Applied Soft Computing 11 (2011) 4677–4691

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Enhanced WiFi localization system based on Soft Computing techniques to deal with small-scale variations in wireless sensors

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ARTICLE INFO

Article history:
Received 31 May 2010
Received in revised form 20 May 2011
Accepted 7 July 2011
Available online 27 July 2011

Keywords:
Wireless localization
WiFi signal strength sensor
Fuzzy logic
Fuzzy modeling

ABSTRACT

The framework of this paper is robot localization inside buildings by means of wireless localization systems. Such kind of systems make use of the Wireless Fidelity (WiFi) signal strength sensors which are becoming more and more useful in the localization stage of several robotic platforms. Robot localization is usually made up of two phases: training and estimation stages. In the former, WiFi signal strength of all visible Access Points (APs) are collected and stored in a database or WiFi map. In the latter, the signal strengths received from all APs at a certain position are compared with the WiFi map to estimate the robot location. Hence, WiFi localization systems exploit the well-known path loss propagation model due to large-scale variations of WiFi signal to determine how closer the robot is to a certain AP. Unfortunately, there is another kind of signal variations called small-scale variations that have to be considered. They appear when robots move under the wavelength λ. In consequence, a chaotic noise is added to the signal strength measure yielding a lot of uncertainty that should be handled by the localization model. While lateral and orientation errors in the robot positioning stage are well studied and they remain under control thanks to the use of robust low-level controllers, more studies are needed when dealing with small-scale variations. Moreover, if the robot can not use a robust low-level controller because, for example, the environment is not organized in perpendicular corridors, then lateral and orientation errors can be significantly increased yielding a bad global localization and navigation performance. The main goal of this work is to strengthen the localization stage of our previous WiFi Partially Observable Markov Decision Process (POMDP) Navigation System with the aim of dealing effectively with small-scale variations. In addition, looking for the applicability of our system to a wider variety of environments, we relax the necessity of having a robust low-level controller. To do that, this paper proposes the use of a Soft Computing based system to tackle with the uncertainty related to both the small-scale variations and the lack of a robust low-level controller. The proposed system is actually implemented in the form of a Fuzzy Rule-based System and it has been evaluated in two real test-beds and robotic platforms. Experimental results show how our system is easily adaptable to new environments where classical localization techniques can not be applied since the AP physical location is unknown.

1. Introduction

Several applications like surveillance tasks require a priori knowledge of the user location. This position can be determined by the user's device or by the environment itself. By knowing the user position it is possible to interact with him, guiding it through the environment and implementing some tasks depending on the area of interest.

Localization is currently applied at several areas. For instance, there are projects that use localization systems in hospitals which can locate doctors and equipment. Other systems are used for medical assistance [21], inventory control at warehouses, robotics [40], etc.

In the last years, applications of localization systems are growing by means of using different technologies [27]. A great example is GPS (Global Positioning System) [12], which is the most extended technology for devices localization. As an example of the localization importance car drivers usually use GPS to be guided through

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doi:10.1016/j.asoc.2011.07.015

cities. This technology can locate devices with an error that varies from centimeters to one hundred meters, but it does not work properly in indoor environments or even in cities with high buildings.

Thus, it is necessary to find a complementary system for such environments. There are some proposals for indoor localization using infrared [42], computer vision [19], ultrasound [34], laser [7], radio frequency (RF) [6], or even cellular communication [33] based systems. Moreover, there is an increasing interest in WiFi localization for these environments using different algorithms, even looking for complementary characteristics of both GPS (outdoor environments) and WiFi (indoor environments) [13].

One of the main advantages of WiFi technology is its quickly growing degree of coverage. There are WiFi Access Points (APs) in most public buildings like hospitals, libraries, universities, museums, etc. In addition, measuring the WiFi signal level (without transmitting-receiving data) is free even for private WiFi networks. Consequently, WiFi technology is a good choice for global indoor localization systems.

WiFi localization systems use 802.11b/g network infrastructure to estimate a device position. This fact makes WiFi localization systems appropriate to be used in indoor environments where traditional techniques do not work properly. With the aim of estimating a device position, a WiFi localization system measures and processes the received signal level (SL) from each AP by means of a WiFi interface. Notice that, SL depends on the distance and the obstacles between APs and the receiver. Looking for indoor localization, the so-called signal strength approaches are very attractive because they can be applied to wireless networks without needing additional specific hardware [11].

There are two main techniques to estimate an unknown position: deterministic and probabilistic. In the first one, the environment is usually divided into cells and the position is obtained in the estimation stage comparing the measures with the stored pattern [6,44]. On the other hand, probabilistic techniques keep a probabilistic distribution over all positions [15,20]. The last technique gets a better accuracy but with a higher computational cost.

In work [24], the authors estimate the distance to each AP using only odometric calculus and the received SL. They consider trilateration with a propagation model and also a probabilistic approach that applies the Bayes rule to accumulate localization probability. Unfortunately, RF signal is affected by reflection, refraction and diffraction in indoor environments. This effect, known as multipath effect, turns the SL into a complex function of the distance [11]. In addition, classical trilateration algorithms can not be applied when the exact AP physical location is unknown.

Looking for a solution to this problem, authors of [6] proposed a WiFi localization system based on a priori radio map, which stored the received SL of each AP belonging to interest locations. This system has two stages: training and estimation stages. In the first one, a manual radio map is built. While in the estimation stage a vector with received SL of each AP is created and compared with the radio map to obtain the estimated position.

Notice that WiFi technology works at a 2.4 GHz frequency, which is closer to the water resonant frequency, therefore SL is affected by so many variations. One of these variations, studied by the authors in a previous work [40], is the small-scale one and it occurs when the robot moves in a small distance under the wavelength $\lambda = 12.5$ cm. As a result, there are significant changes in the average SL and make difficult to estimate the correct location because they can be up to 10 dBm around the same position. To deal with this, authors proposed the use of a robust low-level controller which integrates WiFi and ultrasound measures in a global navigation system. It is able to handle small-scale problems but only when the environment is organized in perpendicular corridors. Otherwise, the uncertainty level with respect to the measures is so huge that many localization errors appear yielding a bad global navigation performance.

Since we would like to apply our localization system to a wider variety of indoor environments, we should relax the necessity of having a robust low-level controller. In consequence, we have to look for another way of tackling with the intrinsic uncertainty attached to the system. To do so, this work proposes the use of a Fuzzy Rule-based System (FRBS) able to improve the localization stage of our previous navigation system [30] when the robust low-level controller can not be used.

The rest of the paper is organized as follows. The next section introduces the localization system we want to enhance, highlighting its main advantages and drawbacks. In addition, Section 2 presents several related works regarding the applicability of Soft Computing approaches in the context of WiFi localization systems. Then, Section 3 describes our proposal of fuzzy system for dealing with small-scale variations during the localization stage. Section 4 presents the results obtained in experiments carried out with two real prototypes in two different test-bed environments. Finally, Section 5 draws some conclusions and future works.

2. Related works

The main goal of this work is to strengthen the localization stage of our previous WiFi Partially Observable Markov Decision Process (POMDP) Navigation System with the aim of dealing effectively with small-scale variations even in challenging environments where the use of our robust low-level controller is not feasible or it yields really bad performance. Let us summarize our previous proposal which represents the starting point for this work.

2.1. Advantages and drawbacks of our previous work

For a global navigation system, in which the objective is to guide a robot to a goal room in a semi-structured environment, a topological discretization is appropriate to facilitate the planning and learning tasks. It is especially indicated when the environment is very large because it uses a discretization of the environment and divides it in a priori known nodes. With this kind of representation, POMDP models provide solutions to localization, planning, and learning in the global robotics navigation context. These models use probabilistic reasoning to deal with sensor and action uncertainties. It is important to highlight, that robot needs a low-level controller to move across the nodes and perform local navigation actions commanded by the POMDP planner. In this context, using sensors with high uncertainty, like WiFi signal strength sensors, Markov models become the most extended models in order to build a robust global navigation system.

When a robot moves across an environment executing several actions (a_t), in execution step t, and the environment observation is free of uncertainty, the system can be modelized as a Markov Decision Process (MDP). The MDP is a mathematical model that allows the characterization of robotic systems without noise in the environment observation. The MDP considers that only the effect of actions has uncertainty. In addition, when a MDP achieves some execution steps and it goes along different states ($s_0, s_1, \ldots, s_n$) executing some actions ($a_0, a_1, \ldots, a_n$), the probability of being in a state (s_{t+1}) in the execution step $t+1$ is computed by Eq. (1).

$$p(s_{t+1}|s_0, a_0, s_1, a_1, \ldots, s_t, a_t) = p(s_{t+1}|s_t, a_t) \quad (1)$$

The action uncertainty model represents the real errors or failures in the execution of the actions. The transition function T incorporates this information to the MDP. In the discrete case, T is a matrix that represents the probability of reaching the state s_{t+1} when the robot is in the state s_t and it has executed the action a_t. There is a reward function R for each state s and action a. The robot