Recognizing Activities from Mobile Sensor Data: Challenges and Opportunities

A.J. Bernheim Brush, John Krumm, James Scott, and T. Scott Saponas
Microsoft Research
{ajbrush, jckrumm, jws, ssaponas}@microsoft.com

ABSTRACT
Mobile sensing data is frequently used to infer a user’s current activity. We argue that while past research on activity recognition has had some notable successes, there are a number of challenges that the community needs to tackle. In particular, establishing an agreed on set of activities would help ensure researchers are collecting and labeling ground truth data in a standard way, make it easier to share data, and compare different recognition algorithms. We also believe it is time to stop focusing primarily on classification accuracy as a measure of success, because the use of the activity recognition results determines the relative importance of accuracy compared to other factors such as computation speed or energy required.

Author Keywords
Activity recognition, mobile devices.

INTRODUCTION
Successfully inferring people’s activities from mobile sensor data enables a wide range of pervasive computing applications. Recent research on activity recognition has demonstrated that it is possible to recognize a variety of activities such as driving, walking, and using stairs and elevators with machine learning techniques including decision trees, Bayes classifiers, and nearest-neighbor algorithms [e.g. 2,9,10,11,14,15,16,18]. Special purpose hardware, such as the Multi-modal Sensor board (MSB) [20], built by researchers at Intel Research Seattle and University of Washington, has enabled exploration of the value of different sensors in inferring activities. Some end-to-end applications using activity recognition have also been developed (e.g. 5, 17).

While we are inspired by existing research, we believe there are steps we can take as a community to enable future breakthroughs that are robust and reproducible. The arguments made in this paper are refinements of ones we presented in [3] and were inspired by our past research. In particular, collecting and sharing GPS data [12], trying to leverage past research when building a mobile activity-based navigation prototype [4], and ongoing work on a human activity recognition system that utilizes a person’s entire computing infrastructure from mobile devices to the cloud [19].

CHALLENGES & OPPORTUNITIES
Given that activity recognition is a relatively young field of research, here are three challenges that are opportunities for improving activity recognition research.

Standardize a Set of Activity Definitions
Currently, there is no standard taxonomy of activities used by researchers. The closest taxonomy is the Activities of Daily Living [1], but these are very general. For example “Moving Around” rather than the types of specific activities researchers have been trying to recognize (e.g. walking, running, going up stairs). Having a shared set of activities and definitions would help ensure that researchers are collecting and labeling ground truth data in a standard way.

In addition, there is typically no common sense reasoning about activities. For example, I’m unlikely to be driving and riding a horse at the same time or brushing my teeth while walking. Lastly, there are no agreed on prior probabilities for activities. The probability that a person is watching television is likely much greater than the probability he or she is fixing a car.

To address this problem, as a community we could define a simple set of activities, which could be augmented and expanded as necessary. Have shared definitions would help us exploit existing common sense reasoning work like the Cyc project [6] to make taxonomies of activities. For example, TV watching might be a subset of relaxing. Similarly, a valuable research contribution would be to discover and catalog probabilities surrounding activities. These include simple priors (e.g. watching television is generally more probable than fixing a car), conditionals (e.g. given a local time of 3 a.m., sleeping is more probable than being awake), and Markov sequences (e.g. after riding a bus, walking is more probable than flying).

Enhance Reproducibility & Clarity
Second, in our experience, it is difficult to build on past work and leverage classifiers others have trained. This is particularly important for researchers interested in building prototypes that could leverage activity recognition. They may not be interested or have the machine learning skills to advance basic research in activity recognition. We
recognize there are many potential hurdles to sharing classifiers and algorithms, including concerns about intellectual property. However, asking each group that wishes to use activity recognition to reinvent the algorithms or recreate classifiers that have been mentioned in research papers strikes us as counter-productive. We would be interested in exploring how fundamental building blocks of activity recognition could be made more widely available to the research community.

A simpler first step may be to share the annotated sensor data that have been used to train and validate activity recognition algorithms. While some researchers have made the effort to provide datasets that other researchers can use (e.g. 7, 8, 12, 13), having a standard format for shared data (e.g. ground truth labels from defined activities, raw sensor data, features computed) would allow people to test their own activity recognition algorithms on much larger datasets. We are excited by work of the Human Activity Sensing Consortium [7], which collected data from 500 participants in their 2010 challenge and shares the collected data with people that contribute to the data corpus. A “grand challenge” contest for applications in a particular domain (e.g. healthcare, eldercare) that use activity recognition and provided labeled data to train from and test with might also encourage innovation.

**Evaluate Activity Recognition in a Usage Context**

Third, evaluations of activity recognition algorithms and systems often only include a discussion of how the algorithms will be used with toy applications. While identifying the set of activities that can be recognized was critical initially, as the field matures, it is important that we start focusing on how activity recognition will be used. For example, an algorithm that infers motion from accelerometer data to determine appropriate times to query the GPS to minimize energy used likely has different accuracy requirements than a health application that is tracking steps taken. More generally, the “correct” activity that should be inferred from sensed data likely also depends on the application. A life logging application may include the time spent stopped at a traffic light as part of a “driving” activity, while a notification application might infer that you are “stopped” and it is okay to interrupt you.

**CONCLUSION**

Research on activity recognition from mobile sensor data enables a wide range of pervasive applications. Working together as a community will help increase the impact of future research in activity recognition.

**REFERENCES**


