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Activity Recognition Using Radio Doppler Effect for Human Monitoring Service

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Abstract: Recently it has become more important to monitor the daily human activities of the elderly and of children. In this paper, we propose a system for practical activity recognition using the Doppler effect in 24 GHz microwaves. It extracts the features from the signals, selects the optimal features, and then classifies activities using a pattern matching technique. We can sense human activities simply with setting Doppler sensors on the wall or tables, without any body-attached sensors. As a result of performance evaluation, our system achieves over ninety percent in the classification of eight actions on average.

Keywords: activity recognition, Doppler sensor, support vector machine

1. Introduction

Human activity recognition is very promising technology for several services, such as daily healthcare, remote caring, safety management, and so on. It is important to monitor human daily activities remotely and to detect usual and unusual events in detail. Today there are various kinds of sensors for monitoring human activities. In this environment, it is important to change raw data into meaningful data according to each application.

In sensing human activities, there are two main sensor types: a body-attached type and a wall-mounted type. For example, in the body-attached type, accelerometers are attached to the arms or legs [1]. It is easy to detect what parts of the body are moved because sensors are fixed to specific parts of the body. However, some problems remain in these systems. Elderly people and children tend to forget to wear these sensors, and some of them are not willing to wear them. It is also difficult to attach sensors to every part of the body. These systems could not work for example when the wearer uses the bathroom or when the batteries are being changed.

However, wall-mounted sensors can solve the disadvantages of body-attached sensors. They are suitable for the long term monitoring of people. Infrared sensors [2] and camera sensors are examples of them [3]. However, the infrared sensor is weakened by heat and dust, and can not detect objects other than human beings and animals. In addition, camera sensors have some problems relating to the privacy and data processing overhead. Compared with a depth camera, a Doppler sensor does not suffer from optical problems, such as range measurement problems caused by highly reflective surfaces that are too close to the depth camera [4]. A Doppler sensor can detect the object even if obstacles exist because of the penetrations and reflections of radio. It also enables one-dimensional processing while depth camera requires two-dimensional processing.

In this paper, we focus on Doppler effect of microwave to recognize human activities. Doppler sensor uses the Doppler effect of waves such as radio and ultrasonic in general. When a wave is transmitted to moving objects, the reflected wave shifts frequency corresponding to their velocity. A Doppler sensor uses this principle, and it outputs a beat signal whose frequency is the difference one between the transmitted and received waves. Doppler sensor can detect very small motions of a user such as breathing and heartbeat when the user is away from the sensor [5], [6]. In the future, wireless sensor networks will be deployed and it provides great opportunities for monitoring and collecting detailed information from the physical world [7]. Doppler effect could also be used in these sensor networks. As a first step, we study the possibilities of Doppler sensor.

We assume that a Doppler sensor is deployed at a fixed place, such as on a wall or a table, and transmits microwave whose frequency is f_t. An object moves towards the sensor with the velocity $\pm v$. Then, the frequency of the received wave f_r is described as follows [8]:

$$f_r = f_t \pm f_d \tag{1}$$

where the Doppler frequency f_d that is the difference between the frequency of the transmission wave and the reception wave. If the object moves towards the sensor on the same line, the observed Doppler frequency f_d will be higher. On the other hand, if the object moves away from the sensor, the observed Doppler frequency f_d will be lower. f_d is calculated as follows:

$$f_d = |f_r - f_t| = f_t\left(\frac{c+v}{c-v} - 1\right) = \frac{2v}{c-v}f_t \simeq \frac{2v}{c}f_t \tag{2}$$

where c is the velocity of a radio.

Then we define the signal of transmitted wave V_t at the time t

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becomes as follows:

$$V_t(t) = K_t \sin(2\pi f_t t) \tag{3}$$

where K_t is the amplitude of the transmitted wave. When the delay between the transmission time and reception time is τ, the received signal at the time t, $V_r(t)$, is as follows:

$$V_r(t) = K_r \sin(2\pi(f_t \pm f_d)t - 2\pi f_t \tau) \tag{4}$$

where K_r is the amplitude of the received wave. It depends on the size of the moving objects and the distance between the object and the sensor. The transmission signal and the reception signal are superimposed in the mixer. After all, the beat signal V_d at the time t is observed as an output signal of Doppler sensor as follows:

$$V_d(t) = K_d \sin(2\pi f_d t - 2\pi f_t \tau) \tag{5}$$

where K_d is the amplitude of the signal and mainly depends on the signal strength of the received wave.

The variances of amplitude and frequency of the signal depend on the range and velocity of motions. Therefore it is possible to recognize the activities of the user by extracting the features of the signals.

The rest of this paper is structured as follows. In Section 2, we introduce the related works of our system and their problems. In Section 3, we propose an activity recognition system using a Doppler sensor for human monitoring service. In Section 4, we evaluate our proposed system and show the effectiveness of our proposed method by the experimental study. In Section 5, we conclude this paper.

2. Related Works

There are some related works on radio-based activity recognition. An existing wireless LAN system is used as action recognition in Ref. [9]. They use the change of the signal strength caused by human motions and recognize whether a person is still or moving. The main advantage of this system is that it is not necessary to set up new additional hardware for activity recognition. However, these systems using signal strength are easy to be influenced by the change of environments and can not detect the actual movement of human activities. In Ref. [10], eight gestures are recognized using one ultrasonic transmitter and two receivers. In general, the more sensors become enabled, the more robust recognition becomes. However, there is a trade-off between the robustness and the cost of deploying sensors and processing data. A study is also being carried out on the analysis on specific actions such as identification and classifying the types of walkers [11], chewing motion [12]. In Ref. [13], seven activities such as running and walking are recognized using support vector machine (SVM). However, there is no certainty with regard to how the six features that are statically selected have effect on the recognition rates.

On the other hand, feature extraction is studied for pattern recognition. The optimal solution is gained only when all the combinations of the features are evaluated [14]. However, the number of combinations of features explodes when the number of features is large. Sequential forward selection (SFS) or sequential backward selection (SBS) is generally used for feature selection. In SFS, no feature is selected at the first time. The features are sequentially selected to maximize the evaluation function such as recognition rate. On the other hand, in SBS, all features are selected at the first time. The features are sequentially eliminated from them to maximize the evaluation function.

Our work is different from these works in that we assume the motions of any parts of the body. Our system can classify the actions including small motions such as shaking the user's leg and typing. In addition, we optimize the combination of features adaptively to each user and to the set of the activities to be recognized. We also analyze the effectiveness of features for accuracy of recognitions.

3. Activity Recognition

3.1 System Component

The component of our recognition system is shown in **Fig. 1**. Our Doppler sensor node is composed of a Doppler module, amplifier, and low-pass filter as shown in **Fig. 2**. We used K-band Doppler module NJR4261JB0916 [15], whose central frequency is 24.1 GHz, produced by New Japan Radio. The output power of it is 6.6 mW (8.2 dBm). Signal amplifier and low-pass filter were applied to the amplify the Doppler signals. The Amplification level was set to a fixed value where enough amplitude is obtained within 1,000 times of the original signal. The voltage of the signal from the Doppler sensor took the range from 0 to 5 V. We set the cut-off frequency of the low-pass filter to 1 kHz.

3.2 Feature Extraction and Selection

Features are extracted from each signal for classifying the actions. Then, the features are selected to optimize the combination

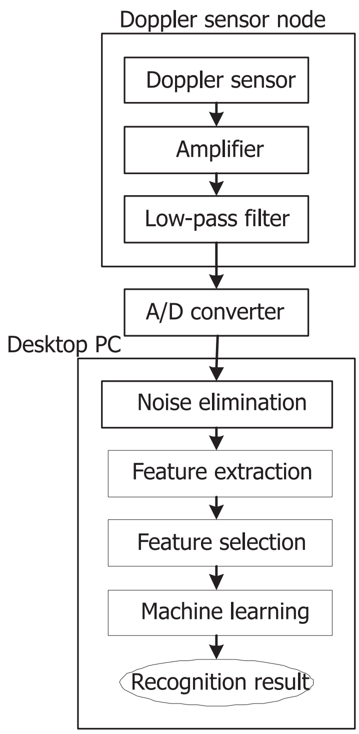


Fig. 1 Recognition system using Doppler sensor.

of features. Before extracting the features, the mean value of a signal has been subtracted in each sample. In addition, in order to eliminate the noise caused by the power supply, frequency elements in each signal around the multiples of 50 Hz are eliminated. In general, there are many kinds of actions. In addition, each action has individual differences. It is difficult to manually optimize the extraction and selection of features. Therefore, we extract many features that are considered to characterize Doppler signals. We extract a total of 101 features in time domain, frequency domain, and time-and-frequency domain as shown in **Table 1**. The five time domain features extracted were the variance, maximum, minimum, medium, and the total value of absolute different values between two consecutive sampled data. The 48 frequency domain features extracted were average frequency, average powers, top frequencies and mean power frequency (MPF) in 0 to 5 Hz, 10 to 15 Hz, 15 to 20 Hz, 20 to 50 Hz, 50 to 75 Hz, 75 to 100 Hz, 100 to 150 Hz, 150 to 200 Hz, 200 to 500 Hz, and 500 to 1,000 Hz. Then, the power and its corresponding frequency are sorted in order with high power value. We extract the average frequency, average power and MPF in the pairs of power and frequency in top 1%, 5%, 10%, and 20% for each. In addition, we perform continuous wavelet transform and extract average and variance of absolute values of the wavelet coefficients as the feature of 48 time-and-frequency domain when the pseudo-frequencies are at 1 Hz, 5 Hz, and each frequency at intervals of 10 Hz from 10 to 250 Hz. The Mexican hat function was used in wavelet transform.

After extracting the features, we selected some features out of them to maximize accurate recognition and reduce the data processing overhead and prevent over-fitting. To study the classifying ability of each feature, sequential forward selection (SFS) [16] was used. SFS is a feature selection algorithm where each feature is sequentially selected so as to maximize the average recognition rate. In general, the optimized combinations of features may be different according to the kind of activities. This is because the classifying ability of each feature depends on them.

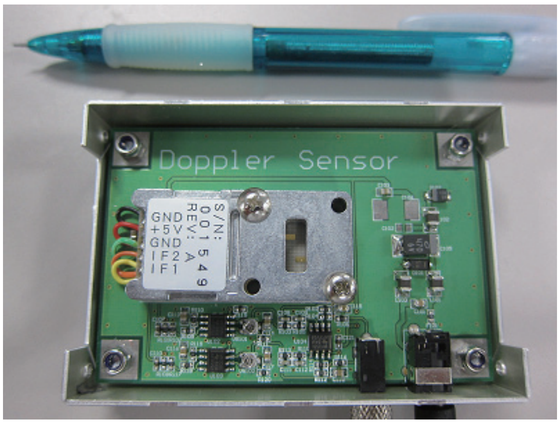


Fig. 2 Our Doppler sensor node including Doppler sensor "NJR4261J" produced by New Japan Radio, amplifier and low-pass filter.

4. Performance Evaluation

4.1 Outline

A Doppler sensor was set at the 0.8 m height of the stand as shown in **Fig. 3**. The distance between the subject and the sensor was set to 1 m. In healthcare services, it is necessary to recognize many activities in human daily life. In this paper, we select eight actions as a set of basic performance indexes, although a huge variety of motion sets would be likely to occur in a human daily life. When actions are performed exactly with reference to a clock or a ruler in the experiment, it does not reflect the variations in an actual action. Therefore, the subjects did the actions consciously operated so that the cycle and the range of motion are the same during one motion. Eight actions are as follows:

(1) Rotating: rotating the subject's right arm back and forth towards the Doppler sensor
(2) Slow: slowly moving the subject's right hand toward the Doppler sensor and away from it
(3) Fast: shaking fast the subject's hand in front of the face
(4) Shaking: shaking the subject's leg
(5) Walking: walking around the Doppler sensor
(6) Typing: typing the keyboard of a laptop PC
(7) Still: Sitting still in a chair
(8) Nobody: the subject is out of sensing range

"Rotating," "slow," "fast," and "typing" are performed while

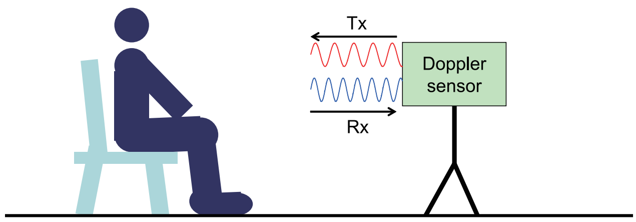
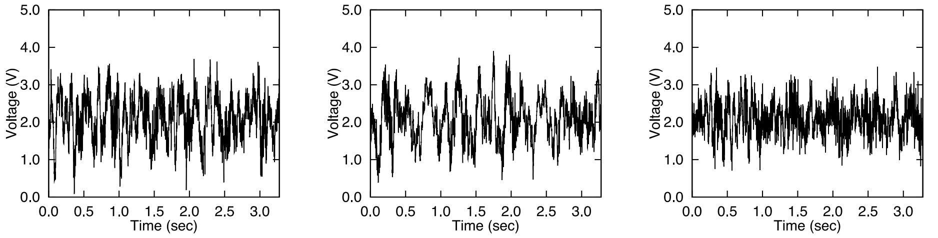


Fig. 3 Experiment environment.

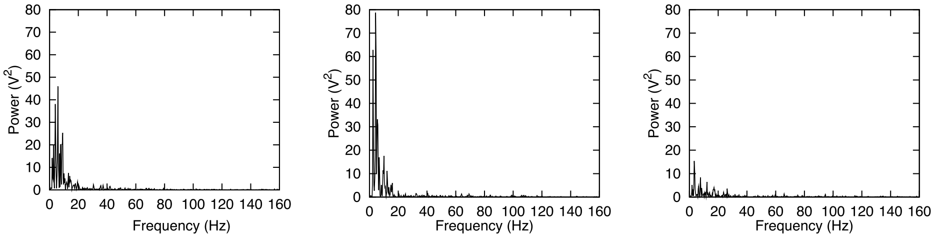
Table 1 101 features extracted from a sample.

No.	Feature
1	variance of amplitudes
2	maximum of amplitudes
3	minimum of amplitudes
4	medium of amplitudes
5	sum of difference of amplitudes
6	mean power frequency
7 to 39	logarithm of mean power, frequency at peak power, mean power frequency ranged from 0 to 5 Hz, 5 to 10 Hz, 10 to 15 Hz, 15 to 20 Hz, 20 to 50 Hz, 50 to 75 Hz, 75 to 100 Hz, 100 to 150 Hz, 150 to 200 Hz, 200 to 500 Hz, 500 to 1,000 Hz
40 to 41	the frequency at highest and second highest peak power
42 to 53	mean frequency, mean power, mean power frequency in the highest 1%, 5%, 10%, 20% in the power
53 to 101	absolute mean and variance of wavelet coefficients at 1 Hz, 5 Hz, every 10 Hz from 10 Hz to 250 Hz



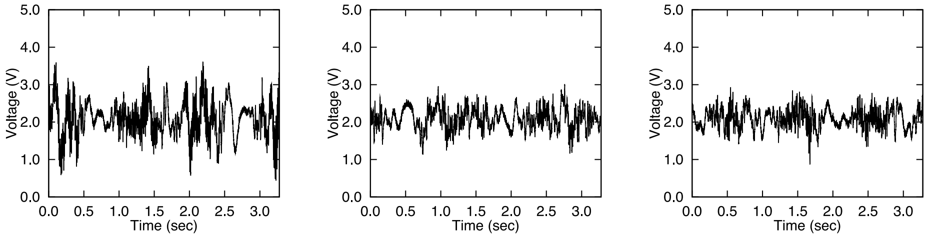
(a) subject "A" (b) subject "B" (c) subject "C"

Fig. 4 Signal of "rotating."



(a) subject "A" (b) subject "B" (c) subject "C"

Fig. 5 Power spectrum of "rotating."



(a) subject "A" (b) subject "B" (c) subject "C"

Fig. 6 Signal of "slow."

Table 2 Parameter settings in performance evaluation.

Parameter	Value
Sampling rate	2.5 kHz
Signal out put range	0 to 5 V
Acquired data range	−10 to +10 V
Resolution	16 bit
Sensing time per sample	3.2768 sec (8,192 points)
Number of samples per action	400

sitting a chair. In "typing," a laptop PC on a desk was set in the front of the user. Next, we got the signals of the actions, and their power spectrums by executing fast Fourier transform (FFT) from the results of multiplying signal and Humming window.

Main parameters in the experiment are shown in **Table 2**. First, we did the experiment for acquiring data of three subjects (subject "A," "B" and "C") and obtained 400 samples in each action (3,200 samples in total) of three subjects by shifting 512 points (0.2048 second interval). We used them as training data for SVM. Second, we did 10-fold cross validation in the training data and selected the optimized features training the data using SFS. Third, we did the experiment for acquiring test data in another day similarly to acquiring training data. Finally, we obtained 400 samples from them and used them as test data, and evaluated the recognition rates.

We used LIBSVM [17] to classify the activities. The parameters of it were set to default values. The recognition rate is defined as the ratio between the total number of samples correctly classified and the total number of samples.

4.2 Signal and Power Spectrum

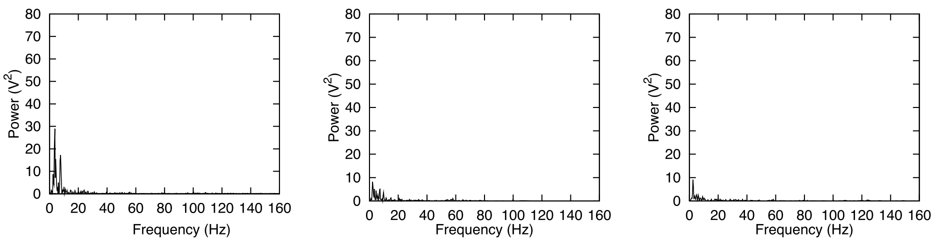
The signals from the Doppler sensor and their power spectrums in each action by three subjects "A," "B," and "C" are shown in Fig. 4 to Fig. 19. In the figures of power spectrum in "still" and "nobody," y-axis scales of them are different from those of the other actions to see the weak spectrums. In general, the frequency depends on the velocity of the body. On the other hand, the amplitude depends on the size of the moving part, range of motion and the distance between the sensor and the object. In addition the subject's actions include intentional operation and unconscious operation. For example, in "typing," a subject is sitting on a chair and moving the fingertips. On the other hand, in "still," his body may happen to move unconsciously although he tries to be still. At the time, the signal magnitude may become greater than that in typing because the body has a large reflective surface while the motions of fingers in typing are small.

In **Fig. 4**, we can see that the amplitudes in "rotating" change from time to time because of the positions of the arm of each subject. In **Fig. 5**, the power spectrums mainly range from 0 to 20 Hz, because the velocities are different according to the parts of the arms.

In **Fig. 6** and **Fig. 8**, the frequencies in "slow" are changing throughout the time while those in "fast" are comparatively constant.

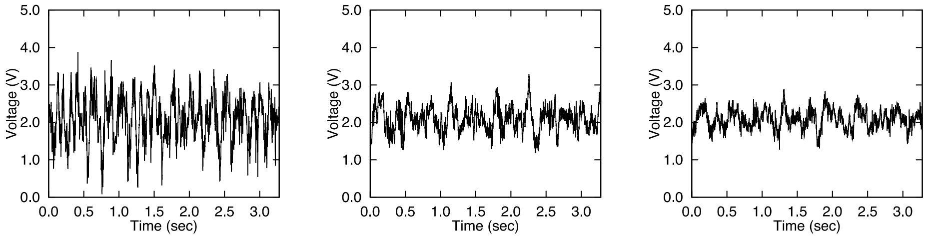
In **Fig. 7** and **Fig. 9**, the peak frequencies in "slow" are lower than in those in "fast."

In **Fig. 10** and **Fig. 11**, the maximum amplitudes and the pow-



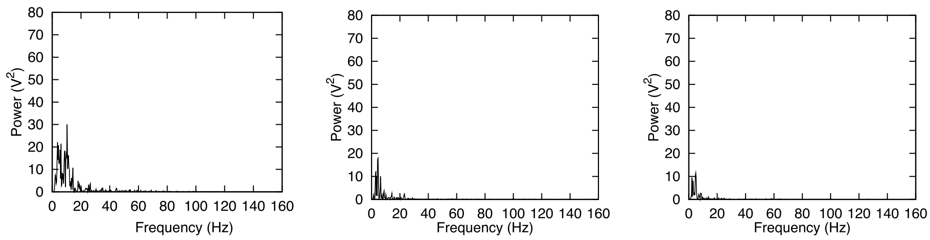
(a) subject "A" (b) subject "B" (c) subject "C"

Fig. 7 Power spectrum of "slow."



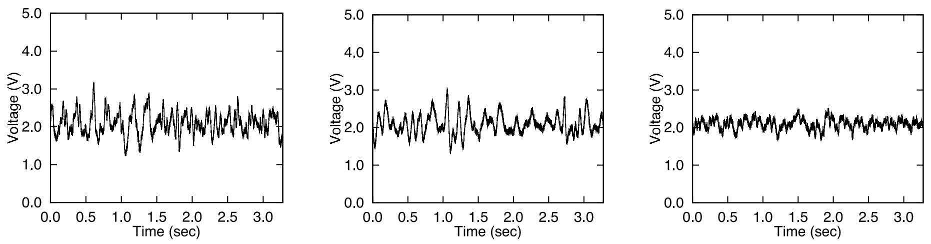
(a) subject "A" (b) subject "B" (c) subject "C"

Fig. 8 Signal of "fast."



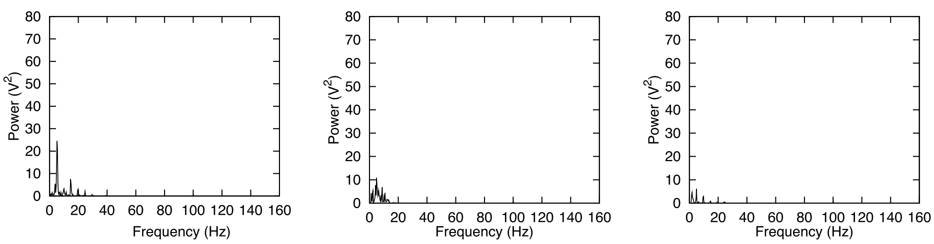
(a) subject "A" (b) subject "B" (c) subject "C"

Fig. 9 Power spectrum of "fast."



(a) subject "A" (b) subject "B" (c) subject "C"

Fig. 10 Signal of "shaking."



(a) subject "A" (b) subject "B" (c) subject "C"

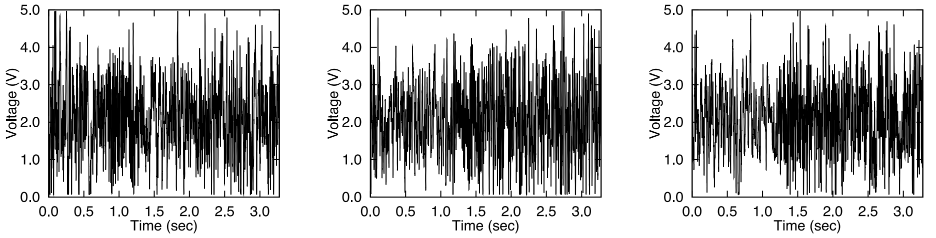
Fig. 11 Power spectrum of "shaking."

ers in "shaking" are lower than those of "fast." This is because the ranges of motions and the size of moving parts of the body in "shaking" are lower than those in "fast."

In **Fig. 12**, the maximum amplitudes in "walking" are the highest of all actions. In **Fig. 13**, the power spectrums contain various frequency components. That is because the Doppler sensor catches the reflection of radio waves from the many moving parts of the body.

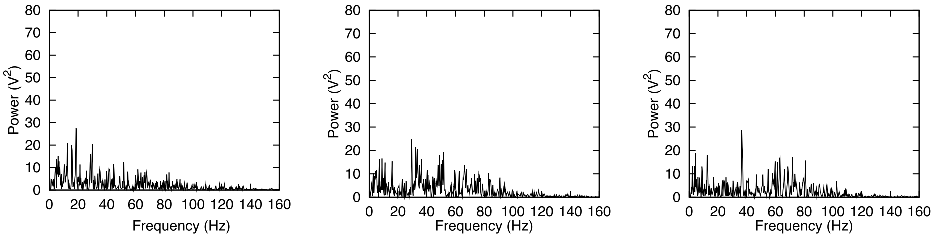
In **Fig. 14**, we can see that the amplitudes change when the fingers move. In **Fig. 15**, amplitudes of the signal in "typing" are lower than that in "shaking." That is because the size of moving parts in "typing" is generally smaller than that in "shaking."

In **Fig. 16**, the small motions of the body such as respiration are detected even if the user is trying to be still. In **Fig. 17**, we



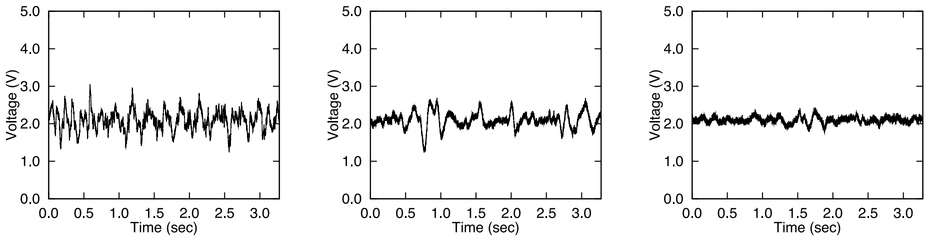
(a) subject "A" (b) subject "B" (c) subject "C"

Fig. 12 Signal of "walking."



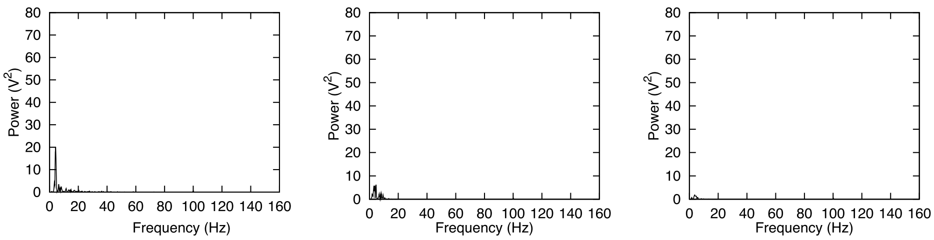
(a) subject "A" (b) subject "B" (c) subject "C"

Fig. 13 Power spectrum of "walking" of subject "C."



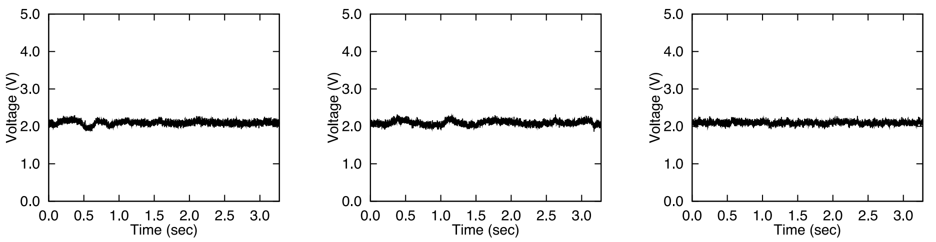
(a) subject "A" (b) subject "B" (c) subject "C"

Fig. 14 Signal of "typing."



(a) subject "A" (b) subject "B" (c) subject "C"

Fig. 15 Power spectrum of "typing."



(a) subject "A" (b) subject "B" (c) subject "C"

Fig. 16 Signal of "still."

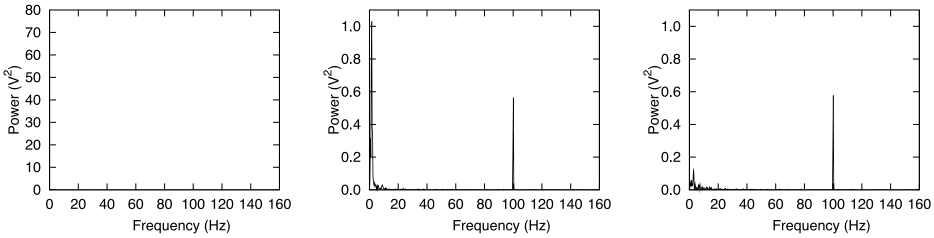
can observe the small spectrums below 10 Hz because of them. We can see the peak at 100 Hz. This originates in the humming noise caused by the power supply. These humming noises are also observed in all the actions.

In **Fig. 18** and **Fig. 19**, almost no amplitudes and no spectrums are detected except for the humming noises.

As a result, we can see that the amplitudes and frequencies are different among the subjects even in the same actions. Each signal has different features that depend on the actions.

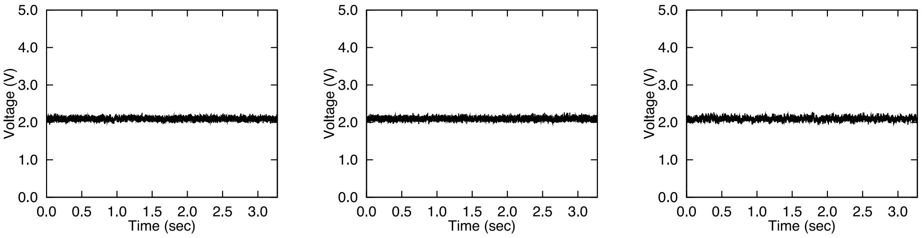
4.3 The Number of Features and Average Recognition Rate in Training Data

Figure 20 shows the relation between the number of the features and the average recognition rates in the feature selection



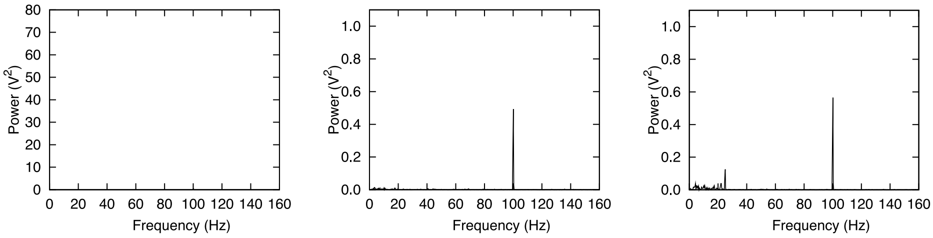
(a) subject "A" (b) subject "B" (c) subject "C"

Fig. 17 Power spectrum of "still."



(a) subject "A" (b) subject "B" (c) subject "C"

Fig. 18 Signal of "nobody."



(a) subject "A" (b) subject "B" (c) subject "C"

Fig. 19 Power spectrum of "nobody."

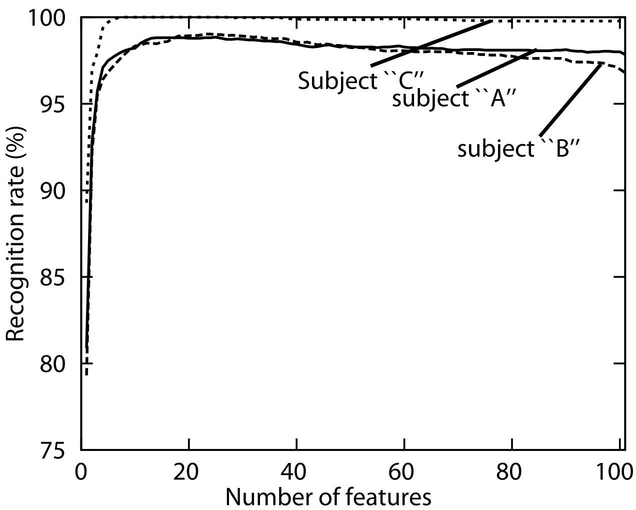


Fig. 20 Number of features and average recognition rate in training data.

using the training data that are gathered in one day. The average recognition rates of subject "A," "B," and "C" increase until the number of features are 25, 23, and 8 for each. The maximum average recognition rates of subjects "A," "B," and "C" are 98.8%, 99.0%, and 100% for each. The number of features required to maximize the average recognition rate depends on the variances of data by each action and each subject. However, the average recognition rates tend to decrease or keep constant after that. That is because, although features are effective to classify actions until the average recognitions become the highest, over-fittings may be caused when the numbers of features increase after those points.

Figure 21 to **Fig. 23** show the relations between the number of features and recognition rates by each action in the feature selection using the training data for each subject. The recognition rates of eight actions increase until around 10 and are almost constant after that. The pattern of increasing and decreasing of the rate in each action is different from those of other actions. This is because effective features for recognition are different with each action and each subject.

Table 3 to **Table 5** show the ten earliest features selected in training data by each subject. The features selected by SFS early are effective for classification of activities. The features selected are different with each subject. We can see that absolute mean wavelet coefficients around 10 to 30 Hz are selected in all the subjects.

In order to study the distributions of values in features that are effective to classify, we show the distributions of values in two most effective features for subject "A" for classifying that are selected by SFS. In each feature, the values of it are standardized within the minimum 0 and the maximum 1. The bottom and the top of each line shows the minimum value and the maximum value of the feature. The bottom and top of each box, and the center line around the box show the quarter order value, the three quarters order value and the median value.

Figure 24 shows the distributions of the mean absolute values of the wavelet coefficients at the frequency of 40 Hz. The distribution of the feature in "walking" has the most different distribu-

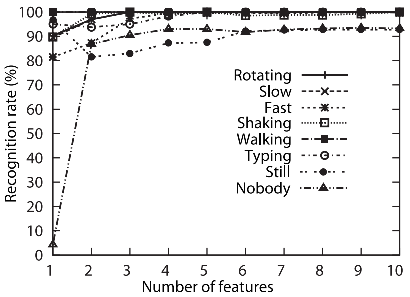


Fig. 21 Number of features and recognition rate of each action of subject "A."

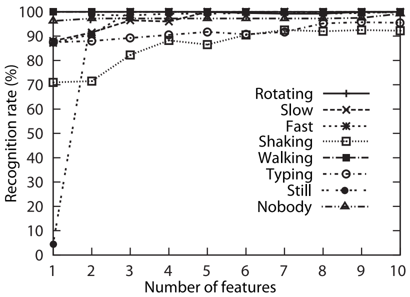


Fig. 22 Number of features and recognition rate of each action of subject "B."

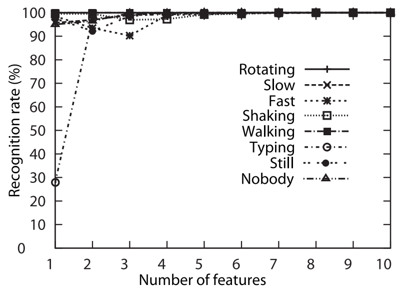


Fig. 23 Number of features and recognition rate of each action of subject "C."

Table 3 The earliest selected features for subject "A."

rank	feature name
1	absolute mean wavelet coefficients at 40 Hz
2	mean power frequency
3	logarithm of mean power from 200 to 500 Hz
4	absolute mean wavelet coefficient at 1 Hz
5	mean frequency in the highest 10% power
6	logarithm of mean power from 5 to 10 Hz
7	logarithm of mean power from 0 to 5 Hz
8	mean power frequency from 200 to 500 Hz
9	logarithm of mean power from 15 to 20 Hz
10	mean power frequency from 0 to 5 Hz

Table 4 The earliest selected features for subject "B."

rank	feature name
1	absolute mean wavelet coefficients at 20 Hz
2	mean power frequency
3	absolute mean wavelet coefficients at 90 Hz
4	mean power frequency in the highest 5% power
5	mean power frequency from 200 to 500 Hz
6	logarithm of mean power from 500 to 1,000 Hz
7	logarithm of mean power from 15 to 20 Hz
8	mean power frequency from 500 to 1,000 Hz
9	mean power frequency from 10 to 15 Hz
10	logarithm of mean power from 0 to 1 Hz

Table 5 The earliest selected for subject "C."

rank	feature name
1	absolute mean wavelet coefficients at 30 Hz
2	logarithm of mean power from 0 to 5 Hz
3	mean power frequency 0 to 5 Hz% highest power
4	mean power frequency in the highest 10% power
5	mean power frequency from 5 to 10 Hz
6	logarithm of mean power from 20 to 50 Hz
7	frequency at peak power 0 to 5 Hz
8	logarithm of mean power from 15 to 20 Hz
9	mean power frequency in the highest 1% power
10	logarithm of mean power from 5 to 10 Hz

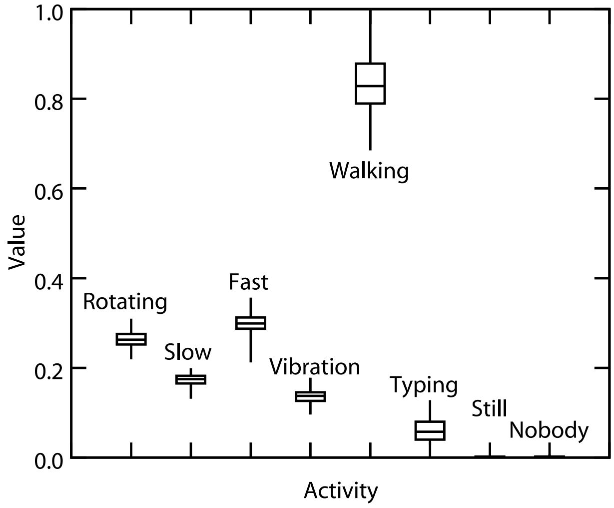


Fig. 24 Distributions of absolute mean wavelet coefficients at 40 Hz.

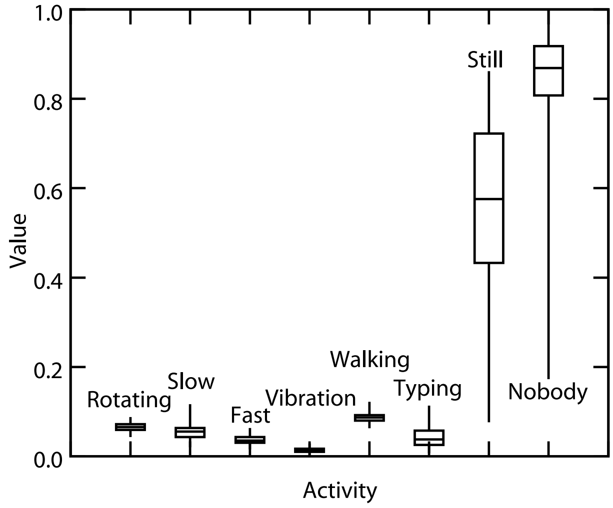


Fig. 25 Distributions of mean power frequency (MPF).

tion among those in eight actions. For this reason, the recognition rates in it reach 100% when only this feature is used. On the other hand, there is little difference in the distributions of the features in "still" and "nobody." This causes the misclassifying among them.

Figure 25 shows the distributions of MPF. "Still" and "nobody" have the most different distributions with each other. Therefore, the feature improves the recognition rates in them when this feature is additionally used. These actions include very small motions or no motion and they are very influenced by high frequency noises. Therefore, the MPFs of them are higher than those of the other actions.

Table 6 Confusion matrix of subject “A” (%).

Classified class Actual class	Rotating	Slow	Fast	Shaking	Walking	Typing	Still	Nobody	Recogni- tion rate
Rotating	**98.8**		1.3						98.8
Slow		**100**							100
Fast	2.5		**97.5**						97.5
Shaking				**100**					100
Walking					**100**				100
Typing						**100**			100
Still						1.3	**98.8**		98.8
Nobody						12.3	57.3	**30.5**	30.5

Table 7 Confusion matrix of subject “B” (%).

Classified class Actual class	Rotating	Slow	Fast	Shaking	Walking	Typing	Still	Nobody	Recogni- tion rate
Rotating	**100**								100
Slow		**99.0**	1.0						99.0
Fast			**100**						100
Shaking				**99.0**		1.0			99.0
Walking					**100**				100
Typing				7.5		**92.5**			92.5
Still						1.0	**99.0**		99.0
Nobody						1.0	46.3	**52.8**	52.8

Table 8 Confusion matrix of subject “C” (%).

Classified class Actual class	Rotating	Slow	Fast	Shaking	Walking	Typing	Still	Nobody	Recogni- tion rate
Rotating	**97.8**	2.3							97.8
Slow		**100**							100
Fast	9.8	25.0	**65.3**						65.3
Shaking				**100**					100
Walking					**100**				100
Typing						**93.0**	6.8	0.3	93.0
Still				1.8		6.8	**57.8**	33.8	57.8
Nobody				4.5		2.8		**92.8**	92.8

4.4 Recognition Rate in Each Action in Test Data

Table 6 to **Table 8** show the classified results of actions by three subjects for each subject when using the combination of features where the average recognition rate is highest in the training data. The sum of the rates of classified results for each subject does not become 100% because they are rounded off.

The average recognition rates of subjects “A,” “B,” and “C” are 90.7%, 92.8% and 88.3% for each. They are lower than those using only training data. This is caused by the differences in the same actions and the same subjects between the training data and the test data. We can see that actions of “walking” by three subjects are correctly classified as “walking.” On the other hand, “typing,” “still” and “nobody” are misclassified among them. This is because the differences in the amplitudes or frequencies in these actions are too small to be distinguished.

5. Conclusion

In this paper, we propose an activity recognition system using a microwave Doppler sensor for a human activity monitoring service. Our system can recognize human activities including both large and small motions without body-attached sensors. It extracts several features from the signals of a Doppler sensor and uses an optimized combination of features for the recognition. As a result of performance evaluation, we found that the average recognition rate in three subjects is 90.6%. In future works, we will use multiple Doppler sensors to get more robust recognition under a noisier environment caused by moving and/or vibrant devices, radio interferences, motions of other people, optimizing parameters in SVM, and so on. We also plan to recognize more complicated actions and states of a person for developing many types of applications.

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