

A Challenge to Biometrics by Sole Pressure while Walking

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Abstract—This paper describes a personal verification method based on fuzzy logic using dynamic sole pressure distribution while walking. The method employs a pair id sole pressure distribution change, and it is acquired by a mat type load distribution sensor. As a preliminary experiment for shoes, we take sole pressure data by bare foot and two kind of slipped foot. We extract thirty nine gait features from each sole pressure distribution change. We calculate a fuzzy degree of a feature from two fuzzy if-then rules and them fuzzy membership functions for a feature. These fuzzy membership functions are statistically determined by learning data. The fuzzy degree of acquisition sole pressure data is calculated by total of fuzzy degree of all features. The method verifies the walking person by using the fuzzy degree of the acquisition sole pressure data. When the fuzzy degree of acquisition data higher than a threshold, we verify the walking person as the target person. In our experiments, we employed 11 volunteers and took sole pressure data six times for each volunteer and foot situation. When the learning data included same kind of test data, we obtained low equal error rate. We obtained low false acceptance rate.

Keywords—biometrics; personal verification; walking; sole pressure; load distribution sensor

I. INTRODUCTION

Recently, personalized services are widely used for many situations. For example, we are use personal computer, e-mail services and several health monitoring services. However, these services frequently demand private and important information. Thus, personal authentication is more important technique for these personalized services. Password and PIN are major verification method, but these methods has disadvantage that we may forget these knowledge and other person can masquerade as us. To solve these problems, biometrics [1]-[3] is widely used in security field, and it has high accuracy and high user friendliness. Biometrics verifies person by physical features or behavioral features. The physical features such as fingerprint [4], [5], iris authenticate person with high accuracy. The behavioral features such as signature [6], voice [7] and walking [8]-[13] has high user friendliness. Personalized services are used in everyday lives. Thus, personal verification system required high user friendliness. By using walking, we are able to verify person passing a door or approaching a device of the service. In addition, the feature never force person to particular act such as speaking or writing. For these reasons, walking has the most high user friendliness.

In this paper, we describe a biometric personal verification method. We acquire walking data as dynamics of sole pressure. We have proposed a biometric personal authentication method using sole pressure while walking [13]. In this method, we employ a pair of right and left sole pressure distribution while walking. In past work, we have authenticated person with bare foot. However, we usually wear shoes at our everyday lives. In our goal, we aim to authenticate walking person wearing shoes. In this paper, we authenticate slipped person wearing slippers as a preliminary experiment for shoes. In this experiment, we take sole pressure data of bare foot and slipped foot, and authenticate them. We employ thinner type and thicker type slippers, and we use these data for learning data and test data. Firstly, we acquire sole pressure distribution while walking by mat type load distribution sensor. The load distribution sensor used here is good enough to obtain the walking data because it requires no special device carrying, no resistance like camera usage and easy tractable for users. Secondly, we extract thirty nine gait features from each sole pressure data. Twelve features are based on footprint and twenty seven features are based on weight movement. Thirdly, we describe fuzzy if-then rules and fuzzy membership functions. The fuzzy membership functions are statistically determined by using learning data. Fourthly, we verify subjects by using fuzzy degree for acquisition sole pressure data. Fifthly, we show experimental result on 11 volunteers. In experiment, we took sole pressure data by three situations. Finally, we conclude the technical results.

II. PRELIMINARIES

A. Load Distribution Sensor

We acquire sole pressure data while walking by a mat type load distribution sensor (Arrow Industry Co., Ltd. AS-64X256-7PM) to authenticate person. Fig. 1 shows the load distribution sensor and our data acquisition system. This sensor is one of pressure sensors. Our experimental system consists of the load distribution sensor, a control device (Arrow Industry Co., Ltd. AS-64X256) and a personal computer. Effective sensing area of the load distribution sensor is 33 cm × 178 cm. The sensor has 64 vertical electrode sheets and 256 transverse electrode sheets. Distance between the nearest electrode sheets is 5.0 mm in a vertical direction (x-axis) and 7.0 mm (y-axis). In every intersection of vertical and transverse sheets, a resistive element is sandwiched in tow electrode sheets and this intersection point is a sensing point. The load distribution sensor has 64 × 256 sensing points. When we put pressure to

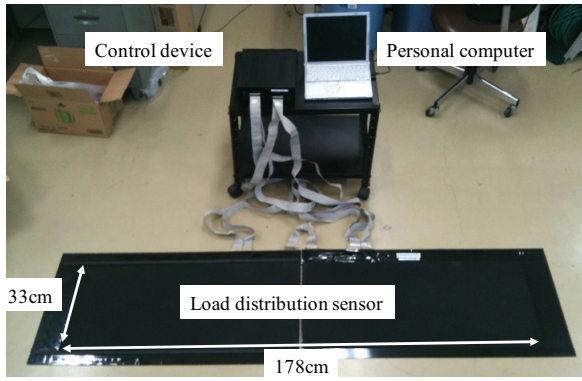


Figure 1. Composition of data acquisition system.

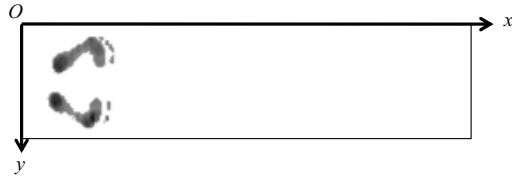


Figure 2. An example of load distribution data of one sampling time.



Figure 3. View of slippers.

the sensing points, the corresponding resistive elements decrease electric resistance. The control device converts the electric resistances of the sensing points into 8-bit (256 level) digital signal, and provides the digital signal for all pressure values to a personal computer. The personal computer stores the pressure value at the sampling interval. In our experiment, sampling interval is 100 ms. Fig. 2 shows an example of load distribution data of one sampling time.

B. Subjects and Data Acquisition Method

In our experiment, we employ 11 volunteers shown in Table I. To acquire sole pressure data, we ask volunteers to walk on the load distribution sensor. We acquire sole pressure data the load distribution change while walking as the sole pressure data. In our experiment, the volunteer walked along x -

TABLE I. SUBJECTS INFORMATION

#	Age [year]	Gender	Body height [cm]	Body weight [kg]
1	24	Male	165	58
2	23	Male	172	63
3	22	Male	173	60
4	23	Male	170	81
5	24	Male	160	44
6	22	Male	171	62
7	22	Male	169	62
8	24	Male	175	62
9	23	Male	172	70
10	23	Male	162	48
11	23	Male	173	63

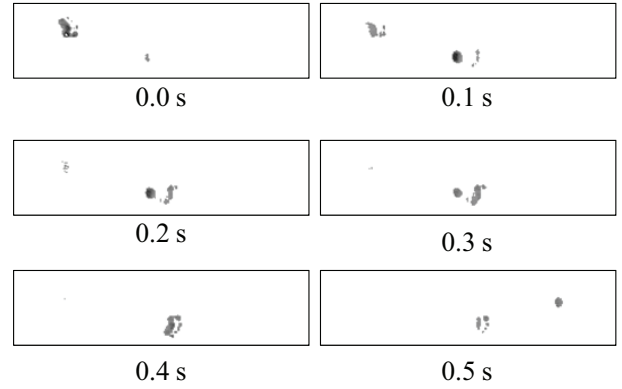


Figure 4. An example of sole pressure distribution change of one sole.

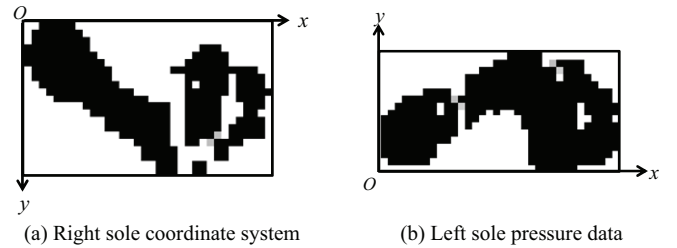


Figure 5. Right and left sole coordinate system.

axis of the sensor by bare foot and two type slippers as shown in Fig. 3. In this figure, *Slippers 1* is thinner type slippers and the thickness is 0.6 cm. On the other hand, *Slippers 2* is thicker one and the thickness is 2.5cm in heel area and 1.5cm in toe area. We acquire sole pressure data six times for each type slippers and bare foot. Fig. 4 shows examples of the right sole pressure change by bare foot.

For personal verification, we extract a right sole pressure data, X_R^S , and left sole pressure data, X_L^S , from the acquisition data, X^S . The notation X^S denotes an acquisition data when person "S" is walking. We define the right and left sole coordinate system in Fig. 5. We set the x -origin at heel side of a circumscribed rectangle, and we set y -origin at thumb side of the circumscribed rectangle.

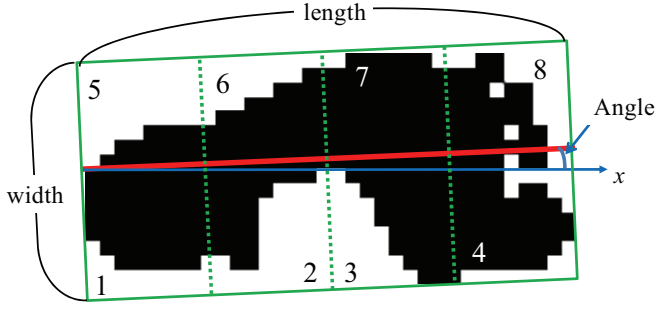


Figure 6. Examples of footprint and its features.

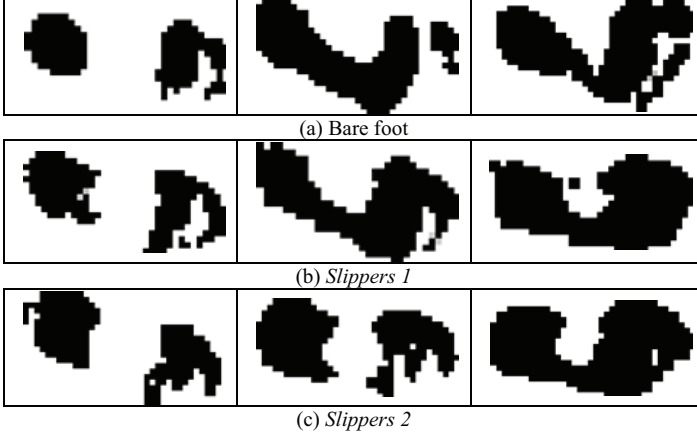


Figure 7. Examples of footprint of three persons.

III. PERSONAL VERIFICATION METHOD

The proposed method verifies person by using fuzzy logic. We extract features based on footprint and weight movement from each sole pressure data. We calculate fuzzy degree, μ_{Sole}^r , for the target person “ r ”. If the fuzzy degree is higher than a threshed parameter, we verify the walking person as the target person.

A. Features of Sole Pressure Chagne

We extract features from sole pressure data X_k^S , where k denotes the index of right sole ($k = R$) or left sole ($k = L$). Twelve features are based on a footprint, and twenty seven features based on weight movement. In this paper, the notation $f_i(X_k^S)$ denotes a feature with respect to a sole pressure data X_k^S where i denotes the index of each feature.

The footprint is made by combining binarized image of sole pressure distribution for all frames. Fig. 6 shows an example of footprint and its features. In this figure, the black area shows sole area, the red straight line is obtained by least squares method for footprint, and green rectangle is the circumscribed quadrangle of the footprint. The length of footprint, $f_1(X_k^S)$, is calculated by the length of long side of the green circumscribed quadrangle. The width of footprint, $f_2(X_k^S)$, is calculated by the length of short side of the green circumscribed quadrangle. The area of footprint, $f_3(X_k^S)$, is calculated by the number of pixels including the sole area. The angle of footprint, $f_4(X_k^S)$, is calculated by the angle between the red straight line and x -axis of the sensor. The distribution of footprint, $f_5(X_k^S), \dots, f_{12}(X_k^S)$ are calculated by numbers of sole pixels in the 1-8 small areas

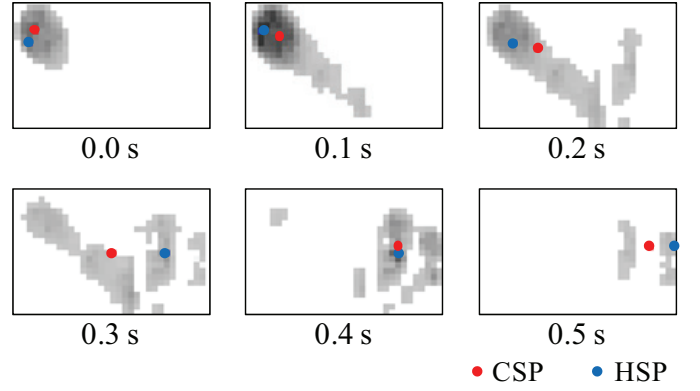


Figure 8. Examples of features from sole pressure of each frame.

shown in Fig. 6. The Green dotted line quarter the circumscribed quadrangle. These features depend on the posture of walk and shape of foot. Several differences appear in the arch of a foot, the part of fingers and direction of footprint while walking. Even if persons wear same shoes, these features are different between persons. Fig. 7 shows examples of footprint of three persons.

We extract features from every frame of sole pressure data. We calculate the center of sole pressure (CSP), the highest sole pressure (HSP) and the area of footprint from each frame. The areas are calculated by the number of sole pixels from each frame. Fig. 8 shows the examples of CSPs and HSPs. There are several valuations among the sole pressure, and the numbers of frames are often different between two sole pressure data. Thus, we normalize these features to nine frames. We consider that the dynamic changes of each feature are similar in one step. We therefore interpolate nine points lining up in a polygonal line by liner interpolation and employ these points as features. The nine CSPs, $f_{13}(X_k^S), \dots, f_{21}(X_k^S)$ and nine HSPs, $f_{22}(X_k^S), \dots, f_{30}(X_k^S)$ are extracted from these trajectory. The nine areas, $f_{31}(X_k^S), \dots, f_{39}(X_k^S)$ are extracted from the polygonal lines.

B. Fuzzy Degree Determination

In this method, we verify walking person by fuzzy degree, μ_{Sole}^r , of the acquisition data, X^S , for the target person, r . The fuzzy degree, μ_{Sole}^r , is calculated from fuzzy degrees of every feature. Firstly, we consider Knowledge 1: features of same person are similar, and Knowledge 2: the feature with higher classification score in learning pressure data is more primary for personal verification. From these knowledge, the following fuzzy if-then rules are derived.

Rule 1: IF feature, $f_i(X_k^S)$, is *CLOSE* to $\alpha_{k,i}^r$ of the registered person y_r , THEN the degree of a feature, $P_{k,i}^r$, is high.

Rule 2: IF classification score, $\beta_{k,i}^r$, of learning sole pressure data is *HIGH*, THEN the degree of a feature, $W_{k,i}^r$, is high.

These fuzzy membership functions *CLOSE* and *HIGH* are defined by Fig. 9. These fuzzy membership functions have statistically determined parameters, $\alpha_{k,i}^r$, $t_{k,i}^r$, $u_{k,i}^r$, $\beta_{k,i}^r$, and sum_k^r , and these are determined by learning process.

Here, we explain the method to determine $\alpha_{k,i}^r$, $t_{k,i}^r$, $u_{k,i}^r$ and $\beta_{k,i}^r$ in Fig. 10 for any k and i . In our learning process, every

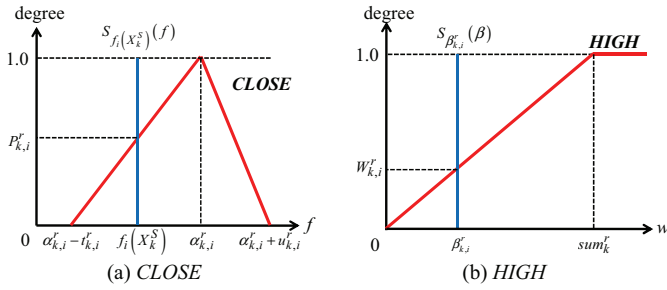
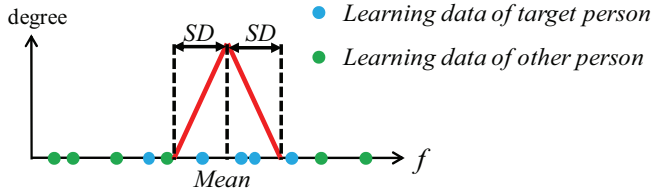
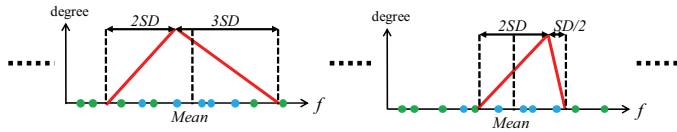


Figure 9. Fuzzy membership functions.



(a) Example of initialized fuzzy membership function CLOSE



(b) Example of deformed fuzzy membership function CLOSE
Figure 10. Examples of fuzzy membership function deformation.

registered subject has N learning data. Firstly, we calculate the mean value $Mean_{k,i}^r$, and the standard deviation, $SD_{k,i}^r$, of learning data for k and i of the target person. Secondly, we initialize $\alpha_{k,i}^r \leftarrow Mean_{k,i}^r$, $t_{k,i}^r \leftarrow SD_{k,i}^r$ and $u_{k,i}^r \leftarrow SD_{k,i}^r$. Here, the membership function, *CLOSE*, is deformed as shown in Fig. 10(a), and we calculate the fuzzy degree, $P_{k,i}^r$, of a feature $f_i(X_k^S)$ for the target person by (1).

$$P_{k,i}^r(X) = \min(CLOSE, S_{f_i(X)}(f)) \quad (1)$$

Here, we define fuzzy singleton function $S_a(x)$ by (2).

$$S_a(x) = \begin{cases} 1 & \text{if } x = a \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

We calculate the fuzzy degree, $P_{k,i}^r$, from every learning pressure data. From these fuzzy degree, the classification score, $\beta_{k,i}^r$, is calculated by the difference between an average fuzzy degree $P_{k,i}^r$ for other person and an average fuzzy degree $P_{k,i}^r$ for the target person. Thirdly, we repeat the calculation of $\beta_{k,i}^r$ for all domains of $Mean_{k,i}^r - SD_{k,i}^r \leq \alpha_{k,i}^r \leq Mean_{k,i}^r + SD_{k,i}^r$, $0 \leq t_{k,i}^r \leq 4 SD_{k,i}^r$ and $0 \leq u_{k,i}^r \leq 4 SD_{k,i}^r$ at the interval of $SD_{k,i}^r / 10$. Fig. 10(b) shows examples of the deformed membership function, *CLOSE*. We obtain the classification score, $\beta_{k,i}^r$, from all domains. We employ the parameters $\alpha_{k,i}^r$, $t_{k,i}^r$ and $u_{k,i}^r$ with the highest $\beta_{k,i}^r$ among all domains for a feature. Fourthly, we repeat the determination process for all k and i . The parameter, sum_k^r , of membership function, *HIGH*, is the total of

classification score, $\beta_{k,i}^r$, of the one sole pressure data, X_k^S , and it is calculated by (3).

$$sum_k^r = \sum_{i=1}^{39} \beta_{k,i}^r \quad (3)$$

The fuzzy degree, $Q_{k,i}^r$, of a feature is defined by (4).

$$Q_{k,i}^r(X_k^S) = P_{k,i}^r(X_k^S) \times W_{k,i}^r(\beta_{k,i}^r) \quad (4)$$

Here, the fuzzy degree, $W_{k,i}^r$, is defined by (5), and it means the effectiveness of the feature for the target person.

$$W_{k,i}^r(\beta) = \min(HIGH, S_\beta(w)) \quad (5)$$

Finally, we calculate the fuzzy degree, $Q_{k,i}^r$, for all k and i . The fuzzy degree, μ_{Sole}^r , of the acquisition data is calculated by (6).

$$\mu_{Sole}^r(X^S) = \frac{1}{2} \left(\sum_{i=1}^{39} Q_{R,i}^r(X_R^S) \right) + \frac{1}{2} \left(\sum_{i=1}^{39} Q_{L,i}^r(X_L^S) \right) \quad (6)$$

C. Personal verification by fuzzy degree

The proposed method verifies walking person by the fuzzy degree, μ_{Sole}^r , of the acquisition data, X^S . For personal verification, we acquire a pair of right and left sole pressure data, and extract features from the acquisition data. We calculate the fuzzy degree, μ_{Sole}^r , for the target person. If the fuzzy degree is higher than a threshold parameter, the proposed method verifies walking person as the target person. On the other hand, if the fuzzy degree is lower than the threshold parameter, we verify the walking person is not the target person.

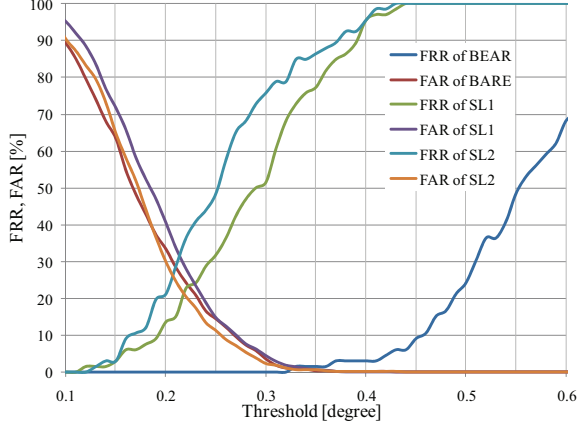
IV. EXPERIMENTAL RESULTS

In our experiment, we employed 11 volunteers. We took the sole pressure data 18 times for a volunteer with bare foot (6 times), *Slipper 1* (6 times) and *Slipper 2* (6 times). In this experiment, we call these data set that *BARE*, *SL1* and *SL2*, respectively. We employ equal error rate (EER) for performance test. EER is the error rate at that false rejection rate (FRR) equals to false acceptance rate (FAR). Here, FRR is concerned with the number of instance defined as an authorized individual being falsely rejected by the system. FAR is concerned with the number of instances defined as an unauthorized individual being falsely accepted by the system.

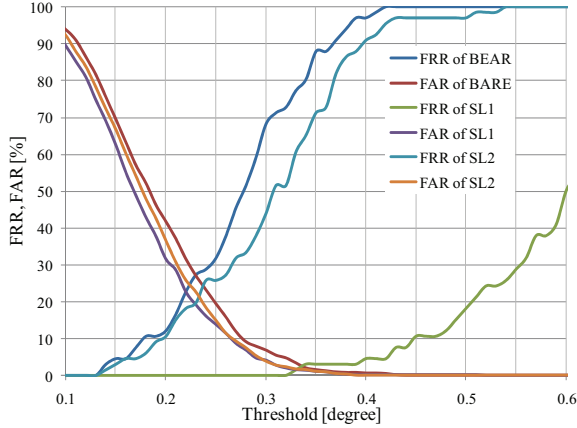
We verified these volunteers by the proposed method. First, we tested our proposed method by learning data of each data set. Table II shows the verification results of each learning data and test data and Fig. 11 shows FRR and FAR with threshold parameter change. The proposed method obtained low EER for the test data of same type data as the learning data. However, we obtained high EER for the other test data. Second, we tested the proposed method by employing two or three type learning data for a volunteer. Table III shows the verification result of employing two or three type learning data for each volunteer. We obtained low EER when the learning data included the

TABLE II. VERIFICATION RESULTS BY ONE LEARNING DATA

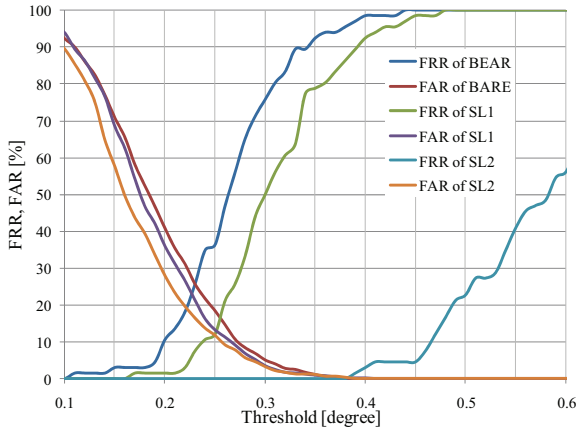
Learning data	EER for each test data [%]			Mean $\pm$ SD
	BEAR	SL1	SL2	
BARE	1.29	23.79	26.7	17.24 $\pm$ 13.90
SL1	27.12	1.15	21.14	16.47 $\pm$ 13.60
SL2	25.68	12.65	0.15	12.82 $\pm$ 12.77



(a) FRR and FAR of learning data, BARE.



(b) FRR and FAR of learning data, SL1



(c) FRR and FAR of learning data, SL2

Figure 11. FRR and FAR change with threshold parameter change.

TABLE III. VERIFICATION RESULTS BY TWO OR THREE LEARNING DATA

Learning data	EER for each test data [%]			Mean $\pm$ SD
	BEAR	SL1	SL2	
BEAR and SL1	4.39	2.26	16.97	8.21 $\pm$ 7.61
BEAR and SL2	2.88	12.58	2.27	5.91 $\pm$ 5.78
SL1 and SL2	19.84	0.83	2.12	7.60 $\pm$ 10.62
BEAR, SL1 and SL2	6.44	3.33	2.87	4.22 $\pm$ 1.94

TABLE IV. FAR IN THRESHOLD PARAMETER WAS 0.35

Learning data	EER for each test data [%]			Mean $\pm$ SD
	BEAR	SL1	SL2	
BARE	0.12	0.00	0.15	0.09 $\pm$ 0.08
SL1	0.61	0.15	0.00	0.25 $\pm$ 0.32
SL2	0.00	0.15	0.00	0.05 $\pm$ 0.09
BEAR and SL1	1.97	1.06	1.06	1.36 $\pm$ 0.53
BEAR and SL2	1.21	1.36	0.91	1.16 $\pm$ 0.22
SL1 and SL2	2.42	0.91	0.91	1.41 $\pm$ 0.87
BEAR, SL1 and SL2	4.09	2.58	1.97	2.88 $\pm$ 1.09

same type data. In addition, we obtained lower EER for the other test than that of employing one test data. Table IV shows the FAR of threshold parameter was 0.40. From these results, the proposed method was able to reject unauthorized individual being.

V. CONCLUSION

In this paper, we have proposed a biometric personal verification system based on fuzzy logic. We employed sole pressure distribution change while walking. The sole pressure data was acquired by mat type load distribution sensor. The proposed method verified the walking person by fuzzy degree of sole pressure data. We extracted features from right and left sole pressure change, and made fuzzy if-then rules with statistically determined membership functions by learning data. The fuzzy degree of sole pressure data was calculated from total of all fuzzy degree of each feature. In the experiments, we took sole pressure data three situations; volunteers walked with bare foot, they walked with thin slipper and they walked with thick slipper. We employed 11 volunteers, and we tested the proposed method. We obtained low EER when the learning data included the same type data. However, we obtained high EER for the other test data. The verification system had low FAR in threshold parameter was 0.40 for any learning data and test data. From these results, the proposed method was able to verify sole pressure data that was acquired same situation. From these results, we think that to verify walking person wearing shoes, the system needs to employ learning data of various situation.

In the future, we will employ newly features of sole pressure for verification. We will try to authenticate person wearing shoes. We will add other biometric feature to the method.

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