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User context recognition using smartphone sensors and classification models

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ABSTRACT

Context recognition is an indispensable functionality of context-aware applications that deals with automatic determination and inference of contextual information from a set of observations captured by sensors. It enables developing applications that can respond and adapt to user's situations. Thus much attention has been paid to developing innovative context recognition capabilities into context-aware systems. However, some existing studies rely on wearable sensors for context recognition and this practice has limited the incorporation of contexts into practical applications. Additionally, contexts are usually provided as low-level data, which are not suitable for more advanced mobile applications. This article explores and evaluates the use of smartphone's built-in sensors and classification algorithms for context recognition. To realize this goal, labeled sensor data were collected as training and test datasets from volunteers' smartphones while performing daily activities. Time series features were then extracted from the collected data, summarizing user's contexts with 50% overlapping slide windows. Context recognition is achieved by inducing a set of classifiers with the extracted features. Using cross validation, experimental results show that instance-based learners and decision trees are best suitable for smartphone-based context recognition, achieving over 90% recognition accuracy. Nevertheless, using leave-one-subject-out validation, the performance drops to 79%. The results also show that smartphone's orientation and rotation data can be used to recognize user contexts. Furthermore, using data from multiple sensors, our results indicate improvement in context recognition performance between 1.5% and 5%. To demonstrate its applicability, the context recognition system has been incorporated into a mobile application to support context-aware personalized media recommendations.

1. Introduction

Mobile phones, with increasingly better processing capabilities, have become personal computing and communication devices for billions of users across the world (Minh et al., 2011). The new generation mobile phones, also known as smartphones, are equipped with more sophisticated capabilities, such as highly functional operating systems (e.g. iOS, Android, Windows Mobile, etc.) and inbuilt sensors (Lane et al., 2010). These sensors range from GPS (for location monitoring), cameras (image and video sensing), microphones (audio or noise sensing), light sensors (illumination), temperature sensors, direction sensors (Magnetometer and Gyroscope sensors), and motion sensors (Accelerometers, Rotation sensors) (Milette and Stroud, 2012; Kwapisz et al., 2010). These smartphone built-in sensors produce events that can be explored to recognize user's activities and contexts automatically to enable the development of more powerful, responsive, intelligent, and adaptable mobile applications capable of providing user's ambient and social awareness (Guo et al., 2013; Figo et al., 2010; Lane et al., 2010; Kwapisz et al., 2010; Yang, 2009; Kawahara et al., 2007; Himberg et al., 2001). Context recognition as a subset of a broader context-aware and ubiquitous computing uses machine-learning techniques to learn patterns of user's behaviors or situations (Minh et al., 2011; Davies et al., 2008; Randell and Muller, 2000). It then uses these learned patterns to induce predictive models to recognize user's current or future contexts. The observations collected by sensors are fed as inputs to the machine-learning algorithms to extract the learning instances, their feature values and classes. The contexts to be recognized are classes and the learning techniques (machine learning algorithms) produce the classification models (Ortiz Laguna et al., 2011).

Given that the majority of work conducted in this area focus on using wearable sensors (Gjoreski et al., 2010; Ravi et al., 2005; Miluzzo et al., 2008; Mase, 2002; Clarkson et al., 2000; Randell

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and Muller, 2000), the outcomes have so far fostered little understanding of how to use these sensors to build practical context-sensitive and adaptive mobile applications. Apart from being discomforting to carry around on one hand, building real-time context-aware applications with these wired sensors has not been fully realized because of their intrusiveness, placing additional burden on users (Dernbach et al., 2012; Kwapisz et al., 2010). On the other hand, smartphone built-in sensor systems offer natural advantages over wearable systems because they are not intrusive. They require less intervention from users than their wearable counterparts (Milette and Stroud, 2012). More importantly, they are now more affordable and have become primary computing platform for over a billion users with a forecast projecting one third of world population becoming smartphone users by 2018 (E-Marketer, 2015). Nevertheless, like the wearable sensors, smartphone built-in sensors produce low-level data, which is a major drawback. These low-level data, in their raw form, are not suitable for mobile applications because they do not provide high-level contextual information from which user's contextual situations can be correctly inferred.

In this paper, we investigate the use of smartphone built-in sensors to collect low-level contextual data and the use of supervised machine-learning (ML) algorithms to infer meaningful high-level contextual information from those low-level data. The goal is to take advantage of mass-marketed smartphone built-in sensors, particularly those sensors not explored by previous studies, to identify important user daily activities and contexts. The article also investigates and evaluates various classification techniques for gleaning context information from low-level smartphone built-in sensor data. This information can be used to build adaptive ubiquitous applications, such as personalized mobile multimedia recommendation systems (see Fig. 1, the functional architecture of this type of system, utilizing activity contexts for personalized content recommendations). Such application requires that user's content consumption history and corresponding contexts be registered while conducting her daily routines. In practice, it requires that an activity/context-based user profile (Contextual user profile management) is developed for registering content consumptions of users (i.e., their preferences), together with the contexts in which those consumptions have occurred. Such user profile enables the application to generate context-aware recommendations. For example, from her context usage history, if it is known that a user likes to watch drama movies with her friends every weekend, and that she enjoys listening to pop music when jogging, the system should be able to suggest movies that are interesting and relevant to the user considering her friend' interests or it should be able to provide her with interesting pop music while she is jogging (recommendation management). Other functions of such systems include recommendation presentation management, adaptation management (for tailoring recommendations to the characteristics of the smartphones), media profile management for filtering candidate media content, user feedback management for learning user feedback in other to improve the relevance of future recommendations.

The present work is an integral part of our broader research agenda in context-aware personalized multimedia recommendations in mobile environments (CAMR) (Otebolaku and Andrade, 2015). The goal of CAMR is to explore research issues related to context-aware personalization to build multimedia content recommendations for mobile users. In this article, however, our focus is to investigate how to use smartphone sensors to capture sensor data and consequently process it to derive high-level contextual information, which can be used to learn mobile user's multimedia preferences. Identifying this type of contextual situation, which we also refer to as user's activities, from smartphone sensor data for this type of application has not yet been fully explored.

In our investigation, Android based devices (such as the Samsung Galaxy S4 in Fig. 2, showing examples of inbuilt sensors that ship with such smartphones) were selected as the mobile platform of choice (Minh et al., 2011). Although the process can be adapted for use in other mobile platforms, we chose Android as our experimental platform because Android provides greater flexibility in terms of programming. Coupled with being open source, Android has become the dominant platform in the mobile phone markets. According to Gartner forecast (Gartner Report, 2015), over 1.1 billion of Android smartphones were sold in 2014. Accordingly, we developed an Android-based application called Context Data Collector (CDC) that interacts with various built-in sensors to acquire low-level contextual data. These data were further processed to evaluate various predictive models' capabilities to recognize user's contextual activities, using a set of popular classification algorithms.

In addition to identifying suitable classification algorithms for context/activity recognition, this work also analyzes the influence of window lengths on their performances. Unlike existing studies (Kwapisz et al., 2010; Himberg et al., 2001; Ravi et al., 2005; Sánchez et al. 2008; Bao and Intille, 2004; Casale et al., 2011; Siirtola and Röning, 2012; He and Jin, 2009) that rely on only accelerometers as the source of low-level context data, our work investigates additional source of smartphone sensor data, such as orientation and rotation to show their capabilities for accurate recognition of mobile user contexts. Finally, various time domain features were evaluated, aiming at identifying and isolating redundant and ineffective features that are not suitable for encoding the contextual data into the predictive models.

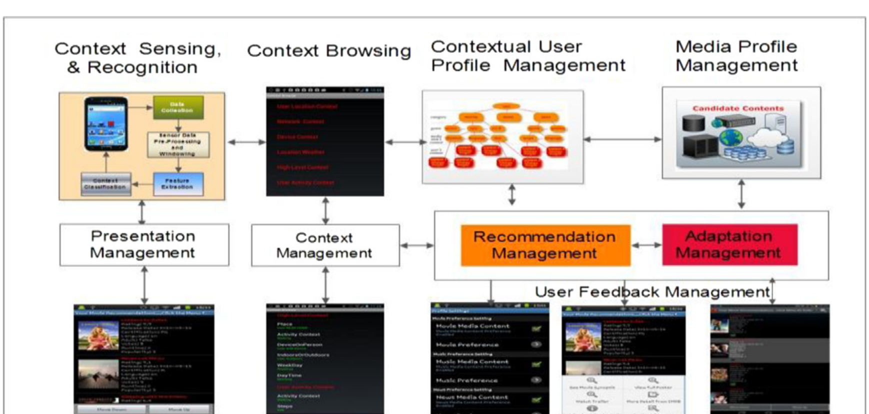

Fig. 1. High-level architecture of a system using the result of work described in this article.