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Movement pattern recognition through smartphone's accelerometer

Armir Bujari, Bogdan Licar, Claudio E. Palazzi

Institutions: University of Padua

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Movement Pattern Recognition through Smartphone's Accelerometer

Armir Bujari, Bogdan Licar, Claudio E. Palazzi
Università degli Studi di Padova
Padova, Italy
Email: abujari@math.unipd.it, cpalazzi@gmail.com

Abstract—**Sensor-enabled smartphones have become a mainstream platform for researchers due to their ability to collect and process large quantities of data, hence creating new opportunities for innovative applications. Yet, the limits in employing sensors to opportunistically detect human behaviors are not clear and deserve investigation. To this purpose, in this article, we discuss movement pattern recognition in day-by-day urban street behavior. As a case study, we restrict at recognizing situations when a pedestrian stops, crosses a street ruled by a traffic light; to do so we only use data coming from the accelerometer of the pedestrian's smartphone.**

Keywords-smartphone; pattern; accelerometer; sensing;

I. INTRODUCTION

An important goal in mobile computing is the ability to sense and react based on the environment (i.e. context awareness) [1]-[3]. In the past years, a lot of researchers have been focusing on movement pattern recognition with the aid of solely accelerometers, especially since the last generation of smartphones all equip precise and reliable accelerometers (along with gyroscopes and compasses as well). For example, several activities such as ambulation, typing, talking were identified in [4] with five small bi-axial accelerometers. Even applications for physical rehabilitation have been proposed based on using the smartphone's movement sensors to verify the correct execution of a therapy (e.g., for wrist rehabilitation [5]). In [6] and [7], daily activities of standing, walking, climbing up/down stairs and brushing teeth, were analyzed based on the data collected from accelerometers. In this context, the work done in [8], probably represents the current state of the art in identifying single isolated activities for it reports the highest accuracy.

However, to enable a wide set of possible operations it is interesting to study whether smartphones' accelerometers could be used to detect more complex and combined actions, not just single ones. To this aim, in this article we analyze more complex human actions, specific urban-related activities such as stopping at red lights and going across roads on green light. The feasibility of recognizing certain specific human movements and complex actions with the help of the sole accelerometer represents a technical challenge that deserves investigation.

Accelerometers detect translational motion, which makes, for instance, recognizing left/right turns an impossible task. So we focused exclusively on the magnitude of the acceleration vector, trying to extrapolate information that could be identified with a pattern.

Of course stopping at a red light and then continuing walking is not different, from the accelerometer point of view, than randomly stopping on the street to ask directions, look at a shop-window or saying hi to a friend. Therefore whichever method one chooses, there will always be false positives, and our approach attempts to address this issue and limit the occurrence of false positives with careful threshold selections.

The rest of this paper is organized as follows. In Section II we present a possible application that could benefit from our method for road crossing recognition. Section III and Section IV overview how we collect and process data, respectively. In Section V we discuss our basic pattern recognition method, whereas possible technical improvements are discussed in Section VI. Finally, in Section VII conclusions are drawn.

II. ROAD CROSSING RECOGNITION: A CASE STUDY

The horizons in human behavior recognition based on smartphones' sensors can be pushed further by devising innovative useful applications based on them. In the era of Web 2.0, with the approaching Web Squared advent [9], more can be done that can be beneficial for the society as a whole. Data generated by a multitude of users could produce results that are more valuable than the sum of those achievable by individuals [10]. Even better, information automatically generated by sensors available on smart phones may integrate the data generated by the community of players, producing new intelligence [11].

As a demonstration of this statement, we have imagined how an application based on smartphones' sensors could help users with sight impairments. In particular, we noticed that a very useful Web 2.0 tool such as Google Maps provides routes for cars and pedestrians but with no information about the accessibility of the path for users with sight impairments. Instead, it would be interesting to integrate in the route search also information about the presence at crossroads of traffic signals with audible signals as shown by Fig. 1.

Figure 1 – An accessible path generator.

This new functionality requires the existence of a database of about each traffic light at each crossroads. Unfortunately, this database does not exist and cannot be created by just hiring somebody to verify all crossroads and populate the database: it would be too time consuming and too expensive.

Instead we could utilize the massive presence of smartphone's in our cities and exploit their sensors to pervasively collect related data. In essence, the microphone of smartphone's could be used to record the noise around traffic lights which will then be sent to a remote server (or cluster of servers) along with GPS coordinates. All recorded audio files will be processed by the remote server(s) to detect audible signals and possibly utilized to compose the aforementioned database. However, a smartphone cannot continuously record and transmit audio files. A solution is needed to know when a users is close to a traffic light and only in that case activate the microphone. To this aim, our proposed technique could embody the ideal solution: a method to detect when the user is crossing a street by exploiting the smartphone's accelerometer.

III. DATA COLLECTION

Data collected from the accelerometer have the following attributes: acceleration along *x* axis, acceleration along *y* axis and acceleration along *z* axis.

The tests were performed by three subjects in different days while performing the following actions with the smartphone in the pocket:

- walking at regular speed;
- stopping at a red light and going across the road at slightly higher speed on green light and then
    - continuing straight forward or turning left/right;
- walking again at regular speed.

We focused on three main activities: walking at regular speed, standing/sitting, walking at slightly higher speed. In the next section we discuss in detail our pattern choices. For this particular tests an iPod Touch 2G tri-axial accelerometer was used with a 30 Hz data rate.

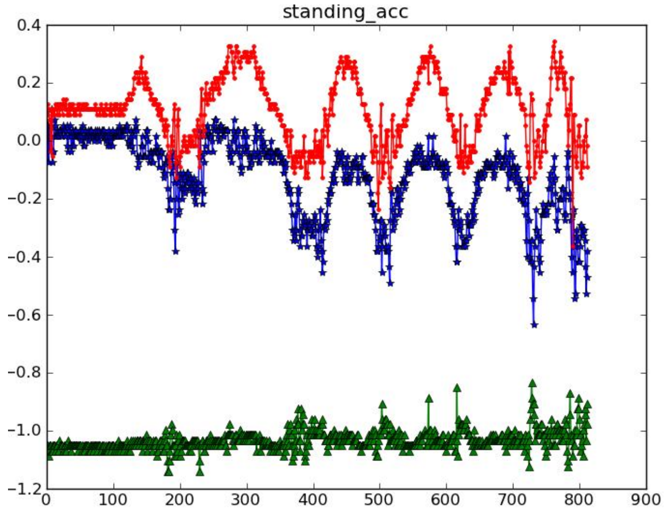

Figure 2 - User standing: XYZ coordinates of the 2G tri-axial accelerometer.

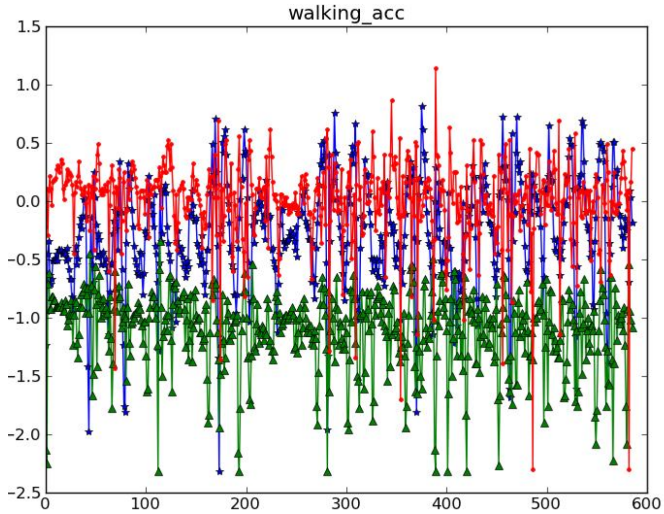

Figure 3 - User walking: XYZ coordinates of the 2G tri-axial accelerometer.

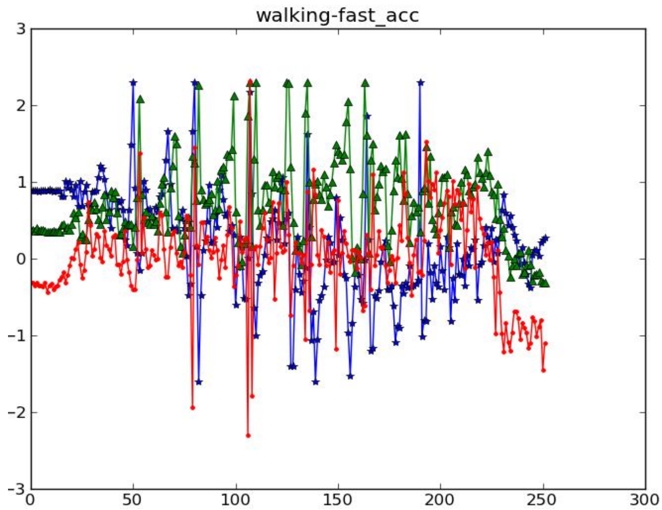

Figure 4 - User standing: XYZ coordinates of the 2G tri-axial accelerometer.

The results of the various activities recorded are showed in Fig. 2, Fig. 3, and Fig. 4 (x-axis in blue, y-axis in green, z-axis in red). The data was logged and then subsequently analyzed off line.

IV. DATA PROCESSING

A. High-pass Filter

A high-pass filter was applied on the collected raw data, in order to obtain only higher values which are the most representative for movements. Thus, we obtained smoother acceleration values to work on, which allow better results than with just raw data.

$$rollx_j = (x_j \times k) + (rollx_{j-1} * (1.0 - k)) \quad (1)$$

$$x_j = x_j - rollx_j \quad (2)$$

with k an appropriate constant. The low-pass value is subtracted from the current value to get a simplified high-pass filter. An example of the filtered data is shown in Fig. 5.

Data features

Additionally, rather than working on three different vectors (x, y, z), we chose to join the three axes into one single vector.

The main reason for doing so is that we do not want to have to discriminate among the various position that a smartphone can have with respect to the user's body (in her/his hand or pocket, etc.). For each acceleration vector its magnitude was computed through (3).

$$magnitude(v) = |v| = \sqrt{v.x^2 + v.y^2 + v.z^2} \quad (3)$$

Using (3) we can have data independent from the smartphone's placement - e.g., it also works when the user holds it in her/his hand. In Fig. 6 the magnitude of the regular walking is shown.

Furthermore, along with the magnitude of the acceleration vector, the mean and the standard deviation of the magnitude array was computed, encoding a set of magnitudes as an instance of {mean, standard dev}.

V. PATTERN RECOGNITION

In the rest of this section we detail on how the pattern recognition process is performed, trying first to recognize all positive scenarios by further improving the method to filter out false positives.

A. Recognizing all positives

Initially, in order to achieve a high-accuracy recognition of the human behavior when encountering a red light, we chose to risk false positives, rather than having false negatives. The main idea was to monitor the speed of movement before, during and after a red light. All test subjects reported the following pattern:

- walk at regular speed toward the light;
- stop and wait the necessary time;
- go across the road at increased speed;
- restore normal speed when finished crossing.

As a matter of fact, this was the only pattern that could be extrapolated with the tri-axial accelerometer. Thus we concentrated exclusively on speed (more precisely on step frequency and intensity) variations.

The results of this recognition pattern are heavily influenced by the assumption that when crossing a road, pedestrians tend to accelerate their walking. So, given that this assumption could be observed in the 90% of the cases logged, this pattern returned an 80% accuracy. This can be easily improved by a better analysis of the variations of speed: dynamically recognizing the subjects' regular speed and thus easily adapt the threshold when the walking speed increases. An easy way to achieve this is to previously train the application when performing these activities.

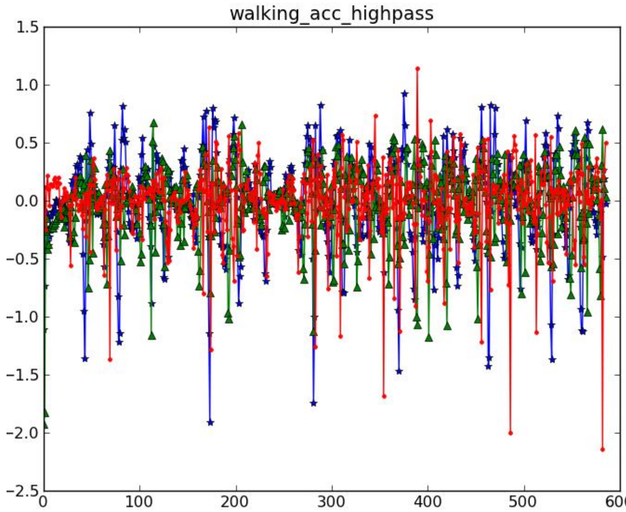

Figure 5 – User walking: high-pass filter on XYZ coordinates.

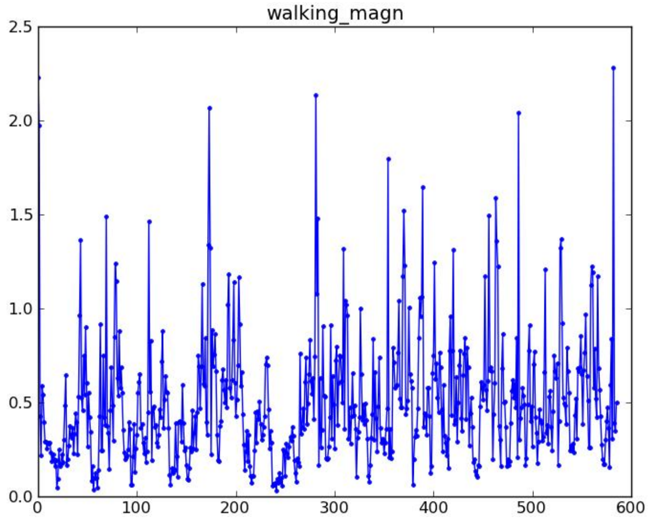

Figure 6 – User walking: sensing magnitude.

B. *Excluding false positives*

This main pattern can be recognized in other activities that have nothing to do with our object of study, hence the false positives mentioned before. The other parameter that the accelerometer returns is time, therefore we employed it for inserting an additional step in the pattern: the duration of the road crossing. After performing tests on different kind of urban streets, a maximum duration of 4-7 seconds was identified. An example of sensing the outcome for user behavior when stopping at a red light and then crossing the street is provided in Fig. 7.

The flow of pattern logic is better sketched as follows:

```
if started_fast_move and ended_stand_still:
        t0 = TIME

if ended_fast_move and started_regular_move:
        if (TIME - t0) > 4seconds
        and (TIME - t0) < 7seconds:
                print "crossed road"
        else:
                t0 = 0
```

In other words a time filter was applied to exclude all actions that resemble the studied one, but have different durations. New tests were performed with the revised pattern, in order to verify the false positives percentage that was captured. In a 30 minutes urban walk, while performing different actions similar to the red light behavior, the positives recognition percentage remained unaltered, whereas the false positive ones dropped to 50% of the cases.

VI. IMPROVEMENTS AND RESULTS

In the following subsections we discuss results achieved by the final version of our solution.

A. *Preliminary Training*

Results can be slightly improved individually by adapting the thresholds after a preliminary training phase for each subject - due to the obvious difference in walking speeds in different subjects. The preliminary training phase can be replaced by a dynamic speed recognition, which assumes that most of the time the subject walks at his/her regular speed.

Automatic threshold setting: In order to achieve this, a function monitors the magnitude of the acceleration vector and after a set amount of time, it automatically updates the thresholds to new values specific to the subject. The faster walking threshold is set to twice as the regular walking one.

$$walkThresh = getMean(walkVectorArray) - 0.1 \qquad (4)$$

And we can compute the following approximated thresholds:

$$fastWalkThresh = walkThresh \times 2 \qquad (5)$$

$$standThresh = \frac{walkThresh}{2} - 0.5 \qquad (6)$$

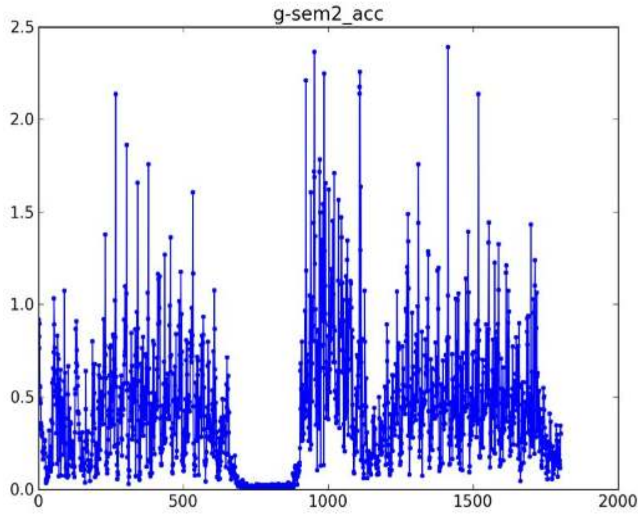

Figure 7 – Example of accelerometer outcome for red light behavior.

These equations are extracted from tests performed on different subjects and for our preliminary studies were quite accurate. But for more accurate results, a training also for fast walking and standing would be necessary.

B. *Results*

As far as the positives rate is concerned, the results are somewhat limited by the unpredictable human behavior: 2- 3 times out of 10 the pedestrian does not accelerate when crossing or does not slow down after crossing. These cases cannot be covered by our pattern.

False positives have a high rate, because of the high frequency of similar behavior in different situations. Therefore, although we tried to obtain results as more independent from human unpredictability as possible, the process and the results are heavily influenced by it; furthermore we believe that an accelerometer-based approach will always have to deal with randomness.

In Fig. 8 the evolution of the positive/false positive rates are shown throughout the process of this research.

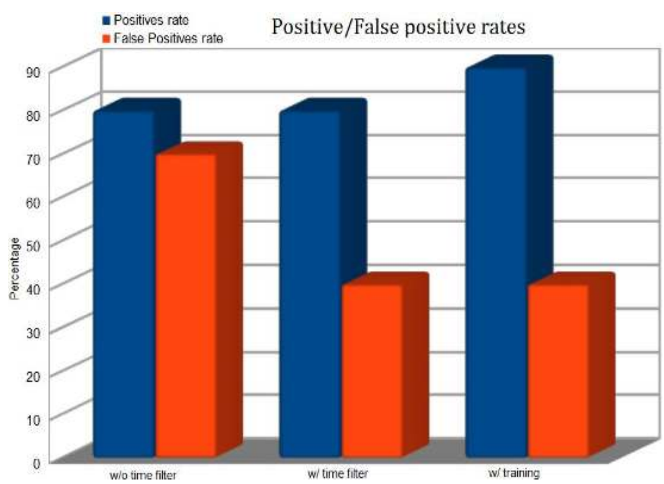

Figure 8 – Positive vs. False positive rates.

VII. CONCLUSIONS AND FUTURE WORK

Sensor-enabled smartphones have made possible the collection of large quantities of data which could help discover patterns in user behavior. To this purpose, in our work, we proposed a case study, which aims at recognizing movement patterns for pedestrians crossing streets ruled by traffic lights. This obtained knowledge could then be used to enhance well known products such as Google Maps, providing new features which are to benefit the community.

To do so we used data coming only from the accelerometer of the pedestrian's smartphone. This proved very challenging as it involved dealing with complex actions which inevitably lead to an increase of false positives. The methods applied for the recognition process considered different filters based on solely threshold settings, however, this process proved beneficial.

For future works, we aim to integrate more reliable data classifiers, for instance, the integration of SVM techniques in our solution could prove more robust [12, 13]. We have also already done some preliminary test with machine-learning base-classifiers such as Naive Bayes, RFB, KStar [14, 15]; so far, they guaranteed high accuracy for recognizing isolated actions, but they did not significantly help yet with the overall complex behavior we are interested in.

REFERENCES

[1] M. Roccetti, A. Semeraro, G. Marfia, "On the Design and Player Satisfaction Evaluation of an Immersive Gestural Game: the Case of Tortellino X-Perience at the Shanghai World Expo", in *Proc. of the 29th ACM International Conference on Design of Communication (ACM SIGDOC 2011)*, Pisa (Italy), ACM, Oct 2011.

[2] M. Roccetti, G. Marfia, M. Zanichelli, "The Art and Craft of Making the Tortellino: Playing with a Digital Gesture Recognizer for Preparing Pasta Culinary Recipes", *ACM Computers in Entertainment*, ACM, Vol. 8, N. 4, Dec 2010.

[3] M. Roccetti, G. Marfia, "Recognizing Intuitive Pre-defined Gestures for Cultural Specific Interactions: An Image-based Approach", in *Proc. of the 3rd IEEE International Workshop on Digital Entertainment, Networked Virtual Environments, and Creative Technology (DENVECT'11) - 8th IEEE Communications and Networking Conference (CCNC 2011)*, Las Vegas (USA), IEEE Communications Society, Jan 2011.

[4] L. Bao, S. S. Intille, "Activity Recognition from User-Annotated Acceleration Data", in *Proc. of PERVASIVE 2004*, Linz, Vienna, Austria, Apr 2004.

[5] D. Deponti, D. Maggiorini, C. E. Palazzi, "DroidGlove: An Android-Based Application for Wrist Rehabilitation", in *Proc. of the IEEE International Workshop on Ubiquitous Multimedia Systems and Applications (UMSA'09) - International Conference on Ultramodern Telecommunications (ICUMT 2009)*, St. Petersburg, Russia, Oct 2009.

[6] J. Mantyla, J. Himberg, T. Seppanen, "Recognizing Human Motion with Multiple Acceleration Sensor", in *Proc. of IEEE International Conference on Systems*, Man and Cybernetics, Tucson, AZ, USA, Oct 2001.

[7] N. Ravi, N. Dandekar, P. Mysore, M.L Littman, "Activity Recognition from Accelerometer Data", in *Proc. of the 17th Innovative Applications of Artificial Intelligence Conference*, Pittsburgh, PA, USA, Jul 2005.

[8] Z. He, L. Jin, "Activity Recognition from Acceleration Data Based on Discrete Consine Transform and SVM", in *Proc. of the 2009 IEEE International Conference on Systems, Man, and Cybernetics*, San Antonio, TX, USA, Oct 2009.

[9] T. OReilly, J. Battelle, Web Squared: Web 2.0 Five Years on, [Available online] http://www.web2summit.com/web2009/public/schedule/detail/10194

[10] S. Ferretti, M. Furini, C. E. Palazzi, M. Roccetti, P. Salomoni, "WWW Recycling for a Better World", *Communications of the ACM*, vol. 53, no. 4, pp. 139-143, Apr 2010.

[11] C. E. Palazzi, L. Teodori, M. Roccetti, "PATH 2.0: A Participatory System for the Generation of Accessible Routes", in *Proc. of IEEE ICME 2010*, Singapore, Jul 2010.

[12] V. Vapnik, The Nature of Statistical Learning Theory, Springer, Berlin, Germany, 1995.

[13] F. Aiolli, "A preference model for structured supervised learning tasks", in *Proc. of the 5th IEEE International Conference on Data Mining (ICDM 05)*, Houston, TX, USA, Nov 2005.

[14] I. Rish, "An Empirical Study of the Naive Bayes Classifier", in *Proc. of 17th International Joint Conference on Artificial Intelligence (IJCAI 2001) - Workshop on Empirical Methods in Artificial Intelligence*, Seattle, WA, USA, Aug 2001.

[15] Y. J. Oyang, S. C. Hwang, Y. Y. Ou, C. Y. Chen, Z. W. Chen, "Data Classification with Radial Basis Function Networks Based on a Novel Kernel Density Estimation Algorithm", *IEEE Transactions on Neural Networks*, vol. 16 no. 1, pp. 225-36, Jan 2005.