Expert Systems with Applications 42 (2015) 125–134

Contents lists available at ScienceDirect

Expert Systems with Applications

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

Indoor localization in a hospital environment using Random Forest classifiers

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ARTICLE INFO

Article history:
Available online 6 August 2014

Keywords:
Indoor localization
Smart health
Hospital
Emergency room
Random Forest

ABSTRACT

This paper proposes a new indoor localization system, based on RFID technology and a hierarchical structure of classifiers. This system has been specifically designed to work in unfriendly scenarios, where transmissions could be disturbed by other electronic devices or shielded walls. The infrastructure has been deployed and evaluated in the emergency unit of a large Italian hospital (48 rooms covering about 4000 m^2) to detect the room where lost or forgotten patients lie. Extensive experiments show the potential of such technology for indoor localization applications in terms of accuracy, precision, complexity, robustness and scalability. In 98% of cases the system localizes the correct room (83%) or one of its adjacency (15%).

1. Introduction

In the last decade the need to track persons and objects in indoor environments has become increasingly important for several reasons. The emergence of smarter environments in urban areas, along with the improvements achieved in the context of global satellite positioning systems, led to an intensive use of outdoor location-aware applications (Calderoni, Maio, & Palmieri, 2012). Meanwhile, the scientific and industrial community realized the potential and benefits of location-aware applications in the indoor environment (Mautz, 2012).

Nowadays, indoor positioning is applied in a wealth of fields: customer navigation in a mall, citizen navigation inside a public building, product localization in a supermarket and indoor location-aware advertisement are just a few examples. Unfortunately, while the performance of outdoor positioning systems has become excellent, indoor positioning seems to be more complicated (Pivato, 2012). Apparently a single multipurpose solution that fits any need in indoor positioning applications is still missing. In fact, the systems proposed in literature rely on several technologies and tailored models designed in order to fit the requirements of each specific context (Liu, Darabi, Banerjee, & Liu, 2007).

Since 2007, the European Union defined several factors that should be considered when evaluating the *smartness* of a city (Giffinger et al., 2007). Healthcare plays a key-role when the quality of life concerning a urban area is to be estimated (Schaffers, Komninos, & Pallot, 2012). The availability of modern and citizen-friendly hospitals is one of the factors that belong to the *Smart Living* macro area: Hernández-Muñoz et al. (2011) state that telemedicine, electronic records, and health information exchanges in remote assistance are meaningful case studies on the subject. The possibility to track patients while they are inside a hospital and especially in first aid area is becoming increasingly important. In these areas emergencies frequently occur and this causes a constant flow of doctors and nurses from one room to another. This to-and-fro together with specific mental disease (e.g., Alzheimer disease), often leads to lost or forgotten patients around the hospital. Hence, knowing the right position of a person inside a medical facility at any time is a meaningful problem within indoor localization research field. Unfortunately, the medical scenario is a particularly hostile context for indoor localization because the transmitters and receivers usually adopted to locate objects have to deal with medical devices; indeed these machineries often come with some limitation on the allowed radio-frequency range to be used near them and so on.

In this paper a focus on the hospital and medical scenario is posed; an expert system capable of locate people within a hospital emergency unit is presented. This system adopts RFID transmitters and receivers and handles their signals through a dedicated infrastructure. Patients are located through a classification of these signals via a hierarchical *Random Forest*-based classifier proposed herein.

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http://dx.doi.org/10.1016/j.eswa.2014.07.042
0957-4174/

1.1. Related works

In recent years several system models concerning indoor positioning were presented. For the purposes of this work it is meaningful to focus on the system models for indoor localization based on classifiers, as the herein proposed method lies in this field.

Honary, Mihaylova, and Xydeas (2012) provide a detailed performance analysis of a *k*-Nearest Neighbour based positioning system and also propose a positioning scheme based on Gaussian Mixture Models in order to locate objects in a generic building.

An indoor positioning technique relying on bayesian classifiers focusing on *smart office* and *smart building* scenarios is presented by Kim, Ha, Lee, and Lee (2009).

A valuable study on the subject was proposed by Villarubia, Rubio, Paz, Bajo, and Zato (2013); it consists of a practical experiment which took place inside a University. Here a Wi-Fi based system is used to gather signals and a wide range of classifiers are compared during the localization process. Shin and Han (2010) suggest that a viable method to improve the classification process in the Wi-Fi indoor positioning context is to combine classifiers, and provide subsequently some practical case studies on the subject (Shin, Jung, Yoon, & Han, 2011).

While Koyuncu and Yang (2010) provide a general survey on indoor positioning methods, Gu, Lo, and Niemegeers (2009) focus on positioning systems for wireless personal networks.

In another key-survey Liu et al. (2007) describe a wide range of indoor localization systems and compare them on the basis of some performance metrics (*Accuracy*, *Precision*, *Complexity*, *Robustness*, *Scalability*, *Cost*). Within this paper a reference to some of these key-features is posed, in order to provide a helpful comparison with other systems. The survey also describes several algorithm and mathematical techniques used for indoor positioning purposes.

Mathematical approaches for indoor localization are however better described by Seco, Jimenez, Prieto, Roa, and Koutsou (2009) and divided in four main categories: *geometry-based methods*, *cost function minimization methods*, *fingerprint methods* and *bayesian methods*. According to this taxonomy, it is reasonable to include our system among the fingerprint based ones. Fingerprint methods rely on two main steps. In the first one, the signal levels from the different base stations are recorded in order to form a training set and calibrate the system. In the localization step, the system tries to locate the source of a new signal classifying it against the previously recorded set. These methods are particularly robust in the *non-line-of-sight* (NLOS) context, where radio transmission across a path is partially obstructed, usually by a physical object.

1.2. Contribution

Most of the ICT (Information and Communication Technology) works in the *Smart Health* field relate to the design of proper information systems for medical purposes or to the innovative techniques adopted to cope with several known diseases (Zeng et al., 2013). On the contrary, this work describes a novel technique to track patients in an emergency room environment in order to find them quickly as needed. Specifically, in this context, it is important to know the room where the patient is located rather than his precise position. The system proposed herein is aimed to locate patients through RFID signals classification. In particular, signals are processed combining several instances of *decision-tree* classifiers called Random Forest (Breiman, 2001). As assessed by Yim (2008) the off-line phase (training) of a fingerprint method is not time critical whereas on-line phase (localization) is really time critical. Decision-tree oriented classifiers behave well according to this time constraint. To the best of our knowledge, this paper represents the first comprehensive contribution completely dedicated to indoor localization in hospital environment.

1.3. Outline

The paper is organized as follows: in Section 2 a description of the hospital context and its related indoor positioning issues are provided, as well as the description of the sensors involved in this work and a detailed map representation of the hospital where the technical surveys were made. After a detailed description of the dataset (Section 3), the indoor classification system designed to fit the hospital scenario is introduced in Section 4 while in Section 5 a discussion on the results based on the previously proposed system model is provided.

2. Operating environment

In general, it is quite complicated to obtain satisfying results concerning indoor positioning inside a hospital or a medical facility using wireless techniques. In this specific scenario, several problems may occur due to location sensors installation. Frequently, medical devices conflict with installed sensors; moreover, these buildings are often equipped with shielded walls. For instance, we could imagine an X-ray examination room equipped with thick leaded walls (Hentila, Taparungssanagorn, Viittala, & Hamalainen, 2005). This leads to a tangible signal reduction or distortion during the communication between transmitters and receivers. In the following a description of the adopted sensors and the operating environment is proposed, in order to better understand both acquisition and localization steps of the designed system.

2.1. Sensors

The deployed infrastructure relies on *Radio Frequency Identification* (RFID) technology and consists of three different sensors. Each sensor communicate in *Ultra High Frequency* (UHF) mode on frequencies *LPD 433 MHz*, *446 MHz* and *860 MHz*. Keeping the frequency range as confined as possible allows the infrastructure not to conflict with other WiFi and medical devices.

Patients are equipped with an active RFID transmitter (RFID Tag). Each *Tag* lies inside a small hypoallergenic bracelet and sends a signal on an user-defined time interval basis. The duration of each signal is limited to a few milliseconds, resulting in a total effective transmission time of few hours per year. The irradiance at a point of the surface is near to 0. One of the main concerns in dealing with active RFID tags is that of batteries and power consumption. Active tags send signals to the receiver on their own and thus need a local power source. As signals related to the adopted tag are really short and energy-preserving, bracelets can be equipped with a small battery which can although keep the tag alive for more than three months.

Signals sent from tags are received from several antennas (RFID Receiver) which store the Tag Identifier (ID) and the strength of incoming signal. Specifically, signal strength is expressed in decibels and varies from −100 db (weak signal) to −30 db (strong signal). Receivers stay idle until a signal from a tag occurs and, after its processing, which lasts for a few milliseconds, go back to sleep mode. Thus, these antennas are energy-preserving as well and can be both plugged to the hospital power supply or equipped with batteries.

Each antenna sends the data to a central receiver (on the same frequency range) which is connected via an *RS232-to-Ethernet* adapter to the local server. This central receiver collects the signals, stores them and performs real-time localization.