



Computational Neuroscience

Hand, belt, pocket or bag: Practical activity tracking with mobile phones

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HIGHLIGHTS

- We use the output of a support vector machine as input to a hidden Markov model to improve accuracy.
- We make simultaneous predictions of a person's activity and how the phone is worn.
- Method successfully applied to people with Parkinson's disease.
- Wearing the phone in a pocket or belt results in the most accurate activity tracking.
- Walking is the best activity to predict how the phone is worn.

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ABSTRACT

For rehabilitation and diagnoses, an understanding of patient activities and movements is important. Modern smartphones have built in accelerometers which promise to enable quantifying minute-by-minute what patients do (e.g. walk or sit). Such a capability could inform recommendations of physical activities and improve medical diagnostics. However, a major problem is that during everyday life, we carry our phone in different ways, e.g. on our belt, in our pocket, in our hand, or in a bag. The recorded accelerations are not only affected by our activities but also by the phone's location. Here we develop a method to solve this kind of problem, based on the intuition that activities change rarely, and phone locations change even less often. A hidden Markov model (HMM) tracks changes across both activities and locations, enabled by a static support vector machine (SVM) classifier that probabilistically identifies activity–location pairs. We find that this approach improves tracking accuracy on healthy subjects as compared to a static classifier alone. The obtained method can be readily applied to patient populations. Our research enables the use of phones as activity tracking devices, without the need of previous approaches to instruct subjects to always carry the phone in the same location.

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1. Introduction

Activity tracking uses wearable sensors, combined with computer algorithms to quantify what we are doing during our everyday lives. Such tracking has been applied to ambulatory monitoring (Albert et al., 2012b; Mathie et al., 2004) and automatic fall detection (Albert et al., 2012a; Kangas et al., 2008; Lee and Carlisle, 2011) to inform clinical providers about patient activity at home and in the community. Precise, objective measures of patient

activity can be used to create, modify, and evaluate individualized treatment plans to improve a patient's outcomes and quality of life.

There are not many ways of evaluating patient mobility in everyday life. For clinical evaluations the patient needs to travel to the health care provider, and testing there is expensive in terms of money and clinician time. This cost prohibits frequent evaluations. Consequently, most prospective studies use patient journaling. However, such self-reporting is associated with various problems. First, the approach is necessarily subjective, leading to changes based on the mental state of the subject. Journaling can also have low compliance rates, in some cases as low as 11% (Stone et al., 2003). It would be helpful to develop a measure of evaluating patient mobility that is both frequent and convenient for the subject.

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Few studies have applied activity tracking systems to people with neurodegenerative diseases. In a study involving patients with Duchenne muscular dystrophy, a single monitoring device worn on the chest reliably quantified walking parameters and time spent performing different activities (Jeannot et al., 2011). Patients with Parkinson's disease wore three body-fixed inertial sensors which were used to accurately identify activities including walking, sitting, standing, lying, sit to stand, and stand to sit transitions (Salarian et al., 2007). It has also been shown that a mobile phone placed in a pocket can be used to recognize activities in people with Parkinson's disease (Albert et al., 2012b). Each of these systems can quantify physical activity, but they require participants to wear sensors in a fixed location, and generally wearing more sensors leads to more accurate tracking (Bao and Intille, 2004). However, wearing sensors can be a burden to the wearer and not practical for everyday use.

Mobile phones have become a practical and popular activity tracking platform because people are accustomed to carry phones on a daily basis. This makes data easier to collect as compared to custom tracking systems. In addition, mobile phones eliminate the need to design custom hardware, because they have built in sensors, memory, and computing power. Furthermore, software creation and distribution are easier because open source tools allow anyone to create applications and deploy them on mobile phones. Thus, mobile phones conveniently contain all of the hardware and software capabilities to create a stand-alone activity tracking system, with the practical benefit that people wear them every day.

Most activity tracking studies using mobile phone accelerometers instruct their participants to wear the phone in a predetermined location and orientation, the most common location being the pocket (Bieber et al., 2009; Kwapisz et al., 2010; Lau and David, 2010). In everyday life, however, people wear their mobile phones in many different ways. In a cross cultural study on phone carrying, 60% of men carried the phone in their pocket while 61% of women carried the phone in their bag (Cui et al., 2007). The next most common locations were the belt clip, upper body, and hand. Instructing people to wear their phone in a specific location disregards their motivations for why they prefer carrying the phone in a particular way, such as ease of carrying, comfort, or fashion. For people with any type of movement disorder, restrictions for how they carry the phone can limit compliance, and consequently both the quality and amount of data collected by the tracking system. To

be both accurate and practical, we must ensure our classifiers work when the phone is worn in different ways.

Here we track activities and phone locations using support vector machines (SVM), a hidden Markov model (HMM), and the idea that activities change rarely, and the location of the phone changes even less often. This idea is made explicit through the HMM with an appropriately constructed transition matrix. Previous work in speech and activity recognition has shown improved prediction accuracy when combining SVMs and HMMs (Ganapathiraju et al., 2000; Lester et al., 2005; Yang, 2009). Incorporating time and transitions into our model improves activity and location tracking accuracy by smoothing out temporal irregularities. With this model, we conduct several analyses to understand the impact of phone location on tracking accuracy, and which phone locations are best for activity tracking. We then use this model in a pilot study to continuously track activities for two people with Parkinson's disease. By improving tracking accuracy when the phone is worn in multiple locations, people using activity tracking can wear their phone, however, they like.

2. Materials and methods

2.1. Protocol

Experimenters guided twelve able-bodied subjects (29.25 ± 6.27 years, mean \pm SD) through a predetermined sequence of activities (see Fig. 1). When prompted, subjects would walk, sit, or stand, and periodically change how they were wearing the phone. For each sequence of activities, the subject wore a phone in a different location: either in their pocket, in a belt clip, in their hand, or in a bag. Sit to stand and stand to sit transitions were included as activities to capture transitory states. The sequence was created to include as many transitions and locations as possible, while also leaving enough time for the person to perform each activity naturally. We used a T-Mobile G1 phone with a built in tri-axial accelerometer capable of measuring $\pm 2.8g$ and operating on Android 1.6 OS. Accelerations were recorded using a custom Android application with a sampling rate between 15 and 25 Hz depending on the movement speed (Fernandes et al., 2011). The experimenter used a stopwatch to ensure each activity was performed for a minimum amount of time, and accelerations were recorded continuously for the entire experiment. This study was

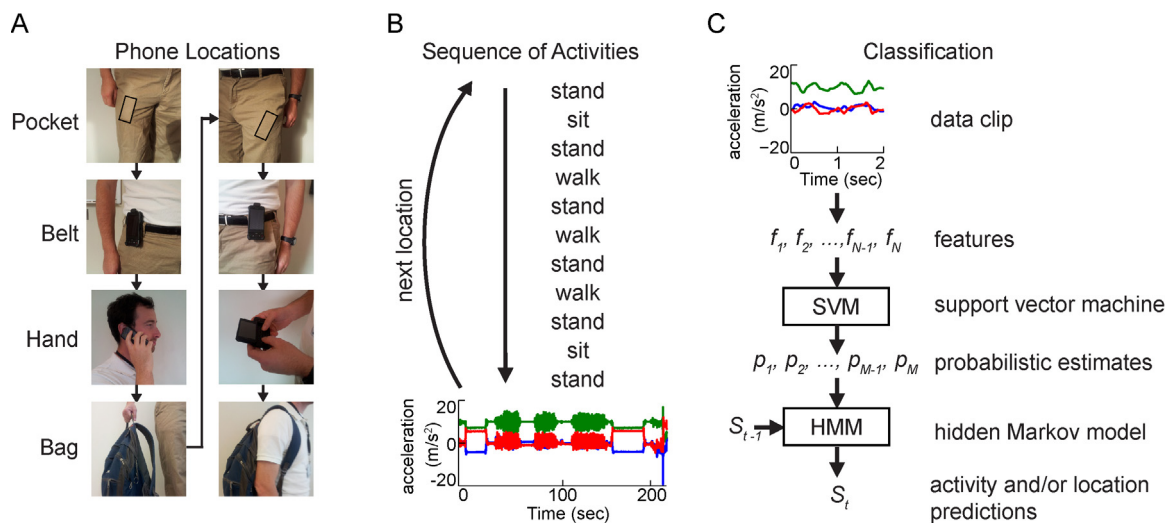


Fig. 1. Experimental protocol and analysis. (A) Subjects carried a mobile phone in their pocket, belt, hand, or bag and (B) performed a predetermined sequence of activities. After performing one full sequence of activities, the subject moved the phone to the next phone location. (C) Data processing pipeline. Accelerometer data was divided into clips that were two seconds long and features were calculated for each clip. The SVM used the features to make probabilistic estimates of the activity and/or location. These estimates were then smoothed over time using an HMM to predict the most likely activity and/or location.

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