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Footprint-based Person Identification Method using Mat-type Pressure Sensor

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Abstract— **Many diverse methods have been developing in the field of biometric identification as human-friendliness has been emphasized in the intelligent system's area. One of emerging method is to use human footprint. Automated footprint-based person recognition was started by Nakajima et al.'s research but they showed relatively low recognition result by low spatial resolution of pressure sensor and standing posture. In this paper, we proposed a modified Nakajima's method to use walking footprint which could give more stable toe information than standing posture. Finally, we prove the usefulness of proposed method as 91.4% recognition rate in 11 volunteers' test.**

Keywords— **biometrics, footprint, mat-type pressure sensor, person recognition**

I. Introduction

Until now, there has been a rapid growth in the field of person identification technique for the purpose of security and personalized service. Among various methods of person identification, biometric identification such as finger scan or iris scan is the most promising methods now [1,2,3].

These techniques could be divided into two categories: high accuracy-oriented one for an unspecified number of the general public and human-friendly one for a specified number of special small group members such as co-workers or family. At this, human-friendliness could be understood as the degree of constraint on the user [4].

As human-friendly methods, there are many possible approaches such as automatic face recognition [5], gait recognition [6], and static footprint recognition [7,8]. And, for the application in residential environment like personalized service, footprint-based person recognition method has some advantages in the aspect of privacy compared with camera-based techniques like face recognition or gait recognition.

The studies about footprint have been mainly focused on the medical diagnosis till now [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 pressure sensing mat. Kennedy [10] showed that 3000 people could be identified clearly with 38 features from inked barefoot impressions. Besides, Nakajima et al. [7] showed just 82.64% recognition rate in 10 people using normalized footprint image and showed 86.55% additionally using the distance and angle of two feet and weight information [8].

Then, what is the major difference between Kennedy's method and Nakajima et al.'s method which resulted in very different recognition rates?

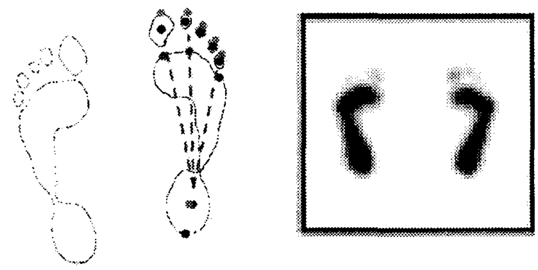
First, there is a big difference in spatial resolution between inked barefoot impression and foot pressure distribution. Figure 1 shows footprint images included in Kennedy's paper and Nakajima et al.'s paper.

Figure 1. Comparison of previous works
: high spatial resolution vs. low spatial resolution

Second, there is a difference in measurement method. In Kennedy's method, each person steps onto the paper in the same manner to make a footprint. Besides, in Nakajima et al.'s method, each person stood straight at the center of mat and looked toward a mark on the wall during 5 sec. And then he used the averaged pressure distribution as a footprint.

Figure 2. Comparison of previous works
: stepping vs. standing

Third, they used different types of feature. The features that Kennedy used are local features like the distances between each toe and heel. Besides, Nakajima et al. used global feature by template matching method.



Kennedy's feature *Nakajima's feature*

Figure 3. Comparison of previous works
: local feature vs. global feature

From the high recognition rate of Kennedy's work, we can assume conversely that the information of toe is an important characteristic for person recognition. But, by low spatial resolution of pressure sensor and measurement during standing posture, Nakajima's method is difficult to use the toe information.

About the spatial resolution, we can ascertain from Table I that the 5 x 5 mm^2 sensor size is the highest resolution in current technology of pressure sensing mat. But, even when we use 5 x 5 mm^2 sensors like Figure 4, the information of toe is still hard to extract from footprint if we use the standing posture-based measurement method.

In this paper, we modify the Nakajima's method to use walking footprint which is similar to Kennedy's stepping footprint and could give more stable toe information. And then we test the modified Nakajima's method using 11 volunteers' data.

TABLE I
COMPARISON OF REPRESENTATIVE COMMERCIAL PRESSURE SENSORS FOR MEASURING FOOTPRINT

	BIG-MAT	F-SCAN	HIGH-RESO MAT	MUSGRAVE system	FOOT ANALYZER
Total sensing size	0.211 m^2 (440mm* 480mm)	0.032 m^2 (100mm* 315mm)	0.211 m^2 (440mm* 480mm)	0.051 m^2	0.320 m^2 (400mm* 800mm)
Sensor size	10 x 10 mm^2	5 x 5 mm^2	5 x 5 mm^2	5 x 5 mm^2	10 x 10 mm^2
# of sensors	44 x 48	60 x 21	86 x 96	2048	40 x 80
sampling speed	30 Hz	100 Hz	60 Hz	60 Hz	30 Hz
Company	NITTA, Japan	NITTA, Japan	NITTA, Japan	Preston communications, Ireland	TechStorm, Korea
Characteristics	FSR-based, Mat-type	FSR-based, Shoe-type	FSR-based, Mat-type	FSR-based, Mat-type	FSR-based, Mat-type

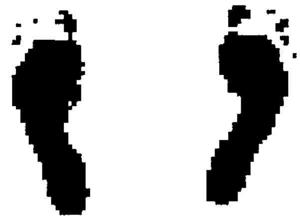


Figure 4. Standing footprint from HIGH-RESO MAT
(5 x 5 mm^2 sensor size)

II. FOOTPRINT EXTRACTION METHOD

To extract footprint during natural walking, we use a mat-type pressure sensor array. Mat-type pressure sensor is more human-friendly than shoe-type one since it needs not 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 [11], we use not single footprint but one-step footprint which includes both left and right foot regardless that which foot appears first. Figure 5 shows an example of one-step footprints and the overlapped footprint during one-step is used as a pattern for comparison.

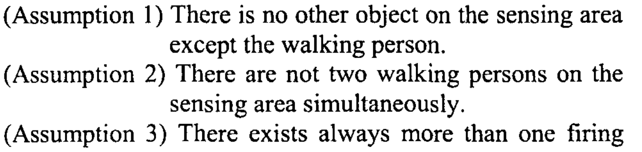


Figure 5. Example of one-step footprint

To make positionally and directionally aligned footprint, we make three assumptions about the experiment.

(Assumption 1) There is no other object on the sensing area except the walking person.
(Assumption 2) There are not two walking persons on the sensing area simultaneously.
(Assumption 3) There exists always more than one firing sensor during human walking.

The procedures for extracting the overlapped footprint during walking are like these:

Step1) Creation of overlapped footprint image:
We update the overlapped footprint image by doing OR operation on all partial footprint images during one-step. And then we make the overlapped footprint image as a binary image. If there is a time during one-step when current pixel value has more than threshold value, then the pixel value in overlapped footprint image is 1, and otherwise the pixel value is 0.

Step2) Determine first foot part and second foot part:
We divide first foot and second foot using k-means algorithm. At starting time, we set the COA (Center Of Area) point considering all blobs as first foot's COA. And then if the distance between current Blob COA point and previous first foot's COA is more than maximum foot length (30cm), we consider the blob as second foot's part and make second foot's COA using that blobs. And then we re-estimate first foot's COA and second foot's COA with these additional blobs. Finally, we can divide first foot and second foot in the overlapped footprint.

Step3) Finding the principal axes of each foot:
We find principal axes using the overlapped footprint. The principal axes of a region are the eigenvectors of the covariance matrix obtained by using the pixels within the region as random variables [12]. So, to find principal axes of left foot, we translate all parts of left foot so that COA of left foot is to be located in the origin. And then we make covariance matrix using translated left footprint. Then, eigenvectors e_{LEFT1} and e_{LEFT2} of covariance matrix, whose eigenvalues were ordered by highest to lowest, are major and minor axis.

Step4) Finding the aligned footprint:
We translate each footprint so that COAs of each footprint become pre-determined points. And then we rotate each footprint to $\angle\, e_{LEFT2}$ (or $\angle\, e_{RIGHT2}$) degree respectively for directional alignment.

III. PERSON IDENTIFICATION RESULTS

We experimented with 11 volunteers and these people were classified into 3 groups like Table II with their foot lengths. We used a mat-type pressure sensor, FOOT ANALYZER (TechStorm Inc., Korea), like Figure 6 whose size is 80*40 cm^2 including 80*40 sensors and sampling time is 30 Hz. Each volunteer tested 10 times in a test day and totally 40 times in 4 test days. And the time interval for next test day is about 20 days so all data were achieved during about two months. Among 40 data, 20 data of first period were used to make templates by averaging method and the remained 20 data were used to test.

Figure 6. Mat-type pressure sensor (FOOT ANALYZER)

TABLE II
BODY DATA OF TEST MEMBERS

User Group	User ID	SEX	Height (cm)	Weight (kg)	Foot length (mm)
Group1	USER1	MALE	174	80	270
	USER2	MALE	172	71	270
	USER3	MALE	173	70	270
	USER4	MALE	177	65	270
	USER5	MALE	174	50	270
Group2	USER6	MALE	175	76	265
	USER7	MALE	164	61	250
	USER8	MALE	170	100	265
	USER9	MALE	176	62	260
Group3	USER10	FEMALE	159	45	240
	USER11	FEMALE	160	57	240

Figure 7 shows templates for each user. Each template is a binary image which was made by averaging each user's one-month data (20 data) and by rounding off to zero or one.

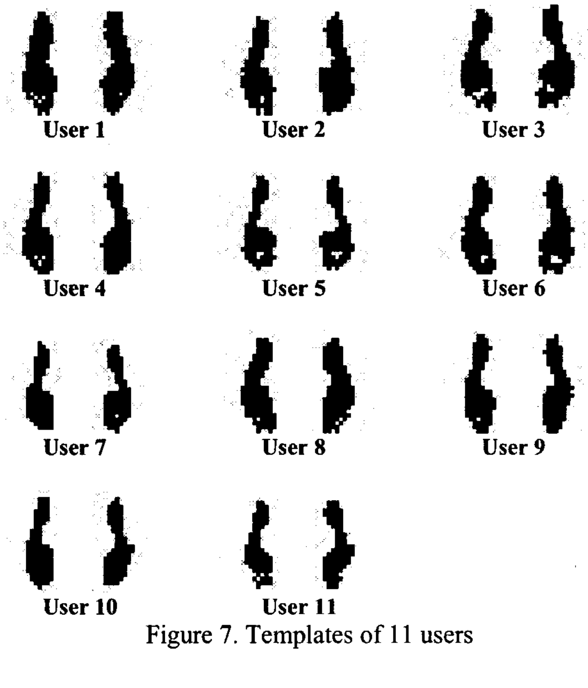


Figure 7. Templates of 11 users

When a new footprint came, this footprint is compared with templates of 11 users and creates the degrees of dissimilarity. To compare two footprints and make dissimilarity values, we tested with two different types of dissimilarity measure (DM). DM1 in (1) is the dissimilarity measure of Nakajima et al. and includes the information of foot size. Besides, DM2 in (2) is normalized by foot size.

$$\text{DM 1} = \sqrt{\sum_{x,y} \{I_A(x,y) - I_B(x,y)\}^2} \qquad (1)$$

$$\text{DM 2} = 1 - \frac{P(A \cap B)}{\sqrt{P(A)P(B)}} \qquad (2)$$

The experimental results are in Table III. For performance test, we used FRR (False Rejection) and FAR (False Acceptance Rate) which are the most famous performance measures in biometrics area. FRR in (3) is concerned with the number of instances an authorized individual is falsely rejected by the system and FAR in (4) refers to the number of instances a non-authorized individual is falsely accepted by the system. Both rates are expressed as a percentage using the following simple calculations: [3]

$$FRR = NFR / NAA * 100\% \qquad (3)$$
$$FAR = NFA / NIA * 100\% \qquad (4)$$

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

From the experimental results, we ascertain that the results of our method (FRR=8.64%, Recognition rate=91.4%) is better than Nakajima et al.'s method (Recognition rate=82.64%) with same dissimilarity measure. This could be conversely understood that walking footprint is more stable than standing footprint in toe part. In addition, we can also find that the information of foot size is helpful for person recognition by comparing the results of DM1 and DM2. Since the recognition rate is strongly dependent on the dissimilarity measure, we could enhance the recognition rate by finding more suitable dissimilarity measure for footprint.

TABLE III
EXPERIMENTAL RESULT OF RECOGNIZERS

user	DM 1		DM 2	
	FRR (%)	FAR (%)	FRR (%)	FAR (%)
1	5	0	0	0.5
2	10	0.5	15	1
3	5	0.5	5	2
4	20	2	15	1.5
5	5	0	5	0.5
6	10	1	10	0.5
7	5	1.5	10	1
8	5	0.5	10	0.5
9	15	2	15	1.5
10	15	0.5	15	0.5
11	0	1	0	0.5
AVERAGE	**8.6364**	0.8636	**9.0909**	0.9091

IV. Conclusion

Automated footprint-based person recognition was started by Nakajima et al. using standing footprints from pressure sensor. But, standing posture is not good to achieve toe information. In this paper, we proposed a modified Nakajima et al's method using walking footprint to include more stable toe information. We proved the effectiveness of our modified method by 11 volunteer's test. Recognition rate is 91.4 % and this could be enhanced by making more suitable dissimilarity measure.

Acknowledgment

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