Context-aware Indoor-Outdoor Detection for Seamless Smartphone Positioning

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***Abstract*—Localization for smartphones typically relies on distinct approaches for indoor and outdoor contexts, since the Global Positioning System (GPS), which is typically used outdoors, does not perform well within buildings. A localization system supporting both needs to detect indoor-outdoor transitions automatically in order to provide seamless operation across the different contexts. This paper proposes a transition detection method that combines GPS signal evaluation with a GPS-less sensor-based machine-learning scheme in order to provide maximal accuracy, reliability and adaptability to new environments without unneccesary power consumption.**

Keywords–IO Detection; Smartphone Positioning; Indoor Positioning; Seamless Transition; Context-aware Computing

I. Introduction

Location-aware mobile applications need capabilities for determining the current position of a mobile device. Smartphone positioning in outdoor areas typically relies on Global Navigation Satellite Systems (GNSS) such as the Global Positioning System (GPS). Numerous indoor solutions have been proposed in the last few years, e.g., hybrid methods that fuse WiFi fingerprinting with sensor-based Pedestrian Dead Reckoning (PDR).

Accurate indoor localization methods typically rely on some infrastructure. WiFi fingerprinting, e.g., leverages a radio map that contains a large set of locations with associated *Received Signal Strength Indication* (RSSI) values for a set of WiFi access points. In order to determine the current position, the radio map is scanned for a location with a signal strength profile similar to that of the current location. Other methods utilize the information contained in building models, e.g., the positions of doors, walls, stairs, etc.

Whereas most recent publications propose indoor-only solutions, the problem of suitably combining indoor and outdoor positioning, e.g., for pedestrian navigation, has deserved far less attention. Larger areas comprising outdoor ranges as well as several buildings, e.g., company premises, will typically be heterogeneous in the sense that a single indoor positioning method which is suitable for one building might not be applicable in another that lacks the required infrastructure. As a consequence, an appropriate localization system has to incorporate multiple indoor positioning methods. In [1], a multi-scheme approach was presented that supports multiple outdoor and indoor positioning methods with seamless transitions. A crucial problem is to detect automatically that a localization method switch is necessary. Moreover, detection should be energy-efficient and without considerable delay.

An important prerequisite for multiple scheme support is the reliable recognition of indoor-outdoor transitions, which is referred to as Indoor-Outdoor (IO) detection in this paper.

The rest of this paper is organized as follows. After presenting related work in Section II, the proposed IO detection system is explained in Section III. In Section IV, we describe the current state of an implementation and the remaining tasks. Finally, Section V reviews some benefits and shortcomings of the presented approach, open problems, and future research plans.

II. Related Work

Using GPS signal strength changes as an indicator for IO transitions is proposed in [2]. Alternatively, the signal-to-noise ratio (SNR) of the GPS signal can be observed, as proposed in [3]. However, continuously searching for GPS signals within buildings will drain the battery quickly. Moreover, the method might be unreliable and inaccurate if the signal is weak, which can occur outdoors as well as indoors, e.g., near a building entrance.

In order to save energy, other approaches try to avoid GPS usage and rely on a restricted set of less power-consuming smartphone sensors only, e.g., for ambient light, cell signal, or magnetic field. Whereas IO detection according to Zhou et al. is based on checking the sensor values cross empirically determined fixed thresholds [4], Radu et al. show that a semi-supervised machine learning approach [5] provides a much better adaptability to different environments.

III. Proposed IO Detection System

This chapter describes an advanced IO detection system that is expected to provide fast and reliable context detection without unneccessary power consumption. In the multi-scheme approach proposed by Jäger et al., a three-level positioning architecture is described, where the top-level algorithm, called Coarse Positioning System (CPS), is responsible for context transition detection and appropriate selection of lower-level localization schemes, e.g., GPS- or WiFi-based. An important property of this system is its context-awareness. Except in the inititialization phase, positioning always uses exactly one scheme, which is the most appropriate for the current location. For example, in outdoors mode, a GPS-based hybrid scheme is selected, also utilizing PDR for better accuracy.

Supposed that at some location GPS is switched on anyway, e.g., for navigation, leveraging the available signals additionally for IO detection will not impact power consumption. On the other hand, if WiFi fingerprinting is used in a building, IO detection reliability can benefit from considering changes of RSSI values without extra battery drain.

Extending the machine-learning approach of [5], context-aware IO detection is not confined to some basic standard sensors, but also incorporates and extends the GPS signal evaluation approaches of [2] and [3] in order to provide the highest possible accuracy at no additional cost with respect to battery life.

Two independent sets of sensor values are used as classifiers in a co-training scheme. After an initial supervised offline training phase, unsupervised learning supplies each classifier with further training data consisting of the labels from the other classifier. The basic data sources include light intensity, cell signal strength, battery temperature, sound amplitude, time, proximity sensor and magnetic field.

In the outdoor context, the classifier contains also the number of GPS satellites in reach, the signal-to-noise ratio (SNR) of the GPS signal, and the angles of visible GPS satellites. If a sufficiently strong signal can be received indoors, the probability that it is received from a near horizon satellite through a door or window is expected to be considerably higher compared to an origin from a vertical one. The SNR and the number of GPS satellites in reach are indicators for the quality of the signal.

Moreover, depending on the available hardware features, non-standard smartphone sensors are also considered. These include ambient temperature, atmospheric pressure, and relative humidity. The atmospheric pressure fluctuates when a door is opened or closed [6]. Additionally, it can be used as a pressure altimeter. The ambient temperature measured indoors in rooms with air conditioning or heating will often be different to the outdoor temperature. Though ambient temperature sensors are not too widespread in smartphones, the value can often be inferred from battery temperature [7].

IV. Current State and Remaining Tasks

Context-aware IO detection has been implemented in a reusable library, which loads and runs two classifiers previously trained in an offline phase. The training data includes both, the sensor data and the ground truth as given by a user.

Once the context is detected, the system can react to the transition by selecting the appropriate positioning method. This allows for turning off GPS when the user enters a building and turning it on again on leaving it. This is crucial for an effective power management.

A mobile application has been developed for ground truth acquisition and persistent storage. Each training data record consists of measurements for each of the classifier's attributes and an associated user-supplied context classification. The mobile application as well as a prototype featuring seamless positioning have been implemented for the Android platform. It supports positioning with GPS outdoors and NFC in combination with PDR indoors.

There are several open tasks left. First, a thorough evaluation is needed to measure the gain in reliability of IO detection resulting from the evaluation of additional data sources. Particularly, the influence of using the GPS signal for detecting outdoor-to-indoor transitions has to be investigated as well as the impact of leveraging WiFi RSSI values for detecting indoor-to-outdoor transitions in a WiFi indoor context. Furthermore, the machine-learning approach can not only be used to detect that a user has entered a building and to switch to another positioning scheme. It can also be applied to determine which building has been entered, e.g., by using building classifiers based on RSSI values. For indoor navigation purposes, the same approach is expected to enable reliable determination of the current floor level within a multi-storey building, particularly, if the classifiers utilize the atmospheric pressure in addition to RSSI measurements.

It can be seen as a drawback that the proposed machine-learning algorithm is to some extend tailored to a specific non-standard sensor equipment, i.e., the IO classifiers exploit athmospheric pressure and temperature measurements. The impact of these sensor values on the IO detection results needs to be evaluated. While both are not expected to be crucial for IO detection, an extended usage of the classifiers for floor level determination will probably benefit considerably from a barometer. However, on a smartphone without one, WiFi RSSI measurements might also allow reasonably reliable floor level classifications.

V. Conclusion

The context-aware IO detection presented in this paper can be used to switch seamlessly between several indoor and outdoor positioning methods. It combines the advantages of the GPS-using and the GPS-less IO detection approaches presented in Section II. Thus, adaptability to unknown contexts by semi-supervised learning is preserved, while classification reliability is expected to increase considerably by context-dependent usage of GPS or WiFi signal information and additional smartphone sensors for classification. The approach can be extended in a straightforward manner to determine also which building is entered or which is the current floor level and, thus, offers multiple new possibilities with regard to context-aware computing.

The system architecture is extensible and expected to work with arbitrary positioning methods in addition to those used in the prototype.

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