

# A Survey of People Localization Techniques Utilizing Mobile Phones

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## INTRODUCTION

With the ongoing diffusion of mobile computing and context-aware applications, knowledge of the current location of an individual can be leveraged in a number of different domains, from personal diaries and fitness-related applications to human behavior analysis and targeted advertising.

Mobile phones are routinely carried by their owner during daily activities, and the embedded sensors commonly found in modern devices can be used to capture data of interest from the area surrounding an individual; these data can then be processed to estimate the current location of the phone user.

Two different categories of localization studies can be identified: indoor/outdoor detection and indoor localization. In the first category, the aim is to differentiate between indoor and outdoor areas, while the second category comprises all the studies addressing the challenges encountered in identifying the location of a person in an indoor environment, where the majority of people spend most of their time, and where the technology typically used for outdoor localization (i.e. satellite-based positioning) is generally not available.

The capability to automatically differentiate between indoor and outdoor environments can be used for example to enable an efficient use of power-hungry sensors such as GPS receivers, possibly selecting alternative localization methods while indoors; applications that recognize and analyze human activities can leverage indoor/outdoor detection for improved accuracy, given that many activities can only be executed either in

indoor environments or outdoors; other examples of possible uses are automatic image annotation when a picture is taken with a smartphone, or adaptation of phone settings to the current environment type (e.g. increasing ringer and notification sound volume when outdoors).

A typical use of indoor localization techniques is for personal navigation, especially useful in large buildings such as shopping malls, hospitals, airport terminals, university campuses, or office buildings; more advanced uses are made possible by the proliferation of mobile apps that can leverage location information: for example, a museum visitor can access detailed information about the nearby items on display; a customer in a grocery store can search for a specific product and easily reach the aisle where the product is located; other applications allow precise tracking of people in need of care, such as children, elders or disabled people. In addition, human activity classification algorithms can greatly benefit from knowledge of the physical location of an individual, since in many cases location is highly correlated to the activity being carried out (e.g. sleeping is typically done in the bedroom, and cooking in the kitchen).

This article presents a review of past research works describing techniques for utilizing smartphone sensors to identify the environment where a smartphone user is located. The review focuses on studies where user location can be computed autonomously and continuously by a smartphone, without the need for an active involvement of the user, and where issues such as power consumption and dependence of sensor readings from the on-body position of the phone are addressed.

## BACKGROUND

In the last few decades there has been an increasing interest in positioning technologies. The deployment of a number of satellites in the Earth's orbit enabled satellite-based positioning, whose main use case was vehicle navigation, but due to poor performance of this technology in indoor areas, indoor location methods have to rely on other means. The first indoor location techniques required carrying specialized devices and/or deploying ad-hoc hardware in the environment; then, the continuous enhancement of mobile phone sensing and computation capabilities, and the widespread deployment of infrastructure for wireless communication opened new frontiers for indoor localization; now, an increasing number of location-based services are made possible by different technologies for locating people in indoor environments.

Many pervasive computing applications are enabled or can be enhanced by knowledge of the current *user context*; while the exact definition of user context can vary between applications, physical location is an important piece of information in defining the context for many applications. Thus, methods for automatic localization of users can be considered as part of the more general issue of user context recognition (Hoseini-Tabatabaei, Gluhak, & Tafazolli, 2013).

Virtually all sensors and communication interfaces embedded in modern smartphones can be used for localization: receivers for wireless technologies such as GSM, GPS, Wi-Fi, Bluetooth, and even FM radio can detect and identify existing infrastructure such as cell towers or Wi-Fi access points; inertial and orientation sensors can detect physical movements and orientation changes of the phone, and thus their readings can be correlated to movements of the phone user; other sensors can capture characteristics of the surrounding environment from which useful information for localization can be extracted.

Two basic methods can be identified in most indoor localization applications: fingerprinting

and dead reckoning (Subbu, Zhang, Luo, & Vasilaikos, 2014). These two methods, which can be used alone or in combination, utilize sensor readings to detect local characteristics of the environment or movements of a mobile device, and are often complemented by additional techniques (Yang et al., 2015) to overcome their inherent limitations and improve localization performance: Shang, Hu, Gu, Wang, & Yu (2015) identified three categories of methods that fuse sensor readings with *spatial contexts*: map matching, landmark fusion, and spatial model-aided methods.

Figure 1 provides a taxonomy for the different studies on indoor/outdoor detection and indoor localization reviewed in this article.

## INDOOR/OUTDOOR DETECTION

In a number of recent research studies dealing with environment detection, the focus is on discriminating between indoor and outdoor environments. Since all smartphones are equipped with cameras, among the different methods that can be implemented in a smartphone to detect the environment type there are vision-based methods that analyze images captured from the camera to extract features useful for scene understanding. These techniques, which have been studied extensively even before the advent of smartphones, will not be reviewed here, since when implemented in a smartphone they usually require active user involvement to capture the scenes of interest, and are not applicable in most situations where the mobile device is worn randomly by the user.

General unavailability of satellite coverage for navigation purposes in indoor areas can be used to infer indoor/outdoor location. For example, Herrmann, Zappi, & Rosing (2012) and Ravindranath, Newport, Balakrishnan, & Madden (2011) used the inability to obtain a GPS location as a hint that the user is indoors; in Cho, Song, Park, & Hwang (2014), from identification of visible satellites and information on their current position in the Earth orbit, the directions on which there is a clear

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