Poster: Enhanced Collaborative Sensing Scheme for User Activity Recognition

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Abstract

Accelerometer data on a user's mobile phone contains abundant information that can be employed for user activity recognition. However, the existing schemes cannot provide accurate inference results under moving environments (e.g. on a train). This is because raw sensor data changes with the motion of the environment as well as the user. In this paper, we propose an enhanced collaborative recognition scheme that exploits neighborhood sensor data shared over a wireless network. Our preliminary experiment showed that the acceleration data of two different subjects on the same train was highly correlated. Further, it was possible to detect whether two subjects were on the same train with an accuracy of 69%. This result indicates that raw sensor data shared by spatially neighboring users can be used to detect transportation modes and enrich social networking applications.

Categories and Subject Descriptors

I.5.4 [**Pattern Recognition**]: Applications—*Waveform Analysis*; I.5.5 [**Pattern Recognition**]: Implementation—*Special Architectures*

General Terms

Design, Measurement, Performance, Experimentation

Keywords

User Activity Recognition, Mobile sensing, Context Awareness, Collaborative Sensing, Trains

1 Introduction

Understanding user context is one of the important challenges for ubiquitous computing applications. Many researchers have proposed activity recognition using accelerometers. However, because most of the methods are optimized for a single user in a static environment, the recognition accuracy significantly drops under moving environments where acceleration data is affected not only by the user's motion but also by the environment. For instance, estimation of calorie expenditure[2] is possible by detecting the user's motion. However, it is difficult to detect the user's activity in a noisy environment and almost impossible to model all aspects of moving environments in daily situations.

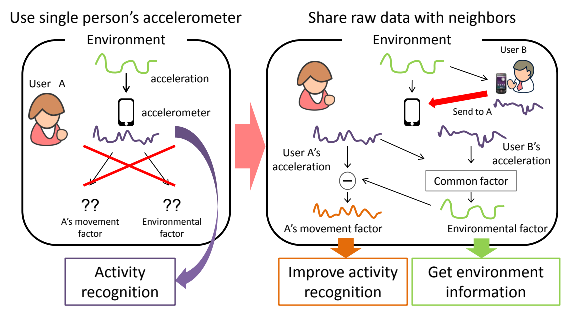

Figure 1. The idea of sharing sensor data

To overcome these limitations, we propose that users should share raw data from their sensors through a wireless network. This proposition enhances activity recognition via the following three benefits: (i) adding clues for inference by collaboration; (ii) sharing sensor data, which includes the effects of the environment; and (iii) collaborating with the neighbors who are within the environment. Factors that are common to different users typically stem from a shared environment, which cannot be understood from only one user's data. Moreover, it would also be possible to extract an individual's motion data by canceling the effects of the environment (Figure 1).

We developed an iPhone-/iPod-based system that allows multiple people to share acceleration data. We performed experiments on a subway in Tokyo. The results showed that the acceleration data were highly correlated between the subjects on the same train. Thus, this system easily recognizes when a user is aboard a train. In addition, this system can detect an enriched activity; two users are on the same train. We believe this information can be useful for social networking services engaged by users on a train; for example, bringing serendipity to commuting passengers. These services will add value to people's commuting time that is mostly wasted by many people.

2 Related Work

Collaboration in sensing and inference has been introduced in Darwin Phones[3]. These phones share a classifier

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model that evolves in each mobile phone. A final inference is then obtained by combining the output from the different phones. This research provided the motivation for our research, i.e., use the concept of collaboration. However, the goal of Darwin system is to obtain an accurate inference as a whole, while our intention is to enhance the inference in each mobile phone by exploiting common features among users.

Even though many researches have tried to minimize the effects of device position, orientation, and user differences, mean and standard deviation are used as the features. The external movement can seriously affect these features.

Ito and Ogawa proposed to detect passengers on the same train using GPS sensors[1]. However, GPS is unavailable in the subway and consumes much battery power.

3 Sharing Sensor Data

As we showed in Figure 1, we assume that users in one another's neighborhood share their sensor data through a wireless network. Because we are interested in data from users who are spatially close, global connectivity is not necessary. Ad hoc networks will be beneficial.

We assume that each user has one smart phone with an accelerometer. The smart phones record acceleration data at the same sampling rate f [Hz]. The phones are synchronized with an accuracy of 0.1 s using the Network Time Protocol.

When a user receives a nearby user's acceleration data, the correlation coefficient of the two acceleration data sets is calculated. For the calculation, we set the number of samples to w, and use the continuous w samples, starting from the original time, t, in each user's data set. Because we allow a difference of up to 0.1 s between two smart phone clocks, the correlation coefficients are also calculated, sliding one user's data by n samples (n is an integer and $-0.1f \leq n \leq 0.1f$). If the maximum of these correlation coefficients, which we name $R_w(t)$, is over a threshold, R_{th}, it is determined that the users are riding on the same transportation vehicle at time t.

4 Experiment and Evaluation

We performed experiments to confirm the system's accuracy. Two test subjects, X and Y, rode on the same train on Tokyo Metro Namboku Line. Each subject had one iPod touch in his waist pocket and recorded acceleration at a frequency of 10 Hz. Three experiments were performed by varying the following parameters: trains, sections, and subject postures.

We evaluate this system on two points: (i) the accuracy; in other words, the likelihood that the subjects who rode on the same train are identified as such in the experimental period, (ii) the false positive rate; the likelihood that subjects on different trains are wrongly identified as being on the same train, which may occur because the data of subjects on different trains can be exchanged by multi-hopping.

4.1 Detecting the Subjects on the Same Train

For data in each experiment, we varied w and R_{th} and calculated $R_w(t)$, adding one second to t. Because the interval between stations is 2 to 3 minutes on the subway, we set the maximum value of w to 600. Table 1 shows the inference result for each pair of w and R_{th}, and the number of windows that was made by adding one second to t. The accuracy is over 80% in all experiments if we set $w = 600$ and $R_{th} = 0.5$.

Table 1. Accuracy of detecting users on same train

Posture	w	R_{th}				No. of windows
		0.5	0.7	0.8	0.9	
X: sit, Y:sit	300	81.9%	74.3%	71.1%	61.3%	315
	600	85.1%	80.0%	49.3%	60.3%	255
X: sit, Y:stand	300	84.0%	76.4%	58.3%	31.4%	369
	600	82.4%	68.9%	60.7%	24.7%	267

Table 2. Error rate in simulation of users on different trains

w	R_{th}				Total No. of windows
	0.5	0.7	0.8	0.9	
150	32.4%	15.1%	7.5%	4.2%	853
300	34.3%	17.1%	6.0%	2.1%	848
600	32.8%	18.0%	5.7%	0.0%	734

4.2 Distinction between Subjects on Different Trains

False positive errors occur when two subjects are on different trains that are parallel, or close to each other. To evaluate the false positive rate, we chose five sections, so that we could simulate the situation in which subjects X and Y ride on different trains. We varied w and R_{th}. Table 2 shows the false positive error rate. The rate is over 30% if we set $R_{th} = 0.5$. If we set $w = 600$ and $R_{th} = 0.5$, which is the best combination in the last subsection, the false negative rate is 18% at its maximum, the false positive rate is 33%. A false positive is a more serious error for a service provided to users in the same train. We conclude that $w = 600$ and $R_{th} = 0.7$ is the best combination to keep high accuracy (the minimum is 69%) and to decrease the false positive rate (to 18%). Although the accuracy seems low, false negative errors mainly happened while the trains were stopped at stations because their acceleration made two subjects' data correlated. It is not necessary to detect users in this period of time because there is no train movement.

5 Conclusion

In this paper, we proposed a new recognition method that exchanges raw acceleration data between different users. This method can potentially be used to extract a new activity mode. We applied this idea to detect whether two users are on the same train. The experimental results showed that the subjects were detected more than 69% of the time, which is practically enough for applications in real situations.

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6 References

[1] Y. Ito and K. Ogawa. Fellow passengers sensing method to provide location-based service on railways. *IEICE Technical Report*, 110(450):137–142, March 2011.

[2] Y. Kawahara, N. Ryu, and T. Asami. Monitoring daily energy expenditure using a 3-axis accelerometer with a low-power microprocessor. *Int. J. on Human-Computer Interaction*, 1(5):145–154, March 2009.

[3] E. Miluzzo, C. T. Cornelius, A. Ramaswamy, T. Choudhury, Z. Liu, and A. T. Campbell. Darwin phones: the evolution of sensing and inference on mobile phones. In *Proceedings of the 8th international conference on Mobile systems, applications, and services*, MobiSys '10, pages 5–20, New York, NY, USA, June 2010. ACM.