MVA2011 IAPR Conference on Machine Vision Applications, June 13-15, 2011, Nara, JAPAN

Classification of pedestrian behavior in a shopping mall based on LRF and camera observations

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Abstract

We analyze pedestrian behavior in a large shopping mall through observations using a laser range finder (LRF) and video cameras. The observed movements are classified into three categories, 'going straight,''finding the way,' and 'walking around,' based on each persons' walking speed, variability of trajectory, stopping ratio, and head motions. Pedestrian behavior reflects the individual's internal state (e.g., interests, preferences), and this analysis is intended to extract such information from the observed behavior. The obtained information is expected to be useful as marketing data for the the target facilities. It can also be useful in providing personalized on-line services to individuals corresponding to their interests and needs. In this paper, we analyze the observed properties from hand-labeled data and categorize a large-scale set of data based on the analysis. We also use our non-contact gaze tracking system to perform gaze analysis of pedestrians who look at a direction signboard in the shopping mall.

1 Introduction

Analysis of pedestrian behavior is a promising research field that covers a wide area of issues, including security, marketing, and architectonics. In computer vision research, much effort has been made in gait analysis over the past few decades [1, 2, 3]. The main focus of these research efforts has been to achieve person recognition/identification by incorporating video surveillance systems. This is an interesting and significant research pursuit that can lead to many application areas, but much more research is still needed for practical use.

On the other hand, recent advances in measurement instruments have enabled us to make long-range and stable observations of human movements. For instance, by using a laser range finder (LRF) for human tracking, it's possible to cover a wide area with a small number of sensors and to detect multiple persons' trajectories stably. Consequently, the coupling of LRF data and camera observations offers a promising method for processing large-scale pedestrian data.

The output of such measurement is a data series composed of the position (trajectory), speed, and visual appearance of each person located in the captured images. An analysis of these data would give much information on the target persons and the areas through which they move.

Recently, several research works [4, 5] have reported analyses of human movements in public facilities. The typical behaviors analyzed in this research are trajectory, head direction, and gaze direction, all of which are considered to have a close relationship with the human internal states of a person (e.g., intention, purpose, and destination). Kiyota et al. examined the relationship between walking speed and the free-space of a walking area [4]. Yamada et al. studied the relationship between the internal states of a person and walking speed, using the head motions detected in a museum [5]. Their investigations provided abundant findings regarding walking behavior, but the generality of their models is still an open issue.

In this paper, we observe pedestrian behavior in a shopping mall with LRF and camera devices and then analyze the relationship between the internal state of each person and their behaviors (walking speed, variability of trajectory, stopping ratio, and head motions). We confirmed that the behavior of a person walking in a shopping mall has similar properties to those reported in the previous research. Based on our observations, we categorized a large-scale quantity of pedestrian data. In addition, we analyzed pedestrians' gaze movement at a direction signboard in the mall; this approach can lead to a more precise analysis of an individual's interests. A typical application of the above analysis is an on-line intelligent guide system that can provide one of various levels of information corresponding to the customer's needs in a shopping mall.

This paper consists of the following sections. In the next section, we briefly summarize the task of estimating intentions/interests at a shopping mall. Section 3 explains the category model for pedestrian behavior that we employ in this paper. Section 4 gives the results of behavior analysis for the captured data based on the model. Section 5 gives our conclusions from this

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paper's work.

2 Behavior analysis for marketing and services

The analysis of customer behavior in a shopping mall is a promising way to gain useful information that directly reflects individual preferences for products and services. Therefore, many approaches have been proposed, and some of them are regularly used in daily marketing activities. One of most successful analysis techniques is the use of a point-of-sale (POS) system. The information a POS system gives is not limited to the sales of each product but includes the sales correlations among multiple products and the relationships between sales and customer characteristics (age, gender, etc.). Such information can be effectively used to determine purchasing plans and product-display strategies. However, the information a POS system provides is limited to 'consumed' products, and thus no information is given for non-consumed products that may still be items of interest. To extend/complement the POS system, the analysis of consumer behavior before purchase has been widely studied [6]. However, most conventional approaches use surveys based on sampling or questionnaire investigations, while little attention has been given to methods based on real-time observation.

In this paper, we observe pedestrian behavior in a shopping mall with LRF and camera devices and analyze the relationship between the state of each person and their behavior. We confirmed that the behaviors of persons walking in a shopping mall reflect their interests and the level of target clarity (i.e., how concrete or definite the walking destination is). Since this information cannot be detected by a POS system, it complements conventional analysis and should lead to better services for customers.

3 Defining categories of pedestrian behavior

In this section, we analyze the observed data and investigate the characteristics of different modes of walking behavior. In general, each person (customer) in a shopping mall has his/her own purpose in coming to or staying at the mall, and his/her walking behavior can be expected to reflect this motivation. We define the following three categories (modes) of behavior and examine the differences among them.

(1) Walking around
People in this category don't have a specific purpose/target place. For example, people are waiting for other person(s) or just killing time. People in this category are assumed to stay in one place for a longer time.

(2) Finding the way
Even if a person has a purpose for coming to the mall, sometimes his/her destination is still unclear. For instance, when a person comes to eat a meal or snack, he/she may not have decided on a particular restaurant yet. In this case, the person will look around the mall to choose a restaurant ('finding the way: place'). In other cases, even though a destination (shop/restaurant) is in the person's mind, he/she might not know how to get there. In this case, the person should find the appropriate route ('finding the way: route'). Though discrimination of these two cases is beyond the scope of this paper, we plan to classify them based on the locations where the peculiar behaviour, such as a slowdown of the walking speed, is observed.

(3) Going straight
When a person clearly recognizes both his/her destination and route, he/she is expected to move directly to the goal.

From the application viewpoint, such categorization will lead to services that are customized to each type of customer. For instance, we can guide people of each category in different ways (e.g., recommending shops/events to members of the 'walking around' group, or giving a floor map to those in the 'finding the way' group). Figure 1 summarizes our category definitions and service examples.

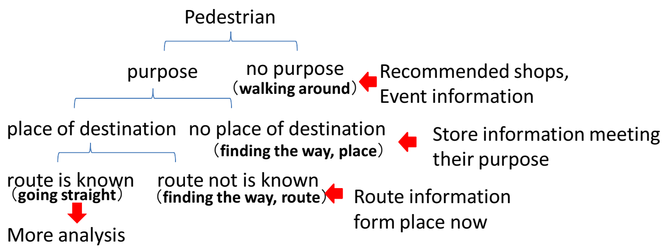


Figure 1. Classification of pedestrians and assumed services

4 Analysis and Classification

4.1 Measurement System

We used an LRF-based human tracking system and a video camera to record human (pedestrian) behavior in our experiment. In this tracking system, the location of each person in the scan area was calculated based on scan data from an LRF. Furthermore, each person was tracked with a particle filter, using a linear motion model with random perturbations. The tracking system can yield 30-Hz position data of multiple persons at about $\pm$6-cm accuracy. Further details on this algorithm are presented in [7]. Figure 2 shows an example of human trajectories captured by this system. We also recorded video sequences of target scenes using multiple camera devices for additional analysis.

For some camera images, we applied our gaze tracking system to detect pedestrians' eye movements (Figure 3). Because the system does not need a calibration process, it is suitable for use with unspecified persons [8]. Figure 4 shows a diagram of the total system. We ran a measurement experiment at a large shopping mall at the Asia and Pacific Trade Center (ATC) in Osaka, Japan for five days. We installed seven LRF sensors and three cameras on the restaurant floor of the mall. These sensors could cover a space of about 400 m^2 in the area (Figure 5).

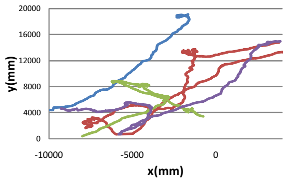


Figure 2. Trajectory of pedestrians

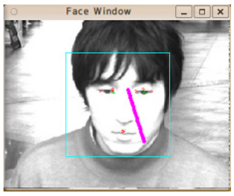


Figure 3. Gaze detection

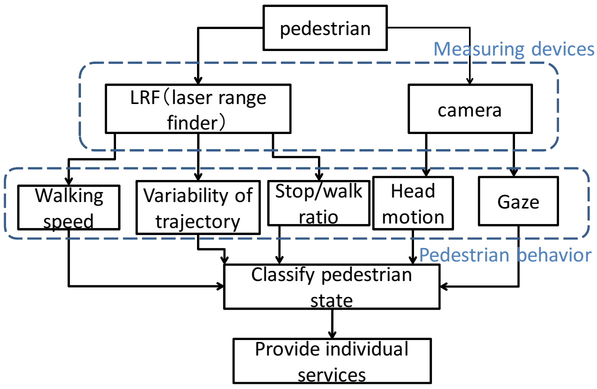


Figure 4. Service system

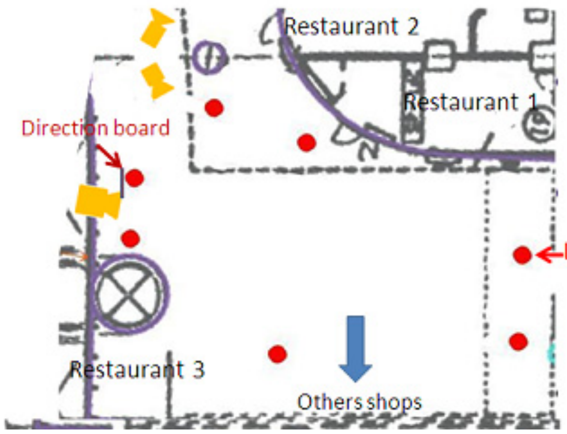


Figure 5. Floor plan for measuring pedestrians

4.2 Sample Data Set

In this section, we quantify pedestrian behavior in terms of their walking speed, variability of trajectory, stopping ratio, and head motion, and we compare these values among the categories. We used the following procedure to obtain samples for the analysis. First, we selected 5 hours of data recorded on a weekday that covers about 5000 pedestrians. After excluding the data of persons just passing through the measurement area, we labeled each of the remaining data items based on the destination and staying time (staying time in the area is longer than 180 seconds: 'waking around'; directly entering a shop/restaurant: 'going straight'; the rest of the data: 'finding the way'). As a result, we selected 10 samples for 'walking around,' 21 for 'finding the way,' and 26 for 'going straight.'

4.3 Behavior analysis for hand-labeled data

In this section, we describe the results of our analysis of the hand-labeled data in terms of the pedestrians' walking speed, variability of trajectory, stopping ratio, and head motions. In addition, we show some results of gaze analysis for people looking at a direction signboard in the shopping mall.

(1) Walking speed

Figure 6 compares the average walking speeds of all three categories (note: average speed calculation excludes data while a person is stopping; see (3)). Here, walking speed for the 'going straight' category was significantly higher than those of the other two. A person in 'going straight' is assumed to have a clear goal location, and this probably makes people walk faster.

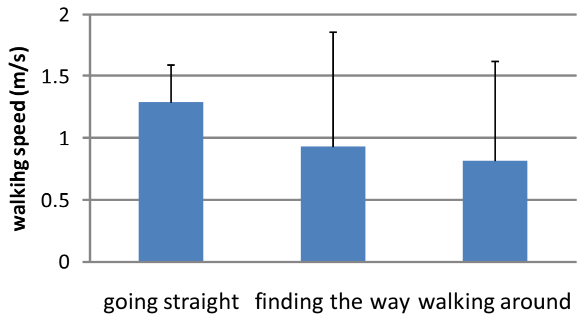


Figure 6. Comparing average walking speeds of three classes

(2) Variability of trajectory

To compare the variability of trajectory of pedestrians, we defined the scalar value d_{t_n} as follows.

$$d_{t_n} = tr\Sigma_{t_n}. \tag{1}$$

Here, Σ_{t_n} denotes the covariance matrix of velocity vector v_{t_n}:

$$\Sigma_{t_n} = \frac{1}{N}\sum_{i=0}^{N}\left(v_{t_{n-i}} - \overline{v}_{t_n}\right)^t\left(v_{t_{n-i}} - \overline{v}_{t_n}\right). \tag{2}$$

Here,

$$\mathbf{v}_{t_n} = \frac{x_{t_n} - x_{t_{n-1}}}{t_n - t_{n-1}}, \overline{v}_{t_n} = \frac{1}{N}\sum_{i=0}^{N} v_{t_{n-i}}. \tag{3}$$

Figure 7 shows the variability values for the three categories. As can be seen, the variability of 'going straight' is significantly smaller than those values for the other categories. This reflects the linearity of trajectory for 'going straight' pedestrians.

(3) Stop/walk ratio in the floor area

We also analyzed how long people in each category stopped relative to the total stopping duration of observations. Here, we assume a person is stopping when his/her observed velocity becomes lower than 0.5 m/s. Figure 8 shows the average stopping time ratios. The figure shows that people in 'going straight' continue walking more than 80% of the time; in contrast, almost all of the people in 'walking around' are likely to stop at any time. In summary, we found significant differences among the three categories.

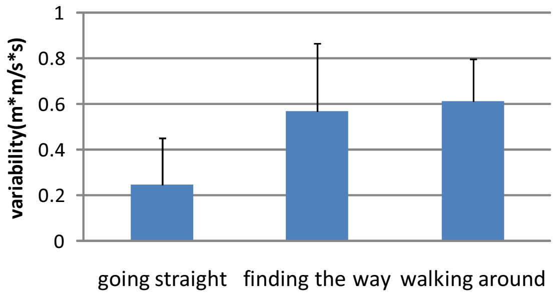


Figure 7. Average variability of trajectory

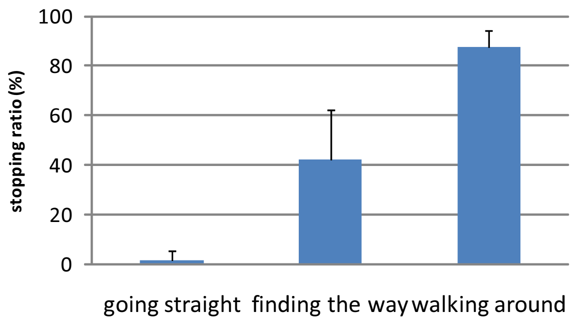


Figure 8. Stop/walk ratio in the floor area

(4) head motion

It is known that head/gaze direction is related to human attention/interests. To examine the relationship between the category and the number of head shakes, we manually analyzed the stored video data and calculated the frequency of head motions (we also applied our gaze detection method (5)).

Figure 9 shows the average frequency of head motions. Although the frequency for 'finding the way' has a larger value on average, we did not find any significant differences. However, we need further analysis of this relation.

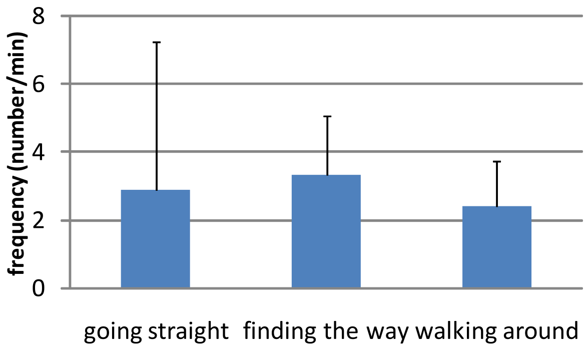


Figure 9. Average number of head motions

(5) gaze detection

In the experiments, we also applied gaze analysis to some data. Figure 10 shows an example of gaze analysis. Here, the gaze of a pedestrian is analyzed in relation to the direction signboard (Fig. 10, left) placed in the shopping mall. The right side of Fig. 10 shows the distribution of the positions to which the person looked. Such data can be used for estimating the purpose/intention of each person, coupled with an analysis of the above trajectory data. We plan to integrate the obtained data to develop effective services.

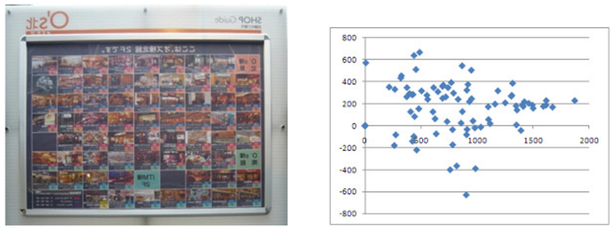


Figure 10. Eye-point of a certain pedestrian on the direction signboard

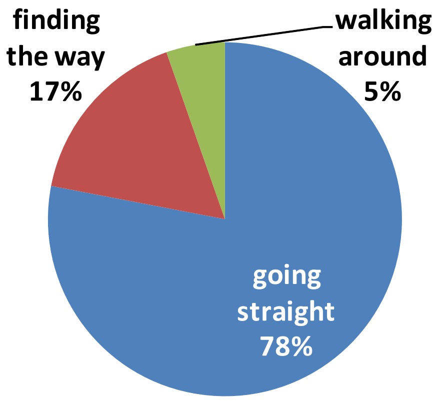
4.4 Behavior classification

In the previous section, we analyzed walking speed, variability of trajectory, stopping ratio, and head motions for samples from the three categories. To confirm the applicability of the results, we classified a larger dataset into the three categories based on the analysis. We processed data of three different time slots (daytime (12:00-14:00) and evening (18:00-19:00) on a weekday and daytime (12:00-14:00) on a holiday) and then compared the results. The time slots have 2072 (weekday daytime), 736 (weekday evening), and 4783 (holiday daytime) data items. This classification is based on walking speed, variability of trajectory and stopping ratio.

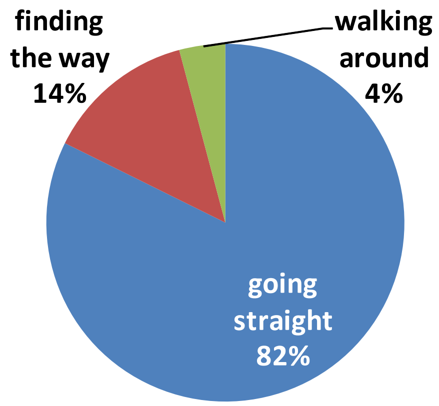
Figure 11 shows the classification results for each time slot. As can be seen, the two weekday data sets (Fig. 11 (a) and (b)) have similar category distributions. In contrast, the distribution of the holiday data (Fig. 11 (c)) looks much different. The ratio of 'going straight' decreased from the weekday data, while that of 'finding the way' increased. On weekdays, many office workers walk through this shopping mall to their office/home. Since they walk through this mall every day, they are very familiar with the types/locations of the shops. On the other hand, on holidays, many families and couples make a special trip to this area, and they are not familiar with its shops and corridors. We believe our results reflect such characteristics of pedestrian behavior, thus showing the effectiveness of our classifications.

5 Conclusions

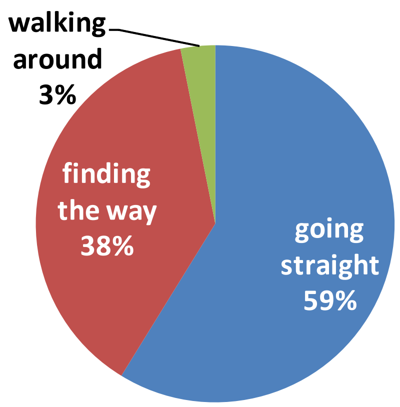
We analyzed pedestrian behavior based on walking speed, variability of trajectory, stopping ratio, and head motions using LRF- and camera-based observations. From these observations, we classified pedestrian states into three typical categories, 'going straight,' 'finding the way,' and 'walking around.' These categories provide an effective means to obtain useful information corresponding to the intentions/interests of the shoppers in a mall. For instance, we can learn how to best display a direction signboard to 'finding the way' customers. We also used our noncontact gaze tracking system to perform gaze analysis of pedestrians in the shopping mall as they look at a direction signboard.



(a) weekday (12:00-14:00)



(b) weekday(18:00-19:00)



(c) holiday(12:00-14:00)

Figure 11. Results of classifying pedestrians

Future work includes developing an interactive guide system for customers in a shopping mall based on real-time analysis of pedestrian behavior.

Acknowledgment

This research was supported in part by the Ministry of Internal Affairs and Communications of Japan.

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