Recognizing Handheld Electrical Device Usage with Hand-worn Coil of Wire

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Abstract. This paper describes the development of a new finger-ring shaped sensor device with a coil of wire for recognizing the use of handheld electrical devices such as digital cameras, cellphones, electric toothbrushes, and hair dryers by sensing time-varying magnetic fields emitted by the devices. Recently, sensing the usage of home electrical devices has emerged as a promising area for activity recognition studies because we can estimate high-level daily activities by recognizing the use of electrical devices that exist ubiquitously in our daily lives. A feature of our approach is that we can recognize the use of electrical devices that are not connected to the home infrastructure without the need to equip them with sensors. We evaluated the performance of our approach by using sensor data obtained from real houses. We also investigated the portability of training data between different users.

Key words: Activity sensing; Electrical devices; Wearable sensors

1 Introduction

Problems closely related to our daily lives such as the aging of society and adult diseases have become serious in modern society. Therefore, such pervasive computing applications as supporting the care of the elderly, fitness monitoring, and lifelogging are attracting attention [15, 14] and various technologies have been studied to realize these applications. In particular, human activity recognition using sensors is one of the most important tasks in relation to the pervasive computing applications. Two main approaches are used for activity recognition studies: environment augmentation and wearable sensing. Many environment augmentation approaches use ubiquitous sensors such as RFID tags and/or switch sensors installed in the environment [20, 17, 19]. The wearable sensing approach attempts to recognize a user's activities by employing such sensors as body-worn accelerometers to capture characteristic body movements and postures adopted for certain activities [1, 9, 13, 12]. On the other hand, sensing the usage of home electrical devices has recently emerged as a promising area for activity recognition because we live surrounded by large numbers of electrical devices, and frequently use them when we perform daily activities. Therefore, we can estimate high-level daily activities by recognizing the use of electrical devices. For example, when we detect that a user is using a hair dryer, we can know that she is drying her hair. Environment augmentation and wearable sensing approaches have been employed to recognize the use of electrical devices. Some studies employ ubiquitous sensor nodes attached to each electrical device to detect its use [6, 19]. However, this distributed sensing approach requires large numbers of sensor nodes for electrical devices. Therefore, its deployment and maintenance costs, e.g., battery replacement costs, are high. Several studies have attempted to monitor the use of electrical devices with small numbers of sensors. For example, the system proposed in [4] employs a single central sensor to monitor the total electrical load of a home's power meter and then separates the individual loads of electrical devices in the home with statistical signal processing methods. Also, the systems proposed in [16, 3] recognize the use of electrical devices by monitoring noise on the home infrastructure (home electrical systems).

The above systems focus on electrical devices connected to home electrical systems via outlets. On the other hand, we attempt to recognize the use of portable electrical devices such as digital cameras, cellphones, electric shavers, video game players, and music players with the wearable sensor approach. Our previous work [11] also focuses on portable electrical devices and employs Hall effect magnetic sensors [8] attached to a user's hands to monitor the magnetic fields emitted by the permanent magnets and relatively large motors incorporated in portable electrical devices. However, the system requires multiple Hall effect sensors (four or more sensors) attached to different parts of the hands to achieve high recognition accuracies. (See section 2 for more detail.) By contrast, in this paper, we describe our attempt to capture the magnetic fields emitted by sources different from those described in [11] and attempt to achieve high recognition accuracies with a single sensor on the hand. In detail, we try to develop a new hand-worn sensor device with a coil that can capture (sense) small time-varying magnetic fields emitted by, for example, electrical circuits, motors, boost converters, and conductive wires, included in portable electrical devices. Then, we extract the characteristic frequencies of the magnetic fields emitted by electrical devices and recognize which electrical device the wearer is using with machine learning techniques. Note that, because wearing several sensors places large burdens on a user in her daily life, sensing with small numbers of sensors is important. Here, we focus on the wearable sensor approach because it allows us to sense users' activities in both indoor and outdoor environments. Portable electrical equipment such as digital cameras and cellphones are frequently used out of doors. Also, with the wearable sensor approach, we can recognize the use of electrical devices that are not connected to the home's electrical systems. In addition, the approach does not require any sensors installed in the user's environment, e.g., ubiquitous sensors attached to each electrical device.

In the rest of this paper, we first introduce work related to detecting the use of electrical devices. Then, we describe the design of our prototype sensor device and show example sensor data obtained from the device when a wearer performs several activities (the use of electrical devices). After that, we introduce a machine learning-based method that identifies which electrical device a wearer is using. In the evaluation, we test user-dependent and user-independent recognition models. In the first case, we evaluate the recognition accuracies of test data obtained from a user at her house by using recognition models trained with sensor data obtained from the same user also at her house. In the second case, we evaluate the recognition accuracies of test data obtained from a user at her house by using recognition models trained with sensor data obtained from other users at their houses. That is, we investigate the portability of training data between different users when the users employ the same model of electrical device in their houses. The contributions of this paper are that we propose and develop a new hand-worn device with a single sensor for recognizing the use of electrical devices that does not place large burdens on the wearer. We also investigate the recognition performance using sensor data obtained from three real houses. To our knowledge, this is the first study that recognizes the use of portable electrical devices with a hand-worn coil.

2 Related Work

As mentioned in section 1, environment augmentation and wearable sensing approaches are used to detect/recognize the use of electrical devices. Some studies employ distributed ubiquitous sensors attached to each electrical device [19, 6]. For example, [19] uses wireless sensor nodes that monitor the state changes of daily objects including electrical devices. The system proposed in [6] employs magnetic or light sensors attached to each electrical device to detect its use and estimate its energy consumption. While these approaches can achieve fine-grained measurements of electrical events, their deployment and maintenance costs, e.g., costs related to battery replacement, are very large. Several studies monitor the use of electrical devices with sensor nodes shaped like a power strip [10, 5]. For example, the sensor node developed in [5] has electrical outlets and supplies electrical devices connected to the outlets with electrical power. The sensor node also monitors electrical current drawn from each outlet. Unlike the above distributed sensing approach, several studies attempt to detect the use of electrical devices with a single or small numbers of sensors that monitor home electrical systems. The system proposed in [4] uses a single central sensor that monitors current and voltage signals in a home's power meter. With statistical signal processing approaches, the system attempts to recognize the use of whole-house electrical devices using only sensor data from the power meter. Also, several studies recognize the use of electrical devices with the infrastructure mediated sensing approach [16, 3]. The systems proposed in [16, 3] monitor the electrical noise on the house power-line infrastructure. The systems detect the unique noise signature emitted by each electrical device and identify which electrical device is being used.

While the above environment augmentation approaches focus on electrical devices connected to home electrical systems, we concentrate on handheld electrical devices and employ the wearable sensing approach. The system proposed in [11] also concentrates on handheld electrical devices and employs a wearable sensor device. The study uses Hall effect magnetic sensors on finger-rings to capture the magnetic fields emitted by magnetic components such as permanent magnets and motors incorporated in portable electrical devices. A Hall effect sensor outputs a voltage in proportion to the magnetic flux density that penetrates its element. Because a Hall effect sensor is also affected by the earth's magnetism, sensor data from the sensor on a finger ring change according to the orientation of the wearer. Therefore, the system employs two or more Hall effect sensors attached to the same hand and attempts to cancel out the effect of the earth's magnetism by using data from the sensors. However, wearing several sensors places large burdens on a user in her daily life. Also, the system proposed in [11] mainly focuses on magnetic components such as permanent magnets and motors that emit strong magnetic fields comparable to the earth's magnetism. On the other hand, we attempt to capture small time-varying magnetic fields emitted by components such as electrical circuits, motors, and conductive wires incorporated in portable electrical devices by using a new single magnetic sensor device that is not affected by the earth's magnetism. Also, because the system proposed in [11] mainly uses static magnetic fields emitted by permanent magnets, (calibrated) sensor data values from the hand-worn sensors are simply used as features for recognizing electrical device usage. By contrast, we focus on time-varying magnetic fields emitted by an electrical device, and so we employ the characteristic frequencies of the device's magnetic fields, which can be robust features because the number of features is larger. (See section 4 for more detail.) Note that we consider that the system proposed in [11] and our system are complementary rather than competing techniques because several simple portable electrical devices such as flashlights do not emit time-varying magnetic fields but only static magnetic fields. Moreover, we consider that, by combining our method with the environment augmentation approaches that focus on electrical devices connected to home electrical systems, we can recognize the use of both portable and stationary electrical devices in both indoor and outdoor environments.

Also, the system proposed in [2] uses the human body as an antenna to capture electromagnetic noise from home electrical infrastructures and electrical devices. The study attempts to recognize gestures by employing the electromagnetic noise.

3 Prototype Sensor Device

3.1 Design

As mentioned in sections 1 and 2, we want to capture time-varying magnetic fields emitted by portable electrical devices. To achieve this, we focus on a coil of wire. The electromotive force will be induced in a coil of wire when the magnetic flux through the coil changes in accordance with Faraday's law of induction $V = -N\frac{d\Phi}{dt}$, where V is the electromotive force in volts, N is the number of turns of wire, and $\frac{d\Phi}{dt}$ is the change in the magnetic flux through the coil given in webers. Therefore, with a coil of wire, we can easily convert the time-varying magnetic fields into time-series voltage values, which correspond to sensor data. Here, because we assume a wearable sensor device, the magnetic flux from the earth's magnetism that penetrates the sensor (coil) changes when the wearer changes her orientation. However, we consider that the effect of the orientation

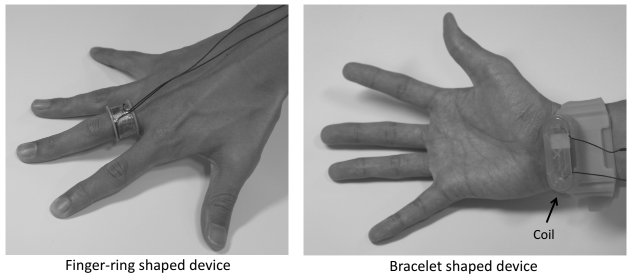


Fig. 1. Our prototype finger-ring and bracelet shaped sensor devices.

change is small because the sensor outputs only the amount of change in the flux. In section 3.2, we show example data obtained from our sensor device.

Here, because the magnetic fields attenuate greatly with distance from the source, we should attach the sensor to or near the wearer's hand so that it is close to the electrical devices she is holding. To achieve transparent activity sensing in daily lives, we should embed the sensor in an item such as a finger ring, bracelet, or wristwatch that are worn on or close to the hand in the wearer's daily lives. Our approach, which employs a coil of wire, is particularly suitable for developing a finger-ring shaped sensor device because we can easily implement such a device simply by winding a conductive wire around a finger ring. Fig. 1 shows our prototype finger-ring and bracelet shaped sensor devices. We made the finger-ring device simply by winding a wire around a plastic shank. We made the bracelet shaped device simply by attaching a coil to a silicon wrist band. Because they are prototypes, each coil of wire in Fig. 1 is connected to a sensor board. The sensor board samples sensor data (voltage values) at about 2000 Hz, amplifies the sensor data, and then sends them to a host PC via a USB cable.

3.2 Sensor data

Here we show example sensor data obtained from our prototype devices. The upper graph in Fig. 2 shows a sensor data sequence obtained from our finger-ring shaped sensor device on the wearer's right middle finger when he used a hair dryer and then used an electric toothbrush. The x-axis indicates time and the y-axis indicates the magnetic sensor data value. The lower part of Fig. 2 shows a frequency spectrogram computed from the time-series sensor data. As shown in the spectrogram, the peak frequencies related to hair dryer use and toothbrush use are different. Note that we can see constant noise in the sensor data that was caused by the amplifier on the sensor board. Also, our finger-ring device may be affected by noise from the human body.

Fig. 3 shows sensor data sequences obtained from our finger-ring device on the middle finger when the wearer used a digital camera, a cellphone, and a flashlight in this order. Fig. 3 also shows a frequency spectrogram computed from the sensor data. We can see a characteristic peak frequency when the motor for the zoom function in the camera was working ('turn on camera' and 'zoom in'

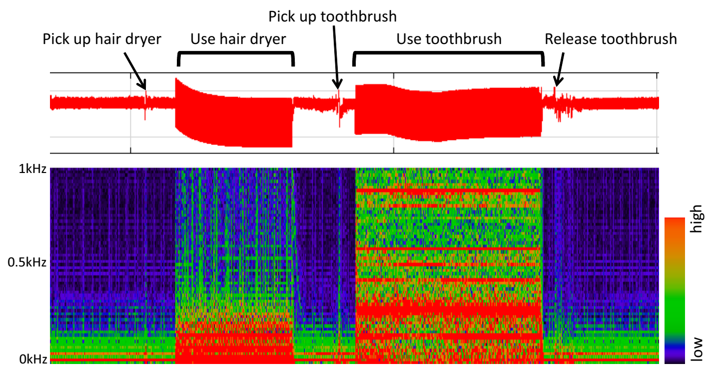


Fig. 2. Example sensor data obtained from our finger-ring device worn on the right middle finger when the wearer used a hair dryer and an electric toothbrush.

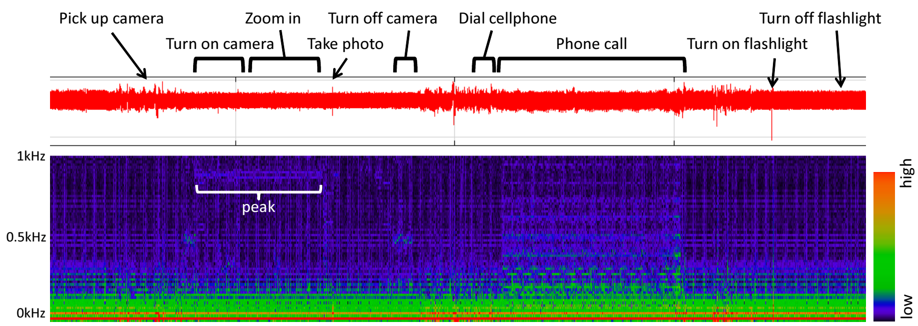


Fig. 3. Example sensor data obtained from our finger-ring device on the right middle finger when the wearer used a digital camera, a cellphone, and a flashlight.

in Fig. 3). However, even when the camera was ON, we could not find any characteristic peaks when the motor was not working. With the cellphone, we could not find any characteristic peaks when the wearer was dialing. However, there were characteristic peaks when the wearer was talking on the phone. This may be caused by an oscillator in the phone. With the flashlight, although we could find transient noise in the sensor data when the wearer turned it on, the duration of the change (noise) was very short. Also, we could not find any characteristic peaks while the flashlight was ON. We consider that it is difficult for our device to detect the use of such simple electrical devices as flashlights. Of course, our device has a limit of detecting magnetic field. Our device could not detect the use of electrical devices with very weak magnetic field, e.g., several cellphones and TV remote controls. On the other hand, Fig. 4 shows a frequency spectrogram computed from sensor data obtained from our bracelet shaped sensor device when the wearer used a hair dryer and then used an electric toothbrush. The spectrogram shows that the bracelet shaped device could not sense any magnetic flux changes when the wearer used the toothbrush. This is because the

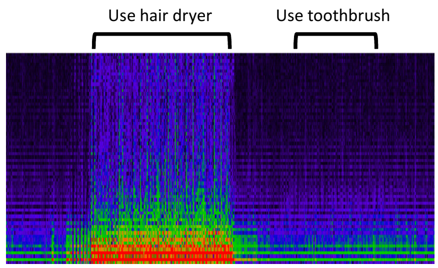


Fig. 4. Example spectrogram computed from sensor data obtained from our bracelet device on the right wrist when the wearer used a hair dryer and an electric toothbrush.

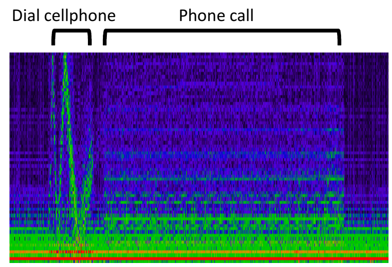


Fig. 5. Example spectrogram computed from sensor data obtained from our finger-ring device on the right middle finger when the wearer used a cellphone in front of an induction heater.

magnetic fields emitted by the toothbrush attenuated greatly, and the coil on the bracelet, which was far from the toothbrush, could not capture the magnetic fields. We consider that it is difficult for the bracelet device to capture magnetic fields emitted by handheld devices.

Here we investigate the effects on our device of external factors present in our daily life environment. Our device may be affected by strong magnetic sources close to the wearer. Fig. 5 shows a frequency spectrogram computed from sensor data obtained from our finger-ring device when the wearer used a cellphone while he was using his left hand to stir a pot on an induction heater, which is one of the strongest magnetic sources in home. The heater had an effect when the wearer was dialing because the phone was in front of his body and close to the heater (about 15-20 cm) at the time. However, the heater had no effect during phone calls because the phone was held to his ear and was far from the heater (about 40-50 cm). The sensor data seem to be very similar to those in Fig. 3. Fig. 6 shows frequency spectrograms computed from sensor data obtained from our finger-ring device when the wearer used a cellphone close to a large LCD TV. Although we could find noises caused by the TV across the entire frequency band when the wearer used the cellphone in contact with the TV (0 cm), there was little or no effect from the TV when the wearer was at a reasonable distance from it. As shown in the above examples, our device is not affected by strong magnetic components as long as it is not extremely close to them because the magnetic fields attenuate greatly according to distance. The effects of strong magnetic sources around the wearer are small except in certain extreme cases. Fig. 7 shows frequency spectrograms computed from sensor data obtained from our finger-ring device on the right middle fingers of two wearers when they were not using any electrical devices. The sensor data in Fig. 7 (a) and (b) were obtained from different wearers at the same place. Even though these data were obtained at the same place, the frequency characteristics indicated by the rectangles in Fig. 7 were somewhat different. The lower portion of Fig. 7 shows the energy computed when we focus only on frequencies indicated by the lower rectangle, and we can also find differences in the energy. The sensor data

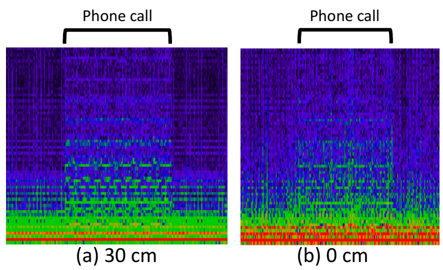


Fig. 6. Example spectrograms computed from sensor data obtained from our finger-ring device on the right middle finger when the wearer used a cellphone 30 and 0 cm from an LCD TV.

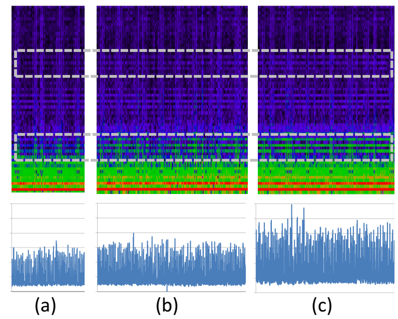


Fig. 7. Example spectrograms computed from sensor data obtained from different two wearers. (a) Wearer A at place 1, (b) wearer B at place 1, and (c) wearer A at place 2.

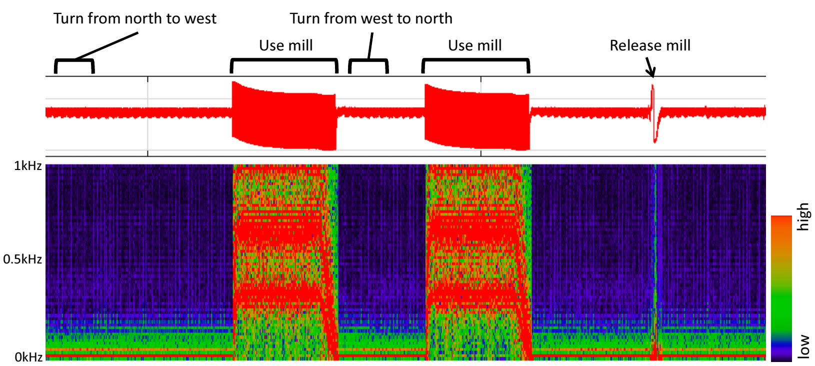


Fig. 8. Example sensor data obtained from our finger-ring device on the right middle finger when the wearer used a mill facing in different directions.

in Fig. 7 (a) and (c) were obtained from the same wearer at different places. The frequency characteristics were also somewhat different. From these data, we consider that our sensor device is slightly affected by both environmental magnetic noise in each house and noise from the human body (finger). These small noises constantly affect sensor data obtained from our device.

In section 2, we mentioned that when the wearer changes her orientation, the magnetic flux from the earth's magnetism that penetrates the sensor (coil) also changes. Fig. 8 shows a sensor data sequence obtained when our finger-ring device was being worn on the right middle finger and the wearer used an electric pepper mill while facing west and north. Fig. 8 also shows a frequency spectrogram computed from the sensor data. Sensor data obtained when the wearer used the mill while facing in different directions look like very similar. This is because our device does not capture static magnetic fields but only time-varying magnetic fields. Even when the wearer is facing north or east, the magnetic flux density from the earth's magnetism is stable and our device is not affected by the earth's magnetism. Moreover, there were no changes in the sensor data when the wearer changed her orientation. This may be because the device outputs only the amount of change in the magnetic flux. We consider that the earth's magnetism has little effect on our device.

4 Recognition Method

By using sensor data obtained from our prototype device, we attempt to identify which electrical device the wearer is using. We first extract features from sensor data and then recognize the extracted feature vector sequence by employing the hidden Markov model (HMM). We describe our method in detail below.

4.1 Feature extraction

We obtain time-series sensor data from our sensor device, and we compute a feature vector for each sliding time window. We extract features based on the FFT components of 128 sample time windows. In section 3.2, we mentioned that the magnetic fields emitted by each electrical device have characteristic frequencies. Therefore, we simply use the FFT component values as features. In addition, we use the variance and energy, which can capture the intensity of sensor data changes, computed in each window as features. The energy feature is calculated by summing the magnitudes of the squared discrete FFT components. The DC component of the FFT is excluded from this summation. For normalization, the sum was divided by the window length. As above, we construct a 66 (64+1+1) dimensional feature vector from each window.

4.2 Classification methodology

With the above procedure, we obtain a feature vector sequence. We classify each feature vector in an appropriate class (electrical device) by employing supervised machine learning techniques. That is, we model each class by using labeled training data (feature vector sequences) in advance. After that, we recognize test data with the learned models. Note that a label includes information about the class label of its related electrical device and the start and end times of its use. We prepare a model for each electrical device by using a left-to-right HMM where the values of the observed variables correspond to extracted feature vectors, and we represent its output distributions by using Gaussian mixture densities. We also prepare an HMM that corresponds to a situation that the wearer does not use any electrical devices. In our implementation, we use four-state HMMs with four Gaussian mixtures in each state. We employ the Baum-Welch algorithm [18] to estimate the HMM parameters. When we recognize test data (feature vector sequence) using the learned HMMs, we use the Viterbi algorithm to find the most probable state sequence in/across the HMMs [18]. From the state sequence, we can know into which HMM (electrical device) a feature vector at time t is classified.

4.3 Adapting user-independent models

When we want to recognize an end user's electrical device usage, it is very costly for the end user to prepare labeled training data by herself. Therefore, in section 5, we try to recognize the end user's electrical device usage (test data) with user-independent models, which are trained on labeled sensor data from other users. In section 3.2, we mentioned that noises in houses and from the human bodies (fingers) constantly affect the sensor data obtained from our device. The features of the noises depend on each house and finger. To reduce the effects of the noises, we adapt the user-independent models to the end user by employing techniques usually employed in speech recognition studies. In detail, we employ maximum-likelihood linear regression (MLLR) adaptation [7] to compute the linear transformation of the mean parameters of the Gaussian mixtures in the user-independent models (HMMs). That is, we shift the output distributions of the models by using the test data so that each state in the HMMs is more likely to generate test data. A new estimation of the adapted mean $\hat{\boldsymbol{\mu}}$ is given by $\hat{\boldsymbol{\mu}} = \boldsymbol{A}\boldsymbol{\mu} + \boldsymbol{b} = \boldsymbol{W}\boldsymbol{\xi}$, where $\boldsymbol{\mu}$ is the initial mean, $\boldsymbol{A}$ is a $k \times k$ transformation matrix, where k is the number of dimensions of the feature vector, $\boldsymbol{b}$ is a bias vector, $\boldsymbol{W}$ is a $k \times (k+1)$ transformation matrix that is decomposed into $\boldsymbol{W} = [\boldsymbol{b}\ \boldsymbol{A}]$, and $\boldsymbol{\xi}$ is the extended mean vector $\boldsymbol{\xi} = [1\ \mu_1\ \mu_2 \cdots \mu_k]^T$. Therefore, we estimate the $\boldsymbol{W}$ that reduces the mismatch between the user-independent models and the test data by using the EM technique. We then try to adapt the user-independent models to the user by employing the estimated linear transformation.

5 Evaluation: Core experiment

In this evaluation, we collect sensor data from three residents (participants A, B, and C) in their own houses and investigate the recognition performance by employing user-dependent models. That is, we learn recognition models by using training data obtained from a participant and then recognize test data from the same participant by using the models. We also investigate the portability of the training data by using user-independent models. That is, we recognize test data from a participant with recognition models trained on sensor data obtained from other participants in their houses. With the user-independent models, an end user need not prepare training data herself. In addition, we adapt the user-independent models to each participant to create user-adapted models by using unlabeled test data obtained from the participant. Then, we recognize the test data using the adapted models of the participant.

5.1 Data set

The most natural data would be acquired from the normal daily lives of the participants. However, obtaining sufficient samples of such data is costly because researchers must observe their normal daily lives. We collect sensor data by using a semi-naturalistic collection protocol [1] that permits greater variability in participant behavior than laboratory data. In the protocol, participants perform

Table 1. Electrical devices used in our experiment.

	Devices		Devices
A	digital camera	H	mill
B	digital camcorder	I	induction heater
C	hair dryer	J	blender
D	electric toothbrush	K	CD player
E	handheld vacuum cleaner	L	laptop PC
F	electric screwdriver	M	game console
G	electric shaver	N	toy (car)

Table 2. Recognition accuracies (overall F-measure) in percentages for each participant with user-dependent models.

Finger	Participant	Accuracy (%)
middle	A	83.7
	B	75.6
	C	84.0
ring	A	78.1
	B	81.8
	C	75.5

a random sequence of activities (use of electrical devices) following instructions on a worksheet. The participants are relatively free as regards how they perform each activity because the instructions on the the worksheet are not very strict, e.g., "vacuum the room" and "listen to an arbitrary track from a CD." During the experimental period, each participant completed data collection sessions that included a random sequence of use of the electrical devices listed in Table 1. A participant wore our device on his right middle or ring finger since people commonly wear rings on these fingers, and completed twelve sessions wearing our device on each hand. The device was connected via cables to a laptop carried in a backpack. To annotate the collected sensor data, each participant also wore a head-mounted camera that captured the region in front of her body.

We selected the devices in Table 1 from common portable electrical devices used in our daily lives that include components which may emit time-varying magnetic fields, e.g., motors, radio communication modules, and coils. The device list also includes an induction heater, which emits strong magnetic fields. We prepared three sets of electrical devices and gave each participant one set. Because we wanted to investigate training data portability, we included the same models of electrical devices in the three sets. For example, when a participant brushes his teeth, he uses the same electric toothbrush model that the other participants use. The electrical devices used in the experiment were located in their appropriate places in each house. For example, an electric toothbrush and shaver were placed on a washstand. Also, with respect to devices that are usually used in various places such as digital cameras and camcorders, we instructed the participants to use the devices at various locations both in and outside the house. We explain the use of several electrical devices in Table 1 in detail. With the 'digital camera,' because our device can capture the magnetic fields from the camera only when its motor is running as mentioned in section 3.2, we regard that 'digital camera' use relates only to when the participant turns it on and employs its zoom function. The 'CD player' used in our experiment is portable and has buttons for operating it on its body, and each participant used the player while holding it. With 'laptop PC,' we instructed the participants to find Yahoo! News with Google and read a news article on the web site. The 'game console' used in our experiment was Sony PlayStation Portable. The 'toy (car)' used in

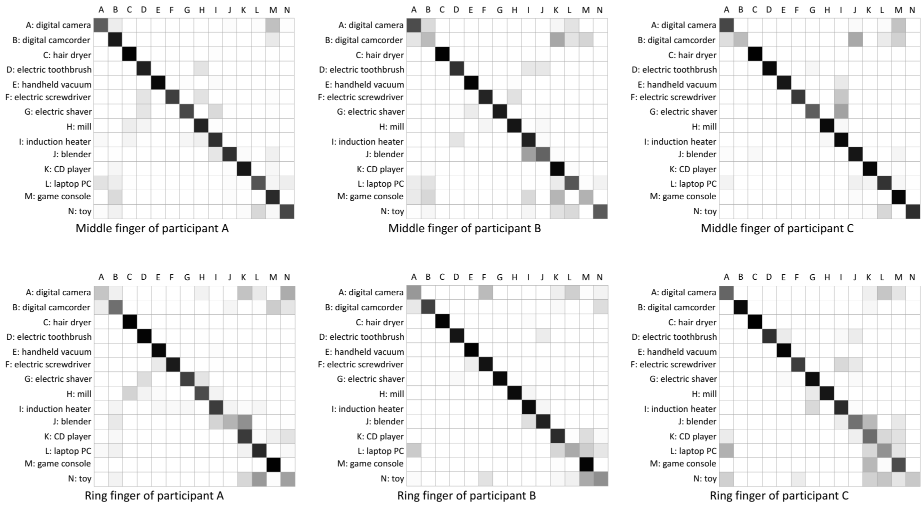


Fig. 9. Visual confusion matrices of the three participants when we use user-dependent models.

our experiment has a remote control that is connected to the car by a cable, and each participant controlled the car using the remote control.

5.2 Results: User-dependent models

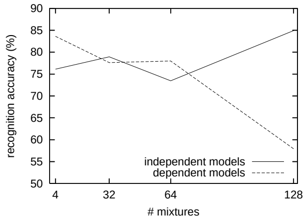
To evaluate the user-dependent models, we conducted a 'leave-one-session-out' cross validation. That is, we tested one session obtained from our device worn on a participant's finger by using models trained on other sessions obtained from our device worn on the same finger of the same participant. To evaluate the performance of our method, we used F-measure ($\frac{2 \cdot precision \cdot recall}{precision + recall}$) calculated based on the results for the estimated class at each time slice. Table 2 shows the recognition performance for each participant and for each finger. We achieved high accuracies of about 80% in each house. While the accuracies for the two fingers were not very different, the accuracies for the middle finger (81.1% on average) were slightly better than those for the ring finger (78.5% on average).

Fig. 9 shows the confusion matrices of the three participants. In these results, the recognition accuracies related to electrical devices that include strong magnetic sources (e.g. motors) such as a hair dryer, toothbrush, and and shaver were very high. However, the recognition accuracies related to electrical devices that do not emit strong magnetic fields such as a digital camera and a toy were sometimes poor. Because the remote control of the toy does not include strong magnetic sources such as motors but only several buttons and conductive wires, it was difficult for our device to capture the magnetic fields in some cases depending on the way the remote control was held. Also, the recognition accuracies related to 'laptop PC' were sometimes poor. The laptop PC includes several components that emit strong magnetic fields such as a CPU and an HDD. However, because these components are distributed throughout the PC, our device was sometimes unable to capture the magnetic fields depending on the hand positions on the PC. Also, the accuracies for the blender were poor in some cases. We used a fixed type blender in our study. When the participants used the blender, they pushed the start button without holding onto the blender. Because relation between the blender and the hand position was not fixed, sensor data obtained from the device worn on the hand were slightly different each time the blender was used. By contrast, the recognition accuracies were high for electrical devices that the user held in her hand. The recognition accuracies were also particularly high for handheld electrical devices that emit strong time-varying magnetic fields. This may be because the sensor data features obtained from such devices are not altered by small changes in the way the devices are held.

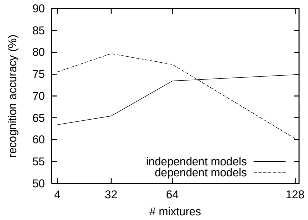
5.3 Results: User-independent models

To evaluate the user-independent models, we conducted a 'leave-one-participant-out' cross validation. That is, we tested sensor data obtained from our device worn on one participant's finger by using models trained with labeled sensor data obtained from our device worn on the same finger of remaining participants. To increase the quantity of training data, we collected sensor data (12-session data) from three additional participants in our home-like experimental environment. That is, we tested sensor data from one participant by using models trained with the sensor data of the other five participants. Note that sensor data from the additional three participants were not used as test data. We tested the sensor data from participants A, B, and C obtained in section 5.1. Here, we used HMMs with four Gaussian mixtures in each state when we constructed the user-dependent models. In this evaluation, we tested larger numbers of Gaussian mixtures in each state because we needed to capture electrical device usage performed by many participants. Fig. 10 shows the transitions of the accuracies when we increased the number of Gaussian mixtures. (Fig. 10 also includes the results for the user-dependent models.) In many cases, a larger number of mixtures provides better results when we used the user-independent models. When the number of mixtures was 128, the average accuracies for the three participants for the middle and ring fingers were 82.2% and 80.3%, respectively. Surprisingly, these results were superior to those of the user-dependent models (81.1% and 78.5% when the number of mixtures was 4). This may be because the user-independent models could capture the various ways that the electrical devices were used by the other five participants. Each user-dependent model for an electrical device was trained based on just 12 occasions of device use. On the other hand, each user-independent model was trained with 60 occasions of device use. As a result, we could recognize a participant's electrical device usage with high accuracy without labeled training data from the participant.

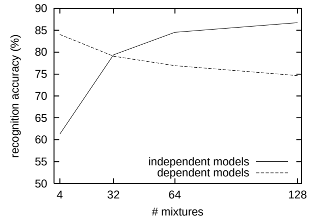
However, the recognition accuracies for participant B were relatively poorer than those for other participants when we used the user-independent models. We consider there to be three main factors that interrupt the sharing of training data among users (participants): (1) The features of the environmental magnetic noise in each house may be different. (2) Our finger-ring device can be affected by noise



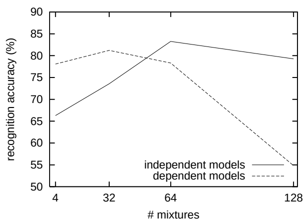
(a) Middle finger of participant A



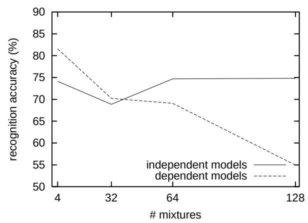
(b) Middle finger of participant B



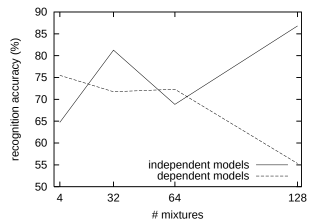
(c) Middle finger of participant C



(d) Ring finger of participant A



(e) Ring finger of participant B



(f) Ring finger of participant C

Fig. 10. Transitions of the recognition accuracies when we increase the number of Gaussian mixtures in each state.

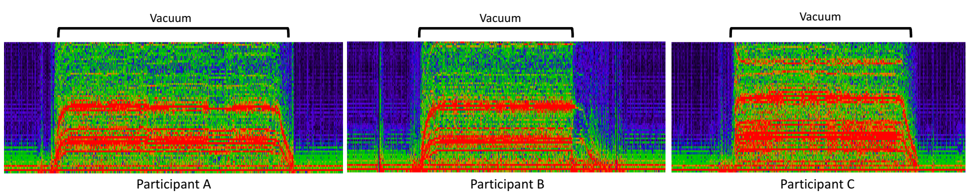
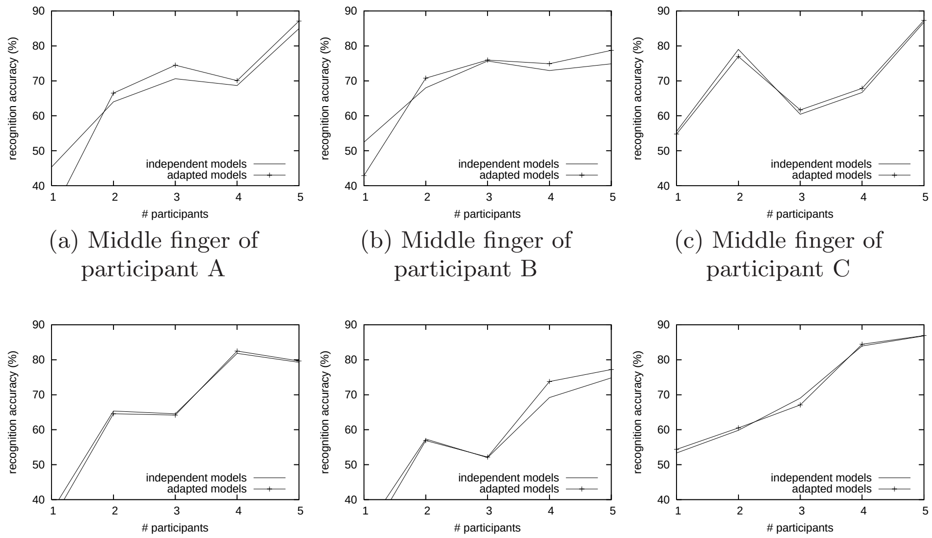


Fig. 11. Spectrograms computed from sensor data obtained from our finger-ring device worn on the right middle finger when the participants used handheld vacuum cleaners.

from the human body (finger) because the magnetic flux densities may be slightly affected by magnetic and diamagnetic materials in the finger. Thus, the features of the noise obtained from each participant's finger may be different. (3) The ways of using (holding) electrical devices may depend on each participant, and so the features of sensor data obtained from each participant may be different. Fig. 11 shows examples of spectrograms computed from sensor data obtained from our device worn on the middle fingers of participants A, B, and C when they used handheld vacuum cleaners. We first focus on sensor data segments where the participants did not use the cleaner. The features of the sensor data segments relate to the noises in the houses and from the human bodies. While these frequency characteristics were similar, the spectrogram for participant B seems to include small noises over the entire frequency band. (This may be caused by a power transmission tower near participant B's house.) We consider that the



(a) Middle finger of participant A (b) Middle finger of participant B (c) Middle finger of participant C

(d) Ring finger of participant A (e) Ring finger of participant B (f) Ring finger of participant C

Fig. 12. Transitions of the recognition accuracies when we increase the number of participants whose sensor data are used as training data. We used 128 mixtures in each state.

noises degrade the recognition accuracies for participant B. On the other hand, the peak frequencies of participant C when he was vacuuming are very different from those of participants A and B. This may be because participant C held the vacuum differently from participants A and B. However, if the user-independent models were trained with sensor data that included the use of the vacuum by other participants that was similar to that of participant C, the models may successfully recognize the use of the vacuum by participant C. Generally, a larger quantity of training data means a better learned model that captures various types of electrical device usage. In fact, the recognition accuracies related to participant C's vacuum usage were good. (81.1% and 85.2% for the middle and ring fingers when the number of mixtures was 128)

Here we investigate the number of participants whose sensor data are used as training data. Fig. 12 shows transitions of the accuracies when we increased the number of participants whose sensor data are used as training data. For example, when the number is two, we train the models by using sensor data from two randomly selected participants. Basically, the recognition accuracies improve as the number of participants shows increases. As described above, employing sensor data obtained from many participants enables us to capture various types of electrical device usage. Fig. 12 also includes the recognition accuracies we obtained when we used the user-adapted models described in section 4.3. In many cases, the accuracies with the adapted models were slightly better than those with the independent models. When # participants was five, the average

Table 3. Electrical devices used in our second experiment.

	Devices		Devices		Devices		Devices
A	hair dryer 1	F	electric shaver 2	K	handheld vacuum cleaner 2	P	blender
B	hair dryer 2	G	electric shaver 3	L	electric toothbrush 1	Q	CD player 1
C	induction heater 1	H	electric screwdriver 1	M	electric toothbrush 2	R	CD player 2
D	induction heater 2	I	electric screwdriver 2	N	electric toothbrush 3	S	cellphone 1
E	electric shaver 1	J	handheld vacuum cleaner 1	O	mill	T	cellphone 2

accuracies were 84.4% and 81.3% for the middle and ring fingers, respectively. These results were superior to those of the user-independent models (82.2% and 80.3%). The adaptation techniques improved the recognition accuracies by about 1 to 2% by employing unlabeled sensor data of the participant. In particular, the improvements related to participant B were significant (3.8% and 2.4%). As described above, the accuracies for participant B were poorer than those for other participants because of the effects of the noises in the house and/or from the human body. We consider that the adaptation techniques reduced the effects of these noises.

6 Evaluation: Scalability of our approach

In this evaluation, we investigate the scalability of our approach. We collect sensor data from a set of many electrical devices that includes the same or similar types of devices, and recognize the data by using user-dependent models.

6.1 Data set

We collected sensor data in our home-like environment. A participant completed data collection sessions that included a random sequence of use of the electrical devices listed in Table 3. The participant wore our device on his right middle or ring finger, and completed twelve sessions wearing our device on each hand. The set of electrical devices listed in Table 3 includes several similar devices, e.g., three electric shavers, two CD players. Note that these devices are different products. For example, the three toothbrushes used in the experiment were developed by different manufacturers.

6.2 Results

With the data set, we could also achieve 81.5% for the middle finger and 82.6% for the ring finger even when we employed similar electrical devices. Fig. 13 shows confusion matrices for the two fingers. As shown in the matrices, the recognition accuracies were very high for electrical devices that emit relatively strong time-varying magnetic fields (from A to P). In many cases, the accuracies as regards these devices were almost perfect. For example, toothbrushes 1 and 3 have similar architectures (rotating-oscillating toothbrushes). However, as shown

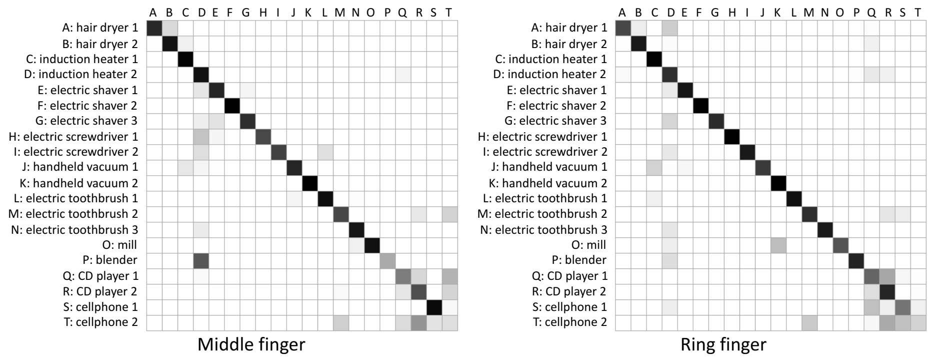


Fig. 13. Visual confusion matrices for sensor data obtained in our home-like environment.

in Fig. 13, we could distinguish between toothbrushes 1 and 3. We consider that the features used in our approach (FFT components extracted from sensor data) have sufficient expressive power even when we want to distinguish similar devices. However, as shown in Fig. 13, it was difficult to distinguish between CD players 1 and 2. While these players are different products, they were developed by the same manufacturer. These players may include the same or similar magnetic components. The accuracies related to cellphone 2 were also poor. This may be because the intensities of the magnetic fields emitted by the phone were not large. Our device sometimes captured only very small magnetic fields from the phone according to the way the phone was held. Therefore, our recognition method mistakenly classified the use of the cellphone as the use of other electrical devices that emit small magnetic fields, i.e., CD players and a different cellphone.

7 Conclusion

In this paper, we described the development of a finger-ring shaped sensor device by employing a coil of wire for recognizing the use of portable electrical devices. With the device, we captured time-varying magnetic fields emitted by electrical circuits, motors, conductive wires, etc. included in the electrical devices. In the evaluation, we were able to recognize a participant's portable electrical device usage with very high accuracy with training data obtained in her real house. Also, we investigated the portability of training data between different participants. That is, we recognized a participant's sensor data by using models trained with many other participants' labeled sensor data, and confirmed that the models achieved higher accuracies than the models trained with the participant's labeled data. In addition, we reduced the effect of magnetic noises in houses and from the human bodies by using adaptation techniques. As part of our future work, we plan to employ these adaptation techniques according to user's location obtained by a GPS sensor attached to the user. In our current implementation, we simply estimate a single transformation for the adaptation for each user. We also plan to increase sensitivity of our device by increasing the number of turns of wire and/or reducing noise in sensor data that is caused by the amplifier.

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