Person Recognition Method using Sequential Walking Footprints via Overlapped Foot Shape and Center-Of-Pressure Trajectory

Jin-Woo Jung†, Sang-Wan Lee†, Zeungnam Bien† and Tomomasa Sato‡

†Department of Electrical Engineering and Computer Science,

Korea Advanced Institute of Science and Technology,

373-1, Guseong-dong, Yuseong-gu, Daejeon, 305-701, Korea

†Tel.: +82-42-869-8415, †Fax: +82-42-869-8750

†E-mail: {jinwoo, bigbean}@ctrsys.kaist.ac.kr, zbien@ee.kaist.ac.kr

‡E-mail: tomo@ics.t.u-tokyo.ac.jp

ABSTRACT

One emerging biometric identification method is the use of human footprint. However, in the previous research, there were some limitations resulting from the spatial resolution of sensors. One possible method to overcome this limitation is through the use additional information such as dynamic walking information in sequential walking footprint. In this study, we suggest a new person recognition scheme based on both overlapped foot shape and COP (Center Of Pressure) trajectory during one-step walking. And, we show the usefulness of the suggested method, obtaining a 98.6% recognition rate in our experiment with eleven people. In addition, we show an application of the suggested method, automatic door-opening system for intelligent residential space.

Keywords: Biometrics, Person Recognition, Footprint, Foot Shape, COP trajectory, Hidden Markov Model, Pressure Sensor

1. INTRODUCTION

To date, there has been rapid growth in the field of person identification techniques for the purpose of security and personalized services. Among the various methods of person identification, biometric identification such as fingerprint or iris scan is currently the most promising method [1][2][3].

These techniques can be divided into two categories; *1)* high accuracy-oriented methods for the application of security in an unspecified number among the general public and *2)* easy-to-use approaches for the application of personalized service in a specified number of specific small group members such as co-workers or family [4].

Automatic face recognition [5], gait recognition [6], and footprint recognition [7][8] are representative easy-to-use methods. Specially, for applications in residential environments such as personalized services, footprint-based person recognition method has some advantages in terms of privacy and light conditions compared with camera-based techniques such as face recognition or gait recognition.

Thus far, studies about footprints have mainly focused on medical diagnosis [9]. The possibility of footprint-based person recognition was suggested by Kennedy [10] and the first automatic footprint recognition scheme was developed by Nakajima et al. [7][8] using a pressure sensing mat. Kennedy [10] showed that 3000 people could be identified clearly with 38 features from inked barefoot impressions. The features that Kennedy used were mainly local features such as the distance between each toe and heel. As such, we can consider the information of toes as an important characteristic for person recognition. Nakajima et al. [7] showed a recognition rate of 82.64% among 10 people using only normalized footprint images and showed the highest rate of 86.55% additionally using the distance and angle of two feet and weight information [8].

Figure 1 shows footprint images included in Kennedy's paper and Nakajima et al.'s paper. From Figure 1 (b), we see that the distortion by the spatial resolution of pressure sensor is very severe and hence toe information is difficult to extract from a footprint. Therefore, in order to make an automated person recognition system with a high recognition rate, additional information is necessary. Furthermore, the size of foot varies about 5mm between the morning and the evening [7] and the volume also varies about 4.4% [11] between the morning and the evening. For these reasons, the use of only a footprint shape appears to have limitations. Therefore, to make an automated person recognition system with high recognition rate, additional information is necessarily needed.

In this paper, we propose a different approach based on overlapped foot shape and center of pressure (COP) trajectory in a sequential walking footprint. As such, it can be understood as the fusion method using foot shape and gait information projected on a floor. Since the human gait is believed to be a unique individual characteristic [2][3], we speculate that sequential walking footprint-based person recognition may be also possible. In Section 2, we explain the extraction process of foot shape and COP trajectory from a sequential walking footprint images and we present a recognizer based on Hidden Markov Model (HMM) and Levenberg-Marquart (LM) learning method in Section 3. Finally, we test our recognizer using eleven people and discuss the results in terms of false rejection and false acceptance rates.

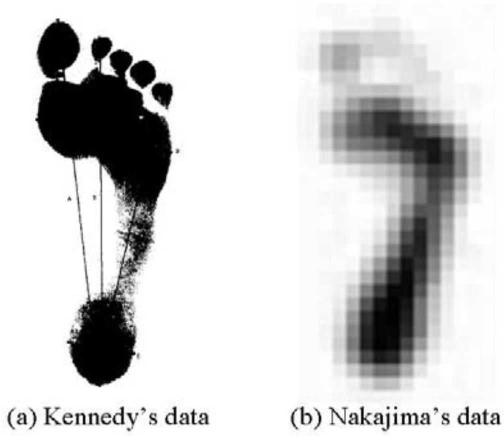

Figure 1. Comparison of previous works
: Kennedy's data and Nakajima's data

2. FEATURE EXTRACTION

To extract footprint during natural walking, we use a mat-type pressure sensor array. Mat-type pressure sensor (MAT sensor) is more human-friendly than shoe-type one since it does not need to be equipped by human, and is more robust to noise than shoe-type sensor since the sensor is fixed on the floor. In addition, since the shape of left foot and right foot are not symmetric generally [12], we use not a single foot's print but one-step footprints which includes both left and right foot regardless that which foot appears first during walking. Figure 2 shows an example of one-step walking footprints.

Figure 2. Example of a one-step walking footprint

To deal with the problem more easily and skillfully, we make eight assumptions (A-1) ~ (A-8).

(A-1) There is no other object on the MAT sensor except the walking person.
(A-2) There is only one walking person on the MAT sensor in each trial.
(A-3) During one's walking one the MAT sensor, at least one

element of the MAT sensor is fired.

(A-4) Normally, users always walk along the designated direction (outdoor-to-indoor) on the MAT sensor.

(A-5) User's step length (the distance between the Center Of Area, COA, point of the first foot and that of the second foot) is greater than a maximum foot length, L_{MAX_FOOT}.

By the assumptions (A-1) and (A-2), we can find the starting time of the one-step walking on the MAT sensor, $t_{FIRST\_FOOT\_START}$, by checking when the total pressure value is greater than the threshold value. The assumption (A-3) indicates that the total pressure value is always greater than the threshold value during a single gait cycle. This assumption (A-3) is a constraint of maximum walking speed and is generally valid during walking, but not during running. And, by the assumption (A-3), we can check the ending time of the one-step walking on the MAT sensor, $t_{SECOND\_FOOT\_END}$. The assumption (A-4) helps us easily to find the reference direction for directional alignment of each foot. And (A-5) is for discriminating the left foot and the right foot part in the one-step footprint. Here, maximum foot length, L_{MAX_FOOT}, is determined according to the analysis of the user group. In our experiment, L_{MAX_FOOT} is determined as 300mm.

The procedure for extracting overlapped foot shape and COP trajectory of each foot in the one-step walking footprint is as follows:

At time t, $t_{FIRST\_FOOT\_START} \leq t \leq t_{SECOND\_FOOT\_END}$: Step1~Step6

Step1) Labeling of each blob

We make a label for each blob in the current footprint image using the scanning line method [7]. When the scanning line meets a segment, a number is given to the segment.

Step2) Finding center of area (COA) point of each blob

We find COA points of all labeled blobs. The COA points are used to determine whether the current blob is a part of the first foot or the second foot.

Step3) Discrimination of the first foot and the second foot

A *k*-means clustering algorithm is used to discriminate the first foot and the second foot. If the distance between the current blob's COA point and the previous COA point of the first foot is greater than the maximum foot length L_{MAX_FOOT}, the current blob is considered as a part of the second foot. And, we re-estimate the first foot's COA point and the second foot's COA point with these additional blobs.

Step4) Checking whether the time of current frame, t, is $t_{FIRST\_FOOT\_END}$ or $t_{SECOND\_FOOT\_START}$

We determine $t_{FIRST\_FOOT\_END}$ by using the number of blobs in the first foot ($t_{SECOND\_FOOT\_START}$ is determined from the second foot). This process is valid under the assumption (A-3).

Step5) Updating COP trajectory of each foot

We calculate the COP points of the first/second foot and update the COP trajectories of each foot.

Step6) Updating overlapped footprint image

We update the overlapped footprint image by doing OR operations on all partial footprint images during $t_{FIRST\_FOOT\_START} \leq t \leq t_{SECOND\_FOOT\_END}$.

At time $t = t_{SECOND\_FOOT\_END}$: Step7~Step8

Step7) Determination of the orientation of each foot using the principal axes of the overlapped footprint image

We find the principal axes of each foot using the overlapped footprint images of each foot. The principal axes of a region are the eigenvectors of the covariance matrix obtained by using the pixels within the region as random variables [13].

Step8) *Finding the aligned overlapped foot shape*

We translate each foot part in the overlapped footprint so that COAs of each foot part become fixed points. And we rotate each foot part with the result of Step7.

Step9) Creation of the aligned COP trajectory

We translate the original COP trajectory so that the starting point of the trajectory becomes the origin and we rotate the translated COP trajectory to $\angle e_{L2}$ (or $\angle e_{R2}$) degrees for directional alignment. The directionally aligned COP trajectory is represented as follows:

$$TRAJ_{FIRST\_FOOT}(t) = [x\ y]^T,$$
$$\text{where } t_{FIRST\_FOOT\_START} \le t \le t_{FIRST\_FOOT\_END}.$$
$$TRAJ_{SECOND\_FOOT}(t) = [x\ y]^T,$$
$$\text{where } t_{SECOND\_FOOT\_START} \le t \le t_{SECOND\_FOOT\_END}.$$

From Step1~Step9, we can obtain the aligned overlapped foot shape (result from Step8) like Figure 3 and COP trajectories of each foot (result from Step9) like Figure 4 from a one-step walking footprint. This information will be used as cues for person recognition in the next section.

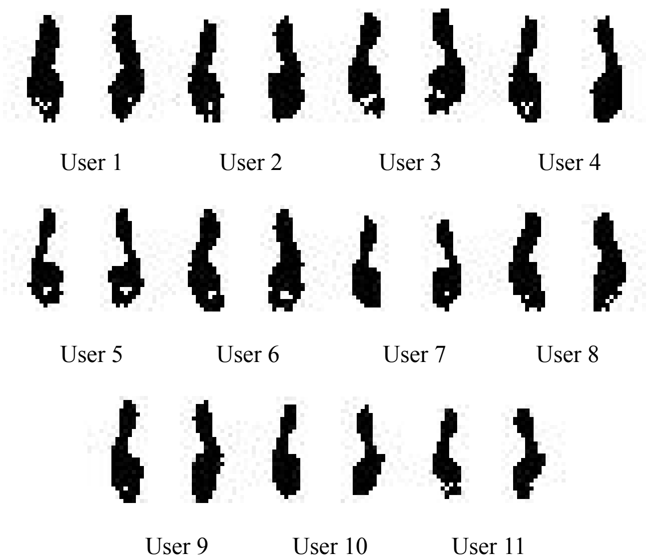

Figure 3. 11 users' Templates for overlapped foot shape

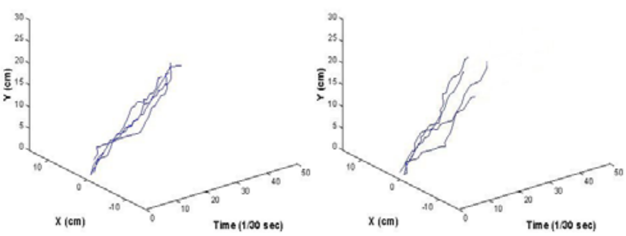

Figure 4. 4 user's COP trajectories

3. PERSON RECOGNITION

Experimental environment

From 11 subjects, we obtained COP trajectories of two feet during natural walking. The average weight and height of all subjects are 67.0 (±15.2) kg and 170.4 (±6.4) cm. As a MAT sensor, we used FOOT ANALYZER (TechStorm Inc., Korea) as shown in Figure 5. The size of sensor is 80×40 cm^2 including 80×40 sensors (1×1 cm^2 resolution) and the frame rate is 30 Hz. In each trial, each subject gives 10 one-step footprints using MAT sensor. During two months, 40 one-step footprints are acquired from each subject. Among 40 one-step footprints, first 20 footprints of each user in one month are used as learning samples to make templates and the other 20 footprints of each user in the next month are used for test.

Figure 5. A mat-type pressure sensor, FOOT ANALYZER

Performance measure

For the performance test, we used *FRR* (False Rejection Rate) and *FAR* (False Acceptance Rate) concepts [2][3] like equation (1) and (2) which are the most famous performance measures in biometrics area.

$$FRR = \frac{NFR}{NAA} \times 100 \quad (\%) \tag{1}$$

$$FAR = \frac{NFA}{NIA} \times 100 \quad (\%) \tag{2}$$

where *NFR* and *NFA* are the numbers of false rejections and false acceptances, respectively. *NAA* and *NIA* are the numbers of authorized attempts and impostor attempts, respectively.

Person recognition: overlapped foot shape

Given the templates like Figure 3, we can compare these templates IA with new overlapped footprint IB by Nakajima et al.'s dissimilarity measure like equation (3)

$$DM = \sqrt{\sum_{x,y} \{ I_A(x,y) - I_B(x,y) \}^2} \qquad (3)$$

Using this template matching method, we got the minimum FRR error 8.64% as written in Table 1.

Person recognition: COP trajectory

Since the COP trajectories of human footprint are temporal sequences with variable length and noisy information, we used hidden markov model (HMM) [14] to compare two COP trajectories. In addition, even in the same person, the left foot and the right foot are not symmetric and have different COP trajectories like Figure 4. So, we used two set of HMM models for the first foot and the second foot in one-step like Figure 6. Using this COP trajectory-based person recognition method, we got the minimum FRR error 20.45% as written in Table1.

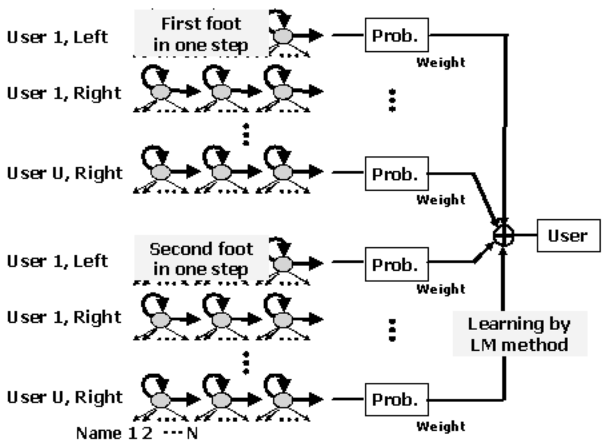

Figure 6. HMM recognizer using quantized COP trajectory

Person recognition: foot shape + COP trajectory

Using previous two recognizers, we made the total recognizer like Figure 7. After comparing the given sequential footprint with *N* existing templates, we got *2N* comparison outputs in the case of *N* users. Using these *2N* outputs and proper weights which were updated by Levenberg-Marquart learning method [15], we can get the final decision output. The minimum FRR error of the total recognizer is 1.36%.

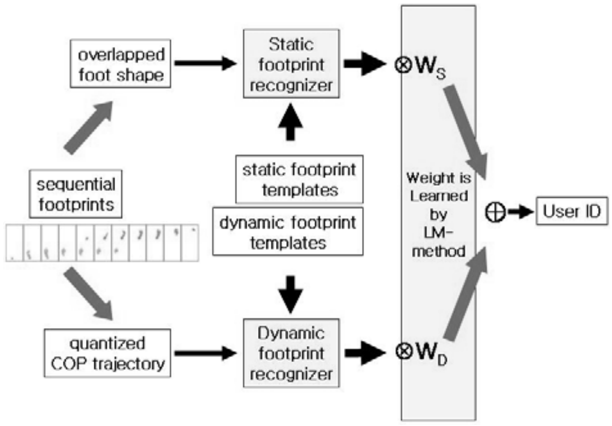

Figure 7. Total recognizer for walking footprint-based person recognition

Table 1. Recognition results (unit: %)

User ID	Foot shape		COP trajectory		Foot shape + COP trajectory	
	FRR	FAR	FRR	FAR	FRR	FAR
1	5.00	0.00	15.00	0.50	0.00	0.00
2	10.00	0.50	0.00	2.00	0.00	0.00
3	5.00	0.50	15.00	3.00	0.00	0.00
4	20.00	2.00	10.00	4.50	0.00	0.50
5	5.00	0.00	35.00	0.00	0.00	0.00
6	10.00	1.00	20.00	2.00	0.00	0.00
7	5.00	1.50	20.00	1.50	5.00	0.00
8	5.00	0.50	35.00	0.50	0.00	0.00
9	15.00	2.00	20.00	3.50	5.00	0.00
10	15.00	0.50	50.00	3.00	5.00	0.00
11	0.00	1.00	5.00	2.00	0.00	1.00
Average	8.64	0.86	20.45	2.05	1.36	0.14

Application: Automatic door-opening system

Using the suggested method presented in this paper, we are implementing an automatic door-opening system like Figure 8, a personalized service system for the futuristic intelligent residential space. When a person walks on the hidden and embedded sensor before the door, the control system like a home server notice who he/she is or whether this person is permitted or not. If the person is permitted, then the system opens the door and tells to him about new message and if not permitted, the system doesn't open the door.

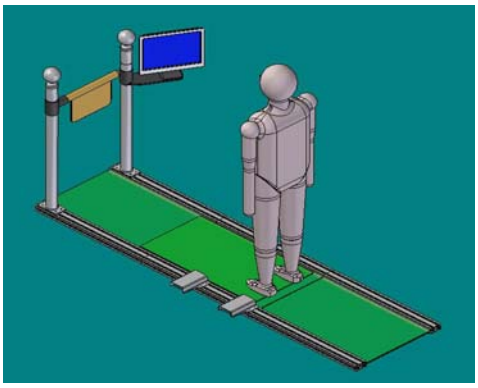

Figure 8. Automatic door-opening system

4. CONCLUDING REMARKS

Automated footprint-based person recognition was started by Nakajima et al. using standing footprints from pressure sensor. But, standing footprint which is used by Nakajima et al. is not good to achieve enough information. In this paper, we proposed a new footprint-based person recognition scheme using both static and dynamic footprint (overlapped foot shape and COP trajectory) which could be extracted by sequential walking footprint. Using HMM and LM learning method, we designed the recognizer and proved the effectiveness of our method as 98.6\% recognition rate in 11 volunteer's test. Since footprint could be extracted without user's consciousness, using footprint as a person recognition method is a highly human-friendly one which was shown in our application, automatic door-opening service, and also could be a good element for multi-modal biometrics.

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