Accurate Indoor Localization with UWB Wireless Sensor Networks

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***Abstract*—Wireless Sensor Networks (WSNs) consist of a collection of spatially distributed radio transceivers with attached sensors that can measure and gather information from the environment. In this paper, we focus on the application of WSNs to indoor localization and, for this purpose, we propose the use of a Ultra Wide Band (UWB) WSN. The use of UWB signals guarantees robust performance in dense multipath environments, making them an attractive choice for indoor localization. In this paper, we discuss on different localization strategies: first classic geometric approaches are considered; then the mathematical framework is re-interpreted as an optimization problem. In the latter context, we propose the use of Particle Swarm Optimization (PSO) in particular, which can overcome limitations of classic (geometric) approaches.**

***Keywords*-Wireless Sensor Newtorks (WSNs); Indoor Localization; Ultra Wide Band (UWB).**

I. Introduction

Cyber-Physical Systems (CPS) represent a new generation of systems in which computational capabilties are integrated with physical processes. The ability to interact with the physical world through computation is a key characteristic for future technology developments and will allow espanding the capabilites of communication and control systems [1]. Wireless Sensor Networks (WSNs) allow collecting physical parameters and process them through cyber resources. In recent years, technological advances have made the production of smart sensors cheaper.

Thanks to the availability of small, cheap, and intelligent sensors, the attention of the scientific community towards WSNs is increasing, since they represent a leading choice to address some of the current challenges, such as smart environments and Internet of Things (IoT). A variety of mechanical, thermal, biological, chemical, optical, and magnetic properties of the environment can be measured. This leads to a large number of applications, including: assisted living; security area surveillance; biomedical monitoring; traffic control and safety; search and of victims in emergency situations; environmental monitoring; smart homes; localization and tracking of people, vechicles, goods [2].

Among all the above interesting and challenging topics, wireless indoor localization plays a key role, as it has an impact on many applications. As a matter of fact, most innovative application require accurate location or real-time tracking of people, vehicles or stored goods inside buildings, such as shopping malls; hospitals; industrial warehouses; and airports. Indoor positioning systems aim at providing a precise position inside buildings, which is a particularly tricky task, due to phenomena such as non-line-of-sight and multipath caused by walls and obstacles. In such environments, the choice of Ultra Wide Band (UWB) signaling is attractive, as it can theoretically reduce the impact of sources of errors such as non-line-of-sight propagation, multipath, and multiple access interference. As a matter of fact, UWB signals are characterized by the capability of penetrating through obstacles, due to the large frequency spectrum that characterizes them [3]. Moreover, due to their large bandwidth, UWB systems transmit very short duration pulses with a low duty cycle, leading to low energy consumption and guaranteeing accurate Time of Flight (ToF) estimation of signals travelling between nodes, hence accurate range estimates. Such unique aspects make the UWB technology a good candidate for accurate, low-cost, and low-power positioning systems. After the definition of the IEEE 802.15.4a standard in 2007, the interest on UWB systems is growing fast and there are some positioning devices already available, produced by companies such as Decawave (http://www.decawave.com), Ubisense (http://www.ubisense.net), and Time Domain (http://www.timedomain.com).

This paper is organized as follows. In Section II, an overview of the classically used approaches to the localization problem is presented. In Section III the use of the Particle Swarm Optimization (PSO) algorithm to solve the localization problem is proposed. Section IV concludes the paper.

II. Localization Techniques - State of the Art

Throughout the paper, we assume to have M nodes with known positions, denoted as beacons. We then assume to have a given number of nodes with unknown positions, which could be both static or moving targets, and we want to

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estimate their positions one after another, given the known positions of the beacons.

Many localization algorithms for WSNs have been proposed to provide per-node location information. With regard to the mechanisms used for location estimation, WSN localization approaches can be divided into two main categories: range-free and range-based [4]. *Range-free approaches* do not require the availability of range measurements between nodes. At the opposite, *range-based approaches* rely on the knowledge of inter-node distances or angle information.

Range-based localization methods can be classified into active and passive [5]. In active systems, all nodes are equipped with sensors and with an electronic device which sends information to a positioning system. Passive localization, instead, is based on the fact that wireless communications strongly depend on the surrounding environment. Relying on the scattering caused by small targets during signal propagation and/or on the variance of a measured signal, changes in the received physical signals can be used to detect and locate targets and for tracking purpose [6].

In this paper, we focus on range-based algorithms, with active tags. More precisely, we consider "two-step" positioning techniques, where the first step consists of the estimation of a signal parameter, such as the Time of Flight (ToF), the Angle of Arrival (AoA), or the Received Signal Strength (RSS). The position of a target is then estimated in a second step, which relies on the signal parameters estimated in the first step.

Range-estimation techniques based on AoA rely on the measurements of angles between nodes, which are usually taken by means of antenna arrays. The installation cost of antenna arrays can be very high. Moreover, the number of paths of UWB signals may be very large (due to their large bandwidth), making accurate angle estimation very challenging, especially in indoor environments where objects can cause relevant scattering [3]. For these reasons, the AoA approach is not suitable for UWB positioning systems.

In the presence of a relation between the received power of a signal travelling between two nodes and their distance, the latter can be estimated from the RSS measurement at the receiver node assuming that the transmitted signal energy is known. The path-loss during propagation is characterized by Friis formula [3]:

$$\bar{P}(d) = P_0 - 10\beta \log_{10} \frac{d}{d_0} \tag{1}$$

where: P_0 is the (known) power at the reference distance d_0; β is the path-loss exponent; and $\bar{P}(d)$ is the average received power at the distance d. From (1), it can be observed that channel knowledge is a strong requirement to accurately estimate the distance, but its estimate in realistic (indoor) environments is a great challenge as well.

Time-based positioning techniques rely on measurements of the ToF of signals travelling between nodes. If two synchronized nodes communicate, the node receiving the signal can determine the Time of Arrival (ToA) of the incoming signal from the timestamp of the sending node. If the nodes are not synchronized, Time Difference of Arrival (TDoA) techniques, based on the estimation of the difference between the arrival times of UWB signals traveling between the current target and the beacons, can be employed. Since the accuracy of time-based approaches can be improved by increasing the bandwidth of the signal, time-based techniques (theoretically) allow extremely accurate location estimates when dealing with UWB signals [3]. A variety of ToF-based localization approaches have appeared in the literature, among which it is worth recalling the Two-Stage Maximum-Likelihood (TSML) method, which is particularly important as it can reach the Cramer-Rao Bound (CRB), which is a lower bound for the variance of an estimator [7].

III. Optimization-based Approaches

In spite of good theoretical features, with some configuration of the beacons, the "geometrical" methods described in Section II may lead, in some scenarios, to (far) inaccurate position estimates, due to ill-conditioning of the matrices involved. These problems can be solved by re-interpreting the localization problem as an optimization one.

Among the large set of optimization algorithms proposed in the literature, the PSO algorithm, introduced in [8], is a good choice to solve this kind of problems, as shown in [9], [10]. According to the PSO algorithm, the set of potential solutions of the considered problem is modeled as a swarm of S particles, each of which, at any instant t, is associated with a position $\underline{x}^{(i)}(t)$ in the region of interest and with a velocity $\underline{v}^{(i)}(t)$, $\forall i \in \{1, \dots, S\}$. The idea of the PSO algorithm is to guide the swarm towards the optimal solution, and the updating rules for the position and the velocity of each particle are meant to simulate "social" interactions between particles. More precisely, in the more general version of this algorithm, the velocity of particle i is updated at each iteration, according to the following rule [8]:

$$\begin{aligned} \underline{v}^{(i)}(t+1) = \omega(t)\underline{v}^{(i)}(t) + c_1 R_1(t)(\underline{y}^{(i)}(t) - \underline{x}^{(i)}(t)) \\ + c_2 R_2(t)(\underline{y}(t) - \underline{x}^{(i)}(t)) \qquad i \in \{1, \dots, S\}. \end{aligned} \tag{2}$$

The first addendum at the right-hand side of (2) is the previous velocity of the particle weighed by means of a multiplicative factor $\omega(t)$ which is denoted as *inertial factor*. The second and the third addends represent stochastic combinations of the direction to the best particle position and to the global best position, respectively. The positive real parameters c_1 and c_2 are denoted as *cognition* and *social* parameters, respectively, and $R_1(t)$ and $R_2(t)$ are random variables uniformly distributed in $(0, 1)$. Finally, $\underline{y}^{(i)}(t)$ and $\underline{y}(t)$ are the position of the $i-$th particle with the best fitness function and the position of the particle with the best (among all particles) fitness function reached until instant t, respectively [8].

The positions of each particle are then updated at each step by adding to the previous positions the velocities obtained according to (2), i.e.:

$$\underline{x}^{(i)}(t+1) = \underline{x}^{(i)}(t) + \underline{v}^{(i)}(t) \qquad i = 1, \ldots, S. \quad (3)$$

Possible stopping conditions for the PSO algorithm can be: the achievement of a sufficiently small value of the fitness function or a given (maximum) number of iterations.

Depending on the considered problem, the PSO parameters introduced in the previous paragraph have to be properly set. In [9], [10], it is shown that a population of only 40 individuals is sufficient to achieve a good accuracy in 50 iterations, in a bidimensional scenario. The small population size is due to the fact that the fitness function is simple if compared to other applications of the PSO algorithm.

In [9], the authors make a comparison between the performance of the TDoA-TSML method and the PSO algorithm, as the average distance between beacons and nodes changes. Regardless of this distance, the PSO algorithm outperforms the TSML method in terms of the Root Mean Square Error (RMSE) of the estimated distance. A comparison between the performance of the TSML method and the PSO algorithm in terms of the number of beacons is carried on in [10], showing that the PSO algorithm guarantees better accuracy with a lower number of beacons. Results obtained in a three-dimensional environment (a cube whose edge is 10 m long) with 4 beacons and 32 nodes to be estimated, show that when using the TSML-ToA method the maximum distance error is 1 m. At the opposite, when using the PSO algorithm the maximum distance error is only 10^{-1} m, which is a tolerable error for many applications.

Many different versions of the PSO algorithm have been studied in the literature, such as binary particle swarm [11] and bare bones particle swarm [12]. In [13] a modified PSO algorithm is proposed, according to which, at each step, the worst particles (i.e., the ones with higher values of the fitness function) are moved in a neighbourhood of the best ones. This guarantees faster convergence with respect to the standard PSO algorithm, even with a small number of particles, which allows reducing computational costs.

IV. Conclusion

Cyber-physical systems are expected to play a major role in the design and development of future engineering systems with new capabilities. Among the possible applications of CPS, in this paper we investigated the indoor localization task, which has recently become a key prerequisite in many applications. We assume to address this problem by means of a UWB WSN. UWB signaling is particularly suited in this context, as the large bandwidth and the short duration of signal pulses allow improving ranging capability and solving multipath component typical of indoor environments. We discuss ToF-based geometrical and optimization-based approaches to the localization problem.

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