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Dynamic-Footprint based Person Identification 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. And one of emerging method is to use human walking behavior. But, in the previous methods based on human gait, stable somewhat long-term walking data are an essential condition for person recognition. Therefore, these methods are difficult to cope with various change of walking velocity which may be generated frequently during real walking. In this paper, we suggest a new method which uses just one-step walking data from mat-type pressure sensor. When a human walk through the pressure sensor, we get quantized COP (Center of Pressure) trajectory and HMM (Hidden Markov Model) is used to make probability models for user's each foot. And then, HMMs for two feet are combined for better performance by Levenberg-Marquart learning method. Finally, we prove the usefulness of the suggested method using 8 people recognition experiments.**

Keywords— **Biometrics, Dynamic footprint, Mat-type Pressure sensor, Hidden Markov Model, Levenberg-Marquart learning, Person recognition**

I. INTRODUCTION

Until now, there has been a rapid growth in the field of person identification technique for the purpose of securing important property of government and company from robbers. Among various methods of person identification, biometric identification such as finger scan or iris scan is the most promising methods now. And palm print, face, retina, voice, signature, keystroke, ear, gait are also good methods for specific situations. [1]

These techniques can be divided into two categories: high accuracy-oriented category 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. [2] (Fig. 1) At this, human-friendliness can be understood as the degree of constraint on the user.

So, in the aspect of human-friendliness, automatic face recognition based on vision technique can be a promising method since it can work without any help of the user. [3] But, changing illumination, occlusion, and hair-style change are still very difficult problems. [2] And automatic gait recognition is another emerging method which doesn't need any operation from the user. [4] But, basically, human gait doesn't always guarantee the meaningful feature for person recognition because of various change of walking velocity which can be generated frequently during real walking. One of possible way to solve this problem is to use remained footprints after human walking behavior.

Footprint-based person recognition method was started by Nakajima in [2] and he showed 85% of recognition rate among ten men using normalized static footprint. And Jung [5] showed the possibility of unconstrained person recognition using position-based quantization of COP (Center Of Pressure) trajectory from shoe-type pressure sensor and hidden markov models. In [5], Jung tested with 5 men's walking data and showed about 100% recognition rate. But, there is a problem that data are considerably correlated since all data were collected in a day. Moreover, using shoe-type sensor could be a serious constraint in the view of users.

In this paper, we propose a new method which use direction-based quantization of COP trajectory, hidden markov model and Levenberg-Marquart learning method to apply in various change of walking velocity in real environment. In chap.2, we will explain the extraction process of COP trajectory from dynamic partial footprint images and direction-based quantization technique for COP trajectory and we show HMM-based recognizer for various change of walking velocity in chap.3. Finally we test our new recognizer using 8 people and discuss the results in the view of false rejection rate and false acceptance rate.

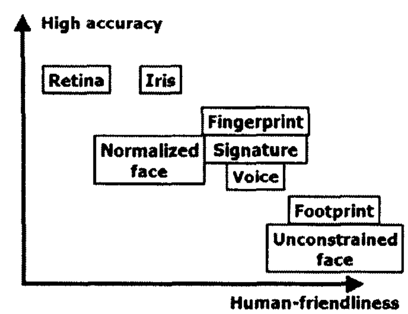

Fig. 1. High accuracy-oriented vs. human-friendly person recognition method

II. QUANTIZED COP TRAJECTORY EXTRACTION

To recognize human using footprint, we can use static feature in stand-up posture or dynamic feature in walking behavior. But, when we use static feature, user should make same stand-up posture at fixed position every time. [2] To release this constraint on user posture, dynamic feature is used in this paper. And to represent both area change and pressure change in pressure distribution, we use COP (Center Of Pressure) trajectory as a feature.

Since the behaviors of left foot and right foot are not seemed to be symmetric in general case, we can guess that some foot will show better result for representing user's own characteristic.

By this reason, we deal with not one foot but both left and right foot. We define these two footprints (left and right footprint regardless of order) as one-step footprint. During the walking behavior, one-step footprint is consisted with first foot and second foot.

A. Extraction procedure of quantized COP trajectory of one-step footprint for mat-type sensor

Step0) We assumed that there is no object on the pressure sensor except the walking person. By this assumption, we can find the starting time of one-step footprint, t_{start}, by checking when totally summed pressure value is more than threshold value after deleting noises (isolated single pixel blobs) in pre-processing. In the same fashion, we check the ending time of one-step footprint t_{end} at each time after t_{start}. And, the pressure distribution image is represented as a monochrome image $f(x,y): -\frac{w_X}{2} < x \le \frac{w_X}{2}, \frac{w_Y}{2} < y \le \frac{w_Y}{2}$ where w_X and w_Y are widths of the sensor.

At time t, $t_{start} \le t \le t_{end}$: Execute from step1 to step4

Step1) We make a label for each blob in current footprint image using scanning line method. I.e. when the scanning line meets a segment, a number is given to the segment.

Step2) We find COA (Center Of Area) points of all labeled blob and these points are used as representative points for each blob to determine where current blob is included between first foot and second foot. The reason that we used COA instead of COP to make a representative point for each blob is that not pressure distribution but foot shape is needed when we determine first foot or second foot.

Step3) We divide first foot and second foot using k-means algorithm. By comparing the distance between Blob COA point and first foot's COA, and the distance between Blob COA point and second foot's COA, we determine where current blob is included between first foot and second foot. And then we re-estimate first foot's COA and second foot's COA with these additional blobs.

Step4) We calculate first foot's COP and second foot's COP. And then we update COP trajectory list for each foot. Step1 ~ step 4 are repeated during $t_{start} \le t \le t_{end}$.

At time $t=t_{end}$: Execute from step5 to step9

Step5) We make original COP trajectory for first foot and second foot by the last update of COP trajectory list at $t=t_{end}$.

Step6) We make an overlapped footprint image by doing OR operation on all partial footprint images $t_{start} \le t \le t_{end}$. All pixel values of overlapped footprint image are 0 or 1.

Step7) 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. [6] So, to find principal axes of left foot $L(x,y)$, we translate all footprint data of left foot so that COA of left foot is to be located in the origin. And then we make covariance matrix H_L like (1). Eigenvectors e_{L1} and e_{L2}, whose eigenvalues were ordered by highest to lowest, are major and minor axis.

$$H_L = \begin{pmatrix} \sum_{x',y'} L(x',y')x'^2 & \sum_{x',y'} L(x',y')x'y' \\ \sum_{x',y'} L(x',y')x'y' & \sum_{x',y'} L(x',y')y'^2 \end{pmatrix} \quad (1)$$

Step8) We translate original COP trajectory so that starting point of the trajectory becomes origin and we rotate the translated COP trajectory to $\angle e_{L2}$ (or $\angle e_{R2}$) degree for directional alignment. And then, we get directionally aligned COP trajectory $Traj(t) = [x \quad y]'$,

where $t_{start} \le t \le t_{end}$ and $Traj(t_{start}) = [0 \quad 0]'$.

This process is essential part since user can walk into the sensor area from every direction.

Step9) We quantize directionally aligned COP trajectory to reduce the feature dimension from 2D to 1D. And since the resolution of usual pressure sensor is too low (about 1cm), absolute position-based quantization method is apt to lose information. So, we use direction-based quantization method which can represent not only direction but only relative displacement (see Table I). Quantization output is like (2).

$$name = (x\ motion + 2) * 5 + (y\ motion + 2) + 1 \quad (2)$$

where greater than 1 or less than -1 are treated as 1 or -1 and real displacement of "+1" motion is determined by spatial resolution of used sensor.

TABLE I
DIRECTION-BASED QUANTIZATION METHOD

name = 1 x motion = -2 y motion = -2	name = 6 x motion = -1 y motion = -2	name = 11 x motion = 0 y motion = -2	name = 16 x motion = 1 y motion = -2	name = 21 x motion = 2 y motion = -2
name = 2 x motion = -2 y motion = -1	name = 7 x motion = -1 y motion = -1	name = 12 x motion = 0 y motion = -1	name = 17 x motion = 1 y motion = -1	name = 22 x motion = 2 y motion = -1
name =3 x motion = -2 y motion = 0	name = 8 x motion = -1 y motion = 0	name = 13 x motion = 0 y motion = 0	name = 18 x motion = 1 y motion = 0	name = 23 x motion = 2 y motion = 0
name = 4 x motion = -2 y motion = 1	name = 9 x motion = -1 y motion = 1	name = 14 x motion = 0 y motion = 1	name = 19 x motion = 1 y motion = 1	name = 24 x motion = 2 y motion = 1
name = 5 x motion = -2 y motion = 2	name = 10 x motion = -1 y motion = 2	name = 15 x motion = 0 y motion = 2	name = 20 x motion = 1 y motion = 2	name = 25 x motion = 2 y motion = 2

B. Experimental results

We experimented with 8 people (see Table II) to find quantized COP trajectory by TECHSTORM's mat-type pressure sensor. (Fig. 2) The size of this sensor is 80*40 cm^2 including 80*40 sensors and sampling time is 30 Hz. Each volunteer tested naturally 35 times during 40 days walking through mat-type pressure sensor. Among 35 steps for one person, 18 steps of first period are used for learning samples and 17 steps of recent period are used for test samples.

TABLE II
BODY DATA OF TEST MEMBERS

ID	SEX	Height (cm)	Weight (cm)	Foot length (mm)
USER0	MALE	174	80	270
USER1	MALE	164	61	250
USER2	MALE	172	71	270
USER3	FEMALE	159	45	240
USER4	MALE	173	70	270
USER5	MALE	170	100	265
USER6	MALE	175	76	265
USER7	MALE	177	65	270

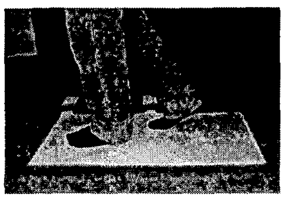

Fig. 2. Mat-type pressure sensor

Fig. 3 shows the directionally aligned and 2D-projected COP trajectories of each test member during natural walking including velocity changes. Since these data are the one before quantization procedure, we can check characteristics of human walking footprint without loss of information.

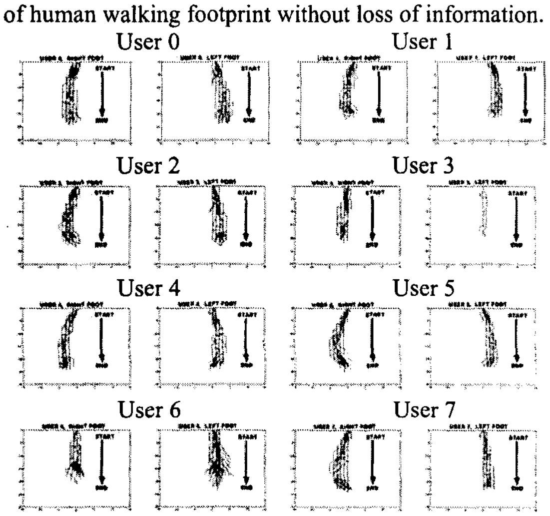

Fig. 3. Directionally aligned COP trajectories of 8 users

Characteristics of human walking footprint:

Fact1) Human walking behavior is different person by person.

Fact2) Walking behaviors could be different in same person.

Fact3) During walking behavior, motions of left foot and right foot are not symmetric.

III. PERSON RECOGNITION BY HMM-BASED RECOGNIZER

Since Quantized COP trajectory that we achieved in chap. 2 is a sequential data, we used left-to-right type HMM for recognizer. And, from the property that left foot and right foot are considerably independent (Fact3), we used two models for each person, left foot model and right foot model. Totally, we used 16 models for 8 people. The input of HMM is the output of quantization procedure, 'name' in Table1. And, we tested HMM with 3 states, 4 states, and 5 states to choose the best number of state in HMM. By the comparison of recognition rate and complexity, 3 states recognizer was selected. In addition, since all models have similar characteristic, all models was set to 3 states.

Since some people have strong characteristic on left foot and other people have it on right foot, we can predict that recognizing with one-step data will show better performance than recognizing with one-foot data. And based on this prediction, we modified HMM like Fig. 4. But, since the comparison of output probabilities of two HMM can be possible only when the lengths of input sequences are equal, we need an additional assumption that walking speed of left foot and right foot are almost equal. And this assumption restricts the application area. So, to overcome this restriction and to solve various walking velocity problem, we use LM (Levenberg-Marquart) method like Fig. 5.

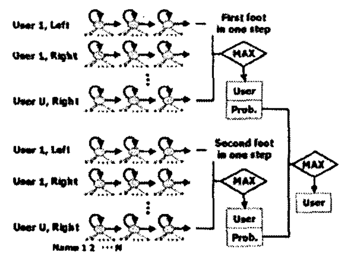

Fig. 4. HMM for one-step

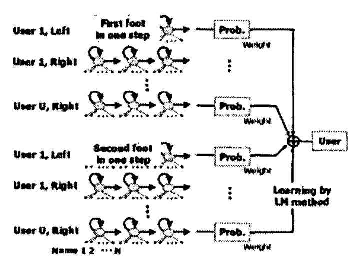

Fig. 5. Modified HMM for one-step

LM method is a combination type of Newton method and standard gradient descent algorithm. Weights-updating rule is like (3) [7] and step size λ was determined by adaptive method.

$$w_{new} = w_{old} - (Z^T Z + \lambda I)^{-1} Z^T \varepsilon(w_{old}), \quad (Z)_{ni} \equiv \frac{\partial \varepsilon^n}{\partial w_i} \qquad (3)$$

Where, ε^n is the error for the n[th] pattern, ε is a vector with elements ε^n, and λ is step size for learning.

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 is concerned with the number of instances an authorized individual is falsely rejected by the system like (4) and FAR refers to the number of instances a non-authorized individual is falsely accepted by the system like (5). Both rates are expressed as a percentage using the following simple calculations: [8]

$$FRR = NFR / NAA * 100\% \qquad (4)$$

$$FAR = NFA / NIA * 100\% \qquad (5)$$

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, respectively.

From the experimental results, we ascertain that the above prediction, that recognizing with one-step data will show better performance than with one-foot data, is correct. And we found that the combination type of HMM and LM learning method is efficient way since the recognition error was reduced from 48.5(%) to 36.0(%). In addition, compared with the previous results about footprint recognition and gait recognition, our method has more advantage in the aspect of naturalness and wide-applicability since our method use just one-step data based on mat-type pressure sensor. But, there are still a big problem that recognition rate is not equally distributed and not enough high.

IV. Conclusion

In this paper, we proposed a person recognition method based on mat-type pressure sensor which can be applied in various change of walking velocity by the help of modified HMM which can identify person regardless of sequence length. Directionally-aligned and quantized COP trajectory was used to be a feature for representing dynamic footprint. And, by the observation that recognizing with one-step, i.e. two-feet, will show better performance than recognizing with one-foot, we made HMM-based recognizer for one-step footprint. And, combined by Levenberg-Marquart learning method, this modified recognizer showed 64% average recognition rate for 8 men's natural walking experiment. This result is not very good recognition rate but it is important in the sense that unconstrained walking person recognition method based on mat-type pressure sensor could be possible under the change of walking velocity.

TABLE III
EXPERIMENTAL RESULT OF RECOGNIZERS

	HMM for each foot		HMM for one-step		HMM +LM
	FRR (%)	FAR (%)	FRR (%)	FAR (%)	FRR (%)
Total	**65.1**	**4.3**	**48.5**	**5.8**	**36.0**
user1, left	11.8	5.5	23.5	1.7	41.2
user1, right	41.2	4.7			
user2, left	58.8	2.4	64.7	2.5	23.5
user2, right	70.6	2.0			
user3, left	70.6	3.5	41.2	1.7	58.8
user3, right	41.2	10.6			
user4, left	52.9	5.1	47.1	11.8	11.8
user4, right	94.1	0			
user5, left	70.6	5.5	52.9	5.9	35.3
user5, right	70.6	10.2			
user6, left	82.3	0.8	47.1	11.8	11.8
user6, right	47.1	3.5			
user7, left	70.6	3.5	35.3	0	17.6
user7, right	70.6	3.5			
user8, left	94.1	4.3	76.5	10.9	88.2
user8, right	94.1	4.3			

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