Road Crossing Recognition through Smartphone's Accelerometer

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Abstract—**Sensor-enabled smartphone's are becoming a mainstream platform for researchers to collect data which could prove useful for discovering patterns in human behavior. Yet, employing sensorial data to extrapolate information is not clear and deserves investigation. In this article, we discuss movement pattern recognition in day-by-day urban street behavior. As a case study, we aim at recognizing 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

To enable a wide set of possible operations it is interesting to study whether smartphone accelerometers could be used to detect complex and combined actions. To this aim, in this article, we analyze more complex human actions related to specific urban 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 [1, 2, 3]. 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.

II. Road Crossing Recognition: A case Study

The horizons in human behavior recognition based on smartphone 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 [4], 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 [5]. Even better, information automatically generated by sensors available on smartphone's may integrate the data generated by the community of players, producing new intelligence [6].

As a demonstration of this statement, we have imagined how an application based on smartphone's 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. This new functionality requires the existence of a database of information 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 Processing

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

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.

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

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

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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. 2.

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).

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

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. 3 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}.

IV. 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.

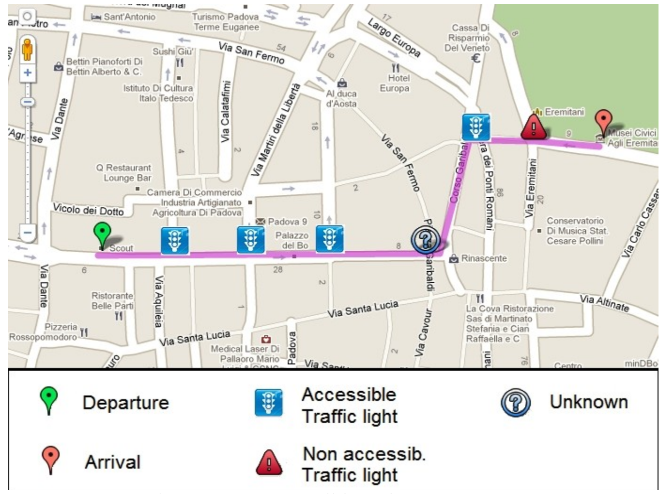

Figure 1 – An accessible path generator.

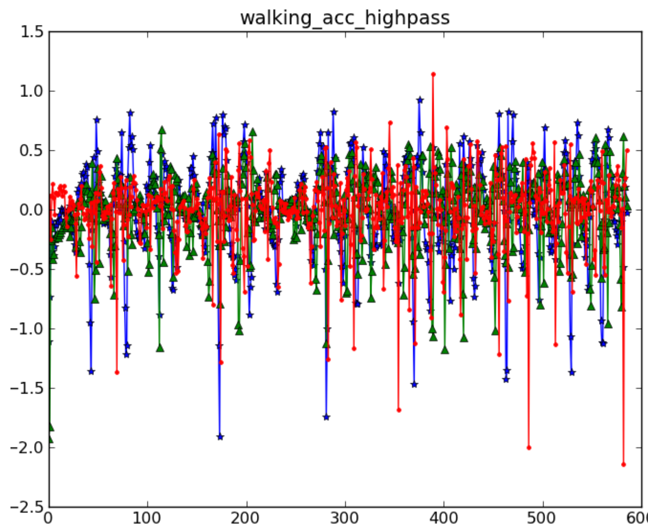

Figure 2 – User walking: high-pass filter on XYZ coordinates

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. 4.

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
```

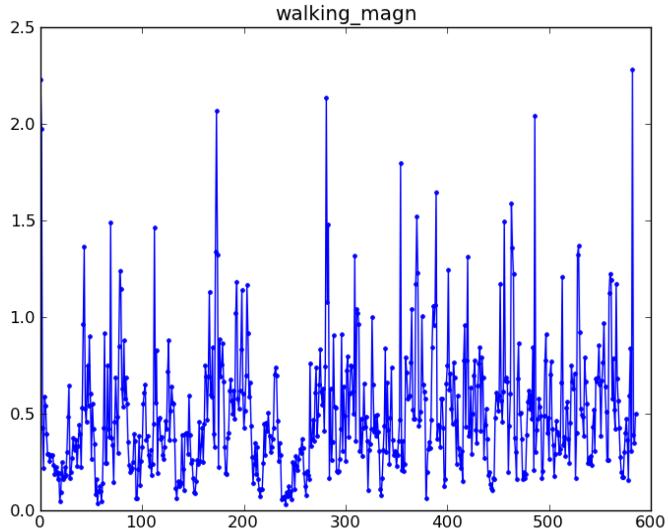

Figure 3 – User walking: sensing magnitude.

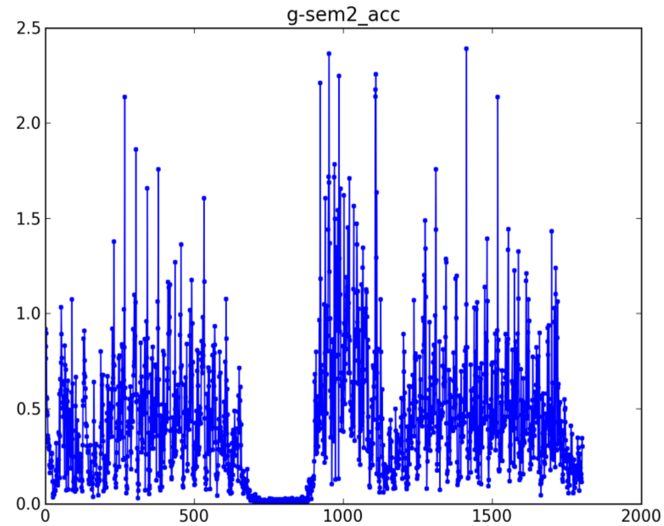

Figure 4 – Example of accelerometer outcome for red light behavior.

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.

V. 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 [7, 8]. We have also already done some preliminary test with machine-learning base-classifiers such as Naive Bayes, RFB, KStar [9, 10]; 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.

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