Person Identification Based on Postural Sway Data: The Effects of Shouldering A Backpack

Yusuke MANABE*1 · Gen FUKUSHIMA*2 · Kenji SUGAWARA*1

1. Introduction

A human postural sway in quietly-standing conditions is one of the major index to assess various human health conditions. Because, for maintaining a posture while standing quietly, it is necessary to control a very complex muscles and joints system. From the scientific and clinical viewpoints, there are a lot of research contributions that deal with an upright postural sway. For example, Collins et al.[1] analyzed Center-of-pressure (COP) trajectories under quiet-standing conditions and proposed stabiliogramdiffusion plot (SDP) analysis. SDP is a plot of mean square COP displacement with time interval. They defined a slope of SDP as a diffusion coefficient and found that it becomes large in short time interval but becomes small in long time interval. It was also shown that the critical changing point of the diffusion coefficient is different for different human subject. This is a pioneering work to quantify the human postural sway. Hernandez et al.[2] pointed out that SDP needs numerous, long duration trials of data measurement to obtain a reliable analysis result. They proposed a new quantity, COP velocity autocorrelation function (COP-VAF). According to the result of experiments with healthy five human subjects’ data, COP-VAF can be used to distinguish quiet-standing conditions with open and closed eyes.

Here the most important thing from the viewpoint of engineering applications is that human postural sway in quietly-standing position involves differences in individuals. For example, Hattori et al. [3] examined characteristics of COP for 13 human subjects and pointed out that the mean velocity of COP has individual differences with statistical significance.

Yanai et al. [4][5] showed the feasibility of person identification based on human postural sway data. They measured shoulder’s position sway data based on image processing as well as COP trajectory data based on a stabilometer. The results of linear discriminant analysis for COP-based features, when each human subject is quietly standing with vision, produced the identification accuracies of 71%, 91% and 100% for 24, 14 and 7 human subjects respectively. In addition, recently Nasu et al. [7] and Qian et al. [6] proposed person identification methods based on pressure data. In the method by Nasu et al., they installed a stabilometer (Wii balance board produced by Nintendo) on the floor in front of a door and measured COP data when human subjects stepped on the stabilometer to open the door. As the result of the experiment based on five human subjects’ data for 15 days, the identification accuracy of 93.7% was achieved. The method by Qian et al. focuses on the case in which human subjects walk on a pressure sensing floor. Technically this method is a little different from the other methods because COP trajectories while walking on the pressure sensing floor are used for person identification. For 11 human subjects, an average recognition rate of 92.3% and false alarm rate of 6.79% are achieved on the best performing feature set.

On the basis of the above works, it is assumed that the upright postural sway data can be an important trait for behavior-based person identification. Developing a novel method of behavior-based person identification can provide us the possibility of transparent person identification technology because the target behavior can be embedded in activities of daily life (ADL). For example, we consider a personal or family assistant system in a smart home. The system has to be able to recognize a person of a

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family member and adaptively provide information and service to them in a specific room. In order to realize the system, it is necessary to develop a person identification technology which can extend the coverage of information and conditions for humans in actual environment.

However, current person identification researches based on postural sway data have the following two problems:

**Problem 1** The most target behavior is the postural sway after completely stepping on a stabilometer.

**Problem 2** The effect of carrying weight on the accuracy of person identification is unclear.

One of the causes of the problem 1 may be that the postural sway data has been originally analyzed from the scientific and clinical viewpoints [1]. In such fields, it is postulated that COP data is measured when human subjects are quietly standing on a stabilometer [8]. But in the engineering applications, we should not ignore that the behaviors of stepping on and off a stabilometer can also involve some individual differences. For the problem 2, there are some investigations [9][10] addressing the effect of load for soldiers who carry or wear very heavy military equipments. But, as far as we know, there is no contribution addressing the effect of normally carried weight in daily life on accuracy of person identification.

Therefore this paper proposes the following two approaches as solutions for the above two problems:

**Approach 1** We measure postural sway data while stepping on and off a stabilometer as well as quietly standing condition. In other words, we extract features related to how to step on and off a stabilometer as well as quietly-standing sway.

**Approach 2** We consider a backpack as an example of the carrying weight, and analyze the effects of shouldering a backpack on the accuracy of person identification.

Experiments on person identification have been done to evaluate our proposed method and to compare identification accuracies with and without a backpack. The results with 10 human subjects data show that carrying a backpack affects the identification accuracy, but the postural sway data in shouldering a backpack has sufficient potential to identify a person. Also, we show some extracted features for stepping on and off intervals have good potential to identify persons.

This paper consists of five sections. Section 2 describes our proposed method. Section 3 describes the experiment and the results to evaluate our proposed method. In section 4, we discuss and analyze the experimental results. Finally we conclude our paper in section 5.

2. **Proposed Method**

In this section, we describe the proposed method.

2.1 **Outline**

Figure 1 shows the process diagram of our proposed method. The method is in line with general person identification system and is classified into registration and identification processes.

In the registration process, postural sway data is measured by a stabilometer. The measured data are pressure time series and a two-dimensional time series of the COP. We measure the postural sway data in the process when a human subject steps on and off the stabilometer. After measurement, the postural sway data is segmented to extract the target interval. Next, some features are extracted from the segmented postural sway data for training a classifier to identify person. Finally the trained classifier is saved in the system and are used at the time of

![Fig. 1 Processing Diagram of Proposed Method](image-url)
identification process.

In the identification process, a postural sway data is first measured by a stabilometer. Secondly, segmentation and feature extraction are done by the same manner as in the registration process. Then, the trained classifier is used for identification of persons. The methods for segmentation, feature extraction and identification are described in the following subsections respectively.

2.2 Stabilometer and Its Measurement Data

In the proposed method, we employed a Wii balance board produced by Nintendo as a stabilometer. According to Yoshikawa et al. [11], it is shown that a Wii balance board is one of the reliable stabilometer on a COP trajectory measurement. Figure 2 and Table 1 show a picture of the sensor and its specification respectively. A Wii balance board has four strain gauge sensors. Each sensor is installed in the four cylindrical legs on the corners (Left-Front, Right-Front, Left-Back and Right-Back) of the Wii balance board and we can obtain time series data of four pressure sensors. On the basis of the four pressure time series, the resultant movements in the COP can be computed as the time series data, which is two-dimensional coordinate time series: \(x(t)\) and \(y(t)\). This study mainly employs the COP time series.

In this study, we measure postural sway data not only while quietly standing but also while stepping on and off a stabilometer. Figure 3 illustrates the action process of a human subject. First a human subject steps on a stabilometer. On the meter, the human subject stands quietly for three seconds. After three seconds, the human subject steps off the stabilometer. The details of data collection are shown in section 3.

2.3 Data Segmentation

The proposed method extracts various features from postural sway data from stepping on to stepping off a Wii balance board, thus data segmentation is an important process. We define four critical time: beginning of step-on time \(T_s\) end of step-on time \(T_e\), beginning of step-off time \(T_f\) and the end step-off time \(T_i\).

Figure 4 (a) shows \(T_s\) and \(T_i\), which can be detected from four pressure time series. \(T_i\) denotes the time when one pressure time series value exceeds more 5.
\( T_1 \) denotes the time when all the four pressure time series values are less than 5.

Figure 4 (b) shows \( T_1 \) and \( T_2 \) based on the variance of pressure time series. The variance time series \( V_p(t) \) is obtained by the following equation,

\[
V_p(t) = \frac{1}{N} \sum_{i=t-N+1}^{t} (p(i) - \bar{p})^2
\]

(1)

where \( N \) denotes the number of data samples \( (N = 60 = 1 \text{ second}) \), \( \bar{p} \) denotes pressure value at time \( i \) and \( \bar{p} \) denotes the mean of \( p(i) \) for 1 second. \( T_2 \) denotes the time when all the variance time series are less than 100. \( T_3 \) is one second ahead from the time when one variance time series becomes more than 100 after \( T_2 \). Each threshold are set heuristically in advance.

### 2.4 Feature Extraction

In this study we extract 15 features from the COP time series.

#### 2.4.1 Average of COP in each interval

We compute the average of two dimensional coordinates \((x, y)\) of COP in each interval: \(T_1\) to \(T_2\), \(T_2\) to \(T_3\), and \(T_3\) to \(T_4\).

\[
f_1 = \frac{1}{T_2 - T_1 + 1} \sum_{t=T_1}^{T_2} x(t)
\]

(2)

\[
f_2 = \frac{1}{T_2 - T_1 + 1} \sum_{t=T_1}^{T_2} y(t)
\]

(3)

\[
f_3 = \frac{1}{T_3 - T_2 + 1} \sum_{t=T_2}^{T_3} x(t)
\]

(4)

\[
f_4 = \frac{1}{T_3 - T_2 + 1} \sum_{t=T_2}^{T_3} y(t)
\]

(5)

\[
f_5 = \frac{1}{T_4 - T_3 + 1} \sum_{t=T_3}^{T_4} x(t)
\]

(6)

\[
f_6 = \frac{1}{T_4 - T_3 + 1} \sum_{t=T_3}^{T_4} y(t)
\]

(7)

where \( x(t) \) and \( y(t) \) denote two dimensional coordinates of COP at time \( t \) respectively.

#### 2.4.2 Step-on Duration and Step-off Duration

The step-on duration \( f_8 \) denotes the time required to step on the stabilometer. \( f_6 \) is computed as follows:

\[
f_7 = \frac{T_2 - T_1}{F_s}
\]

(8)

where \( F_s \) denotes a sampling frequency. The step-off duration \( f_8 \) is the time that human subjects step off the stabilometer.

\[
f_8 = \frac{T_2 - T_3}{F_s}
\]

(9)

#### 2.4.3 Anteroposterior Sway Range and Mediolateral Sway Range

The anteroposterior sway range \( f_9 \) is computed as follows:

\[
f_9 = |Y_{max} - Y_{min}|
\]

(10)

where \( Y_{max} \) and \( Y_{min} \) are a maximum and a minimum values of \( y(t) \) respectively. The mediolateral sway range \( f_{10} \) is computed as follows:

\[
f_{10} = |X_{max} - X_{min}|
\]

(11)

where \( X_{max} \) and \( X_{min} \) are a maximum and a minimum values of \( x(t) \) respectively.

#### 2.4.4 Total Trajectory Length of COP

The total trajectory length of COP \( f_{11} \) is defined in the following equation.

\[
f_{11} = \sum_{t=T_1}^{T_4} \sqrt{(x(t+1) - x(t))^2 + (y(t+1) - y(t))^2}
\]

(12)

#### 2.4.5 Area of Circumscribing Rectangle in COP Trajectory

The area of circumscribing rectangle \( f_{12} \) in COP trajectory is computed as follows:

\[
f_{12} = |X_{max} - X_{min}| \times |Y_{max} - Y_{min}|
\]

(13)

#### 2.4.6 Average of COP in Entire Interval

The average of COP from \( T_1 \) to \( T_4 \) is computed as follows:

\[
f_{13} = \frac{1}{T_4 - T_1 + 1} \sum_{t=T_1}^{T_4} x(t)
\]

(14)
\[ f_{14} = \frac{1}{T_4 - T_1 + 1} \sum_{t=T_1}^{T_4} y(t) \]  

(15)

2.4.7 Correlation Coefficient between Anteroposterior Sway and Mediolateral Sway

The Correlation Coefficient \( f_5 \) between Anteroposterior Sway \( y(t) \) and Mediolateral Sway \( x(t) \) is computed as follows:

\[ f_{15} = \frac{\sum_{t=T_1}^{T_4} (x(t) - \bar{x})(y(t) - \bar{y})}{\sqrt{\sum_{t=T_1}^{T_4} (x(t) - \bar{x})^2 \sum_{t=T_1}^{T_4} (y(t) - \bar{y})^2}} \]

(16)

where \( \bar{x} \) and \( \bar{y} \) denote the average of \( x(t) \) and \( y(t) \) from \( T_1 \) to \( T \), respectively.

2.5 Identification Method

The person identification problem is a kind of pattern classification problem, so many existing machine learning algorithms can be applied to it. In this study, we employ support vector machine (SVM) as a popular machine learning algorithm. Thus SVM identifies human subjects based on the above fifteen dimensional feature vectors.

3. Experiments and Results

This section describes the experiments done for person identification based on postural sway and their results.

3.1 Data Collection

We collected the postural sway data from 10 human subjects by using the Wii balance board. The human subjects are males, with an age range of 21–23. The height and weight histograms of human subjects are shown in Table 2. For each subject, we collected 30 postural sway data samples (=15 samples \( \times 2 \) conditions). The two conditions are the standing without load and the standing with load (shouldering a backpack). Figure 5 shows the backpack used in the experiment. The weight of the backpack is 2 kg and it is adjusted by plastic bottles of water. This is a light weight condition, such as some notebooks and writing tools are inside the backpack.

The program of data collection is written in C# language and WiimoteLib v 1.7 [12] in Microsoft Visual Studio 2010. The sampling frequency \( F_s \) is 60 Hz.

<table>
<thead>
<tr>
<th>Table 2</th>
<th>Height and Weight Distribution</th>
</tr>
</thead>
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<tr>
<td>Height (cm)</td>
<td>Freq</td>
</tr>
<tr>
<td>165 ( \leq )</td>
<td>3</td>
</tr>
<tr>
<td>170 ( \leq )</td>
<td>4</td>
</tr>
<tr>
<td>175 ( \leq )</td>
<td>2</td>
</tr>
<tr>
<td>180 ( \leq )</td>
<td>1</td>
</tr>
</tbody>
</table>

Fig. 5 Backpack

We put the stabilometer on the floor, so the difference in height between the stabilometer and the floor is 53.2 mm.

In the data collection process, each human subject behaved in accordance with the following instructions:

1. A human subject stood in front of the stabilometer and stepped on it with one foot by one foot. Each human subject was taught to use the same foot order all the time.
2. On the stabilometer, the human subject stand quietly for three seconds. The time for quiet- standing period was measured by an experimenter, who observed the step-on actions of human subject and measured the time with a stop-watch.
3. After three seconds, the experimenter told the human subject to step off the stabilometer.
4. The human subject stepped off the stabilometer with one foot by one foot. All human subjects were asked to use the same foot order for step- ping down the stabilometer.

For each human subject, the measurement was continuously done at the same day. The measurement interval between samples was around 30 seconds to 1 minute. We didn't control the other conditions about meals or exercises, but all measurement timings were not immediately after taking meals or...
exercising. A total of 300 data (10 human subjects × 15 samples × 2 conditions) were collected.

3.2 Experimental Settings

In this experiment we used ksvm function in kernlab library in the statistical computing tool R [13]. The kernel function is Gaussian kernel and margin strategy is soft-margin. The hyperparameter \( \gamma \) for the Gaussian kernel is automatically tuned in every learning processes. The cost parameter \( C \) for soft-margin is set to 1.0. For multiclass-classification problem, ksvm uses the one-against-one approach.

We carried out the person identification experiments using the four combinations of data set, which is shown in Table 3. The experiment 1 is based on the data set only for persons not carrying load (unloaded data set), the experiment 2 is based on the data set only for persons carrying load (loaded data set). In the experiment 3, we employed the unloaded data set for training, and the loaded data set for test. The experiment 4 was the setting which was reverse of the experiment 3. We compared the identification accuracies of the four conditions.

In each experiment, we randomly picked up \( N \) human subjects data from 10 subjects for 100 times. Then, in each time, 5 data samples are used as test samples and the rest 10 samples are used for SVM training. This data division is randomly carried out for 100 times. Therefore identification accuracy \( \alpha \) is computed as follows:

\[
\alpha = \frac{\text{# of Correctly Identified Samples}}{N \times 100 \times 5 \times 100}
\]

(17)

where \( N \) is set to 2, 3, 4, 5, 6, 7, 8, 9 and 10. For example, in case of \( N = 2 \), it means the identification of 2 human subjects, which are randomly picked up. In case of \( N = 10 \), it means the identification of 10 human subjects.

3.3 Results

Figure 6 shows the results of identification accuracies in the four experiments. The horizontal axis denotes the number of human subjects to be identified and the vertical axis denotes identification accuracies. Each colored line represents each experimental setting. The average values of identification accuracy were 97.9% in the experiment 1, 98.4% in the experiment 2, 84.4% in the experiment 3 and 84.3% in the experiment 4. We can find that the identification accuracies are changing for the number of human subjects but they are over 75%. Especially, classifiers in the experiment 2 and 4 are based on the data shouldering a backpack. Thus the postural sway data in shouldering a backpack also has sufficient potential to identify persons.

In addition, we can find that the experiment 1 and 2 outperform the experiment 3 and 4. As the number of human subjects increases, the identification accuracies decrease in all of the experiments. This decreasing tendency is quite remarkable in the experiment 3 and 4. For example, in the experiment 1 and 2, the accuracies keep over 95% even if the number of human subjects increased. On the other hand, in the experiment 3 and 4, although the accuracies for the 3 human subjects are over 90%, they fall under 80% for 8 human subjects identification. This result implies that carrying a backpack causes change in characteristics of postural sway and it affects the identification accuracy.

4. Discussion

In this section, we discuss the analysis results of extracted features from the two view points: inter- and intra-class variability and optimal feature for
4.1 Inter-and Intra-class Variability

In order to assess the extracted features, we evaluated 15 features by using the Fisher criterion $J_i$ which can be computed as follows:

$$J_i = \frac{B_i}{W_i}$$  \hspace{1cm} (18)

$$W_i = \frac{1}{N} \sum_{j=1}^{N} \sum_{k=1}^{N^j} (f_{ij}^{jk} - \bar{f}_{ij})^2$$  \hspace{1cm} (19)

$$B_i = \frac{1}{N} \sum_{j=1}^{N} N^j (\bar{f}_{ij} - \bar{f}_j)^2$$  \hspace{1cm} (20)

where $W_i$ is the within-class variability, $B_i$ is the between-class variability, $N^j$ denotes the number of human subjects to be identified, $N$ denotes the number of data samples in the $j$-th class, $N$ the total number of data samples based on $N = \sum_{j=1}^{N} N^j$. $f_{ij}^{jk}$ denotes the $k$-th sample of feature $f_i$ in the $j$-th class. $\bar{f}_{ij}$ denotes the mean of feature $f_i$ in the $j$-th class and $\bar{f}_j$ is the overall mean of feature $f_i$. Fisher criterion is one of the most popular criterion to evaluate the characteristics of feature space.

Figure 7 shows the results of the Fisher criterion $J_i$ for each feature. The horizontal axis denotes features, the vertical axis denotes the natural logarithm of $J_i$. Also features are sorted by the log $J_i$ in descending order.

First, we discuss effective features for person identification. From Figure 7, we can find that feature $f_9$, $f_6$, $f_4$, and $f_7$ better discriminability in the both unloaded and loaded data set. This means that the average of the COP in the stepping on and off intervals have good characteristics to identify persons. Meanwhile, feature $f_6$, $f_4$ and $f_3$ have low discriminability in the both unloaded and loaded data set. These features are the anteroposterior sway range, the total length and the area of the COP trajectory for entire interval. This result implies that the sway range of human subjects can be constrained by the size of a stabilimeter and the short measurement time in this experiments. Consequently, we can show that some features, which are related to stepping on and off a stabilimeter, have efficient potentials to identify persons.

Next, in order to discuss the effects of shouldering a backpack for person identification accuracy, we compare the results between unloaded and loaded data sets in Figure 7. In these graphs, the log $J_i$ values in some high-ranking features ($f_1$, $f_5$, $f_6$ and $f_7$) are almost in same range (2.0 to 3.1) in the unloaded and the loaded data sets. On the other hand, the values of low-ranking features ($f_6$, $f_1$, and $f_3$) are markedly different between the both graphs. For example, the value of $f_3$ in the unloaded data set is -1.6 (actual $J_i$ value is 0.21), but in the loaded data set it is -3.0 (actual $J_i$ value is 0.05). Thus, in the feature $f_3$, the discriminability of loaded data becomes about a quarter of the unloaded data under Fisher criterion. This tendency can be found in the other low-ranking features. The cause of this result is an increase of $W_i$ in the loaded data sets.
son of the within-class variabilities for the low-ranking features \(f_8, f_{11}\), and \(f_{16}\). We can find that shouldering a backpack makes variabilities of the length and the area of COP trajectories become large.

### 4.2 Optimal Feature Selection for SVM

Although Fisher criterion \(J\) is used as a popular measurement to assess the characteristics of feature space, it is a criterion for linear discriminant analysis. As this study employs the Gaussian kernel-based SVM, a nonlinear identification model, we carried out the optimal feature selection based on a greedy forward selection strategy.

Under the same conditions as the experiment 1 and 2 in Table 3, we carried out 100 times identification for 10 human subjects. In each time, 5 data samples are used as test samples and the rest 10 samples are used for SVM training. This data division is randomly carried out.

Figure 8 shows the results of recognition rate for each feature subset. The horizontal axis means each feature, which is ordered by recognition rate. As we use the greedy forward selection, the dimension of feature vector becomes large from left to right. For example, in case of \(f_i\) in Figure 8 (A), it means the use of four-dimensional feature vector \(\{f_8, f_9, f_1, f_i\}\). That is, a feature vector is composed of all elements from the leftmost feature and the target feature.

From this figure, we can find that the best identification accuracy reaches into 98% at the 10-dimensional feature vector in both the unloaded and the loaded data. In the 10-dimensional vector, the features selected in common between the unloaded and the loaded data are \(f_8, f_9, f_3, f_8, f_{11}, f_{16}\). Among them, \(f_8, f_9, f_3, f_{11}\) and \(f_{16}\) can be extracted from the step-on or step-off duration. This result implies that we can extract the effective features for person identification from the step-on or step-off duration.

On the other hand, the unselected features in common between the unloaded and the loaded data are \(f_8, f_{11}\), and \(f_{16}\). Especially, \(f_{11}\) was also low rank in Fisher criterion. Thus, it is assumed that the total trajectory length of COP is relatively an ineffective feature for person identification.

![Identification Accuracies for Feature Subsets](image)

**Fig. 8** Identification Accuracies for Feature Subsets

### 5. Conclusion

In this paper, we handled the person identification task based on postural sway data during quietstanding conditions as well as stepping on and off conditions. Also we examined the effects of shouldering a backpack for person identification accuracy. The person identification experiments with 10 human subjects data have been performed under different experimental settings. We could obtain 97.9% accuracy for the unloaded data (without a backpack), 98.4% accuracy for the loaded data (with a 2 kg backpack) on average. This result says that the postural sway data has a possibility to identify persons even if they are shouldering a backpack. In case of the experiments with the unloaded for training and the loaded data for testing, 84.3%–84.4% accuracies are achieved on average. This result shows that shouldering a backpack causes to change the characteristics of postural sway (specifically, the variabilities of the length and the area of COP trajectories become large) and it affects the identification accu-
racy. Moreover, as the comparison results of features between the unloaded and the loaded data set, we could show that the extracted features in stepping on and off intervals have high discriminability and they can contribute to person identification with high accuracy.

As the future work, we have to assess the effect of baggage weights because here we only handled 2 kg weights of a backpack. We need to consider using the variation of baggage, that is, a briefcase, a shoulder bag and so on.

References

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Abstract:

It is said that human postural sway in quietly-standing position involves individual differences. From this viewpoint, some contributions have been made for person identification problem. However, current researches on person identification problem based on postural sway data have the following two problems: (1) the most target behavior is the postural sway after completely stepping on a stabilometer, (2) the effect of carrying weight for person identification accuracy is unclear. Therefore in this study we measure postural sway data while stepping on and off a stabilometer as well as standing quietly. In addition, we analyze the effects of shouldering a backpack for person identification accuracy. The results of experiments with 10 human subjects data show that carrying a 2kg backpack affects the identification accuracy, but the postural sway data in shouldering a backpack has a possibility to identify persons. Also, we show some extracted features in stepping on and off intervals have good effect to identify persons.

Keywords: Postural Sway, Center of Pressure Trajectory, Person Identification, Behavioral Feature

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951