
Working-Relationship Detection from Fitbit Sensor Data

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Abstract

This paper proposes an innovative way to detect working relationships by using only the step tracking data acquired from pedometers like Fitbit [1].

The idea makes the cost of working-relationship detection much lower than that of previous approaches. We can find out if people have a working relationship and spend their daily lives together by making them wear a pedometer. Results of an experiment in Japan showed that this approach is very effective and practical. An organizations profile can be written automatically by analyzing the data.

Author Keywords

Working-relationship detection, life-logging, sensor

ACM Classification Keywords

H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous.

General Terms

Design, Data visualization

Introduction

Detecting working relationships can inform us about human relationships and help us to evaluate a company's organization. To detect working relationships, many

researchers have analyzed mobile GPS data, WiFi-access data [2], proximity sensors with infrared light or Bluetooth [3], and so on. However, gathering data from such devices is often very costly because it may intrude on peoples privacy and cause battery problems. Moreover, it is costly to provide measuring tools and annoying for users to carry some devices in order to allow others to search for working relationships.

This paper proposes an innovative way to detect working relationships. By tracking the similarity of steps per minutes between users, their working relationships can be detected easily. All users have to do is to wear the pedometers and upload their steps-per-minutes data to the calculation server. The results of an evaluation show that the proposed method is practical from the viewpoint of detection accuracy.

Working-Relationship Detection

This section explains how to detect a working relationship by pedometer data. The main idea of the calculation is that the strength of a relationship can be measured by the amount of time spent somewhere together, such as going to lunch or dinner, to meetings, on trips, and so on. When some people go somewhere together, they simultaneously start or stop walking. These activities are easily detected by comparing Fitbit data of two people.

We assume a situation in which all users' pedometer data can be measured precisely by calculating the similarity of data steps-per-minute data. Figure 1 shows samples of steps data of two users.

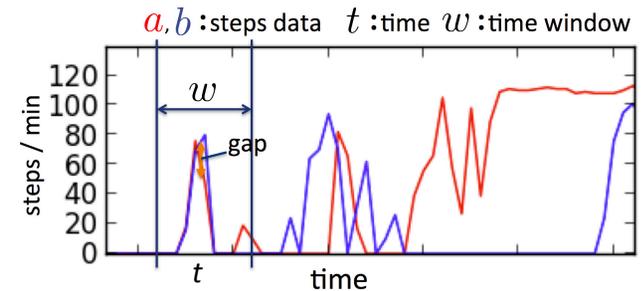


Figure 1: Example of two users' steps-per-minute data

Model of Working-Relationship detection

Here, \mathbf{a}, \mathbf{b} respectively denote step sequences of two people. a_t, b_t shows the steps data in time t . We denote total activity by $\alpha(\mathbf{a}, \mathbf{b})_t$ defined by

$$\alpha(\mathbf{a}, \mathbf{b})_t = \sum_{\tau=t}^{t+w} (a_{\tau}^2 + b_{\tau}^2) \quad (1)$$

where w denotes time window width. When α_t is smaller than an activity threshold θ_{α} , it is too small to compare (sleep, desk work, etc.).

Then dissimilarity of \mathbf{a} and \mathbf{b} is defined as follows:

$$\Delta(\mathbf{a}, \mathbf{b})_t = \left(\sum_{\tau=t}^{t+w} (a_{\tau} - b_{\tau})^2 \right) / \alpha_t \quad (2)$$

Δ_t is normalized value, so the range of value is $0 \leq \Delta_t \leq 1$. The trend of Δ_t in one day is shown in Figure 2. These two people meet and eat lunch between 10 and 13. Thus, the value of dissimilarity lowers during this time. If dissimilarity Δ_t is smaller than threshold θ_{Δ} , these two people are defined as being together.

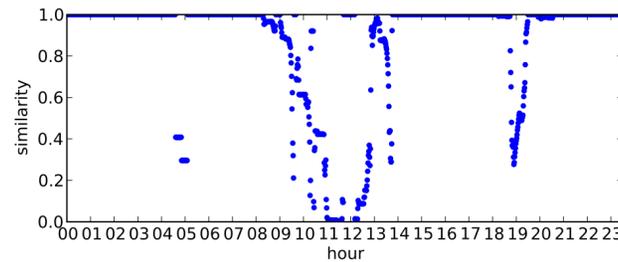


Figure 2: Trend of dissimilarity value between two users in one day

Relationship Model

To make the relationship model, we define the strength of the relationship. The strength of the relationship W shows count t satisfying the below condition in total time T . The condition shows that t satisfies condition (2) in c minutes continuously.

$$W = \sum_T \delta_t \tag{3}$$

$$\delta_t = \begin{cases} 1 & \bigcap_{\tau=t}^{t+c} (\alpha_\tau > \theta_\alpha \cap \Delta_\tau < \theta_\Delta) \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Evaluation test

This section shows the evaluation test. Following the explanation of the overview, the results are described.

Overview of the test

Table 1 shows the overview of the evaluation test. Eighteen male participants wore the Fitbit as a sensor device for about one month. Nine of them were office workers, eight were students, and one was the students supervisor. The building which they work are different between organizations. Their ages ranged from 21 to 42

years old. To detect working relationships, calculation variable are defined as follows: $w=60$, $\theta_\alpha=5500$, $\theta_\Delta=0.05$, $c=15$. In

Table 1: Overview of evaluation test

Device	Fitbit one
Period	2013.01.17 - 2013.02.17
Member	18 people from two organization
Age range	21yrs - 42 yrs
Weight range	61kg - 71kg
Height range	167cm - 182cm

Result of evaluation

Figure 3 shows the results of calculated human relationships. Each node shows users, and the organizations to which they belonged are classified by different colors.

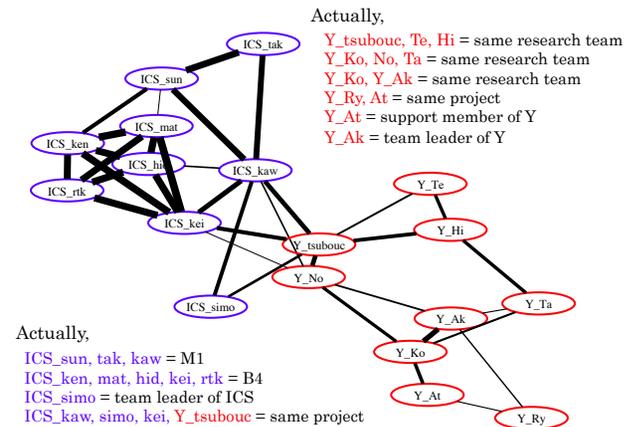


Figure 3: Organization map acquired from Fitbit data.

Width of the link in figure is defined as $\log W$. Thicker lines mean stronger relationships that could be detected in more working relationships. The actual relationships are described above right and below left.

Discussion

The results of the experiment showed that the organization situation calculated by step data acquired from Fitbit described the actual situation precisely. The different organizations can be separated and co-research project members can be connected because they had meetings at the same time or went to conferences together. The organization labeled "ICS_" is a laboratory of a university, which is located in Bunkyo-ku, Tokyo. Students were studying for master's (M1) or bachelor's degrees (B4). As a result, the degree different cluster can be confirmed. The organization labeled "Y_" is a company conducting many research projects, which is located in Minato-ku, Tokyo. Precise connections are confirmed in the calculated figure. There are connections between Y_No, ICS_kaw, ICS_kei in the figure, though Y_No is not involved in this research. In fact, an informal gathering was held for co-researchers, and Y_No was a guest of this dinner. Therefore, weak connection is shown.

Conclusion

A novel way to detect working relationships was proposed and evaluated in this paper. Working relationships can be detected only by analyzing the step data from a pedometer. We present an organizations relationships as a demonstration.

Obtaining an appropriate variable to detect working relationships is a future work. Moreover, Figure 2 shows that occasional outliers can be detected in this method. To overcome such outliers is also future work.

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