Estimation of Walking Direction with Vibration Sensor based on Piezoelectric Device

Shinya Akiyama[1], Makoto Yoshida[1],Yumiko Moriyama[1], Hirohiko Suwa[2,3] and Keiichi Yasumoto[2]

[1]ONKYO corporation, Osaka 541-0041, Japan

[2]Nara Institute of Science and Technology, Ikoma, Nara 630-0192, Japan

[3]RIKEN, Center for Advanced Intelligence Project, Tokyo 103-0027, Japan

***Abstract*—Recently, device-free indoor positioning and tracking of persons is attracting attention. Some approaches use vibration sensors installed on the floor to identify the position of the vibration source by measuring and analyzing vibration strength and vibration fingerprints. However, vibration sensors can give the output information only on the strength of the vibration which shows that the vibration source is near or far from the sensor. Since the moving direction cannot be measured, it is difficult to apply the vibration sensor to track persons walking around in indoor space. In this paper, we propose a method for estimating the walking direction of a person using two vibration sensors. In the proposed method, we capture floor vibration using a pair of piezoelectric vibration sensors installed at a certain distance, calculate frequency domain features and estimate walking direction by machine learning. We conducted an experiment in a smart home where we installed our vibration sensors on the floor, asked four participants to pass near the sensors 20 times in two directions and estimated the walking direction by the proposed method. As a result, the walking direction was estimated with a maximum accuracy of 90%.**

***Index Terms*—Estimation of walking direction, Vibration sensor, LDA (Linear Discriminant Analysis), Machine learning**

I. Introduction

In recent years, a lot of studies have been conducted in various ways to identify people and their activities in homes and stores, so on for application to monitoring services and anomaly detection for crime prevention. For example, there are methods using camera [1]–[3], microphone [4], wearable accelerometer [5], [6], sensor detecting electrical potential of human body [7], radio [8] and pressure sensor installed under the floor [9]. However, the method using a camera or microphone can get more information than necessary, so there are concerns about privacy violations. The method using wearable accelerometers needs the devices attached to the target, thus it is difficult to sense unspecified persons. The method using electrical potential of a person, radio or pressure sensor requires a considerable number of sensors, and there is a difficulty in installation.

A method using a vibration sensor does not require wearable sensors and can reduce the number of required sensors (thus does not violate privacy). Kashimoto et al. [10] proposed a method to locate the position of the user with a vibration sensor. This method uses a piezoelectric vibration sensor installed on the floor, and estimates user's position based on changes in vibration intensity and a vibration fingerprint unique for each location and activity. In this approach, the information output from the piezoelectric vibration sensor is only the magnitude of the vibration, and it is possible to detect the movement of the person approaching or moving away from the sensor. Since walking behavior is frequent and accompanied by movement among human behaviors, it is an important behavior to be identified among human behaviors in a room. In particular, the information on the walking direction is useful for detecting a flow line in the room. The advantage of this method is the ease of installation of the sensor. The piezoelectric vibration sensor can be installed simply by placing it on the floor, and does not require any large-scale construction, so the piezoelectric vibration sensor is very easy to install even in an existing house. As a use case, we can install a vibration sensor in a house of senior citizens and use it for monitoring them.

In this paper, we propose a new method using two piezoelectric vibration sensors installed on the floor to detect the walking direction of a person only with piezoelectric vibration sensors. Moreover, taking into account real-world usage, we estimate the walking direction of a target person using a machine learning model trained with other parsons data.

The organization of the paper is as follows: We briefly survey related studies using vibration sensors in Section II, and describe the detail of the proposed vibration sensor system and the walking direction estimation method in Section III. We provide experimental results showing effectiveness of the proposed method in Section IV and discussion in Section V. Finally we conclude the paper in Section VI.

The methods proposed in this paper and the evaluation experiments are targeting Japanese-style houses where people rarely wear shoes inside their homes, so the effects of shoes are not considered.

II. Prior study of vibration sensors

A. Related research on vibration sensors

Human footsteps have been studied for a long time, and analysis of vibrations caused by footsteps in buildings has been actively conducted [11]–[13]. Also, in recent years, detection of human falls using vibration sensors [14], [15], measurement of health by footsteps [16], [17], person identification by walking speed [18], and person identification using vibration sensors attached to the object (e.g., door) and sensing waveform pattern of the vibration of the action which has different characteristics by person (e.g., knocking) [19] have been studied. Among them, in human behavior tracking, Pan et

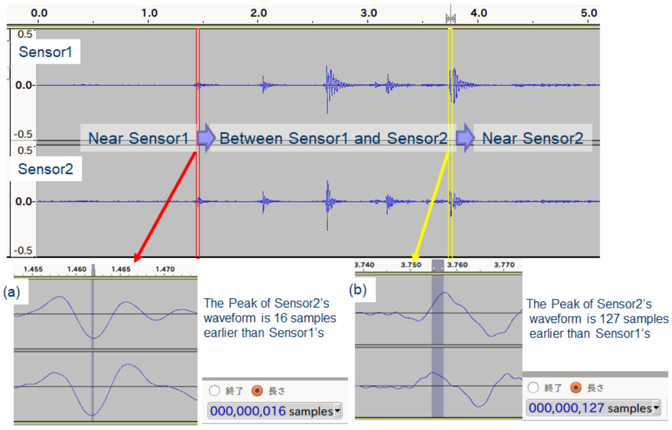

Fig. 1. Waveform when walking from a position near sensor 1 to sensor 2 (unexpected result at point (a): the peak of sensor 2's wave form is 16 samples earlier than sensor 1; expected result at point (b), the peak of sensor 2's waveform is 127 samples earlier than sensor 1)

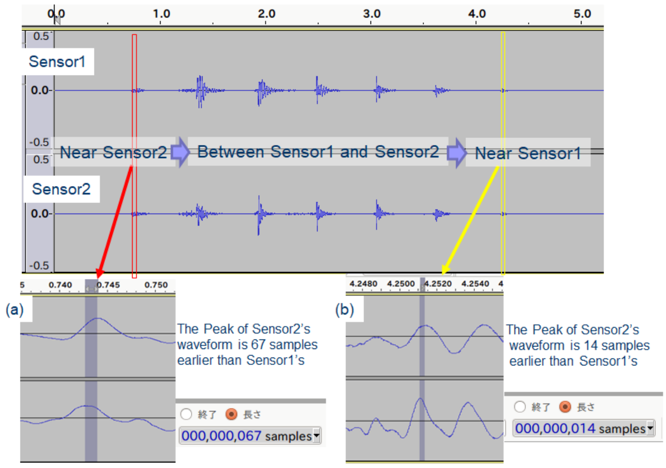

Fig. 2. Waveform when walking from a position near sensor 2 to sensor 1 (expected result at point (a): the peak of sensor 2's wave form is 67 samples earlier than sensor 1; unexpected result at point (b), the peak of sensor 2's waveform is 14 samples earlier than sensor 1)

al. [20], [21] proposed a vibration sensor system called BOES. That system can track human behavior by counting the area occupancy which changes dynamically.

B. Estimation of walking direction

In general, the moving direction of an object can be estimated by the temporal change of the object's position estimated based on TDoA (Time Difference of Arrival) or AoA (Angle of Arrival) with multiple sensors. However, these methods do not always work for vibration sensors. As a pilot study, we installed two piezoelectric vibration sensors on the floor at very close distances (referred to as Sensor 1 and Sensor 2) and tried to estimate the position of persons by TDoA. Then, as shown in Figs. 1 and 2, the result was contrary to the expectation. That means the vibration generated by walking reached the far sensor earlier than the near sensor. This is because the floor which the vibration sensor is attached is comprised of various materials, so the density and elastic modulus of the vibration medium are not uniform, resulting in non uniform propagation speed of vibration [22]. Based on these physical phenomena, Shi et al. [23] collected data using four sensing systems based on Geophone, detected footstep events by continuous wavelet transform and estimated the walking direction of people using TDoA.

In this paper, we propose a method to estimate waking direction using a lower cost sensing system consisting of two vibration sensors placed at a short distance and using machine learning.

III. Vibration Sensor System and Walking Direction Estimation Method

A. Configuration of vibration sensor system

Fig. 3 shows the configuration of our vibration sensor system that captures floor vibrations. The system has two piezo vibration sensors (Lch and Rch) arranged at a distance of 15cm between the centers, and they are used as sensor pairs. The voltage signal output from each sensor is amplified with an amplifier and sampled as an audio signal with a USB interface. At this time, in order to reduce the crosstalk between the two sensor signals, a bi-amplifier configuration is adopted where an amplifier is provided to each vibration sensor and the power source is also provided separately for each of the two sensors. In order to reduce the noise of the amplifier, Field Effect Transistors (FETs) are connected in parallel to increase the current amplification factor, and metal film resistors are used. We tested the various distance between two sensors in preliminary experiments and concluded that 15cm is optimal to make the sensor system itself as compact as possible while maintaining the high accuracy of our proposed method.

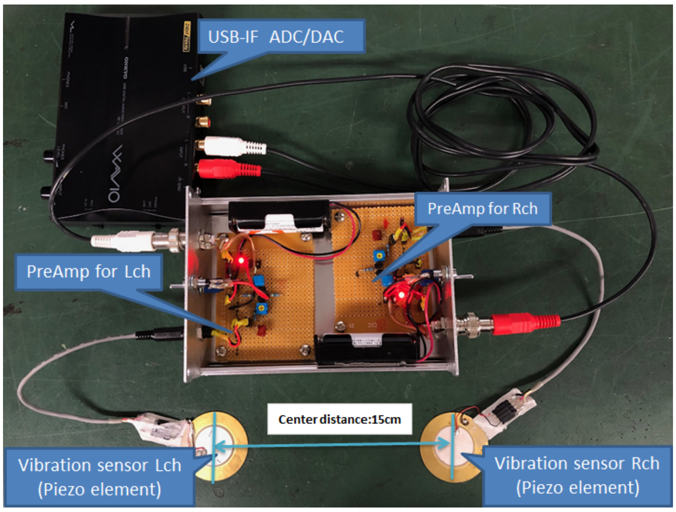

Fig. 3. Configuration of vibration sensor system

B. Walking direction estimation method

1) Pre-processing by Digital Signal Processing: Fig. 4 shows the overall flow of pre-processing by Digital Signal Processing (DSP). As shown in Fig. 4 (a), first the waveform

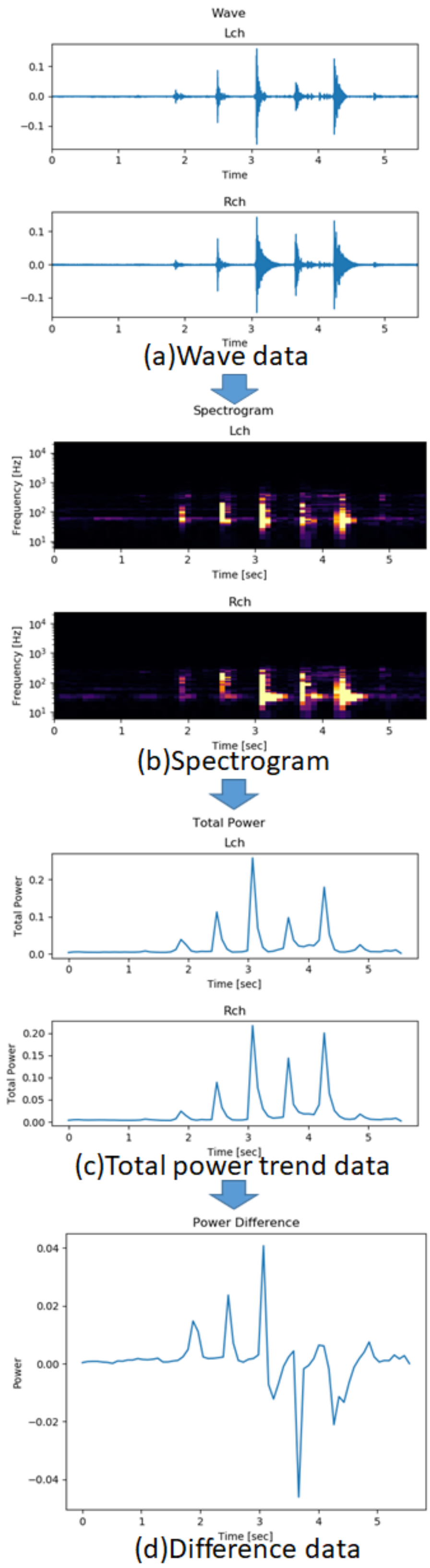

Fig. 4. Preprocessing for feature extraction using sensor signals

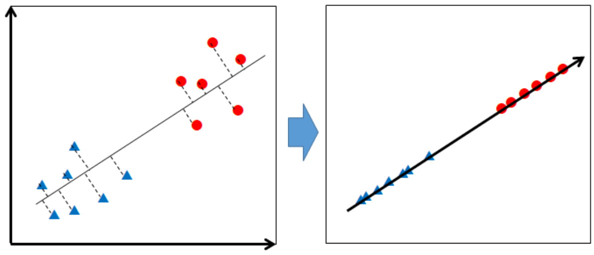

Fig. 5. Image of LDA

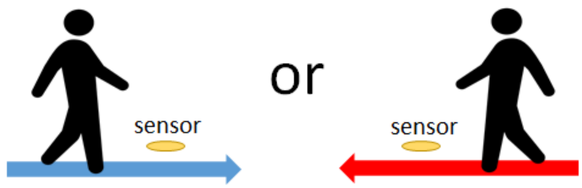

Fig. 6. Image of walking direction

of 5 seconds is measured with the sensor pair during a walking activity. Then the spectrogram is obtained by transforming the waveform data using Short-Time Fourier Transform(STFT) with the division number $n = 8192$ as shown in Fig. 4 (b). Next, as shown in Fig. 4 (c), the power spectrum of all frequencies on the same time axis is summed to create trend data, which is the temporal change in signal energy. Finally, as shown in Fig. 4 (d), the difference of the signals is calculated by (Sensor Lch Trend Data)-(Sensor Rch Trend Data).

2) Linear Discriminant Analysis: In the proposed method, we apply Linear Discriminant Analysis(LDA) to the difference data to extract and classify features used for machine learning. LDA is a linear transformation to search for feature subspaces that maximize class separation as shown in Fig. 5. This is a supervised algorithm, so each dataset must be tagged. In the proposed method, we reduce the number of dimensions to two by LDA.

3) Machine learning: After dimensionality reduction by LDA, we classify the features using machine learning. We use the following six machine learning algorithms and compare classification performance: k-NN, Logistic regression, SVM (Liner), SVM (RBF), Decision Tree, and Random Forest.

IV. Evaluation Experiments and Results

A. *Overview of experiments*

The vibration sensor system was installed on the flooring made by woods, and we asked each of the four participants (3 males: A, B, C and 1 female: D) to walk in parallel to the line connecting two vibration sensors as shown in Fig. 6. Data was collected 20 times each for the walk from the sensor Lch side to the sensor Rch side, and the walk from sensor Rch side to the sensor Lch side, respectively. Each data is labeled "Start: L" or "Start: R." The number of data collected was 40 with 20 for Start: L and 20 for Start: R, respectively. In addition,

TABLE I
ESTIMATION ACCURACY OF WALKING DIRECTION BY RANDOM DATA

Algorithm	k-NN	Logistic regression	SVM(Linear)	SVM(RBF)	Decision tree	Random Forest
Accuracy	84.4%	84.4%	88.9%	75.6%	84.4%	80.0%

TABLE II
EVALUATION OF SIX ALGORITHM BY 10-FOLD CROSS VALIDATION

Algorithm	k-NN	Logistic regression	SVM(Linear)	SVM(RBF)	Decision tree	Random Forest
Accuracy	75.6%	71.7%	73.3%	74.4%	70.0%	70.0%

20 data when no person walked in front of the sensor was collected and labeled "Silent." Therefore, the total number of data is 180 (data of 4 participants × two directions × 20 walks + 20 no walk data).

In order to evaluate the basic estimation accuracy of the proposed method, we validated the data in two ways: (Data 1) 75% of the data is used as training data and the remaining 25 % as the test data and (Data 2) 10-fold cross validation where the data is divided to 10 subsets, then 9 are used as traing data and the remaining 1 is used as test data, and the result is averaged over 10 combinations of selecting a test data. Here, we assume that four residents are living together in a house, and we evaluate accuracy of estimating walking direction when one of the four residents passes in front of this system that has already learnt the data for all of them.

In addition, assuming the real world usage (e.g., tracking unspecified person in store), we applied leave-one-person-out cross validation (Data 3) where the data of one participant (say A) is used as the test data and the data of remaining participants (say B, C, and D) are used as training data, and the results of four combinations are averaged. This is an evaluation of whether this system, for example, can detect the walking direction of an unknown person who enters a house where three residents live, with the model learnt from the three residents.

B. Evaluation results of the basic estimation accuracy

Fig. 7 shows the result by applying LDA to Data 1. Although the samples are scattered over a wide range, we can confirm that "Start: L" and "Start: R" are clearly separated. Then we applied six machine learning algorithms to this result to estimate the walking direction.

Table I shows the results of walking direction estimation accuracy obtained by applying machine learning algorithms to Data 1 (75% for training and 25% for test). As a result, the SVM (Liner) achieved the highest accuracy of 88.9% for estimating the walking direction. The k-NN, logistic regression, and decision tree achieved the second best accuracy of 84.4% to estimate the walking direction.

Table II shows the results of walking direction estimation accuracy for each machine learning algorithm applied to Data 2 (10 fold cross validation dataset). As a result, the k-NN showed the highest accuracy of 75.6% for estimating the walking direction. On the other hand, SVM (Liner) which

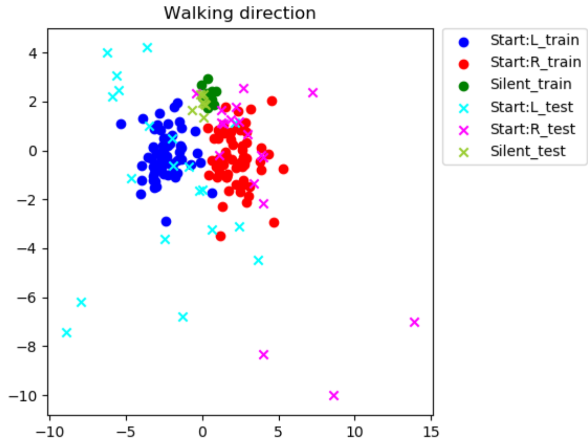

Fig. 7. Result of LDA (Data 1)

achieved the highest accuracy for Data 1 resulted in accuracy of 73.3%. This result suggests that the effective algorithm differs depending on the dataset and the validation method.

C. Estimation accuracy by leave-person-out cross validation

Fig. 8-Fig. 11 show the results obtained by applying LDA to Data 3 (leave-one-person-out cross validation; four combinations of test data and training data). In these figures except for Fig. 10, we can clearly see that "Start: L" and "Start: R" are separated by two dimensional features.

Table III shows the results of walking direction estimation accuracy for each participant using six machine learning algorithms for Data 3. As a result, it was confirmed that the walking direction could be estimated with high accuracy of about 80% or more except when the data of participant C was used as test data. It was also confirmed that the two algorithms the k-NN and logistic regression are suitable for estimating walking direction of unspecified person assuming the real world.

V. DISCUSSION

The results of walking direction estimation experiments in the previous section showed the effectiveness of the proposed approach using two vibration sensors and machine learning algorithm in walking direction estimation. Additionally, the

TABLE III
ESTIMATION ACCURACY OF WALKING DIRECTION ASSUMING THE REAL WORLD

c	k-NN	Logistic regression	SVM(Linear)	SVM(RBF)	Decision tree	Random Forest
TestData:A	90.0%	87.5%	90.0%	87.5%	85.0%	87.5%
TestData:B	87.5%	87.5%	82.5%	75.0%	80.0%	85.0%
TestData:C	52.5%	52.5%	52.5%	50.0%	55.0%	55.0%
TestData:D	77.5%	82.5%	82.5%	77.5%	82.5%	77.5%

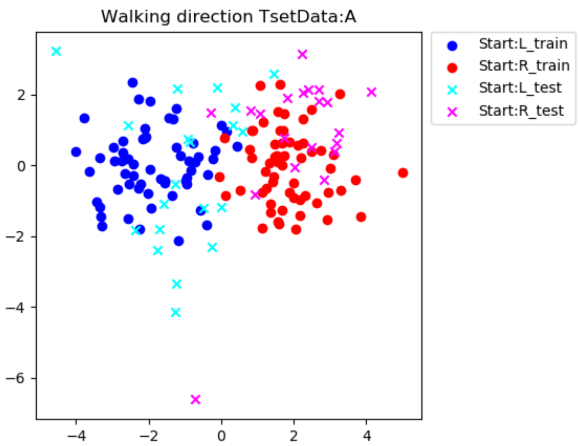

Fig. 8. Result of LDA (TestData:A)

Fig. 10. Result of LDA (TestData:C)

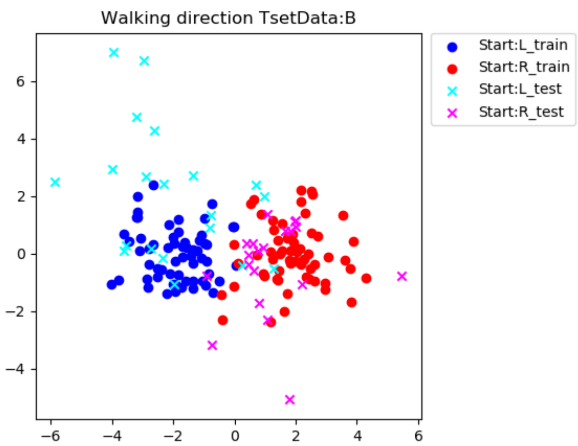

Fig. 9. Result of LDA (TestData:B)

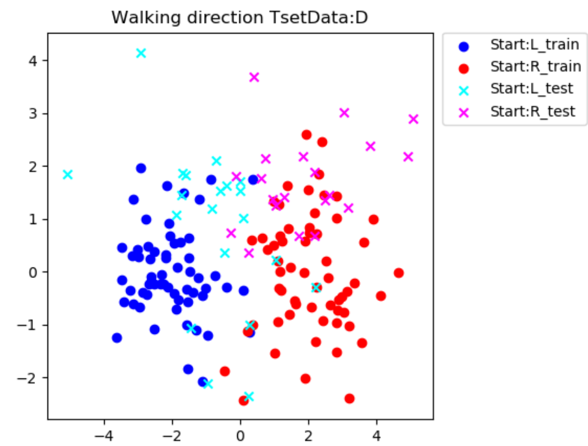

Fig. 11. Result of LDA (TestData:D)

result of leave-person-out cross validation showed the effectiveness of the proposed for real-world usage (except for participant C).

The estimation accuracy drastically decreased when data of participant C used as test data. To clarify the reason, we interviewed all participants. As a result, participant C answered that "I changed a walking way between each trial deliberately." This suggests that our proposed method can estimate the walking direction with an accuracy of about 80% or more as long as walking is normally performed like other participants A, B, and D.

VI. CONCLUSION

In this paper, we examined the vibration sensor device and the method of estimating the walking direction in a home. Specifically, we showed that the proposed method can estimate walking direction with high accuracy in a practical environment, utilizing an idea that information other than the magnitude of the amplitude is given in addition to the sensor signal by arranging two sensors as a pair at a certain distance. As a result, we can expect merits such as improvement of indoor walking direction estimation accuracy and reduction of sensor installation locations.

In the proposed method, the walking direction is estimated by LDA and machine learning model that learn vibration transmission information based on the floor material. Therefore, if the installation position of the vibration sensor and/or the floor material is changed, re-training of the model is needed. This is part of our future work.

In the experiment, the walking direction was parallel to the line connecting the two sensors, but we need to investigate the possibility of detecting the walking direction in the vertical, diagonal and other arbitrary directions by arranging another pair of sensors. For further generalization performance evaluation, we would like to conduct evaluation experiments in the real environment (normal life) instead of scenario-based. We also plan to develop an algorithm that can identify person from vibration data.

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