Person Authentication and Activities Analysis in an Office Environment Using a Sensor Network

Shuai Tao, Mineichi Kudo, Hidetoshi Nonaka, and Jun Toyama

Division of Computer Science, Hokkaido University, Japan
{taoshuai,mine,nonaka,jun}@main.ist.hokudai.ac.jp

Abstract. Person authentication and activities analysis are indispensable for providing various personalized services in a smart home/office environment. In this study, we introduce a person localization algorithm using an infrared ceiling sensor network, and realize person authentication anywhere and anytime. The key problem is how to distinguish different persons meeting at the same position. We solve this problem by different moving directions depending on individuals. Furthermore, with the locations and the known identities, multiple persons can be tracked and their interactive behaviors can be analyzed by our system.

Keywords: localization, person authentication, activities, sensor network, infrared sensors.

1 Introduction

Person surveillance and activity analysis have been applied to various circumstances, such as security control, person tracking, assisted living and human-computer interface (HCI), etc [1-6]. In recent years, along with the rapid development of computer vision and many kinds of network devices, person authentication, tracking and human-behavior understanding have become indispensable for providing many kinds of personalized services in response to the implicit/explicit demands of the users. In such a smart environment, the face, voice, gait, individual trajectories and other features are used to realize the recognition and real-time tracking of multiple persons. Meanwhile, recording the activities of multiple persons is an effective way to analyze the labor degree of individuals, to improve the room layout and to measure the ability of daily living of elderly persons.

Traditional authentication systems based on various biometric evidences, such as fingerprint, iris, speech and palm vain, can maintain a high level of security, but the cooperation of users is necessary. There have also been many studies using cameras for human activities analysis, however, to some extent, cameras might violate the privacy of users. In daily life, misidentification of users or misrecognition of activities does not cause a serious problem. While, physical/psychological disturbance should be seriously considered.

Video cameras and sensor networks have been used in many studies for person monitoring, tracking and behavior analysis [7-14]. Zhao et al. [7] succeeded in tracking

R. Wichert, K. Van Laerhoven, J. Gelissen (Eds.): AmI 2011 Workshops, CCIS 277, pp. 119–127, 2012.

persons with their modes of movements (e.g. walking, running) using several outdoor cameras. Sogo et al. [8] tracked two persons by multiple cameras. In another study, by the human shape model for gait, Yam et al. [10] tracked persons with a single camera in an outdoor environment. In these studies, vision is sometimes not obtained due to the existence of obstacles and greatly affected by light conditions. Schulz et al. [11] tried to use an ID badge for person localization and authentication. For many people, especially elderly people, such sensing devices might bring troubles to daily lives. The other studies realized the recognition of human activities by using cameras [12-13] and IR sensors [14].

In our previous work [15], an infrared ceiling sensor network has been used to keep tracking up to five persons in an office environment. However, the tracking/identification precision decreases with the pass of time, even though the degradation can be recovered if some other pieces of evidence are occasionally available. Recently, in order to increase the sampling rate and reduce the noise, we have developed an improved system using binary infrared sensors attached to the ceiling [16]. In this system, sampling rate of 80 Hz for up to 128 nodes using 250 kbps equilibrium line has been realized. By this system, we also proposed a novel method for person localization and soft authentication [17]. In the experiments, we confirmed that walking path and speed give useful information for authenticating the user. However, there are more problems to be solved. For example, due to the characteristics of infrared sensors, the information we obtain is still binary, that is, all we can know is if someone is under or just passed by the active sensor. Therefore, when multiple persons meet at one place, they cannot be distinguished anymore. We have to explore other pieces of evidence as supplemental information. In an office environment, it is natural that a person tends to go to his/her own desk immediately after entering the room or after meeting with someone, and walk straight after crossing with another person. Therefore, the moving directions, e.g. a direction from the entrance to his/her own desk, or a direction from a meeting point to his/her own desk are expected to provide reliable hints for person authentication.

2 Infrared Sensing System

We attach ”pyroelectric infrared sensors”, sometimes called ”infrared motion sensors”, to the ceiling [16]. This sensor detects an object with a different temperature from the surrounding temperature. The photographs of the sensor module and the interconnection of sensor nodes with cables are shown in Fig. 1. Such infrared sensors are easy to set up at a low cost ($20/unit). Light conditions and movable obstacles do not affect the performance.

Forty-three sensors were attached to the ceiling of our research room (15.0 m $\times$ 8.5 m) so as to cover all the area and not to produce any dead space. The average distance between each other is 1.5m. Figure 2 shows the layout of the room and the arrangement of the sensors. A binary response from each sensor can be read at the sampling rate from 1 Hz to 80 Hz.

Fig. 1. The sensor module and the interconnection of sensor nodes with cables

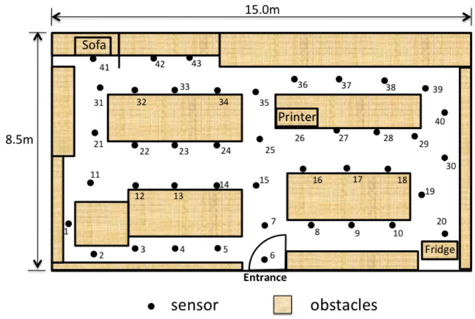


Fig. 2. Layout of infrared sensors

In our sensor network, motions of one person often make multiple sensors active. There is also a *get-out delay* of sensors in response to motions, that is, an active sensor keeps the active status for a few seconds after a person left the sensing area. There is no *get-in delay*. Another important fact is that the sensor sometimes cannot be active if the person is motionless or moves slightly, such as, keyboard typing or browsing with a mouse.

3 Person Localization Algorithm [17]

In the ceiling sensor system of our laboratory, we can assume that: (1) the walking speed of persons in our laboratory follows Gaussian distribution: $N(v, \sigma^2)$. So, we set the speed to v approximately in experiments; (2) detection area is a circle of radius R; (3) active status will be kept for D_{delay} (sec.) after the person getting off the detection area and D_{delay} does not depend on the speed v. In Fig. 3, we assume that the person enters the detection area with an incident angle α and the duration D of active status is decomposed as $D = t_e - t_s = D_{detect} + D_{delay}$ if the person gets out of the detection area at time frame t ($> t_e$).

From the sensor model in Fig. 3, we see that there are four cases to be considered: (1) at position P_0 (at time frame t_0 before detection), the distance from the sensor is $r_0 > R$, (2) at position P_1 (at time frame t_1 under detection), $r_1^2 = D^2v^2 + R^2 - 2RDv\cos\alpha$ ($D = t - t_s < \frac{2R\cos\alpha}{v}$), (3) at position P_2 (at time frame t_2 out of detection area but the sensor is still active), $r_2^2 = D^2v^2 + R^2 - 2RDv\cos\alpha$ ($\frac{2R\cos\alpha}{v} < D < \frac{2R\cos\alpha}{v} + D_{delay}$), (4) at position P_3 (at time frame t_3), the sensor becomes inactive again, and the distance from the sensor is $r_3 > R$.

For situations (2) and (3), with the expected value $\frac{2}{\pi}$ of $\cos\alpha$ in range $-\frac{\pi}{2} < \alpha < \frac{\pi}{2}$, we use the expected value of squared distance as $E(r^2) = D^2v^2 + R^2 - \frac{4}{\pi}RDv$.

Algorithm

(1) If a sensor S_i has already been active for duration D_i, we estimate the distance to the person by $r_i = \sqrt{D_i^2v^2 + R^2 - \frac{4}{\pi}RD_iv} = \sqrt{(D_iv - \frac{2}{\pi}R)^2 + (1 - \frac{4}{\pi^2})R^2}$.

(2) Gathering all the information D_i and thus r_i ($i = 1, \cdots, n$) from all active sensors, estimate the position $P_t = (x_t^*, y_t^*)$ at time frame t by solving

$$\min_{P_t} \sum_{i=1}^{n} (r_i - ||S_i - P_t||)^2 = \min_{(x,y)} \sum_{i=1}^{n} \{r_i - \sqrt{(x_i - x)^2 + (y_i - y)^2}\}^2.$$

The solution (x_t^*, y_t^*) satisfies:

$$\begin{cases} x = \sum w_i x_i / \sum w_i \\ y = \sum w_i y_i / \sum w_i \end{cases}, \quad w_i = \frac{\sqrt{(x_i - x)^2 + (y_i - y)^2} - r_i}{\sqrt{(x_i - x)^2 + (y_i - y)^2}}.$$

Therefore, with appropriate initial values, we can find the solution P_t by iteration.

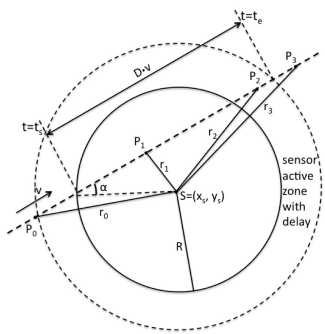


Fig. 3. The sensor model that contains four cases when a person passes by. Without generality, we may assume that he/she enters at the left end of x-axis.

4 Person Authentication

4.1 Entrance Authentication

Each person in an office room has individual living habits and tends to stay around some certain areas. By observation we found that persons tend to go to their own desks immediately after entering the room. Therefore, the walking directions are expected to hold information for recognizing multiple persons at the entrance. In our first

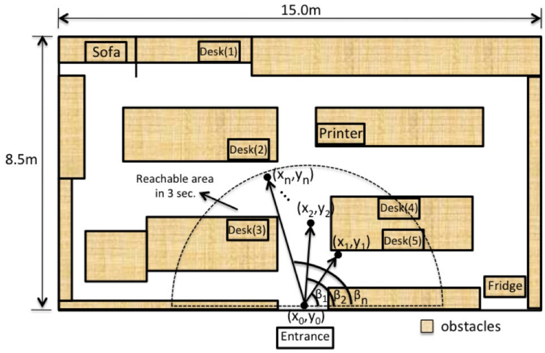


Fig. 4. The description of the directions. The direction of the person at time t is calculated by $\beta_t = arctan(\frac{y_t - y_0}{x_t - x_0}), t = 1, 2, \cdots, n$.

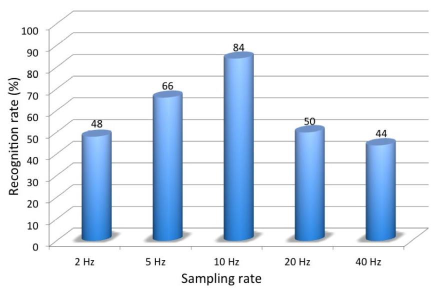


Fig. 5. Recognition rates of the entrance authentication

experiment, the walking direction for a short period (3 sec.) is used for identifying multiple persons. Here, we use only a short period because we want to identify entering users as soon as possible. The description of the directions is shown in Fig. 4.

In the experiment, five subjects (laboratory students) were asked to enter the room from outside and then to go forward to their own desks directly without stopping for twenty times. The locations of the five desks and the reachable area in 3 sec. are shown in Fig. 4. We used five kinds of sampling rate: 2Hz, 5Hz, 10Hz, 20Hz and 40Hz. The number of features is the product of the sampling time (3 sec.) and the sampling rate (2Hz-40Hz). The recognition rate was calculated by 20-fold cross-validation. The classifier was a support vector machine (SVM) with a radial basic kernel with default parameter values. The results are shown in Fig. 5.

From Fig. 5 we can see that the best recognition rate 84% of five persons is obtained at 10Hz sampling rate. The accuracy is not high enough, however, might prove the availability of the direction information for entrance authentication.

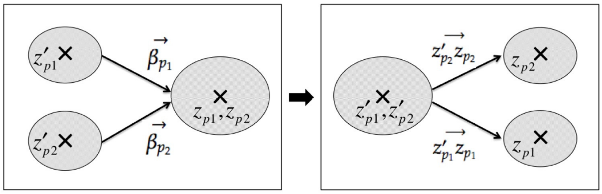
4.2 Distinguish Process

In our office environment, there are two typical situations required to distinguish persons from one active region (a connected region of active sensors). One situation happens when two persons approach to each other and pass through (Fig. 6(a)), in which they will share one active region and be localized to the same position. In this situation, we employ the empirical knowledge that a person tends to walk straight without changing direction after a cross with another person. The other situation happens when multiple persons meet at a place (Fig. 6(b)), in which they cannot be distinguished neither. At this moment, we rely on the knowledge that people tend to go back to their desks after meeting. The difference between above two situations is that the time duration when multiple persons have been localized at the same position. The duration of the latter one is longer according to the experience. We use $z_p = (x_p, y_p)$ to denote the estimate location of person p at the present time, use $z'_p = (x'_p, y'_p)$ to denote the estimate location one step before and use d_p to denote the desk of person p . The direction of person p at the present time is denoted by $\vec{\beta_p}$ and $D_{p_1p_2}$ describes the time steps that person p_1 and person p_2 were localized at the same position. The two situations are illustrated in Fig. 6. The distinguish algorithm is as follows:

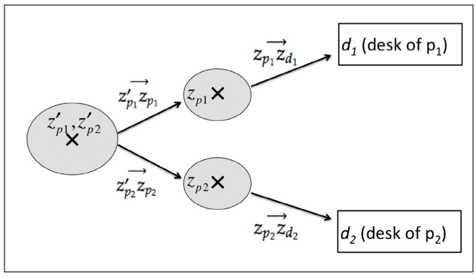
for *person* p_1, *person* p_2 **do**

  if $z'_{p_1} = z'_{p_2}$ and $z_{p_1} \neq z_{p_2}$ and $D_{p_1p_2} \leq 6$ (crossing case) **then**
    if $|\vec{\beta_{p_1}} - \overrightarrow{z'_{p_1}z_{p_1}}| + |\vec{\beta_{p_2}} - \overrightarrow{z'_{p_2}z_{p_2}}| > |\vec{\beta_{p_1}} - \overrightarrow{z'_{p_2}z_{p_2}}| + |\vec{\beta_{p_2}} - \overrightarrow{z'_{p_1}z_{p_1}}|$ (if the two persons tend to change their moving directions after the cross) **then**
      $z_{p_1} \leftarrow z_{p_2}, z_{p_2} \leftarrow z_{p_1}$
    end if
  end if
  if $z'_{p_1} = z'_{p_2}$ and $z_{p_1} \neq z_{p_2}$ and $D_{p_1p_2} > 6$ (meeting case) **then**
    if $|\overrightarrow{z'_{p_1}z_{p_1}} - \overrightarrow{z_{p_1}z_{d_1}}| + |\overrightarrow{z'_{p_2}z_{p_2}} - \overrightarrow{z_{p_2}z_{d_2}}| > |\overrightarrow{z'_{p_1}z_{p_1}} - \overrightarrow{z_{p_2}z_{d_2}}| + |\overrightarrow{z'_{p_2}z_{p_2}} - \overrightarrow{z_{p_1}z_{d_1}}|$ (if the two persons do not tend to move in the direction to their own desk after the meeting) **then**
      $z_{p_1} \leftarrow z_{p_2}, z_{p_2} \leftarrow z_{p_1}$
    end if
  end if
end for

According to the person localization algorithm, we can obtain the location of each individual person at any time. With the person authentication algorithms, all the persons in our office room can be recognized. Therefore, we can know who the users are and where they are at any time. If the location is connected to a special equipment, e.g., a printer, we might also get their behavior information.



(a) The situation when two persons approach to each other and pass through



(b) The situation when multiple persons meet at a place

Fig. 6. The two typical situations required to distinguish persons from one active region

4.3 Experiments

We evaluate the assumptions in a more practical situation that up to five persons spent about half a day (more than four hours) in the laboratory room without any instructions. They behaved naturally because they were not aware that the system was in operation.

The experiment was conducted from 10 a.m. The behaviors of five persons were recorded. For about 1/4 of the period, they walked around or left/(re)entered, while, in the other 3/4 of the period, they stayed at their desks. The algorithms in Sec. 4.1 and 4.2 were used for realizing person authentication in different situations. The recorded numbers of different events and the identification results are summarized in Fig. 7.

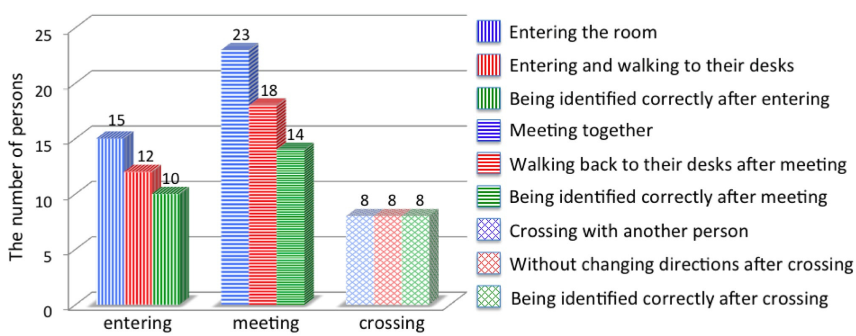


Fig. 7. The recorded numbers of different events and the person authentication results

From Fig. 7, we see that for the entering event, 12 of 15 persons (including the same persons) walked to their desks directly after entering the room, 10 of them were identified correctly. For the meeting event, 23 persons have met in different groups, 18 persons of them went back to their desks after meeting. Finally, 14 persons were correctly recognized. For the situation of crossing, all the 8 persons can be identified.

5 Discussion

In this study, we designed an improved system for person authentication and interactive human behaviors analysis. Our system consists of forty-three infrared ceiling sensors with low cost and easy installation. However, due to the simplicity of the binary sensors, the information we obtain is limited to the event that someone is under or just passed by the active sensor. Therefore, we have to explore other pieces of evidence as supplemental information for realizing person authentication and activities analysis.

Each person in our office room has an individual living habit. Persons tend to go to theirs own desks immediately after entering the room. We also find that persons always tend to go back to their own desks after meeting some others and a person tends to walk straight without changing direction after a cross with another person. In our study, the walking directions are expected to provide information for recognizing multiple persons.

On the basis of person localization and authentication, multiple persons can be tracked simultaneously and the activities of them can be recorded by our system. According to which, the interactive human behaviors can be analyzed in a convenient way. Usage of our system may reveal some groups of friends, redundant labor, and inefficient layout of equipments.

6 Conclusion

To realize localizing and authenticating multiple persons behaving naturally in a relatively large room, we have developed new algorithms to authenticate users at the entrance and to recover their lost identities because some of them have met at the same place. The idea is that every person tends to walk straight after a cross and return to his/her own desk after meeting, so the direction of walking gives us a strong piece of evidence. Indeed, our experiments showed that the current system is able to identify five persons and has the potential to track multiple persons and analyze their interactive behaviors.

References

1. Shankar, M., Burchett, J., Hao, Q., Guenther, B., Brady, D.: Human-tracking systems using pyroelectric infrared detectors. Optical Engineering 45(10), 106401(1)–106401(10) (2006)
2. Song, B., Choi, H., Lee, H.S.: Surveillance tracking system using passive infrared motion sensors in wireless sensor network. In: Information Networking, ICOIN 2008, pp. 1–5 (2008)

3. Zhou, J., Hoang, J.: Real time robust human detection and tracking system. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, CVPR Workshops, pp. 149–156. IEEE (2005)
4. Sixsmith, A., Johnson, N., Whatmore, R.: Pyroelectric IR sensor arrays for fall detection in the older population. J. Phys. IV France 128, 153–160 (2005)
5. Toreyin, B., Soyer, E., Onaran, I., Cetin, A.: Falling Person Detection Using Multi-sensor Signal Processing. In: IEEE 15th Signal Processing and Communications Applications, pp. 1–4 (2007)
6. Hengstler, S., Prashanth, D., Fong, S., Aghajan, H.: Mesheye: a hybrid-resolution smart camera mote for applications in distributed intelligent surveillance. In: Proceedings of the 6th International Conference on Information Processing in Sensor Networks, IPSN 2007, pp. 360–369 (2007)
7. Zhao, T., Nevatia, R.: Tracking multiple humans in complex situations. IEEE Trans. Pattern Anal. Mach. Intell. 26(9), 1208–1221 (2004)
8. Sogo, T., Ishiguro, H., Trivedi, M.: Real-time human tracking system with multiple omnidirectional vision sensors. Syst. Comput. Jpn. 35(2), 79–90 (2004)
9. Lee, T.-Y., Lin, T.-Y., Huang, S.-H., Lai, S.-H., Hung, S.-C.: People Localization in a Camera Network Combining Background Subtraction and Scene-Aware Human Detection. In: Lee, K.-T., Tsai, W.-H., Liao, H.-Y.M., Chen, T., Hsieh, J.-W., Tseng, C.-C. (eds.) MMM 2011, Part I. LNCS, vol. 6523, pp. 151–160. Springer, Heidelberg (2011)
10. Yam, C., Nixon, M.S., Matsuo, J.N.: Automated person recognition by walking and running via model-based approches. Pattern Recognition 37(5), 1057–1072 (2003)
11. Schulz, D., Fox, D., Hightower, J.: People tracking with anonymous and id-sensors using rao-blackwellised particle filters. In: Proceedings of International Joint Conference on Artificial Intelligence (IJCAI), pp. 921–928 (2003)
12. Ramasso, E., Panagiotakis, C., Pellerin, D., Rombaut, M.: Human action recognition in videos based on the Transferable Belief Model. Pattern Analysis and Applications 11(1), 1–19 (2008)
13. Turaga, P., Chellappa, R., Subrahmanian, V., Udrea, O.: Machine recognition of human activities: A survey. IEEE Transactions on Circuits and Systems for Video Technology 18(11), 1473–1488 (2008)
14. Zappi, P., Farella, E., Benini, L.: Tracking Motion Direction and Distance With Pyroelectric IR Sensors. IEEE Sensors Journal 10(9), 1486–1494 (2010)
15. Hosokawa, T., Kudo, M., Nonaka, H., Toyama, J.: Soft authentication using an infrared ceiling sensor network. Pattern Analysis and Applications 12(3), 237–249 (2009)
16. Nonaka, H., Tao, S., Toyama, J., Kudo, M.: Ceiling sensor network for soft authentication and person tracking using equilibrium line. In: The 1st International Conference of Pervasive and Embedded Computing and Communication Systems (PECCS), pp. 218–223 (2011)
17. Tao, S., Kudo, M., Nonaka, H., Toyama, J.: Person Localization and Soft Authentication Using an Infrared Ceiling Sensor Network. In: Real, P., Diaz-Pernil, D., Molina-Abril, H., Berciano, A., Kropatsch, W. (eds.) CAIP 2011, Part II. LNCS, vol. 6855, pp. 122–129. Springer, Heidelberg (2011)