J-032

A Method for Grouping Smartphone Users based on Wi-Fi Signal Strength

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1. Introduction

The increasing variety of sensors in smartphones enables researchers to develop application which more accurately describe the activities [8] and or the environments in which a user may find itself at any given time. An application, that observes a group of users instead of individuals [10], falls under the category of crowd-sensing applications [1].

A Pedestrian flock is defined as a cohesive group of people walking in a certain direction for a given amount of time [3]. Pedestrian flock detection can be used for construction [9], where the determination of where and how bottlenecks form in a building can help floor planning. Additionally, the detection of flocks in real time, can be used to route people in emergency situation, avoiding the saturation of passages and exits [4].By detecting how prone a person is to join a flock, can help the advancement of social psychology applications in terms of describing the mood of a person based on this information [11].

Our method uses the Wi-Fi signal strength measurements in a time series fashion. Namely, we take the full vector of measurements and separate it in equally sized bins. Then after filtering the measurements which were below a given threshold, we proceeded to calculate the average of the Wi-Fi signal power. The resultant vectors are then compared using the cosine similarity method, which we used due to how simply it is to implement. We will specify the details of the implementation in the “methodology” section. We collected the data from 10 smartphones using an android application to collect the Wi-Fi signal strength along with the sensor data from several other modalities, to verify our method.

The paper is structured in 7 sections. The first 2 sections, introduction and background, summarize the content of this paper and describe the necessary concepts, respectively. Section 3 shows the method we used to analyse the Wi-Fi signal strength and describe the experiment we had to do for collecting the data. Section 4 displays the result for a couple of the scenarios from the experiment and section 5 shows related work on this research topic. Finally, in section 6 we draw some conclusions from the experiment and the results and in section 7 we state what our future work will consist about.

2. Background

Our method for grouping smartphones users according to the Wi-Fi signal strength of the access points perceived by the smartphone is only buy the first step for our concept application described in [7] for flock detection which factors in the energy consumed by each modality, and through several iterations finds the most energy efficient combination of modalities to sustain a certain degree of accuracy of flock detection. The full system architecture is shown on figure 5. The application can be best viewed as a 3 stage process. First, smartphones start collecting sensor data according to the instructions of in the score list, which includes parameters of which sensor modalities to use and how to use them and ranks the modalities regarding their accuracy and power consumption, based on previous data collections iterations. Then, phones start calculating the clusters based on the features of the sensor data and may use location-based static data from a web service to help in the calculations. The web service static data is information that does not change during the period of the particular iteration of the application. Once the flocks are identified in stage 3, this information is made available as a web service and the score list is updated for the following iteration by evaluating the sensor modalities of this iteration. Our method does not require any backend server to process the Wi-Fi data obtained by the smartphone, which means that it is also immune to changes in the infrastructural network, unlike traditional Wi-Fi fingerprint based localization methods [2].

Ultimately, we believe it is energy efficient to develop a decentralized mobile agent-based method for pedestrian flock detection, because we can reduce data communication costs by moving computational load into the devices. Since we are taking data from every sensor in the phone, we decided to classify the sensor into two categories. We think there sensors which can be used to describe the environment of the user, and sensors that describe the movement of the user (inertial sensors). In this work, we used our framework to harvest sensor data from a small set of smartphones, and operated specifically on the Wi-Fi data. Wi-Fi falls under the category of sensors that describe the environment, as well as the light sensor, magnetometer and barometer sensor. Using these sensors we can characterise the environment and infer features that will allow us to group the phones according to their similarity. The case of inertial sensors such as the accelerometer and gyroscope describe the user movements. For example, in the case of the gyroscope, we might be able to infer when users turn in a corner, by deriving the appropriate features.

3. Method

Our method uses the Wi-Fi signal strength measurements from the smartphone in a time series fashion. The smartphone will conduct Wi-Fi access point scans every 2 seconds.

We filter the data by discarding every Wi-Fi signal strength measurement whose signal strength was below -70 [dBm]. We observed that measurements of very low signal strengths only reduce the accuracy of our method; in case we set the filtering threshold too low, we will have many measurements which are not in fact representative. On the other hand, if we set the threshold too high, the accuracy drops anyway, as there are very few access point which can be seen by the smartphone at such high signal strength. In our experiment, we determined empirically that -70 [dBm] maximized the similarity gap between phones in different groups. However, this issue requires further study.

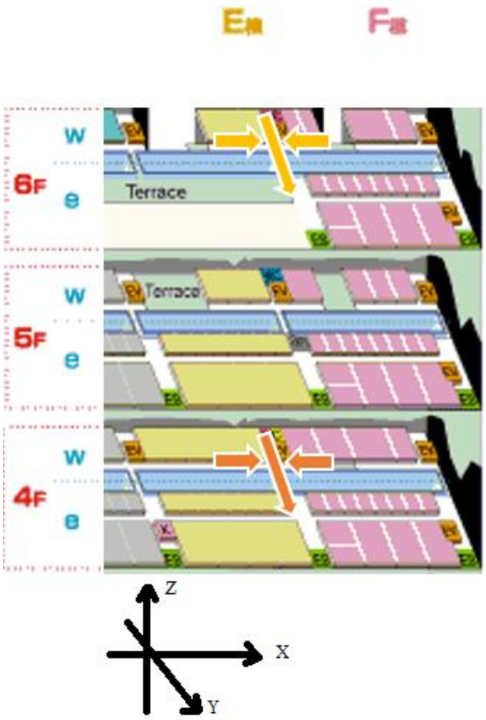

Figure 1. UT, Komaba campus II west building E block; place of the experiment.

After filtering the low power measures, we partition the measurement vector into equally sized pieces (except for the last segment which has the size of the original vector modulo the partition size). Similarly to the signal strength filtering threshold, we tried many bin sizes and found that bin size equal to 40 measurements maximises the gap between similarity calculations of smartphones in different groups. Having small sized segments will make taking the average of measurements in the bin pointless, as the smaller the segment is, less measurements are covered. In the contrary, if the segments are too big, we average over a large portion of the segment, losing the time vicinity information.

Then, we calculate the average signal strength for each MAC address of Wi-Fi access points registered during the experiment over each filtered partition. We decided to partition the vector into equally sized pieces, because we want to preserve the time vicinity information as much as possible. If we were to average the full measurement, as it has been done in other methods [2], then we would lose this information.

Finally we calculate the cosine similarity of the partitioned vectors, by calculating the dot product between two portioned vectors and dividing the result by the product of the norm of these two vectors as shown in equation 1.

$$Cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|} \qquad (1)$$

Finally we average the similarity measurements over all the bins, as shown in figure 3, yielding a similarity measurement per device pair.

Index/Floor	Flocks sizes	Description/Axes involved
1/Same	5,5	Crossing each other/X
2/Same	5,5	Parallel trajectory/X
3/Same	5,5	Perpendicular crossing/XY
4/Same	5,4,1	2 flocks crossing idle person/X
5/Same	5,4,1	2 flocks crossing idle person perpendicularly/XY
6/Different	5,5	Parallel trajectory/X different Z
7/Different	5,5	Crossing each other/X different Z
8/Different	5,5	Perpendicular crossing/XY different Z

Table 1. Different Scenarios for the Experiment.

Figure 2. Samsung Galaxy sIII phones used in the experiment

3.1 Experiment

We conducted a number of data collection experiments with smartphones in a real-world environment, where we had 10 participants who used 10 Samsung Galaxy sIII smartphones with integrated sensors. The application for the sensor data collection was installed on every phone. Each participant held the phone in front of their faces collection sensor data from the accelerometer, light sensor, gyroscope, magnetometer, barometer, proximity sensor, recorded sound and Wi-Fi signal strength data during the 8 scenarios we designed for this experiment

The experiment took place in the 6^{th} and 4^{th} floor the Komaba II campus of the University of Tokyo west building, shown in figure 1. We designed a series of scenarios for the experiment, where we divided the participants into three groups for experimenting and evaluating the method. All the scenarios can be appreciated in table 1.

Each scenario was design in order to stress different aspects of pedestrian flock detection. The first five scenarios were located in the same floor (6^{th}), having 2 flocks crossing each other, walking in opposite yet parallel directions and then in perpendicular directions. In the perpendicular scenarios, we did so that the flocks crossed each other despite the distance walked by one of the groups was shorter. We are interested on observing how the application will behave when flocks cross each other, if the flocks will be merged, or kept intact.

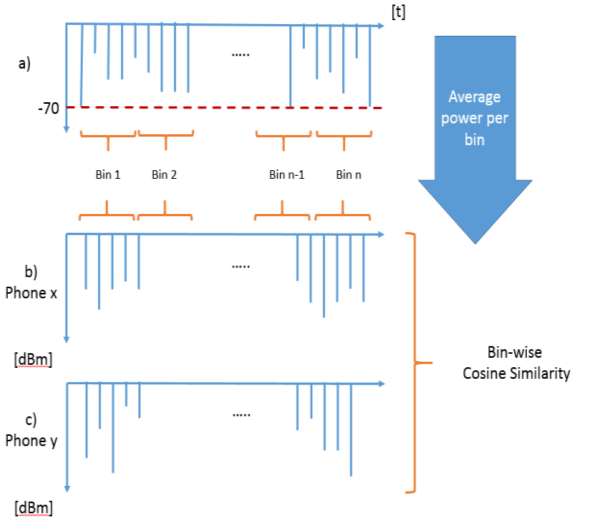

Figure 3. a) Filtering of low power measurements, b) average over equally sized bins and c) cosine similarity between phone x and y.

The following 3 scenarios were done in different floors. Additionally, we wanted to experiment with different sensor modality other than Wi-Fi, for users in different flocks; in this case the integrated barometer sensor. Justification being that, we think that if we can use the barometer instead of Wi-Fi, we can identify groups with less power hungry sensors.

There are 2 scenarios which have 3 flocks instead of 2, the third flock in fact is just 1 idle person. We think this scenario is also relevant, because it will serve us to evaluate if the application joins this user or not to any of the other two flocks at the moment of the crossing (which occurs on the exact same spot where the idle person is standing). Additionally, we think that the data derived from inertial sensors will be different from a user standing versus the one from a user walking in a group.

4. Results

The results for scenario 1 and 6 in table 1, are shown in table 2,a and table 2,b, which are the most representative of this method with Wi-Fi and barometer measurements. In scenario 1, the groups are on the same floor and in scenario 6 they are in different floors. The reason we selected these 2 scenario was because we wanted to contrast the situation where the phones were located on the same floor versus on a different floor.

As it can be appreciated from the data on tables 2,a and 2,b, the similarities for phones on the same group (cells painted in green) are approximately in average 40% higher than those of phones in different groups (cells coloured in red). For the case of scenario 6, we show the barometer data in figure 4. This is to demonstrate that the same conclusions, in terms of grouping the phones, can be drawn from either the Wi-Fi data or the barometer data. However, despite the two groups identifiable on the graph in figure 4 for the barometer data, there are 2 phone measurements which are out of the expected range of values. We believe this is due to the lack of calibration of different smartphone hardware models (8 were Galaxy SIII GT-I9300

	0	1	2	3	4	5	6	7	8	9
0										
1	0.751									
2	0.721	0.817								
3	0.825	0.795	0.721							
4	0.786	0.674	0.683	0.822						
5	0.522	0.335	0.389	0.53	0.631					
6	0.4	0.208	0.258	0.403	0.494	0.84				
7	0.504	0.3	0.546	0.369	0.416	0.79	0.769			
8	0.33	0.224	0.371	0.273	0.263	0.655	0.819	0.787		
9	0.429	0.376	0.436	0.493	0.519	0.81	0.861	0.913	0.855	

Table 2,a. Similarity values for scenario 1.

	0	1	2	3	4	5	6	7	8	9
0										
1	0.46									
2	0.625	0.599								
3	0.544	0.717	0.777							
4	0.759	0.589	0.776	0.735						
5	0	0.021	0.021	0.024	0					
6	0	0.014	0	0	0	0.766				
7	0	0.013	0	0	0	0.68	0.774			
8	0	0	0	0	0	0.843	0.833	0.77		
9	0	0.034	0.05	0.054	0.044	0.769	0.847	0.719	0.827	

Table 2,b. Similarity values for scenario 6.

model and 2 were Galaxy SIII SC-06D). When considering different floors, the accuracy of Wi-Fi increases drastically, the similarity gap between phones in different groups broadens to 75% approximately in average.

5. Related Work

Previous works have taken into account both indoor and outdoor scenarios [2, 5, 6] for detecting pedestrian flocks. For outdoors scenarios GPS (Global Positioning System) was used [5]. In [6], clustering of features, such as movement direction and position, derived from Wi-Fi infrastructure were used for indoor pedestrian flock detection. Reference [2] advances this previous approach by adding more modalities to the feature space of the application. Wi-Fi, accelerometer and magnetometer are used to derive the features to be clustered. Wi-Fi signal strength is used to infer spatial information similarly to how it was done in [5]. Results in [2] yielded that for higher density of access points, the accuracy of the feature comparison derived from Wi-Fi increases.

The main difference between our work and the work done in [2] is the slightly different focus as that we do not aim to locate the flocks we detect, we only group the smartphones. For this same reason, we can strip our system of a server backend holding the fingerprints required for indoor location, fitting our distributed requirement appropriately.

6. Discussion

In this work, we demonstrated a method for grouping smartphone users by collecting solely the Wi-Fi access point signal strengths. Additionally, we experimented with barometer sensor data to assist in grouping in different floors of buildings. However, we only harvested data in an indoor scenario because the density of visible access point in an outdoor scenario is generally lower, where this method would have been less fruitful. Because our method does not require Wi-Fi signal strength

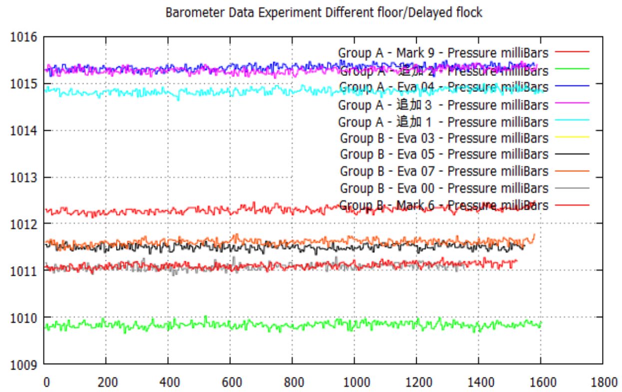

Figure 4. Barometer data for scenario 6.

fingerprinting pre-step, we additionally gain immunity to changes in the infrastructural Wi-Fi network of the indoor location where the instance of the application is running at a given time. This comes with a trade-off, as we think it could be useful to derive more features from the Wi-Fi data, but only if we can do so by not altering the distributed nature of our concept application.

Despite using exclusively Samsung Galaxy sIII phones for the experiment, we experienced incongruence in the data due to the lack of calibration. This issue was clearly seen with the barometer data, thus a minimum degree of calibration is required. This data can be compensated of course, but we think that pervasive applications should also behave consistently over a variety of devices. We think that due to the distributed nature of our solution, we can share the calibration share among the phones to allow dynamic calibration to accomplish the degree of pervasiveness we challenged ourselves with.

This paper will only cover the initial steps leading to the development of our concept application. Our framework for pedestrian flock detection in the future has to be as pervasive as possible, for this reason we believe it is essential to make experiments in outdoor environments as well as in indoor ones.

7. Future Work

In future work, we would like to use additional sensor modalities to group the smartphones to fulfil the goal of finding most energy efficient set of sensor modalities [7]. Additionally, we believe it's necessary to start observing which features will be the most useful to extract from the sensor data and from the sound recordings.

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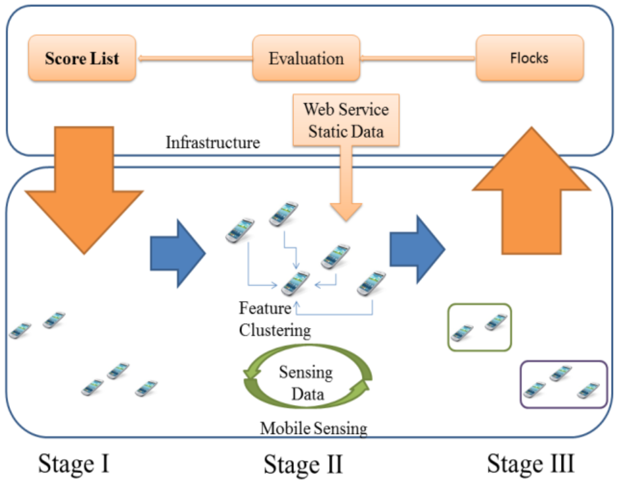

Figure 5. System architecture for our concept application [7].

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