Key Features to Classify Shopping Customer Status from Gait Vectors Acquired with RFID Technology

Yoshihiro Uemura
Graduate School of Information Science and Engineering
Ritsumeikan University, Shiga, Japan
e-mail: y_uemura@de.is.ritsumei.ac.jp

Yusuke Kajiwara, Hiromitsu Shimakawa
College of Information Science and Engineering
Ritsumeikan University, Shiga, Japan
e-mail: {kajiwara, simakawa}@de.is.ritsumei.ac.jp

***Abstract*—This paper proposes a method to estimate the state of user to provide proactive hospitality from features of their gait pattern acquired with an Radio Frequency Identifier (RFID) system. This method uses RFID readers on each shoe, as well as RFID tags installed on the floor. The ID of each tag is organized as a map, to show the precise position of the user. The reader and tags communicate while the user is walking. We classify tag IDs detected by readers into each step with Ward Method. We calculate stride, walking speed, and so on, as feature components of a gait vector in each step. We recognize the state of the user from these components with the Random Forest. In an experiment, we have imposed subjects on walking under several kinds of conditions. We have evaluated the classification result through F-measure calculated from 10-fold cross-validation. It implies we can classify each state of users. We discuss why we can classify each state of users from gait vector components with the variable importance and their correlation. In addition, we have verified whether we can detect discomfort caused by the way to carry luggage. Finally, we discuss the feasibility of our proposed method.**

Keywords–shopping; customer; hospitality; gait; RFID; status;

I. INTRODUCTION

The number of tourists visiting Japan has reached to more than 10 million in 2013.The government aims that every tourist can feel “Omotenashi” in Japan [1]. “Omotenashi” is a Japanese word, which means proactive hospitality. First, an Omotenashi provider grasps the state of customers in advance to provide some services before it is required. There are many tourists who are looking forward to going shopping in Japan [2]. We focus on Omotenashi services in a shopping mall. It is impossible for the shopping mall to provide Omotenashi services for each customer, because it costs too much to train and arrange Omotenashi providers. We need a system that can provide Omotenashi services at a low cost. In this paper, we consider Omotenashi services using the Information and Communication Technology. We propose the two kinds of Omotenashi services in the shopping mall. The first one is to care customers who are suffering from discomfort for luggage, or are fatigued for some reason. The second is to keep safety for distracted customers. For customers who have heavy luggage like electrical appliances as a souvenir, it proposes to use luggage storages and lockers, as well as to inform the location of the elevator. For customers who have fatigue after long shopping, it recommends a resting place like a cafe. It warns distracted customers watching the advertisements or smartphones while walking. We also consider that customers feel uncomfortable when they hold luggage in a different way than usual. For example, they sometimes have to carry luggage with one hand to hold their baby. In these cases, services should also be changed. It is necessary to identify when they are forced to have luggage with an uncomfortable way by external factors to provide more comfortable services.

Omotenashi services found on grasping the state of a customer in advance. This paper refers to the information as a user status. In this paper, we define the following user status; They are carrying luggage, tired, texting (i.e., using smartphones) while walking, and focusing on advertisements. We assume our services are provided in major streets or in front of display windows. We estimate user status in the areas from their gait patterns. We discuss the variables which play an important role in the estimation. Section 2 introduces existing works. Section 3 explains our method to calculate the feature of customers’ gait. In Section 4 and Section 5, we indicate the experiment and evaluation. In Section 6, the paper discusses the practical possibilities. Section 7 summarizes our work.

II. RELATED WORK

Several methods are proposed to detect user status. Ikeda et al. identify some kinds of luggage like carts and backpacks, using more than one Laser Range (LR) sensors installed around the user [3]. Qi et al. identify whether the user has a suitcase and a backpack from the ratio of left and right contours against the center of the body detected by a camera [4]. Yonekawa et al. detect user fatigue from changes of pressure values measured with sensors installed in shoe insoles [5]. Arif et al. show the fatigue is related to the stability of walking, using 3D accelerometer sensors [6]. Music et al. detect texting while walking from the standard deviation of meter readings from accelerometer sensors [7]. Thepvilojanapong et al. calculate the degree of attention from the staying judgement, the movement of people, discrimination of people, and so on, using LR sensor placed beside walls [8]. Clippingdale et al. detect attention state and estimate interest from direction and expression of the face, direction of the upper body, and so on, using cameras installed in TVs [9]. However, these sensors can only identify one or few kinds of user status. Moreover, positional information is necessary to provide Omotenashi services on the spot. Some of these sensors, pressure sensor and accelerometer sensor, cannot grasp positional information by themselves. Since cameras are poor at shielding privacy, it is difficult to install them in public places like shopping malls. LR sensors are expensive. We need a system to accurately

 ISBN: 978-1-61208-426-8

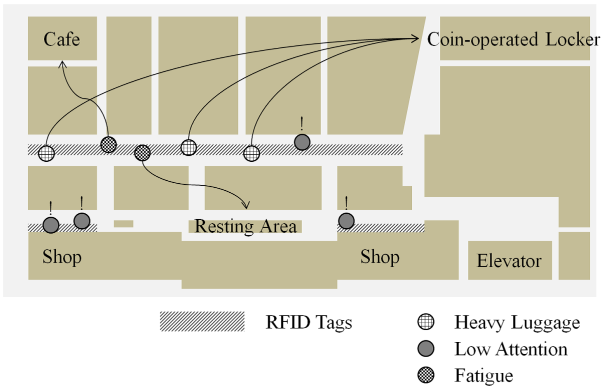

Figure 1. Omotenashi services in actual environment

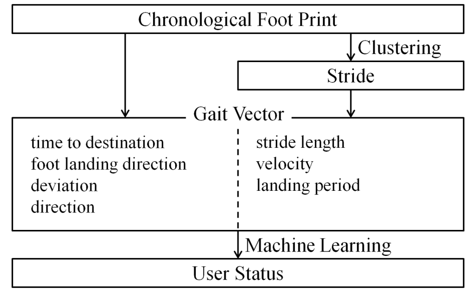

Figure 2. User Status Estimating System

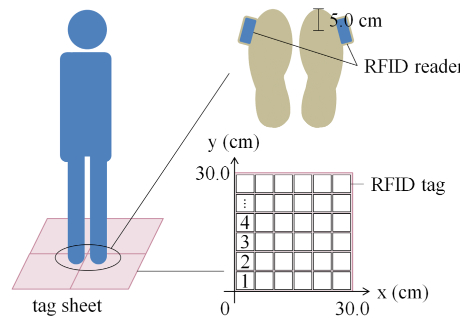

Figure 3. Localization system using RFID

grasp multiplex status of a user, causing no problem in the issues above.

Gaits vary with user states [10]. We focus on gaits which have positional information as well as are good at shielding. To detect gaits, it is required to grasp accurate positions where the user foots ground. Cho et al. get precise positional information for mobile robot localization with RFID [11]. Wang et al. use hybrid RFID systems to position pedestrians [12]. According to these studies, an RFID can detect accurate positional information. However, it is not studied to detect gaits and to estimate the user status using RFID.

III. Gait Measurement with RFID

A. Gait Vector

We aim at realizing a system to provide Omotenashi services using RFID. Figure 1 shows how the system works in an actual environament. The system provides services suitable for the current status estimated for every user. An RFID reader and an RFID tag costs about 20 US dollars and several US cents for each, respectively. Our system has high scalability, because the range of our positioning system depends on only the density of RFID tags installed on floors. We assume a shopping mall lends customers readers they wear like anklets, as well as installs tags on areas such as a part of the main street and spaces in front of show windows. Services suitable for each user status make users comfortable, when they are provided before the users request. It realizes Omotenashi services. It leads to acquisition of repeaters and new customers. If every shop installs tags in front of their show windows, it can calculate the degree of attention of users to their merchandise. Understanding constituency, they can improve their services.

In this paper, we estimate user status from a gait, using RFID. Figure 2 shows our method. RFID readers get chronological foot prints based on the foot landing position. 19-dimensional features compose a gait vector for each foot print. Suppose a learner on a computer, which takes gait vectors measured with the RFID system. We train the learner so that it identifies user status. Since there are individual differences in gaits, a learner is trained for each user.

B. Detection of landing position

RFID is a short-range wireless communication technology consisting of a tag with a unique ID and a reader to detect the ID [13]. We use the HF-band RFID technology whose communication distance is several centimeters.

The proposed method uses 45 mm$\times$45 mm square-type RFID tags. It prepares a tag sheet paved with the RFID tags every 50 mm vertically and horizontally. It assumes the tag sheets cover the floor of a specific area. A user wearing an RFID reader on the point 5.0 cm away from the toe walks on the tag sheets as depicted in Figure 3. A unique ID detected by the RFID reader is transformed into the coordinates representing the user position in the area. When the user walks, the coordinates are obtained chronologically.

C. Clustering

The sample rate of the reader is 0.20-0.25 seconds per detection. Generally, the walking speed and a stride is approximately 4.0 km per hour and 1.2-1.8 m [14], respectively. It takes one stride about 1.1-1.6 seconds. The sample rate is high enough to detect it, even if the walking speed has changed up to 5 times faster than the normal one. Depending on the direction in which the reader approaches the tag, more than one tag may be detected in the one step. To understand this reason, let us consider the movement of a foot. Its landing to or rising from the ground at a moderate angle makes some tags meet the communication range. Plural coordinates should be treated as one record, if they correspond to one step. We cluster more than one coordinates corresponding to one step with the Ward method [15], which is a hierarchical cluster analysis method using the ratio of the variance within and between groups. Here, to find one step, we cut out a cluster whose centroid is away by a specific distance from that of the cluster corresponding to the previous step. It allows us to cluster coordinates even if a user takes various steps at a constant interval. We refer to clusters generated by the Ward method as step clusters.

 ISBN: 978-1-61208-426-8

D. Feature Components of the Gait

It is assumed that the user status causes changes in gaits as follows.
Because of heavy luggage,

- Position of the center of gravity is not stable.
- Walking Direction is deviated.
- Walking speed gets slower.

Because of fatigue,

- Stride gets smaller.
- Walking speed gets slower.
- Landing time of the foot gets extended.

Because of low attention,

- Walking speed gets slower.
- Walking Direction is deviated.
- Landing time of the foot gets extended.

This paper defines a gait vector, which presents features of gaits, to identify the user status. We calculate the walking time, the number of detection, the deviation, the direction, the landing period, the stride, and the velocity from recent N step clusters in a fixed interval. The walking time, w_t, is difference between the start point, t_b, and the end point, t_e, of detected time.

$$w_t = t_e - t_b \quad (1)$$

We consider $c_w(i)$ as the j-th detected tag in the i-th detected step cluster. We regard $n_g(i)$ as the number of detection of tags in $c_w(i)$. The total number of detection, w_{nd}, is calculated as follows.

$$w_{nd} = \sum_{i=1}^{N} n_g(i) \quad (2)$$

We assume the proceeding direction of the user is the positive direction of the y-axis, and the direction turning clockwise it 90 degrees is the positive direction of the x-axis. We refer to $(g_x(i,j), g_y(i,j))$ as a detected coordinate. When a user walks stably, $g_x(i,j) = 0$. Deviation, g_{dev}, is the standard deviation of the x-coordinate.

$$g_{dev} = \sqrt{\sum_x \sum_y g_x(i,j)^2} \quad (3)$$

Let us consider slope a of the regression line, regarding the x-coordinate as the explanatory variables and the y-coordinate as the objective variables. In $c_w(i)$, let the first tag is detected at time $g_t(i,b)$ and the last one at $g_t(i,e)$. The landing period, $g_t(i)$, is calculated as follows;

$$g_t(i) = g_t(i,e) - g_t(i,b) \quad (4)$$

Here, we consider the following distance values to calculate a stride and the walking speed.
w_{w_1}: Cluster center-to-center distance between the current step and the next step.
w_{w_2}: Distance of the landing position between the current step and the next step.
w_{w_3}: Distance of the rising position between the current step and the next step.
w_{w_4}: Distance between the current landing position and the rising position of the next step.

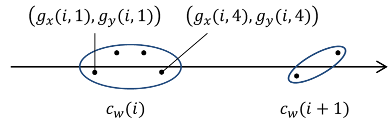

Figure 4. Detail of Step Cluster

w_{w_5}: Distance between the current landing position and the rising position of the next step.
Figure 4 shows details of a step cluster.

We calculate distances between the n-th step cluster and $(n+1)$-th one. $w_{w_1}(i)$ is an Euclidean distance between coordinates which has central time. $w_{w_2}(i)$ is an Euclidean distance between coordinates which has minimum time. $w_{w_3}(i)$ is an Euclidean distance between coordinates which has maximum time. $w_{w_4}(i)$ is an Euclidean distance between a coordinate which has minimum time of the n-th step cluster and a coordinate which has maximum time of the $(n+1)$-th one. $w_{w_5}(i)$ is an Euclidean distance between a coordinate which has maximum time of the n-th step cluster and a coordinate which has minimum time of the $(n+1)$-th one. We also consider the following velocity values using distance values. w_{v_1} is a velocity between coordinates which has central time. w_{v_2} is a velocity between coordinates which has minimum time. w_{v_3} is a velocity between coordinates which has maximum time. n is related from 1 to 3.

$$w_{v_n} = \frac{\sum_1^{N-1} w_{w_n}(i)}{w_t} \quad (5)$$

After we calculate both of the right foot gait vector and the left foot one, we combine them to a single gait vector.

E. Learning and Identification

We examine relationships of the gait vector to the user status. We distinguish features of a gait to identify the user status with the machine learning method, Random Forest (RF) [16]. RF is a group learning method using a tree model, and it is suitable for analysis of the case containing many explanatory variables. RF has two steps, the learning step and the identification step. In the learning step, it creates tree models from pairs of a gait vector and a user status presented as an instruction signal. In the identification step, it identifies the user status corresponding to a new gait vector through the tree model generated in the learning step.

IV. Possibility of Detection of Use Status

A. Experimental Purpose and Overview

We experiment to identify 4 kinds of user status discussed in chapter 2 from the disturbance of a gait while walking. In the experiment, we use ASI4000USB which is an HF band (13.56 MHz) RFID reader. Its communication distance is about 3.0 cm. We use Tag-It HF-I as an RFID tag. The threshold of clustering shown in session 3.C is 100. Subjects are 11 males and 3 females whose age ranges from 21 to 24. Each of them wears an RFID reader on the point 5.0 cm away from the toe. We install tag sheets on the floor as shown in Section 3.B. The RFID reader attached to each shoe is connected to a laptop PC with USB cables. The walking range is 10.0 m×0.6 m. Among it, the range where tags are installed is 6.0 m×0.6 m, excluding 2.0 m in the both sides as Figure 5 shows. We

 ISBN: 978-1-61208-426-8

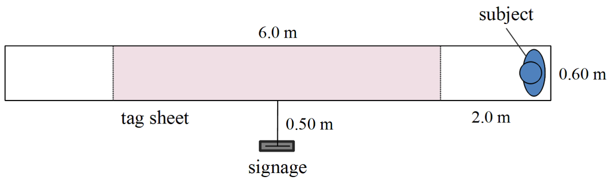

Figure 5. Experimental Environment

record gaits during the following 5 kinds of behavior before and after the physical fatigue uniformly brought by an exercise presented in Section 4.B. We repeat this trial 50 times.

- S_N Walking with no stress.
- S_{LB} Walking with two packages of luggage of 5.0 kg held in both hands.
- S_{LO} Walking with luggage of 5.0 kg held in the right hand.
- S_T Texting while walking, watching a Web site on a smartphone.
- S_A Walking with paying attention to a signage in the middle of the walking range.

Each subject takes a rest for about 30 minutes after each trial. The number of data acquisition per day is less than 100 times to prevent fatigue from affecting on a specific person. After the experiment, we ask the subjects what action is the most uncomfortable.

B. Uniform Fatigue

To artificially make subjects run into a physical fatigue state (S_F), uniformly in each trial, we impose the following exercise on them. We use the exercise intensity calculated from Karvonen method using the heart rate as a measure of S_F [6]. For a subject at age a, the maximum heart rate (M) is calculated with $(220 - a)$. The stable heart rate (R) is measured after a rest for 30 minutes. The real-time heart rate (C) is measured while walking. The exercise intensity (H) is calculated every second with

$$H = \frac{C - R}{M - R} \times 100 \tag{6}$$

Subjects go up and down the stairs at a pace of two steps per second, calculating H every second. They repeat this exercise until the value of H exceeds 60 in total 600 times.

C. Result

We divide input data into 10 groups to take 10-fold cross-validation. We train RF with 9 groups, while measure its performance with 1 group. We evaluate the performance with the F-measure (f) calculated from the precision (p) and the recall (r). The following equation shows how to calculate f.

$$f = \frac{2 \cdot p \cdot r}{p + r} \tag{7}$$

The trained RF classifier distinguishes 5 kinds of behavior: S_N, S_{LB}, S_{LO}, S_T, and S_A . It also discriminates S_F and other user status corresponding to S_{NF}. We show the result in Table I and Table II.

In the upper part of Table I, the table head shows an actual behavior, while each row shows the number of correct

TABLE I. IDENTIFICATION AMONG 5 KINDS OF BEHAVIOR

	S_N	S_{LB}	S_{LO}	S_T	S_A
S_N	960	157	242	46	37
S_{LB}	175	907	271	67	30
S_{LO}	191	259	796	74	36
S_T	41	62	64	1084	167
S_A	33	15	27	129	1130
p	0.666	0.626	0.587	0.764	0.847
r	0.686	0.648	0.569	0.774	0.807
f	0.676	0.636	0.578	0.769	0.827

TABLE II. IDENTIFICATION WHETHER THE USER IS FATIGUE

	men		women	
	S_{NF}	S_F	S_{NF}	S_F
S_{NF}	1746	877	561	228
S_F	1004	1873	189	522
p	0.666	0.651	0.711	0.734
r	0.635	0.681	0.748	0.696
f	0.650	0.666	0.729	0.715

TABLE III. VARIABLE IMPORTANCE

variable	5 behavior	S_{NF} and S_F
w_t	13.899	6.023
w_{nd}	5.499	3.757
g_{dev}	9.592	6.768
$M\ of\ g_t(i)$	5.375	4.413
$SD\ of\ g_t(i)$	4.672	4.779
w_{v_1}	30.005	8.571
w_{v_2}	17.407	6.383
w_{v_3}	17.899	6.507
$M\ of\ w_{w_1}$	5.763	5.040
$M\ of\ w_{w_2}$	5.553	4.662
$M\ of\ w_{w_3}$	5.317	4.670
$M\ of\ w_{w_4}$	4.365	4.547
$M\ of\ w_{w_5}$	7.464	5.352
$SD\ of\ w_{w_1}$	4.205	4.686
$SD\ of\ w_{w_2}$	4.375	4.796
$SD\ of\ w_{w_3}$	4.253	4.628
$SD\ of\ w_{w_4}$	4.243	4.286
$SD\ of\ w_{w_5}$	4.207	4.723
a	5.503	5.161
mean	8.400	5.250
standard deviation	6.638	1.107

classification. The result reveals the user status is classified fairly correctly.

After experiment, 11 of 14 subjects have told S_{LO} is the most uncomfortable behavior. In spite of the opinion, the uncomfortable behavior does not have the highest classification rate. It implies there are not obvious features in the gait even if the user feels strong discomfort. In Table I, many misclassified cases are found within the group of (S_N, S_{LB}, S_{LO}) and the group of (S_T, S_A). It leads features of S_N, S_{LB}, and S_{LO} are similar, as well as features of S_T and S_A are similar. Through the comparison of the classification result in Table II, the classification is more successful in women. It implies women is likely to show more fatigue features in their gaits than men.

Let us consider the importance of each component of a gait vector in Table III. We simplified the mean and the standard deviation as M and SD for each. w_{v_1}, w_{v_2}, w_{v_3}, and w_t are higher than the mean in the classification among the 5 kinds of behavior. The standard deviation of the variable importance is also large for the 5 kinds of behavior. It implies these are important components for classification. In the discrimination between S_{NF} and S_F, w_{v_1}, g_{dev}, and some of other importance are higher than average. However, standard

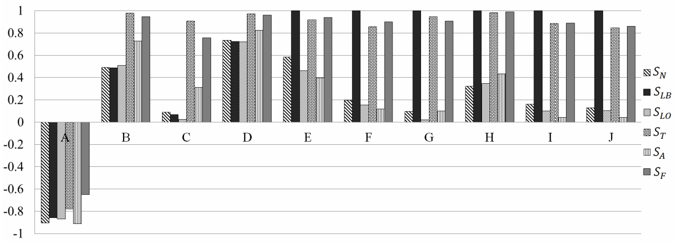

Figure 6. Components with high correlation coefficients

TABLE IV. COMBINATIONS OF COMPONENTS

	Combination	
A	w_t	w_{v_1}
B	w_t	$M\ of\ g_t(t)$
C	w_t	$SD\ of\ g_t(t)$
D	w_t	w_{nd}
E	w_{v_1}	$M\ of\ w_{w_1}(i)$
F	w_{v_1}	$SD\ of\ w_{w_1}(i)$
G	w_{v_1}	a
H	$M\ of\ w_{w_1}(i)$	$SD\ of\ w_{w_1}(i)$
I	$M\ of\ w_{w_1}(i)$	a
J	$SD\ of\ w_{w_1}(i)$	a

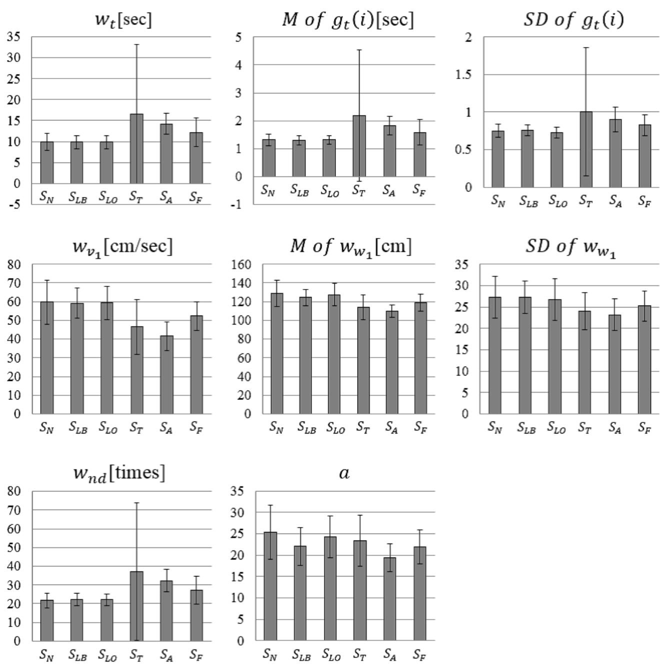

Figure 7. Average and standard deviation of each component

deviation is not large. It indicates each component shows the physical fatigue. Let us discuss each component through the correlation analysis. It is obvious that each stride has strong correlation with the walking time. Excluding these ones, Figure 6 compares combinations of 2 gait vector elements, which has correlation higher than 0.8 or lower than -0.8. In the figure, the symbols from A to J stand for the combinations shown in Table 4. In addition, Figure 7 shows the average and the standard deviation of each component value for all subjects.

Let us discuss every behavior compared with behavior S_N where no load is imposed on subjects. S_{LB} shows negative correlation between w_t and w_{v_1}, and positive correlation among w_{v_1}, $M\ of\ w_{w_1}(i)$, $SD\ of\ w_{w_1}(i)$, and a. Compared with S_N, S_{LB} has no difference in average and standard deviation except $M\ of\ w_{w_1}(i)$, which means each step gets shorter. These imply subjects slow down with shorter walking cycle. S_{LO} shows negative correlation between w_t and w_{v_1}. It has no difference in average and standard deviation from S_N. These imply S_{LO} is similar to S_N. However, Table I indicates S_{LO} is distinguished from S_N fairly well. It seems each subject feels load in an individual way. S_T has positive correlation among w_{v_1}, $M\ of\ w_{w_1}(i)$, $SD\ of\ w_{w_1}(i)$, and a as well as positive correlation among w_t, w_{nd}, $M\ of\ g_t(i)$, and $SD\ of\ g_t(i)$. In cases of S_T where subjects are texting while walking, the standard deviation of some components is much larger than others. It means the walking way varies with persons. The correlation means subjects take smaller strides and longer landing duration when they slow down. S_A shows negative correlation between w_t and w_{v_1}, while positive correlation between w_t and w_{nd}. The average and the standard deviation of strides are smaller than others in S_A. These imply subjects slow down with smaller and fixed strides which increase their stepping. S_F has positive correlation among w_{v_1}, w_{nd} and $M\ of\ g_t(i)$, and positive correlation among w_{v_1}, $Mofw_{w_1}(i)$, $SD\ of\ w_{w_1}(i)$, and a. The observation implies subjects slow down with smaller strides. We can identify each behavior of the user status, if we check the characteristics discussed above.

V. GAIT DIFFERENCE BY WAY OF CARRYING LUGGAGE

A. Experimental Purpose and Overview

Let us see whether some features appear on gaits when people are forced to have luggage with uncomfortable way by some external factors. We examine features of gait vectors under various way of carrying luggage or various feelings of subjects while carrying luggage. Subjects are 1 male and 11 females, whose age ranges from 19 to 22 years old. Experimental conditions are same as session 4.A. We record gaits under the following 3 kinds of behavior.

- S_{LH} Walking with luggage of 4.0 kg holding in the right hand.
- S_{LE} Walking with luggage of 4.0 kg slinging over the right arm.
- S_{LS} Walking with luggage of 4.0 kg slinging on the right shoulder.

Every subject takes each kind of behavior 10 times, interleaving 5 minute break. We have inquired of the subjects what action makes them most comfortable and most uncomfortable.

B. Classification

We have classified 3 kinds of behavior in the same way as section 4.C. The result reveals we can identify each behavior roughly.The F-measure values of S_{LH}, S_{LE}, and S_{LS} are 0.599, 0.516, and 0.562, respectively. The standard deviation of the F-measure among subjects is 0.17804. It implies there is big difference in each individual. As for the importance of components, 2 groups are found; g_{dev} and w_{v_1} are high in one group, while g_{dev} and $M\ of\ w_{w_1}(i)$ is high in the other. The 3 variables, g_{dev}, w_{v_1}, and $M\ of\ w_{w_1}(i)$, are important for identification. According to the interview after the experiment, all subjects feel S_{LH} and S_{LE} uncomfortable (5 subjects and 7 subjects), while S_{LS} comfortable (12 subjects) for each.

Copyright (c) IARIA, 2015. ISBN: 978-1-61208-426-8

We divide S_{LH} and S_{LE} from S_{LS} to make the two groups, uncomfortable one and comfortable one, respectively. Let us classify the two groups with gait features. Because of the difference of the number of cases in each group, we randomly sample 100 cases. The F-measure values of uncomfortable one and comfortable one are 0.679 and 0.657 for each.

The result implies we can classify each behavior. The importance of components are high at g_{dev}, w_{v_1}, and M of $w_{w_1}(i)$. The way to carry luggage affects gaits, which enables us to guess how subjects feel when walking. In addition, behavior a in this experiment corresponds to S_{LO} in the former experiment. We can distinguish uncomfortable behavior from other kinds of behavior. The interview indicates subjects feel the least load on the body, if they carry luggage slinging on shoulder. The number of sample data might be the reason of variance in the classification. It might be caused by subjects carrying luggage in an unusual way. The importance of components suggests the center of gravity of the body is not stable by the luggage. It seems they slow down or change their steps to ease their uncomfortable feelings.

VI. Discussion

In this paper, we have mentioned the problems of cost, classification ability, and so on in section 2. An RFID reader is about 20 US dollars and a RFID tag is several US cents for each. Our system has high scalability, because the range of our positioning system depends on only RFID tags. The experiment has revealed we can identify all kinds of user status, and whether the user is carrying luggage with uncomfortable way at a certain range, using only the RFID system. If our system is installed in the shopping mall, we can grasp the customer status to provide Omotenashi services suitable for each of them. We assume the shopping mall lends customers a pair of readers, and install tags at some areas like a part of major streets or spaces in front of show windows. Stores in the shopping mall can also easily install the RFID tags, because it is relatively at low cost, and we only have to install them in a specific area of each store.

Since we can know the status of customers from their gaits, we can provide suitable services for each status. We propose the following services for each status. In case of behavior S_{LB}, carrying luggage with both hands, subjects tune various components of the gait vector. It means customers accommodate themselves to the load of luggage. To make the enduring time short, the system should recommend the shortest way to their destination. On the other hand, subjects tune few components of the gait vector in S_{LO}, carrying luggage with one hand. It is too high load for them to carry luggage. The system should recommend to take rests at cafes near them, or to ride on vehicles. The system should call their attention to avoid accidents in advance when they are in S_T, texting, and S_A, low attention. The system provides details of the advertisement customers look at when they are in S_A. Recommendation like S_{LO} is preferable when they are is in S_F, fatigue. Customers experience the high level of satisfaction, which lead to increase of customers. In the experiments, subjects are only their age of 20s. However, features of gaits are not different between 20s and 60s [17]. In addition, the rate of foreign visitors to Japan consists of 17.7% men of 30s, 13.5% women of 20s, 13.0% men of 40s, and 12.8% men of 20s [2]. Our method based on gaits covers many visitors to Japan.

VII. Conclusion

In this paper, we have proposed the method to provide customers high quality Omotenashi services using their gait pattern acquired with the RFID technology. In experiment, we have proved the method identifies the state of users from features of their gait. In addition, we have shown we can find out users carrying luggage in unusual ways. However, to classify the state of carrying luggage accurately, we need to train the system individually. We must consider accuracy improvement and generalization from individual as future works. In addition, we consider the RFID readers shape and more specific services.

References

[1] Japan Tourism Agency, “To the realization of the 20 million foreign visitors era”, http://www.mlit.go.jp/common/000059772.pdf [retrieved: July, 2015] (in Japanese).

[2] Japan Tourism Agency, “Consumption trends of foreign visitors”, 2013, http://www.mlit.go.jp/common/001032143.pdf [retrieved: July, 2015] (in Japanese).

[3] Ikeda, T. et al., “A Method to Recognize 3D Shapes of Moving Targets based on Integration of Inclined 2D Range Scans”, IEEE International Conference on Robotics and Automation, 2011, pp. 1237-1240.

[4] Qi, Y. et al., “Carrying Object Detection and Tracking Based On Body Main Axis”, IEEE International Conference on Wavelet Analysis and Pattern Recognition, 2007, pp. 1237-1240.

[5] Yonekawa, K. et al., “FASH: Detecting Tiredness of Walking People Using Pressure Sensors”, Mobile and Ubiquitous Systems: Networking & Services, 2009, pp. 1-6.

[6] Arif, M. et al., “Analysis of the effect of fatigue on walking gait using acceleration sensor placed on the waist”, International Journal of Engineering Intelligent Systems, 2010, pp. 93-103.

[7] Music, J. wt al., “Is it Possible to Detect Mobile Phone User’s Attention Based on Accelerometer Measurment of Gait Pattern?”, IEEE Symposium on Computers and Communications, 2013, pp. 522-527.

[8] Thepvilojanapong, N. et al., “Evaluating People’s Attention in the Real World”, ICROS-SICE International Joint Conference, 2009, pp. 3702-3709.

[9] Clippingdale, S. et al., “Level-of-Interest Estimation for Personalized TV Program Recommendation”, IEEE International Conference on Consumer Electronics, 2013, pp. 11-14.

[10] Abiko, T. et al., “Influence of Different Methods of Carrying a Load on Gait Parameters of Healthy Young Adults”, The Society of Physical Therapy Science, 2014, Vol. 29, No. 1, pp. 147-149(in Japanese).

[11] Choi, B. et al., “A Hierarchical Algorithm for Indoor Mobile Robot Localization Using RFID Sensor Fusion”, IEEE Transactions on Industrial Electronics, 2011, Vol. 58, No. 6, pp. 2226-2235.

[12] Wang, H. et al., “Hybrid RFID System-based Pedestrian Localization: A Case Study”, 2013 10th Workshop on Positioning, Navigation and Communication, 2013, pp. 1-6.

[13] R. Weinstein, “RFID: a technical overview and its application to the enterprise”, IT Professional, 2005, Vol. 7, No. 3, pp. 27-33.

[14] Perry, J. and Burnfield, J., “Gait Analysis: Normal and Pathological Function”, Chapter 20, Slack Inc (2010).

[15] Ward, J. H., “Gierarchical grouping to optimize an objective function”, Journal of the American Statistical Association, 1963, vol. 58, no. 301, pp. 236-244.

[16] Breiman, L., “Random Forests, Journal of Machine Learning”, 2001, vol. 45, pp. 5-32.

[17] Jin, B. et al., “Walking-Age Analyzer for Healthcare Applications”, IEEE Journal of Biomedical and Health Informatics, 2014, pp. 1034-1042.