Sensors & Transducers, Vol. 194, Issue 11, November 2015, pp. 76-83

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Sensors & Transducers

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Estimating Human Physical States from Chronological Gait Features Acquired with RFID Technology

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Received: 31 August 2015 /Accepted: 15 October 2015 /Published: 30 November 2015

Abstract: This paper proposes a method to estimate the state of the user to provide proactive hospitality from features of their gait pattern acquired with a 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 extract feature components which represents gait patterns. Two-way ANOVA test and correlation analysis are conducted to find significant features. We classify the state of the user from these components with the Naïve Bayes, the Support Vector Machine, and the Random Forest. Compared with each combination of the analysis and the machine learning method, the most efficient way is found to identify the state of the user. The experimental results show that different state of users can be classified appropriately. Finally, variable importance and the feasibility of proposed method are discussed to show potential implications of the proposed approach. *Copyright © 2015 IFSA Publishing, S. L.*

Keywords: Shopping, Customer, Hospitality, Gait, RFID, The states of the user.

1. Introduction

The number of tourists visiting Japan has reached to more than 10 million in 2013 [1]. The Japanese government aims that every tourist can feel “Omotenashi” in Japan. “Omotenashi” is a Japanese word, which means providing proactive hospitality [2]. First, an Omotenashi provider grasps the state of customers in advance to provide some services before it is requested. There are many tourists who are looking forward to going shopping in Japan [3]. Our research focuses on Omotenashi services in a shopping mall. However, it is impossible for the shopping mall to provide Omotenashi services for each tourist, 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 using the Information and Communication Technology. We propose two kinds of Omotenashi services in the shopping mall. The first one is to care tourists who are suffering from discomfort for luggage, or are fatigued for some reason. The second is to keep safety for distracted tourists. For tourists who have heavy luggage like electrical appliances as a souvenir, it proposes to use luggage storages and lockers, and to inform the location of the elevator. For tourists who are exhausted after long shopping, it recommends a resting place like a café. It warns distracted tourists watching the advertisements or smartphones while walking.

Omotenashi services are founded to grasp the state of a customer in advance. This paper refers to the information as a user status. In this paper, we define four user states. They are:

1) Carrying luggage;

2) Tired;

3) Texting (i.e. using smartphones) while walking;

4) Focusing on advertisements. We assume our services are provided in major streets or in front of display windows. User status in areas is estimated from gait patterns of customers. We then discuss variables which play a significant role in the estimation.

2. 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 [4]. 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 [5]. Yonekawa, *et al.* detect user fatigue from changes of pressure values measured with sensors installed in shoe insoles [6]. Arif, *et al.* show that the fatigue is related to the stability of walking, using 3D accelerometer sensors [7-8]. Music, *et al.* detect texting while walking from the standard deviation of meter readings from accelerometer sensors [9]. 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 [10]. Clippingdale, *et al.* and Naemura, *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 [11-12]. 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 cannot grasp positional information by themselves. Since cameras are poor at shielding privacy [13], it is difficult to install them in public places like shopping malls. LR sensors are expensive. We need a system to accurately grasp multiplex states of a user, causing no problem in the issues above.

Gaits vary with user states [14-15]. 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 [16-17]. Wang et al. use hybrid RFID systems to position pedestrians [18]. 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.

3. Gait Measurement with RFID

3.1. Gait Vector

We aim at realizing a system to provide Omotenshi services using RFID. Fig. 1 illustrates how the system works in an actual environment.

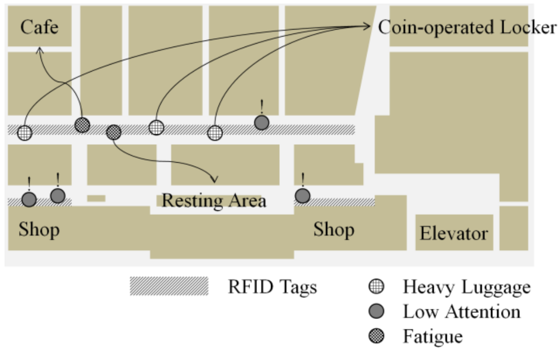

Fig. 1. Omotenashi services in actual environment.

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 only on 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 area 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 states from a gait, using RFID technology. Fig. 2 shows our method.

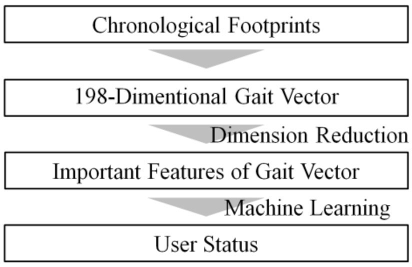

Fig. 2. User status estimating system.

As shown in Fig. 2, RFID readers get chronological footprints based on the foot landing position. 99-dimentional features compose a gait vector for each foot print. Important features are picked up by some dimension reduction methods. Suppose a learner implemented 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.

3.2. Detection of Landing Position

RFID is a short-range wireless communication technology consisting of a tag with a unique ID and reader to detect the ID [19]. We use the HF-band RFID technology whose communication distance is several centimeters. The proposed method uses 45 mm×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 Fig. 3.

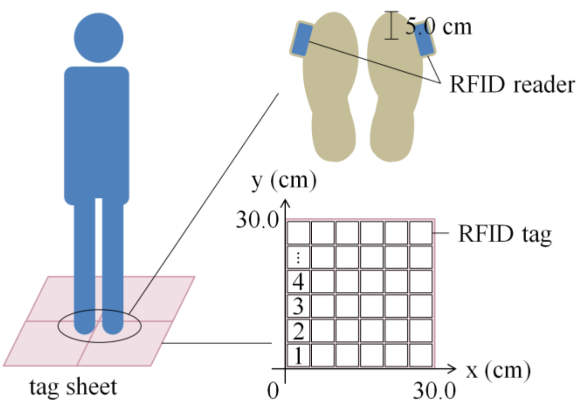

Fig. 3. Localization system using RFID.

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. The sample rate of the reader is 0.20-0.25 seconds per detection. Generally, the walking seed and a stride are approximately 4.0 km per hour and 1.2-1.8 m [20], 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.

3.3. 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 unstable;
- Walking direction is deviated;
- Walking speed gets inconstant.

Because of fatigue,
- Stride gets smaller;
- Walking speed gets slower;
- Landing time of the foot gets extended.

Because of low attention,
- Walking speed gets inconstant;
- Walking direction is deviated;
- Landing time of the foot gets unstable.

This paper defines a gait vector, which presents features of gaits, to identify the user status. The gait vector contains various feature components as shown in Table 1.

Table 1. Feature components of gait vector.

c_x	chronological x-coordinates
d_x	difference of x-coordinates
d_y	difference of y- coordinates
d_t	difference of detected timestamps
n_{d02}	number of detections in 0.2 seconds
n_{d05}	number of detections in 0.5 seconds
n_{d10}	number of detections in 1.0 seconds
v	velocity

d_x, d_y and d_t are the difference between one detected coordinate or time and the previous adjacent one. v is calculated as follows:

$$v = \frac{d}{t}, \quad (1)$$

where d is the distance between the last detected position and the first detected position, t is the period of time of walking. Mean, standard deviation and sum are calculated for each feature component except v. Moreover, we define various extrema feature factors for each feature component based on signal analysis [21]. The extrema features we extracted include: the number of peaks and valleys, the height of each peak, duration, and area of d_x, as shown in Fig. 4. All feature components include same extrema factors. Area a is calculated from the height of peak h_p and duration dur.

$$a = \frac{h_p \times dur}{2} \quad (2)$$

These factors also contain mean, standard deviation and sum. After calculation of both of the right foot gait vector and the left foot one, we combine them to a single gait vector.

3.4. Important Feature Components

In machine learning, extraction of significant elements from numerous feature components allows us to identify user status more efficiently. We conduct two-way ANOVA test to find significant features. A correlation analysis (CA) is also conducted as a dimension reduction processing. The two-way ANOVA test finds features which have a significant impact on identifying each user status. CA reduces variables which has similar features with each other.

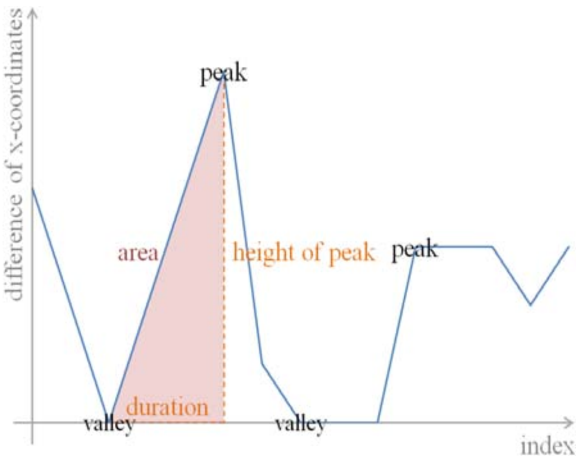

Fig. 4. Each factors of d_x.

3.5. Learning and Identification

We examine relationships between the gait vector and the user status. Various widely used machine learning methods have been applied to classify user status based on features of gait. The machine learning methods used in this paper include Naive Byes (NB), Support Vector Machine (SVM), and Random Forest (RF). The NB classifier applies the Bayes' theorem, and it considers each feature to have contributed independently. While it can be trained very efficiently, it nonetheless contains oversimplified assumptions. SVM is potentially advantageous for capturing complex relations o the data without manual intervention. RF computes multiple decision trees during the training of the data. It predicts the class, taking the mode of the individual trees. These machine learning methods have two steps: the learning step and the identification step. In the learning step, it creates models from a pair of 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 model generated in the learning step.

4. Possibility of Detection of User Status

4.1. Experimental Purpose and Overview

An experiment was conducted to identify 4 kinds of user status discussed in Section 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 used Tag-It HF-I as an RFID tag. Subjects were 11 males and 3 females whose age ranges from 21 to 24. Each of them wore an RFID reader on the point 5.0 cm away from the toe. We installed tag sheets on the floor as shown in Section 3.2. The RFID reader attached to each shoe was connected to a laptop PC with a USB cable. The walking range was 10.0 m × 0.6 m, excluding 2.0 m in the both sides as Fig. 5 shows.

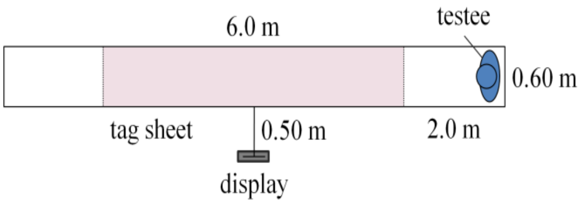

Fig. 5. Experimental environment.

We recorded gaits during the following 5 kinds of behavior before and after the physical fatigue uniformly brought by an exercise presented in Section 4.2. We repeated this trial 50 times.

- N_O Walking with no stress.
- L_B Walking with two packages of luggage of 5.0 kg held in both hands.
- L_O Walking with luggage of 5.0 kg held in the right hand.
- T_X Texting while walking, watching a Web site on a smartphone.
- P_A Walking with attention to a signage in the middle of the walking range.

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

4.2. Uniform Fatigue

To artificially make subjects run into a physical fatigue state (F_G), uniformly in each trial, we imposed the following exercise on them. We used the exercise intensity calculated from Karvonen method using the heart rate as a measure of F_G [22]. For each subject, the maximum heart rate (M) is calculated with ($220 - age$). The stable heart rate (R) is measured after a rest for 30 minutes. The exercise intensity (H) is calculated every second with

$$H = \frac{C - R}{M - R} \times 100 \qquad (3)$$

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

4.3. Result

We divide input data into 10 groups to take 10-fold cross-validation in classifications. Each machine learning method shown in Section 3.5 is trained with nine groups, while measuring its performance with one group. We evaluate the performance with the F-measure calculated from the precision and the recall. Each trained classifier distinguishes 5 kinds of behavior: N_O, L_B, L_O, T_X, and P_A. It also discriminates F_G and other user status corresponding to N_O (N_F). The classification performance is compared across features based on the two-way ANOVA (AN), CA, both of them (ACA), or original feature components (O), as well as across each machine learning method. In the two-way ANOVA test based approach, we chose significant features for each classification. The mean value of F-measure is shown in Table 2 and Table 3. Gray columns in the tables denote that the result is the best one compared with others.

Table 2. Classification of 5 kinds of behavior.

	Naïve Bayes				Support Vector Machine				Random Forest			
	AN	**CA**	**ACA**	**O**	**AN**	**CA**	**ACA**	**O**	**AN**	**CA**	**ACA**	**O**
N_O	0.606	0.564	0.512	0.596	0.673	0.638	0.593	0.664	0.721	0.685	0.633	0.719
L_B	0.556	0.486	0.473	0.522	0.639	0.581	0.564	0.617	0.696	0.652	0.640	0.691
L_O	0.573	0.518	0.437	0.553	0.629	0.584	0.510	0.612	0.675	0.643	0.578	0.673
T_X	0.690	0.622	0.535	0.605	0.758	0.712	0.677	0.751	0.770	0.754	0694	0.769
P_A	0.777	0.745	0.687	0.759	0.831	0.803	0.779	0.825	0.851	0.842	0.791	0.852
Ave.	0.640	0.587	0.529	0.607	0.706	0.664	0.625	0.694	0.743	0.716	0.667	0.741

Table 3. Classification of the fatigue.

	Naïve Bayes				Support Vector Machine				Random Forest			
	AN	**CA**	**ACA**	**O**	**AN**	**CA**	**ACA**	**O**	**AN**	**CA**	**ACA**	**O**
F_G	0.593	0.540	0.483	0.503	0.640	0.618	0.599	0.623	0.661	0.656	0.621	0.651
N_F	0.573	0.564	0.575	0.552	0.640	0.610	0.590	0.616	0.657	0.649	0.606	0.649
Ave.	0.583	0.552	0.529	0.528	0.640	0.614	0.595	0.620	0.659	0.653	0.614	0.654

The results reveal the user status is classified fairly correctly. The comparison of classification results shows the classification based on features with two-way ANOVA test outperforms other methods. RF also outperforms other classifiers in user status classification and fatigue classification. Based on this observation, the following analysis focuses on the classification based on two-way ANOVA test and RF.

After experiment, 11 of 14 subjects told L_O was the most uncomfortable behavior. Despite 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 4, many misclassified cases are found within the group of (N_O, L_B, L_O) and the group of (T_X, P_A).

Table 4. Sum of classification among 5 kinds of behavior.

	N_O	L_B	L_O	T_X	P_A
N_O	1058	169	194	79	37
L_B	117	960	176	55	21
L_O	155	177	928	60	22
T_X	48	79	67	1093	147
P_A	22	15	35	113	1173

The table head represents an actual behavior, while each row shows the number of correct classification. From Table 4, it shows gait patterns of N_O, L_B, and L_O are similar, as well as gait patterns of T_X and P_A are similar.

5. Discussion

5.1. Significant Feature Components

According to the two-way ANOVA test, we found significant feature components. The initial number of components is 198 pieces. Fig. 6 shows the number of components and the rate of classification of each subject. Line chart shows the number of significant feature components, while bar chart shows the rate of classification. There are more significant feature components in the classification of 5 kinds of behavior than in that of the fatigue. The result shows the number of significant components is different for each subject, and subject 3 has 112 significant feature components in identification regardless of fatigue. Subject 2 has only 26 significant feature components. However, both of them can estimate fatigue state with accuracy of about 70 %. In addition, subject 3 shows about 60 % accuracy to distinguish 5 kinds of user status, whereas subject 7 shows about 85 % accuracy. They have almost same number of significant feature components. There is no obvious relationship between the number of the significant feature components and the classification accuracy through correlation analysis ($|r| < 0.8$).

5.2. Variable Importance

This subsection discusses the importance of each component of a gait vector. The finding of common important feature components can help the improvement of classification accuracy. RF provides variable importance based on the Gini impurity index in the calculation of splits during training [23].

Table 5 shows mean and standard deviation of original variable importance generated by RF, and variable importance of relatively important variables which are higher than mean and in common with each subject. Seven common feature components are found in the classification among the 5 kinds of behavior for all subjects. In the right foot, the mean of c_x ($mean_{cx}$), the sum of d_t (sum_{dt}), and the sum of h_p of d_y (sum_h_{dy}) are found. On the other hand, in the left foot, the standard deviation of d_t (sd_{dt}), the sum of d_t (sum_{dt}), the sum of h_p of d_y (sum_h_{dy}), and velocity (v) are found. s_i denotes different subject. This result implies these seven feature components have strong impact on identification of user status. Especially, sum of d_t and velocity are higher than others. Therefore, in particular, the accuracy of classification will get decreased without these components.

5.3. Difference Among 5 User Status

In this section, let us discuss every behavior compared with behavior N_O where no load is imposed on subjects. Fig. 7 shows the average and the standard deviation of each important component value for all subjects.

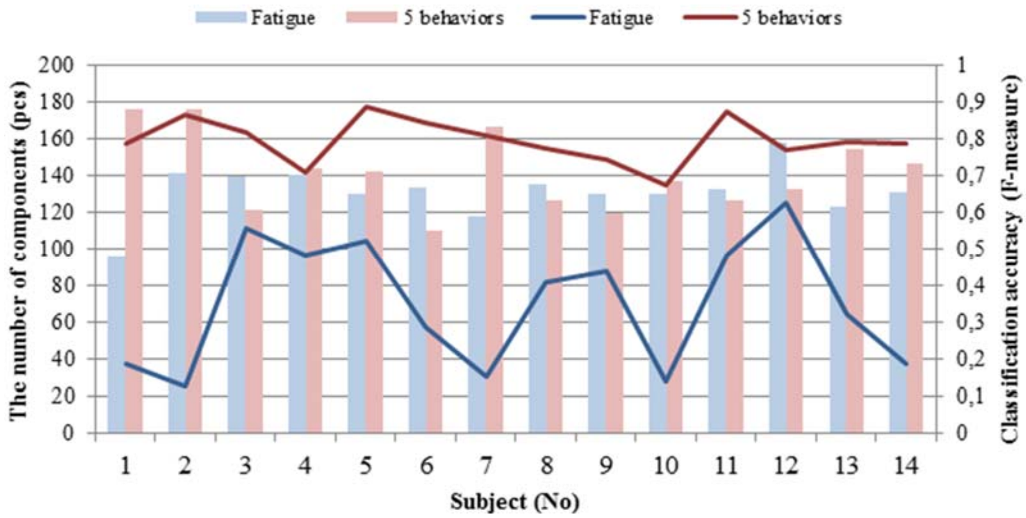

Fig. 6. The number of components and classification rate.

Table 5. Variable Importance.

	Original mean±sd	Right foot			Left foot			
		$mean_{cx}$	sum_{dt}	sum_h_{dy}	sd_{dt}	sum_{dt}	sum_h_{dy}	v
s_1	22.74±41.03	92.83	207.24	45.41	86.09	228.89	67.04	305.11
s_2	20.76±31.11	111.70	169.05	62.91	50.94	180.25	35.49	222.83
s_3	21.90±21.33	58.75	110.32	34.94	73.77	126.33	48.51	146.49
s_4	25.30±20.22	104.73	100.39	36.15	50.53	106.41	43.81	131.22
s_5	20.18±20.16	100.68	89.71	40.53	60.58	111.83	43.30	145.47
s_6	21.25±19.59	41.42	130.71	50.59	99.06	98.02	48.37	102.43
s_7	22.17±24.91	64.94	77.45	23.84	72.11	92.04	25.46	143.52
s_8	23.17±21.29	92.29	103.30	35.93	29.37	130.79	38.76	167.91
s_9	24.11±22.58	83.57	113.00	34.31	36.36	121.29	40.94	154.64
s_{10}	26.61±24.91	108.91	136.02	33.00	90.13	143.81	37.97	189.22
s_{11}	20.53±22.43	38.69	130.57	53.89	59.77	127.72	79.21	159.55
s_{12}	23.32±23.79	154.54	102.52	51.51	32.54	125.88	67.48	146.73
s_{13}	22.59±26.89	34.47	131.76	36.75	53.14	184.07	62.27	181.36
s_{14}	22.73±25.61	139.18	96.29	24.51	61.05	132.40	46.18	185.17
Ave.	22.67±24.70	87.62	121.31	40.31	61.10	136.41	48.91	170.12

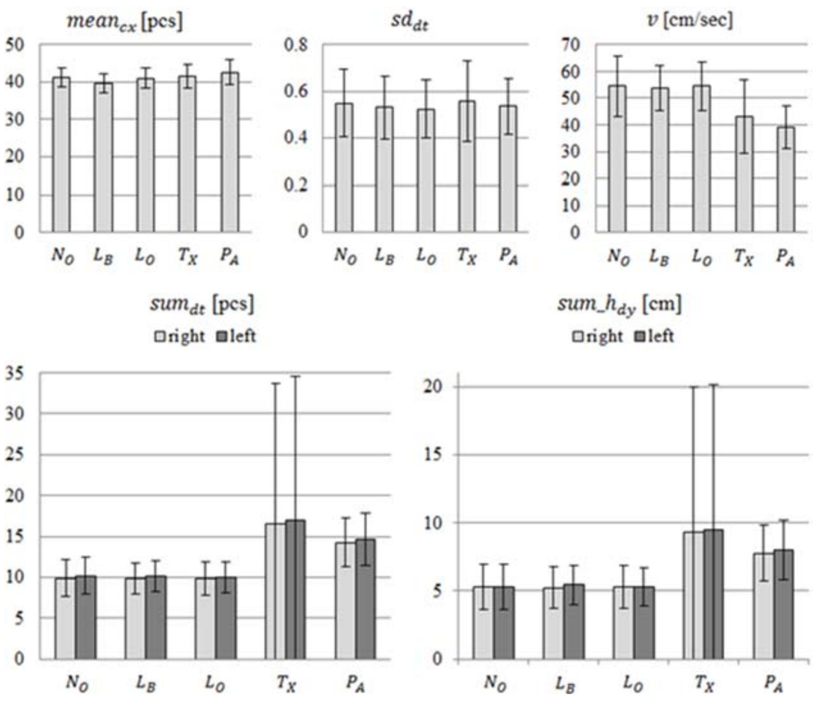

Fig. 7. Average and standard deviation of each component.

The comparison shows that N_O and L_B has no difference in average and standard deviation except $mean_{cx}$ and v, which indicates the distance between the right foot and the left foot is small and each subject walks stable. This implies subjects walk very carefully. L_O has no difference in average and standard deviation from N_O, that is, L_O is similar to N_O. However, Table 4 indicates L_O is distinguished from N_O fairly well. It seems that each subject feels load in an individual way. In cases of T_X where subjects are texting while walking, the standard deviation of some components is much larger than others, especially sum_{dt} and sum_h_{dy}. It means the walking way varies with persons. Generally, subjects get slower than usual. The average is smaller than others in P_A, as well as sum_{dt} and sum_h_{dy} are higher than N_O. However, the standard deviation is not so large. These imply subjects walk slowing down with smaller and fixed strides. We can identify each behavior of the user status, if we check the characteristics discussed above.

6. Applicability to Real Environment

In this paper, we have mentioned the problems of cost and classification ability in Section 2. An RFID reader is about 20 US dollars and an 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 that we can identify all kinds of user status at a certain range, using only the RFID system. If our system is installed in a shopping mall, we can grasp the customer status and provide Omotenashi services suitable for each of them.

We assume that 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 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 L_B, 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 L_O, 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 T_X, texting, and P_A, low attention. The system provides details of the advertisement customers look at when they are in P_A. Recommendation like L_O is preferable when they are in F_G, fatigue. Customers experience the high level of satisfaction, which leads to increase of customers in the shopping mall. In the experiment, subjects were only in their ages of 20 s. However, features of gaits are not different between 20 s and 60 s [24]. In addition, the rate of foreign visitors to Japan consists of 17.7 % men of 30 s, 13.5 % women of 20 s, 13.0 % men of 40 s, and 12.8 % men of 20 s [3]. Our method based on gaits covers many visitors to Japan.

7. Conclusions

In this paper, we have proposed the method to provide tourists high quality Omotenashi services using their gait pattern acquired with the RFID technology. In the experiment, we proved that the proposed method identified the state of users from features of their gait. 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 the future work. In addition, the installation method of actual RFID equipment in the shopping mall and more specific services will be considered in the future work.

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