

Response Time Improvement in Accelerometer-based Activity Recognition by Activity Change Detection

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ABSTRACT

A method has been developed to improve response time of accelerometer-based activity recognition. Our method firstly detects a point of change in activity from sensor data and then applies a classifier trained with short window data immediately after the point. Results of experiments show that our method achieves a response time more than one second faster than that of a conventional method.

Author Keywords

Activity recognition, Accelerometer, Response time

ACM Classification Keywords

I.5.m Pattern Recognition: Miscellaneous.

General Terms

Algorithms, Experimentation, Performance

INTRODUCTION

Recognizing users' activity is one of the keys to enabling context-aware services. Many studies on activity recognition have been conducted in recent years using several kinds of sensors. Due to its portability, one of the most common sensors is an accelerometer.

One of the most common topics in activity recognition is investigating the applicability for several applications in several sensor setting. Also, since activity recognition generally uses machine learning techniques and requires labeled data beforehand, another common topic is how to decrease the labeling effort.

However, another significant issue in activity recognition is its response time, though it is dealt with infrequently. Conventional recognition techniques process some sensor data and obtain a recognition result a few seconds after the user's motion. This decreases the practicality for real-time applications. Fujimoto *et al.* developed a real-time dance support system using activity recognition [1]. However, their way

to obtain fast response of activity recognition is to use prior defined timing in music. This cannot be applied for people's daily, unpredictable activity.

Thus, we propose a method to decrease response time in accelerometer-based activity recognition. Our method first finds a point of change in a user's activity from a sensor data stream. Then, an activity classifier dedicated to small amounts of data and activity transition terms is applied to obtain recognition results quickly.

CURRENT TECHNIQUE AND ITS PROBLEM

Current activity recognition techniques use sliding windows as their preprocess. Sequential data are split into subsequences applying a window function. Then, a classification algorithm obtains an activity label, such as "running" and "standing", with feature values from a subsequence.

This sliding window technique mainly keeps response time of activity recognition long. Even if a window contains more than the half the data of an activity to extract appropriate features of it, the probability of obtaining wrong results significantly increases. Thus, a window is demanded to be applied to contain one activity data. While a window is applied with no rule (free-run window) in most current techniques, a window to extract appropriate activity features is applied a long time after activities change in many cases.

One possible way to obtain fast response time is to decrease shift width of sliding window to a very short time, especially the same as that of the sampling rate of sensor data. However, this brings high computational load because a feature value calculation and classification algorithm run at very high frequency.

PROPOSED METHOD

Thus, we propose the following method: 1) find the point of change in activity in its sensor data by using a signal processing technique, and 2) apply a shorter window immediately after the point and run a special classifier for the term.

Detection of Activity Change

To detect users' activity change, we use two methods alternatively. One detects sudden changes in sensor data when the current recognition indicates inactivity, such as "standing" and "sitting". The other detects spectrum changes in sensor data when current recognition indicates motional activity such as "running" and "walking".

To detect sudden changes in sensor data, the deviation from moving average of previous data is detected as follows

$$\begin{cases} \text{if } |x(t) - \bar{x}(t)| > \epsilon & \Rightarrow \text{change point} \\ \text{otherwise} & \Rightarrow \text{not change point} \end{cases} \quad (1)$$

Where t , x , \bar{x} , and ϵ denote current time, sensor data, moving average of sensor data of past m samples, and acceptable difference in sensor data, respectively.

On the other hand, activity change in motional activity is detected by measuring the change in sensor data spectrum. For decreasing the response time, an IIR bandpass filter bank is used to obtain a frequency component instead of Fast Fourier Transform (FFT), which requires some amount of time domain data. Each filter in the bank is implemented with short order and is set to pass different frequency. Then, the peak value of i th frequency component p_i is calculated by

$$p_i(t) = \begin{cases} x_i(t-1) & \text{if } |f_i(t-1)| > |f_i(t-2)| \\ & \text{and } |f_i(t-1)| > |f_i(t)| \\ p_i(t-1) & \text{otherwise} \end{cases} \quad (2)$$

where f_i denotes sensor data passed by i th IIR filter. Then, after moving average of p_i is calculated, \bar{p}_i ,

$$crma_i(t) = \frac{\bar{p}_i(t)}{\sum_{k=1}^n \bar{p}_k(t)} \quad (3)$$

$$cr_i(t) = \frac{p_i(t)}{\sum_{k=1}^n p_k(t)} \quad (4)$$

are calculated. Finally, our method finds the point of change in activity by

$$\begin{cases} \text{if } \sum_{k=1}^n (cr_k(t) - crma_k(t))^2 > \text{threshold} \\ \text{otherwise} \end{cases} \Rightarrow \begin{cases} \text{change point} \\ \text{not change point} \end{cases} \quad (5)$$

Classifier with shorter window

After a point of change in activity is detected, ordinal recognition, in which a free running window is used, is stopped. Then, a window function, which is smaller than for an ordinal window, is applied immediately after the point. Then, a special classifier, which is trained by short window data immediately after points of change in activity in labeled data, classifies these window data.

EVALUATION

The f_C settings of five filters in the IIR filter bank were 1.000, 1.414, 2.000, 2.828, and 4.000Hz. Two subjects, wearing 100Hz tri-axial accelerometers on both wrists, both arms, and lower backs, participated in our experiments. They did “standing”, “sitting”, “walking”, and “running” (this includes “standing up”, and “sitting down”) without experimenter’s instructions.

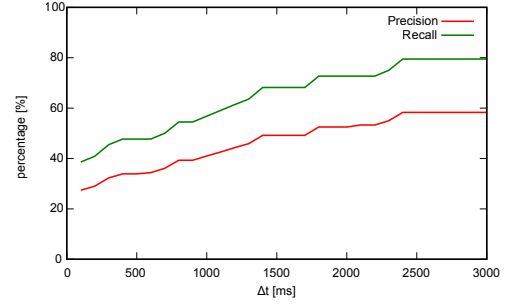


Figure 1. Precision and recall of point of change detection

	Conventional	Proposed
Average	2530ms	1459ms
Standard Deviation	916ms	1045ms
Min	952ms	62ms
Max	5569ms	3635ms

Table 1. Response time of activity recognition

Detection of activity change

We first evaluated the accuracy and delay of the activity change detection. Since labeled data are annotated by hand, a correct detection is defined as being in the range between 200 ms before and Δt ms after the hand-labeled activity change.

Figure 1 shows the precision and recall when varying the Δt . In this result, recall, which is more important than precision for the change detection, can be more than 50% when Δt is about 700 ms. That is, about 50% of activity transition is detected less than 700 ms after the actual point of change.

Response time

We used a 2560-ms window with 50% (1280ms) shift for ordinal sliding window parameter and a 320-ms window for the window after activity change.

Table 1 shows the results of the response time of the proposed and conventional methods. The proposed method correctly detected 72.7 % of activity change, and 27.3 % of the results of the proposed method in Table 1 are the same as those of the conventional method. While activity change detection has to be made more accurate, our method obtains a response time more than 1 sec faster on average.

CONCLUSION

To improve response time of accelerometer-based activity recognition, we proposed a method that detects activity transition and uses a special classifier for a small window and transition. Point of change detection should be made more accurate, but our method achieves a response time that is more than 1 sec faster than that of the conventional method.

REFERENCES

1. M. Fujimoto, N. Fujita, Y. Takegawa, T. Terada, and M. Tsukamoto. A motion recognition method for a wearable dancing musical instrument. *Wearable Computers, IEEE International Symposium*, pages 11–18, 2009.