wireless network infrastructure (i.e. not equipped with a transceiver). In such a situation, neither signal processing techniques (e.g. methods based on time of arrival (ToA) or on direction of arrival (DoA)) nor radio-frequency (RF) methods based on classical radio propagation pathloss models [4, 5] can be used.

In this Letter, the problem of tracking moving transceiver-free objects is addressed by integrating the Received Signal Strength Indicator (RSSI) measurements available at the nodes of the WSN architecture with a learning-by-examples (LBE) technique. Starting from the RSSI data collected at the WSN nodes, which are spatially distributed in the observation area (i.e. where the objects are moving), the proposed approach is aimed at defining a real-time map of the locations of the objects. The support vector machine (SVM) classifier is trained once and offline to exploit the relationship between the unknowns (i.e. the objects' positions at each time instant) and the data (the signals received by the nodes and quantified by the RSSI values) for a successive and real-time prediction (test phase). No other a priori information on the scenario is necessary to perform the data fitting process (training phase). A selected set of experimental results is proposed to validate the RSSI-based formulation and to point out the potentialities of the approach.

RSSI-based classification approach: With reference to the two-dimensional scenario shown in Fig. 1, let us consider a WSN composed by a set of N sensor nodes located at known positions (x_n, y_n); $n = 1, \ldots, N$. Moreover, let us assume that a set of unknown objects move in the investigation domain $I_D = \{-X_D/2 \le x \le X_D/2, -Y_D/2 \le y \le Y_D/2\}$ to which the sensor nodes belong. At the mth node, the indicator $\mathrm{RSSI}_{(n)}^{(m)}$ proportional to the signal transmitted by the nth node is available. Such a quantity depends on the power radiated by the transmitting node, the distance between the two nodes, and the presence/absence-locations of the unknown objects inside I_D. As a consequence, it contains some information on the scenario useful to determine the locations of the moving objects at each time-instant. However, since the relationship between $\mathrm{RSS}_{(n)}^{(m)}$ and the objects' positions is not trivial because of the complex scattering interactions, it is determined in an implicit form through an LBE technique. Towards this end, the domain I_D is partitioned in a two-dimensional lattice of C square cells centred at (x_c, y_c), $c = 1, \ldots, C$ and the localisation problem is recast as the definition of the probability of the presence of an object in each cell starting from the knowledge of the RSSI values of the whole set of $N \times (N-1)$ node links, $\Lambda = \{\mathrm{RSSI}_{(n)}^{(m)};\ \mathrm{m} = 1, \ldots, \mathrm{N};\ \mathrm{n} = 1, \ldots, \mathrm{N}-1\}$. Mathematically, the problem solution is the computation at each time-instant (test phase) of the a posteriori probability distribution

$$\Pr\{\delta_c = 1 | (\Lambda, c)\} = \frac{1}{1 + \exp\{\gamma\hat{\Phi}(\varphi(\Lambda, \mathrm{c})) + \theta\}}, \quad \mathrm{c} = 1, \ldots, \mathrm{C} \quad (1)$$

δ_c being the state of the cth cell ($\delta_c = 1$ if an object lies into the cell, $\delta_c = -1$ otherwise), in correspondence with the current set of RSSI measurements, Λ. Towards this end, θ and γ are determined according to the Platt method [6] once the decision function $\hat{\Phi}$ has been estimated during the off-line training phase. More in detail, starting from the knowledge of a training set consisting of S known examples $\{(\Lambda, \delta_c;\ \mathrm{c} = 1, \ldots, \mathrm{C})^{(s)};\ \mathrm{s} = 1, \ldots, \mathrm{S}\}$, Φ is determined by means of an SVM classifier as the linear discriminant function (or hyperplane in the so-called 'feature space') that maximises the separating margin between the classes $\delta_c = 1$ and $\delta_c = -1$.

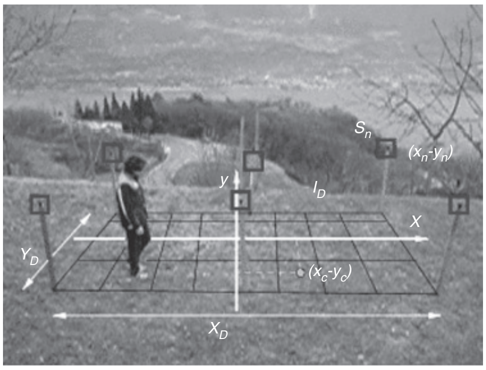

Fig. 1 *Problem geometry*

Experimental validation: The experimental assessment deals with an investigation area characterised by $X_D = 40\lambda$ and $Y_D = 24\lambda$ (λ being the free-space wavelength at $f = 2.4$ GHz). $N = 6$ Tmote Sky WSN nodes have been distributed along the perimeter of I_D (Fig. 1) and a training set of $S = 500$ different and randomly-chosen examples has been considered. With regards to the probability map, the area under test has been partitioned into $C = 60$ equal cells.

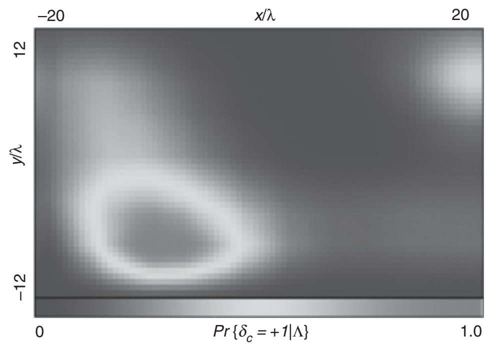

Fig. 2 *Probability map estimated when actual target located at* ($x_c = -11\lambda$, $y_c = -10\lambda$)

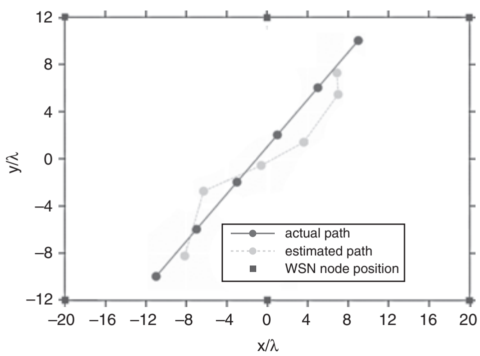

Fig. 3 *Moving target tracking*

The representative test case is concerned with a human being moving inside I_D as shown in Fig. 1. Its starting position has co-ordinates $x_c = -11\lambda$, $y_c = -10\lambda$ and its walk is described through the straight trajectory in Fig. 3. As an illustrative example, Fig. 2 shows the probability map estimated at the initial time-instant. As can be observed, the unknown target is correctly located and its actual position is carefully estimated since the object co-ordinates lie in the region with maximum value of probability. Concerning the real-time processing,

Fig. 3 gives an indication of the efficiency of the method in tracking the moving target by comparing the actual path and the estimated one.

Conclusions: A classification approach based on RSSI measurements for the real-time localisation of transceiver-free objects moving in a WSN area is presented. The feasibility and effectiveness of the proposed approach have been assessed by considering experimental test cases.

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