Recognizing the Use of Portable Electrical Devices with Hand-Worn Magnetic Sensors

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Abstract. The new method proposed here recognizes the use of portable electrical devices such as digital cameras, cellphones, electric shavers, and video game players with hand-worn magnetic sensors by sensing the magnetic fields emitted by these devices. Because we live surrounded by large numbers of electrical devices and frequently use these devices, we can estimate high-level daily activities by recognizing the use of electrical devices. Therefore, many studies have attempted to recognize the use of electrical devices with such approaches as ubiquitous sensing and infrastructure-mediated sensing. A feature of our method is that we can recognize the use of electrical devices that are not connected to the home infrastructure without the need for any ubiquitous sensors attached to the devices. We evaluated the performance of our recognition method in real home environments, and confirmed that we could achieve highly accurate recognition with small numbers of hand-worn magnetic sensors.

Keywords: Wearable sensing; Activity recognition; Magnetic sensor.

1 Introduction

Activity recognition is one of the most important technologies in relation to context-aware and lifelogging applications, e.g., elder care support and fitness monitoring. We can categorize activity recognition technologies into two main approaches; wearable sensing and environment augmentation. The wearable sensing approach recognizes activities by using sensor data obtained from such body-worn sensors as accelerometers and microphones [1,11,12,13]. In many cases, the environment augmentation approach uses ubiquitous sensors such as RFID tags and/or switch sensors installed in the environment [20,17,19,14]. Although the environment augmentation approach places a smaller burden on the user than the wearable sensor approach, ubiquitous sensors are expensive to deploy because we have to attach them to various indoor objects and maintain a large number of them. On the other hand, several studies have used a sensor device attached to a single point in the environment [5,16]. For example, [16] recognizes electrical device use by monitoring electrical noise on residential power lines. Many environment augmentation approaches detect the use of daily objects in the environment by using small sensors attached to the objects and/or a single point

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device that monitors the objects and then estimates high-level daily activities using the detected information. This approach is based on the idea that objects in use relate to an activity the user is performing. For example, when a user is using a razor and preshave lotion, we can easily assume that the user is shaving.

On the other hand, because many wearable sensing approaches use body-worn accelerometers, they can recognize only simple low-level activities such as walking and running. However, unlike the environment augmentation approach, the wearable sensing approach can sense users' activities in both indoor and outdoor environments. Also, as mentioned above, its deployment cost is smaller than that of the environment augmentation approach. In this paper, we try to recognize the use of daily objects solely by employing wearable sensors that have the above advantages. That is, we recognize which object is in use by employing only wearable sensors without any sensors embedded in the user's environment. This permits us to realize a low deployment cost and place-independent high-level activity recognition. In this work, by using hand-worn magnetic sensors, we try to recognize the use of portable electrical devices such as digital cameras, cellphones, electric shavers, video game players, and music players. That is, we sense the magnetic fields that the devices emit and determine the device a wearer is using by analyzing the sensor data. In modern societies, because we are surrounded by large numbers of electrical devices, we can estimate high-level activities by recognizing the use of these devices. For example, when we recognize that a wearer is using a hair dryer, we can know that she is doing her hair. Such high-level activity recognition is a fundamental technology of context-aware systems and lifelogging. Therefore, many studies have been undertaken with the aim of recognizing the use of electrical devices. However, several approaches require a sensor node for each electrical device [8]. Also, because other approaches utilize the existing infrastructure in a home, i.e., power lines [16], they cannot recognize the use of electrical devices that are not connected to the infrastructure via power outlets. Because the new method proposed in this paper recognizes the use of portable electrical devices by employing a magnetic field emitted from magnets and ICs embedded in the devices, we can recognize the use of devices that are not connected to the infrastructure. In addition, we can recognize the use of the devices in outdoor environments. Portable electrical equipment such as digital cameras and cellphones are frequently used out of doors.

In the rest of this paper, we first introduce work related to activity recognition with sensor data, and then describe the magnetic field emitted from electrical devices and the mechanism of the magnetic sensors. After that, we describe the design and implementation of our proposed sensor device, and explain our method, which recognizes the use of portable electrical devices by employing magnetic sensor data. By using the sensor device, we collect sensor data in three actual home environments and then evaluate our method by using the data. The contributions of this paper are that we propose a new method that recognizes the use of portable electrical devices without the need to install any sensors in environments, i.e., without attaching sensor nodes to the devices. In addition, we experimentally investigate the appropriate number and locations of magnetic sensors attached to wearer's hands. To achieve this, we attempt to recognize the use of devices accurately with small numbers of sensors. This enables us to reduce the burden it places on wearers.

2 Related Work

As mentioned in section 1, activity recognition methods are categorized into environment augmentation and wearable sensing approaches. Many environment augmentation approaches employ a large number of small sensors such as switch sensors, RFID tags, and accelerometers installed in the corresponding environments [20,17,19]. Although the approach can achieve fine-grained measurements of daily lives, its deployment and maintenance costs, e.g., costs related to battery replacement, are very large. Several studies employ a single point sensor device that can monitor home infrastructures to detect the use of electricity, water, or gas in home environments [3,5,16]. However, the approach cannot monitor the use of devices and objects that are not connected to the home infrastructure such as the plumbing or electrical systems. The method proposed in this paper can recognize the use of portable electrical devices that are not connected to the home infrastructure by employing wearable sensors. However, as described below, our approach may not be able to recognize the use of many large stationary electrical devices such as washing machines and refrigerators, which are usually connected to power lines. We consider that, by combining our method with the infrastructure-based method, we can recognize the use of both portable and stationary electrical devices in both indoor and outdoor environments with small deployment costs.

Most wearable sensing approaches use multiple accelerometers attached to the wearer's body [1,18]. Although these approaches can recognize the wearer's activities in outdoor environments, they place a burden on the wearer because she has to wear several sensors. Also, unlike approaches that leverage the use of daily objects, the wearable sensing approaches recognize just simple low-level activities such as walking and running because they only use accelerometers. On the other hand, some studies can recognize high-level activities by employing such rich sensors as body-worn microphones and cameras [2,10,12,13,15]. However, the methods that employ such rich sensors as cameras and microphones may generate privacy concerns. Because the method proposed in this paper employs magnetic sensors, there is less of a privacy issue than with camera and/or microphone based methods. The magnetic sensor simply outputs a sequence of numerical values in the same way as accelerometers. In addition, rich sensors such as cameras and microphones must handle a large amount of data and/or consume a lot of energy.

3 Magnetic Field and Magnetic Sensor

Before explaining our approach, we describe the magnetic field emitted by electrical devices and the magnetic sensor mechanism.

3.1 Magnetic Field Emitted by Electrical Devices

The magnetic fields in electrical devices have two main sources. The first source is permanent magnets embedded in the devices. Because permanent magnets are widely used components of motors, speakers, and earphones, they are familiar in our daily lives. The intensity of the magnetic field emitted by a permanent magnet attenuates greatly according to the distance from the magnet. The attenuation feature depends on the form and strength of the magnet. With a horizontally-located pillar-shaped magnet 5 mm in diameter, 3 mm thick, and with a residual magnetization of 1.2 T, for example, the magnetic flux density values 5 mm and 10 mm away in the vertical direction are 36.0 and 7.1 mT, respectively. 1.2 T magnets are commonly used as speaker components. The second source is the flow of an electric current in the devices. An electric current flowing through a device produces a magnetic field, and the intensity of the magnetic field also attenuates according to the distance. Such a magnetic field is emitted by conductive wires, coils, and ICs included in electrical devices. On the other hand, to restrict the harmful effects of a time-varying magnetic field on a person's health, some organizations have established exposure guidelines [4,6]. Based on these guidelines, many electrical devices are designed to limit magnetic field leakage by surrounding the magnetic sources with such magnetic materials as iron. This effect is called the shielding effect. The intensity of magnetic fields emitted by conductive wires and ICs is much smaller than that by permanent magnets and coils, and the intensity is also smaller than that of the earth's magnetism (0.03 - 0.04 mT) in many cases. It is difficult to capture the small magnetic fields by using body-worn magnetic sensors that are affected by the earth's magnetism. Therefore, we mainly focus on permanent magnets and coils.

3.2 Magnetic Sensor

Magnetic field detection has various applications such as current sensing, orientation sensing, diagnosis of disease, and paper currency validation, and so various kinds of magnetic sensors have been developed [9]. Here, we introduce the widely used Hall effect sensors. A Hall effect sensor is a kind of magnetic sensor that utilizes the electromotive force integrated in an electrical conductor carrying a current when it is placed in a magnetic field perpendicular to the current. A Hall effect sensor outputs a voltage in proportion to the magnetic flux density that penetrates its element. Because of its simple mechanism, very small and inexpensive sensors, e.g., from about 1 to 2 mm square, have become commercially available.

4 Sensor Device Design

4.1 Manual Use of Electrical Devices

To obtain a design guideline for our sensor device, we first categorize the ways of using electrical devices into two types. The first is that the user picks up the device and uses it. The second is where the user employs a fixed static device by pushing its buttons, turning its knobs, etc. The ways of using many large devices such as refrigerators and washing machines fall into the second category. Most large devices are connected to power outlets, and so the methods that monitor power line infrastructures can recognize the use of these devices [16]. On the other hand, most of the devices employed in the first way are small because the user holds the devices in her hand when using them. Also, because these devices are portable, many of them are battery powered, which makes them impossible to recognize with the methods that monitor power line infrastructures. As mentioned in the previous section, electrical devices emit magnetic fields from their embedded magnets, coils, etc. The idea we propose in this paper is that we recognize the electrical device a user is using by employing the magnetic field. In particular, we recognize the use of portable electrical devices with hand-worn magnetic sensors. As described in the previous section, a magnetic field attenuates greatly because of its characteristics and the shielding effect. Thus, if a user holding a portable device wears a sensor on her hand, we can effectively detect the magnetic field emitted by the device. Then, we analyze the detected magnetic field and recognize which device the wearer is using. We detail the recognition method later.

Here, we examine the parts of the hands to which we should attach magnetic sensors. We consider there to be two criteria for selecting the parts. (i) Although the magnetic sensors are small, we should select locations where the attached sensors do not place a large burden on the wearer. For example, when we attach sensors to a person's fingertips, the sensors may impede the operation of buttons and keyboards. Moreover, if we attach sensors to the regions surrounding the finger joints, they will be uncomfortable when the wearer bends her fingers. (ii) We should attach sensors to locations where the sensors can effectively detect the magnetic fields emitted by portable devices held in the wearer's hands. As mentioned in the previous section, because magnetic fields attenuate greatly, we should attach sensors to locations where they can monitor devices near them.

Here, we look at the ways of holding various kinds of portable electrical devices in the hands. We found that button position and shape of a device affect the way it is held as shown in Fig. 1. For example, when holding a device with buttons as shown in Fig. 1 (a) and (c), we usually hold the device in a way that enables us to access the buttons with our fingers. Moreover, a device with a handle, as shown in Fig. 1 (c), is normally held by the handle. As above, we basically hold the devices with the fingers and palm. In addition to the shape and button position, its size affects the way it is held. We often hold small and lightweight devices with just our fingers. For example, when holding a small camera as shown in Fig. 1 (a), we can hold it using only our fingers. We hold slightly larger and heavier devices with part of the palm in addition to the fingers, e.g., when holding a relatively large smart phone as shown in Fig. 1 (b). That is, we hold devices mainly with the fingers and also with part of the palm. Based on the above facts, we decided to sense the magnetic fields from portable devices by mainly focusing on the fingers. In particular, we focus on the parts of the fingers where sensors would

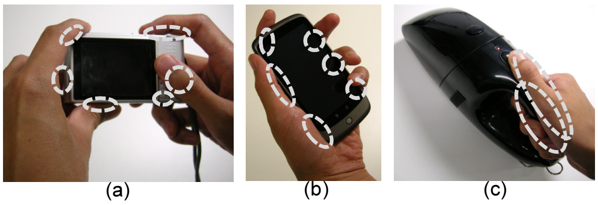


Fig. 1. Ways of handling portable devices: (a) digital camera, (b) smart phone, and (c) hand-held cleaner. Regions circled with dashed lines represent those parts of the devices that the hand touches.

not impose a large burden on the wearer, i.e., between the first and second joints and between the second joint and the base of the finger. We considered that, by embedding a magnetic sensor in a finger ring, which is usually worn between finger joints, we could achieve a low burden and convenient sensing.

In our investigation, we also found that the way a portable device is held depends on the device (or the operation of the device). As mentioned above, the ways devices are held are determined by their shape and the positions of their buttons. That is, the way a device is held is almost identical whenever the user performs a certain operation.

4.2 Basic Idea of Recognition Method

As described above, we try to distinguish which portable electrical device a user is using by analyzing time-series sensor data obtained from hand-worn magnetic sensors that sense magnetic fields emitted by various components embedded in the devices. Therefore, we should solve the multi-class recognition problem, namely we must classify sensor data at each time slice into an appropriate activity class (use of an electrical device). Here, to solve the problem, we look at two discriminative characteristics of sensor data obtained from hand-worn magnetic sensors. The first is strength of magnetic field (magnetic flux distribution). Assume that a permanent magnet is embedded at a certain position on a device. When the way of holding the device is identical whenever the wearer performs a certain operation, a magnetic sensor fixed to a certain hand position may output similar sensor values whenever the operation is performed. This is because the strength of a magnetic field depends on the intensity of the magnet and distance from the magnet. Because the intensity and positions of the embedded magnets differ from device to device, we consider that we can recognize which device a wearer is using by utilizing the strength of a magnetic field picked up by hand-worn magnetic sensors. The second discriminative feature is the temporal change in the strength of a magnetic field. For example, when the amount of current flowing in a device changes or a wearer changes the way of holding a device when operating it, the strength of the magnetic field obtained from a hand-worn magnetic sensor may change. Such characteristic temporal variations in the magnetic field can allow us to distinguish between activity classes.

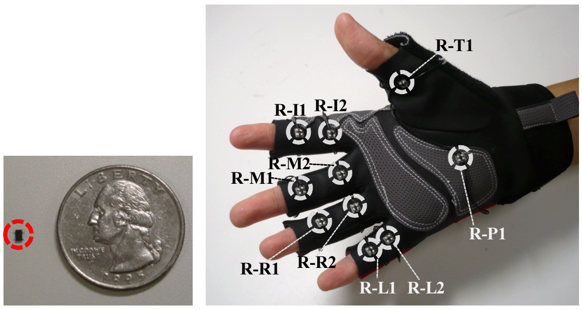


Fig. 2. A magnetic sensor shown next to a quarter dollar coin (left) and our prototype sensor glove (right). We provided each sensor on the glove with an identifier. The identifier is labeled with an initial letter indicating the left or right hand, an initial letter showing its position, and a serial number. For example, the identifier of the first sensor attached to the little finger of the right hand is R-L1.

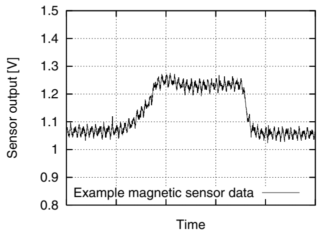


Fig. 3. Time-series raw magnetic sensor data of R-I1 obtained when we brought a cellphone close to the sensor and then moved the phone away from the sensor. (The voltage values are shifted.)

4.3 Design and Implementation of Prototype Device

Based on the characteristics of a magnetic field mentioned in section 3.1 and the ways of using portable electrical devices mentioned in section 4.1, we design and implement a sensor device that focuses on the fingers and palm. However, it is not clear which of the finger parts that we focus on are actually effective for recognizing the use of portable devices. Moreover, it is unclear how many sensors are needed to achieve highly accurate recognition. Thus, in this paper, we first develop a sensor device that is equipped with many sensors at important locations on the hand mentioned above, and then we determine the good locations experimentally. The prototype device developed in this study is in the form of a glove with ten magnetic sensors as shown in Fig. 2. We attached magnetic sensors to the important parts of the hand mentioned in section 4.1. We also attached a magnetic sensor to the center of the palm. We used Asahi Kasei's HW105A Hall ICs as magnetic sensors, and also used a glove that fitted the hand well. As shown in Fig. 2, the sensor is sufficiently small. Because the device is a prototype, these sensors are connected to a USB port of a host PC via cables and a sensor board. The board samples the sensor data at a sampling rate of about 330 Hz. We implemented the devices for both right and left hands. If we can recognize the use of electrical devices with a small number of sensors, we can achieve convenient sensing by using a small finger ring shaped device with a magnetic sensor because we assume that the sensors will be attached between finger joints. Note that several magnetic sensor products are sensitive to temperature changes. That is, output voltage characteristics of the sensors change according to ambient temperature. When we use such sensors, we should correct sensor outputs by using temperature data.

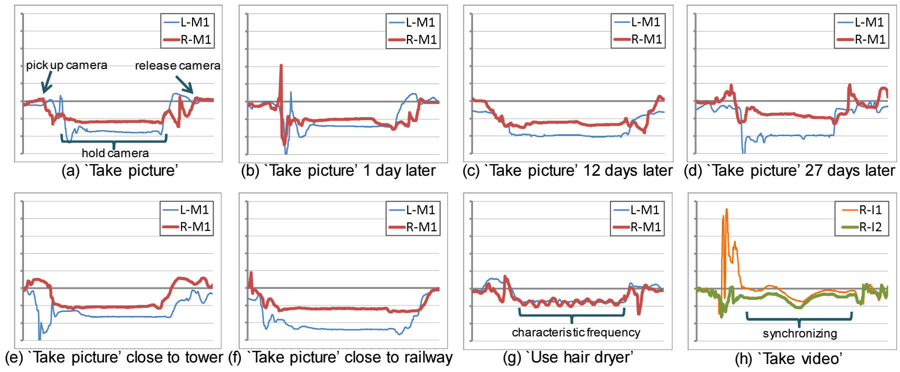


Fig. 4. Sensor data sequences obtained from our devices. Positive or negative sensor data values indicate the direction of the magnetic flux that penetrate a sensor.

4.4 Characteristics of Sensor Data

We examine sensor data obtained from our implemented sensor device. Fig. 4 (a)-(f) show time-series sensor data sequences obtained from sensors attached to the middle fingers of both hands when the wearer was performing a certain activity at different times and at different locations. (The sensor identifiers are L-M1 and R-M1 as shown in Fig. 2.) The activity consists of the wearer picking up a digital camera, turning on the camera, taking a picture, turning off the camera, and then releasing the camera. The x- and y-axes of the graphs represent time and the output voltage of the magnetic sensor, respectively. (The voltage values are amplified, smoothed, and then shifted.) From Fig. 4 (a)-(d), we can find that the sensor data values obtained on different days while holding the camera were similar. Also, Fig. 4 (e) and (f), respectively, show sensor data sequences obtained at places close to a power transmission tower and an electric train line, which may generate magnetic fields. As mentioned in section 3.1, because the magnetic field attenuates greatly, magnetic sensors were not affected by magnetic field sources located at a distance. In addition, although these data change depending on the orientation of the sensor as a result of the effect of the earth's magnetism, the amount of change was small. On the other hand, Fig. 4 (g) shows sequences of sensor data obtained when the wearer was using a hair dryer. The sequences are different from those obtained when the wearer was taking a picture.

5 Recognition Method

We attempted to recognize the use of electrical devices by using the sensor data sequences introduced above. Fig. 5 shows the architecture of our recognition method. In this architecture, we first amplify the output voltages from hand-worn magnetic sensors and then denoise them. As shown in Fig. 3, we can detect the presence of high-frequency noise in a sequence of raw output voltage signals. Therefore, we remove the noise by employing a low-pass filter (moving average).

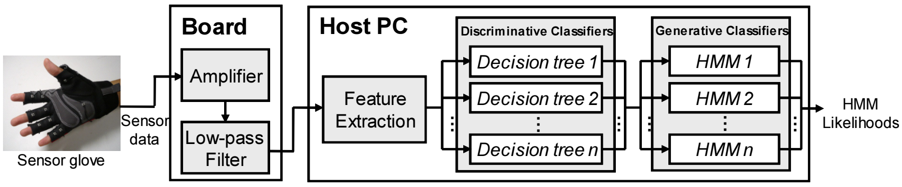


Fig. 5. Architecture of our recognition method

The charts in Fig. 4 show smoothed signals. The host PC samples the smoothed sensor data from the board at a sampling rate of 33 Hz. The host PC then extracts features from the data and classifies the extracted feature vectors at each time slice into the appropriate activity class. We describe the feature extraction and the classification method below.

5.1 Feature Extraction

We extract features from sensor data that are used to model/recognize activity classes. We compute features from each sample of sensor data. Thus, because the host PC samples sensor data from the board at a sampling rate of 33 Hz, about 30 feature vectors are generated per second and become inputs of the classification method. In addition to the smoothed output voltage values from the hand-worn magnetic sensors, we also use (i) energy, (ii) dominant frequency, and (iii) the difference between the output voltage values of different sensors as features.

The energy and dominant frequency are computed for each sensor data sequence. We extract the energy and dominant frequency features based on the FFT components of each 64-sample window because we can find a characteristic frequency in the sensor data captured during the performance of several activities as shown in Fig. 4 (g), which may be caused by motor rotation. The energy can be used to distinguish low intensity changes in sensor data from high intensity changes. The energy feature is calculated by summing the magnitudes of squared discrete FFT components. For normalization, the sum was divided by the window length. Note that the DC component of the FFT is excluded from this summation. The dominant frequency is the frequency that has the largest FFT component, and this component should be ten times larger than the average component of all the frequencies in this implementation.

We also compute the difference between the output voltage values of two different sensors sampled at the same time. We compute the differences for all combinations of two sensors attached to the same hand, and then use them as features. As mentioned in section 4.4, magnetic sensors are affected by the earth's magnetism. Fig. 4 (h) shows sequences of sensor data obtained during digital camcorder use. We found temporal changes in the sensor data sequences and the changes of these sequences were synchronized. This was caused by changes in the wearer's orientation when using the camcorder. That is, the magnetic sensor data change according to the orientation of the sensor. Our idea is that, by using the difference between the sensor data values of two sensors, we cancel out the changes caused by earth's magnetism (the orientation change).

As described above, we use the smoothed sensor data value, energy, dominant frequency, and difference as features. When a user wears 10 sensors on the right hand and 10 sensors on the left hand, the generated feature vector consists of a total of 150 feature values ($(10 + 10 + 10 + 45) \times 2$), i.e., the vector has 150 dimensions.

5.2 Classification Methodology

We classify an extracted feature vector in an appropriate class by employing supervised machine learning techniques. That is, we first model each activity (use of a device) by using labeled training data and then recognize test data with the learned models. Note that a label includes information about the class label of its related activity and activity start and end times. Here, the classification approaches used in machine learning are divided into two groups: one group uses discriminative techniques that learn the class boundaries, and the other uses generative techniques that model the conditional density functions of the data classes. The classification performance of the discriminative techniques, which find the discriminant boundaries of the classes, often outperform those of generative techniques. By contrast, handling missing data is often easier with the generative techniques. State of the art activity recognition studies achieve high accuracy by employing a hybrid discriminative/generative approach that can combine the advantages of the two techniques [7,10,11,13].

These facts provide our motivation for using the hybrid discriminative/generative approach shown in Fig. 5. Our classification method employs two main modules: discriminative classifiers and generative classifiers. The input of the first module is the extracted feature vector sequence. The first module consists of some decision tree based binary classifiers trained with feature vectors. We build each decision tree to recognize its corresponding activity class. That is, the number of decision trees n corresponds to the number of activities the method learns. Each decision tree computes its associated class probability for each feature vector in the feature vector sequence. That is, each decision tree outputs the class probability sequence. For example, a decision tree for the 'vacuum activity' class outputs the probability of the class for each feature vector.

Table 1. Information about experimental environments and participants

Houses	House A	House B	House C
Type	house	house	apartment
#rooms	7	5	2
#days	8	4	7
#sessions	10	6	12
#residents	3	3	1
Age	60	35	32
Gender	male	male	male

Table 2. Activities performed in our experiment

	Activities		Activities
A	talk on cellphone	H	vacuum
B	operate cellphone	I	watch TV
C	use smart phone	J	play video game
D	listen to music	K	listen to radio
E	shave	L	use flashlight
F	use hair dryer	M	take picture
G	brush teeth	N	take video

The input of the second module consists of n-dimensional class probability sequences computed by the n decision trees. The second module also comprises n HMM classifiers [21], which can be used to recognize signals with temporal patterns, trained with a sequence of output class probabilities of the discriminative classifiers. We also build each HMM to recognize its corresponding activity class, that is, each HMM also outputs the likelihood of its corresponding activity. The class with the highest likelihood is the classified class.

6 Evaluation

In this section, we evaluate our activity recognition approach by using sensor data obtained in real environments. We also investigate how many magnetic sensors are required and to which parts of the hands we should attach them to achieve highly accurate activity recognition that imposes the minimum burden on the wearer.

6.1 Data Set

We collected sensor data in three different dwellings; one seven-room house (house A), one five-room house (house B), and one two-room apartment (house C). One resident (an experimental participant) in each house wore our prototype devices on both hands and collected sensor data. Our devices were connected to a laptop PC in a backpack via cables. To annotate the collected sensor data, each participant also wore a head-mounted camera that captured the region in front of the participant's body. Table 1 shows an overview of the experimental conditions. During the experimental periods, the participants collected sensor data without being supervised by researchers.

Here, the most natural data would be acquired from the normal daily lives of the participants. However, obtaining sufficient samples of such data is very costly. 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 a random sequence of activities (obstacles) following instructions on a worksheet. The participants are relatively free as regards how they perform each activity because the instructions on the worksheet are not very strict, e.g., "shave your face" and "vacuum the room with a hand-held cleaner." During the experimental period, the participants completed data collection sessions that included the random sequence of activities (use of portable electrical devices) listed in Table 2. We selected these portable devices (activities) from those frequently found in appliance stores and online stores.

Here we describe how these activities were performed in detail. In activity B, each participant operated his cellphone, i.e., texting and dialing. In activity C, we instructed the participants to browse an arbitrary web page on a smart phone. In activity E, each participant shaved his face with an electric shaver. In activity G, each participant brushed his teeth with an electric toothbrush. In activity H, we instructed the participants to vacuum their house with a hand-held cleaner. In activity I, we instructed the participants to operate a TV with a remote control, e.g., control its volume and switch channels. In activity J, each participant operated a video-game console such as Nintendo DS or Wii in his house. In activity K, we instructed the participants to listen to a radio program on a portable radio. In activity M, we instructed the participants to take a picture with a digital camera. In activity N, we instructed the participants to take a video with a (digital) camcorder. Here, the electrical devices used in the experiment were located in their appropriate places in each house. For example, an electric toothbrush was placed on a wash stand. Note that, with respect to devices that are usually used in various places such as cellphones and digital cameras, we instructed the participants to use the devices in various places both in and outside the house. Also, when a participant did not have a device, we asked him to buy the device. (We paid for it.)

6.2 Evaluation Results

We evaluated the performance of our approach by using the collected and annotated sensor data. We conducted a ‘leave-one-session-out’ cross validation evaluation. That is, we tested one session obtained in a house by using classifiers trained on other sessions obtained in the same house. To evaluate the performance of our method, we used the precision and recall calculated based on the results for the estimated class at each time slice.

Performance of our method. The left part of Table 3 shows the precision and recall of our recognition method in each house when we used sensor data obtained from all 20 magnetic sensors. As shown in the table, our method achieved very high recognition accuracy simply by using wearable sensors. We achieved about 80% average precision and recall in each house. The accuracies for houses A and C were higher than that for house B. This may be because the amounts of training data in houses A and C were sufficient. With large amounts of training data, we can capture various ways of using electrical devices. However, in house A, the precision of the ‘take picture’ activity was not good. As shown in the confusion matrix of house A in Table 4, other activities such as ‘use smart phone’ and ‘watch TV’ were mistakenly classified in the ‘take picture’ class. This may be because we could not model the ‘take picture’ class well. When the participant in house A took a picture, he changed the way he held the camera slightly depending on the type of photograph he was taking, e.g., closeup photograph or telephotograph. Although the changes were very small, the data values obtained from the sensors were very different as shown in Fig. 6 (a) and (b). The time-series sensor data sequences in Fig. 6 (a) were obtained when the participant in house A took a picture of the landscape in front of him. The time-series sensor data sequences in Fig. 6 (b) were obtained when the participant took a picture of an object by pointing the camera directly at it. Although the data values obtained with the R-M2 sensor were similar to each other, those obtained with the L-M1 sensor were different. This was caused by the magnetic field, which attenuates greatly with distance, as mentioned in section 3.1. Depending on the sensor position, the sensor data values change considerably. This phenomenon

Table 3. Accuracies (precision / recall) of the recognition method in each house. The values are percentages. The left portion of this table shows the accuracies when we use the sensor data from all 20 sensors. The right portion shows the accuracies when we use the sensor data of only the top-4 contributing sensors.

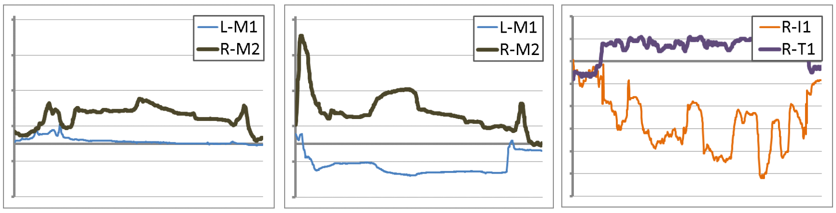
	All 20 sensors			Only top-4 sensors		
	House A	House B	House C	House A	House B	House C
A: talk on cellphone	95.1/82.2	25.2/80.2	27.2/89.9	89.6/88.8	58.5/43.1	43.7/75.0
B: operate cellphone	89.5/84.9	89.4/73.3	98.2/80.4	70.0/79.9	58.1/73.5	91.9/89.7
C: use smart phone	92.5/76.0	91.4/85.5	91.6/83.6	68.0/64.9	77.4/61.7	98.4/93.4
D: listen to music	87.2/71.0	63.4/65.5	73.0/89.5	75.1/72.8	59.6/37.2	81.3/89.5
E: shave	78.8/78.8	99.9/100.0	93.9/68.8	84.9/84.9	86.4/71.8	81.1/67.1
F: use hair dryer	95.9/99.4	94.4/89.9	91.2/89.3	91.4/93.7	96.1/95.5	97.2/94.0
G: brush teeth	95.4/95.5	79.6/51.2	79.2/67.4	65.7/79.0	50.8/81.0	55.7/72.0
H: vacuum	90.0/83.3	99.4/66.0	98.0/85.4	82.8/79.6	26.6/58.5	93.6/86.2
I: watch TV	79.4/78.9	84.3/73.8	89.3/69.4	76.8/74.1	72.3/69.5	95.2/83.5
J: play video game	95.5/97.7	99.3/99.5	95.9/85.8	88.8/96.0	99.1/100.0	88.8/89.8
K: listen to radio	89.0/73.6	92.9/81.2	69.8/70.1	59.3/41.5	74.9/78.9	72.7/73.2
L: use flashlight	86.9/90.7	95.2/80.0	98.3/71.6	58.3/80.8	22.7/21.6	80.9/73.2
M: take picture	35.3/77.2	98.4/92.0	90.8/99.9	82.5/82.8	99.0/88.8	73.8/75.2
N: take video	91.4/78.7	53.3/28.7	99.3/92.2	96.7/82.2	40.6/29.0	98.0/80.9
Average	85.9/83.4	83.3/76.2	85.4/81.7	77.9/78.7	65.9/65.0	82.3/81.6
Overall	83.3/83.3	79.6/79.6	81.2/81.2	77.6/77.6	68.8/68.8	82.7/82.7

was also observed for 'talk on cellphone' in houses B and C. However, this result indicates that, when we have sufficient amounts of training data, we may be able to achieve very fine-grained recognition of electrical device operation, e.g., distinguish a closeup photograph from a telephotograph. As above, the various ways of holding the electrical devices reduced the accuracy in our experiment.

We found another reason for recognition failure, namely the positions of the components in electrical devices. The accuracies of 'brush teeth' and 'take video' in house B were poor because the intensities of magnetic fields that the hand-worn sensors sensed in these activities were very small. That is, the magnetic components included in the devices that were used in these activities may have been located far from these sensors when the devices were used. It is very difficult to recognize the use of such devices with our approach because our approach employs the intensity of the magnetic field. This problem occurred with 'brush teeth' and 'take video' in house B, and 'watch TV' in house C. However, although the hand-worn sensors could not sense the high intensity magnetic field emitted by the electric toothbrush in house B, the accuracy of 'brush teeth' in house B was not very bad. When the participant in house B brushed his teeth, he controlled the toothbrush so that it brushed his front teeth, back teeth, upper teeth, and lower teeth. That is, he moved his hand to control the toothbrush and then the posture of his hand changed. In section 4.4, we mentioned that magnetic sensors are slightly affected by the earth's magnetism. When the posture of the hand changes, sensor data obtained from hand-worn sensors also change

Table 4. Confusion matrix in house A when we use sensor data of all 20 sensors. The values are percentages.

	A: talk on cellphone	B: operate cellphone	C: use smart phone	D: listen to music	E: shave	F: use hair dryer	G: brush teeth	H: vacuum	I: watch TV	J: play video game	K: listen to radio	L: use flashlight	M: take picture	N: take video
A	82.2	0.0	2.2	0.0	0.0	0.0	4.7	0.0	9.1	0.0	0.0	0.9	0.8	0.0
B	0.0	84.9	0.0	0.7	0.4	0.0	0.2	0.1	0.2	0.0	0.4	2.4	9.4	1.3
C	0.0	0.7	76.0	0.0	0.3	0.0	0.0	0.0	3.7	5.6	0.0	1.1	12.2	0.4
D	0.5	4.2	0.6	71.0	5.1	0.3	0.6	0.6	1.1	0.8	6.0	0.6	6.4	2.0
E	0.2	3.0	0.0	0.9	78.8	0.3	0.1	2.2	0.9	0.0	0.4	0.0	12.5	0.6
F	0.3	0.0	0.0	0.0	0.0	99.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3
G	0.0	0.0	0.0	0.7	0.0	0.0	95.5	0.0	1.2	0.0	0.0	0.0	0.4	2.2
H	0.0	0.8	0.0	0.1	0.0	0.0	0.0	83.3	0.0	2.2	0.1	2.6	10.6	0.3
I	0.0	0.0	2.0	0.0	0.2	0.5	0.0	0.5	78.9	0.1	1.7	0.0	15.3	0.8
J	0.0	0.2	0.1	1.1	0.1	0.0	0.0	0.1	0.2	97.7	0.0	0.0	0.5	0.0
K	0.0	2.0	1.3	4.2	2.2	0.0	0.8	1.5	4.8	0.4	73.6	0.0	9.1	0.0
L	0.0	0.2	0.0	0.0	0.0	0.0	0.0	1.8	0.8	0.2	0.0	90.7	6.3	0.0
M	0.0	0.0	0.4	2.0	10.2	0.8	0.4	0.0	3.9	1.0	1.7	1.1	77.2	1.4
N	0.0	0.1	0.0	0.1	0.0	0.1	0.0	0.0	10.9	0.0	0.5	0.6	9.1	78.7



(a) `Take picture' at house A (b) Another `take picture' at house A (c) `Brush teeth' at house B

Fig. 6. Example sensor data sequences obtained in our experiment

because the orientation of the sensors changes. Fig. 6 (c) shows sensor data sequences obtained when the participant in house B brushed his teeth. We can see that the sensor data value of R-I1 suddenly changes several times. These changes were caused by changes of hand posture. We could find such sensor data changes in other 'brush teeth' activities in house B. We consider that our method modeled the 'brush teeth' activity class by using the characteristic changes of sensor data. As above, even though the hand-worn sensors cannot sense high intensity magnetic fields emitted by electrical devices, our method may be able to recognize activities that involve characteristic changes of hand posture, e.g., walking and running in addition to tooth brushing.

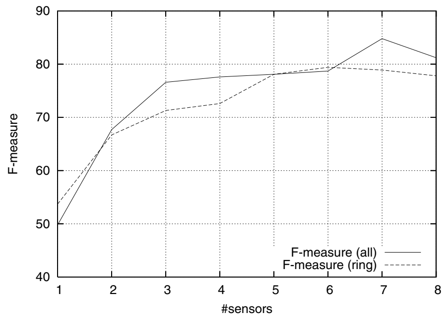
Recognition with small numbers of sensors. In the above evaluation, we confirmed that our approach could achieve very high accuracy activity recognition with 20 hand-worn magnetic sensors. However, it is impractical to wear a large number of sensors on the hands continuously in our usual daily environment. To reduce the number of required sensors, we investigated which magnetic sensors on which parts of the hand were effective for recognizing the use of electrical devices by employing our obtained data sets. That is, we find sensors that help us to recognize the use of electrical devices. More specifically, we find extracted features that help us to discriminate the feature vectors of activity classes. Once we obtain discriminative features, we then also obtain effective sensors from the features. For example, when we find that the energy feature of the L-M2 sensor data assists us to recognize many activities, we can say that the L-M2 sensor is important.

The problem of finding a discriminative feature is called the feature selection problem. Several studies have found discriminative features by employing the concept of information gain. The information gain of a feature increases the better the feature classifies the instances. For more detail, see [22]. In our case, an instance corresponds to a feature vector at a time slice. By using the information gain, we obtained the ranking of 20 magnetic sensors on hands by the contribution to the classification of instances. We employ the simple ranking method described below. (1) We compute each feature's information gain when distinguishing feature vectors of an activity class from those of other activity classes by using its feature values in the training data. This permits us to obtain the measure of the contribution, i.e., the information gain, of each feature to distinguish the activity class from other classes. We describe the information gain of the ith feature to distinguish the jth class as $gain(f_i, C_j)$. By applying this procedure to all activity classes, we can obtain the information gain of a feature for each activity class. (2) We compute the sum of the information gain of all activity classes for each feature. We regard the sum as being an overall measure of the contribution of the feature. We describe the overall measure of ith feature as $score_f(i) = \sum_j gain(f_i, C_j)$. (3) To obtain a measure of the contribution of the kth sensor, we again compute the summation of $score_f(i)$ related to the sensor. We can describe the measure of the kth sensor as $score_s(k) = \sum_{f_i \in F(k)} score_f(i)$, where $F(k)$ denotes a set of features computed from the kth sensor data. (4) We rank the 20 magnetic sensors by $score_s(k)$.

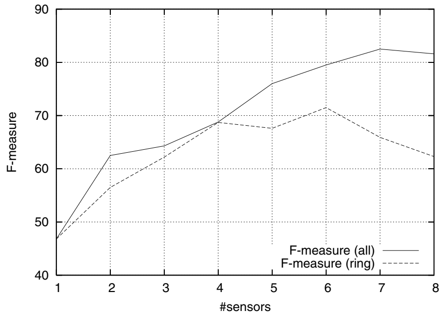
The table in Fig. 7 (a) shows the rankings of the top 8 sensors in each house computed by employing the above procedure. As described above, in the rankings, the magnetic sensors are listed in descending order of contribution to the feature vector classification. The 'all' columns in the table show the rankings of the top 8 sensors among all 20 sensors. In the rankings, we can see that the rank orders of sensors on the right are high in all three houses. This is because the participants are right-handed. They used electrical devices with their right hands in many activities, and thus the importance of the sensors on the right hand became high. Of the sensors on the right hand, the sensors on the middle finger were particularly important. This may be because the middle finger is positioned in the center of the hand. We consider that sensors in the center of the hand tend to be located nearer electrical devices held in the hand than outlying sensors such as those on the little finger. On the other hand, the 'ring'

	House A		House B		House C	
	all	ring	all	ring	all	ring
1st	R-M1	R-M2	R-T1	R-T1	R-I1	R-I2
2nd	R-M2	R-R2	R-M1	R-M2	R-M1	R-M2
3rd	R-R1	R-I2	R-M2	R-I2	R-I2	R-T1
4th	R-R2	R-T1	R-I2	L-R2	R-M2	R-L2
5th	R-I2	L-I2	R-P1	L-L2	R-R1	L-T1
6th	R-T1	L-M2	L-P1	L-I2	R-P1	L-I2
7th	L-I1	L-T1	R-I1	L-M2	R-L1	L-R2
8th	L-M1	R-L2	L-R2	R-R2	R-T1	L-L2

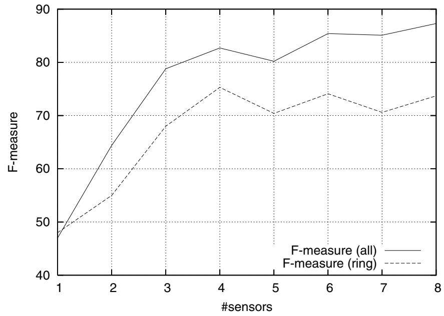
(a) Ranks of sensors



(b) House A



(c) House B



(d) House C

Fig. 7. (a): Rankings of magnetic sensors in each house. The table shows the rankings of the top-8 sensors of all 20 sensors and the rankings of just 10 sensors on hand positions where common forms of finger rings are attached. (b), (c), (d): Transitions of the overall F-measure when we increase # sensors in descending order of the rankings in each house. ($F\text{-}measure = \frac{2 \cdot precision \cdot recall}{precision + recall}$.)

columns in the table in Fig. 7 (a) show the top 8 sensors in the ranking of just 10 sensors at hand positions where common forms of finger rings are worn, i.e., (L|R)-T1, (L|R)-I2, (L|R)-M2, (L|R)-R2, and (L|R)-L2. That is, we assume that magnetic sensors are embedded in finger ring-form devices. This is a practical condition. In these rankings, the sensors on the right hand were also important.

Fig. 7 (b), (c), and (d) show the transitions of the overall F-measure when we increased the number of sensors in descending order of the rankings in Fig. 7 (a). For example, when the number of sensors is 2 in the line chart of house A, the y-axis value of the 'F-measure (all)' line indicates the recognition accuracy computed by using sensor data obtained from only the R-M1 and R-M2 sensors, which are the top 2 sensors in house A. We use these charts to investigate the required number of sensors. From the charts, we find that we can achieve high accuracies equaling those obtained with 20 sensors with only about seven sensors. The accuracies were still high (over 75%) with only three sensors in houses A and C. The right part of Table 3 shows the detailed recognition accuracies when we used the sensor data of the top 4 sensors. Even though we used only four sensors, the average and overall accuracies decreased by only about 5 to 10% compared with those obtained when using all 20 sensors. As shown in the charts in Fig. 7 (b), (c), and (d), when we limit the sensor positions to common finger ring positions, the accuracies decreased somewhat. However, with only four or five sensors, we could achieve accuracies of over 75% in houses A and C. Here, the accuracies in house B are not stable because the amount of training data may be insufficient.

The above results show that we can achieve the highly accurate recognition of the use of portable electrical devices with small numbers of magnetic sensors. Strictly speaking, the importance of the sensor positions was different in each house as shown in the table in Fig. 7 (a). However, in any environment, by simply attaching several sensors to a dominant hand, we consider that we can achieve fairly good accuracy. (In fact, by simply using the R-M1, R-M2, R-I1, and R-I2 sensors, we could achieve 76.8, 67.6, and 82.7% overall F-measures in houses A, B, and C, respectively.) In particular, attaching sensors to the middle fingers may significantly improve the accuracy.

7 Conclusion

In this paper, we proposed a new method that recognizes the use of portable electrical devices with hand-worn magnetic sensors. In modern societies, we live with large numbers of electrical devices. Many studies have attempted to detect/recognize the use of electrical devices because this would allow us to recognize various high-level activities. The method proposed in this paper can recognize the use of portable electrical devices that are not connected to the home infrastructure without using any sensors attached to the devices in both indoor and outdoor environments. In this paper, we evaluated our recognition method in real environments and achieved very high accuracies. We also confirmed experimentally that we could achieve highly accurate recognition with small numbers of hand-worn sensors. As part of our future work, we will attempt to recognize simple low-level activities that do not involve the use of electrical devices, such as walking and running, with hand-worn magnetic sensors because we found in our experiment that our method may be able to recognize activities involving characteristic hand movements. This is because magnetic sensors are affected by the earth's magnetism, and so the hand-worn sensors can capture characteristic hand movements. This permits us to recognize both the use of electrical devices and low-level activities with only hand-worn magnetic sensors.

References

1. Bao, L., Intille, S.S.: Activity recognition from user-annotated acceleration data. In: Ferscha, A., Mattern, F. (eds.) PERVASIVE 2004. LNCS, vol. 3001, pp. 1–17. Springer, Heidelberg (2004)
2. Blum, M., Pentland, A.S., Troster, G.: Insense: Interest-based life logging. IEEE Multimedia 13(4), 40–48 (2006)
3. Cohn, G., Gupta, S., Froehlich, J., Larson, E., Patel, S.N.: GasSense: Appliance-level, single-point sensing of gas activity in the home. In: Floréen, P., Krüger, A., Spasojevic, M. (eds.) Pervasive Computing. LNCS, vol. 6030, pp. 265–282. Springer, Heidelberg (2010)

4. The Swedish Confederation for Professional Employees, http://www.tco.se/
5. Froehlich, J.E., Larson, E., Campbell, T., Haggerty, C., Fogarty, J., Patel, S.N.: Hydrosense: Infrastructure-mediated single-point sensing of whole-home water activity. In: Ubicomp 2009, pp. 235–244 (2009)
6. ICNIRP Guidelines. Guidelines for limiting exposure to timevarying electric, magnetic, and electromagnetic fields (up to 300 GHz). Health Physics 74(4), 494–522 (1998)
7. Huynh, T., Schiele, B.: Towards less supervision in activity recognition from wearable sensors. In: Int'l Symp. on Wearable Computers, pp. 3–10 (2006)
8. Kim, Y., Schmid, T., Charbiwala, Z.M., Srivastava, M.B.: ViridiScope: design and implementation of a fine grained power monitoring system for homes. In: Ubicomp 2009, pp. 245–254 (2009)
9. Lenz, J.E.: A review of magnetic sensors. Proceedings of the IEEE 78(6), 973–989 (1990)
10. Lester, J., Choudhury, T., Borriello, G.: A practical approach to recognizing physical activities. In: Fishkin, K.P., Schiele, B., Nixon, P., Quigley, A. (eds.) PERVASIVE 2006. LNCS, vol. 3968, pp. 1–16. Springer, Heidelberg (2006)
11. Lester, J., Choudhury, T., Kern, N., Borriello, G., Hannaford, B.: A hybrid discriminative/generative approach for modeling human activities. In: IJCAI 2005, pp. 766–772 (2005)
12. Lukowicz, P., Ward, J., Junker, H., Stäger, M., Tröster, G., Atrash, A., Starner, T.: Recognizing workshop activity using body worn microphones and accelerometers. In: Ferscha, A., Mattern, F. (eds.) PERVASIVE 2004. LNCS, vol. 3001, pp. 18–32. Springer, Heidelberg (2004)
13. Maekawa, T., Yanagisawa, Y., Kishino, Y., Ishiguro, K., Kamei, K., Sakurai, Y., Okadome, T.: Object-based activity recognition with heterogeneous sensors on wrist. In: Floréen, P., Krüger, A., Spasojevic, M. (eds.) Pervasive Computing. LNCS, vol. 6030, pp. 246–264. Springer, Heidelberg (2010)
14. Maekawa, T., Yanagisawa, Y., Kishino, Y., Kamei, K., Sakurai, Y., Okadome, T.: Object-blog system for environment-generated content. IEEE Pervasive Computing 7(4), 20–27 (2008)
15. Mayol, W.W., Murray, D.W.: Wearable hand activity recognition for event summarization. In: Int'l Symp. on Wearable Computers, pp. 122–129 (2005)
16. Patel, S.N., Robertson, T., Kientz, J.A., Reynolds, M.S., Abowd, G.D.: At the flick of a switch: Detecting and classifying unique electrical events on the residential power line. In: Krumm, J., Abowd, G.D., Seneviratne, A., Strang, T. (eds.) UbiComp 2007. LNCS, vol. 4717, pp. 271–288. Springer, Heidelberg (2007)
17. Philipose, M., Fishkin, K.P., Perkowitz, M.: Inferring activities from interactions with objects. IEEE Pervasive Computing 3(4), 50–57 (2004)
18. Ravi, N., Dandekar, N., Mysore, P., Littman, M.L.: Activity recognition from accelerometer data. In: IAAI 2005, vol. 20, pp. 1541–1546 (2005)
19. Tapia, E.M., Intille, S.S., Larson, K.: Activity recognition in the home using simple and ubiquitous sensors. In: Ferscha, A., Mattern, F. (eds.) PERVASIVE 2004. LNCS, vol. 3001, pp. 158–175. Springer, Heidelberg (2004)
20. van Kasteren, T., Noulas, A., Englebienne, G., Krose, B.: Accurate activity recognition in a home setting. In: Ubicomp 2008, pp. 1–9 (2008)
21. Welch, L.R.: Hidden markov models and the baum-welch algorithm. IEEE Information Theory Society Newsletter 53(4) (2003)
22. Witten, I.H., Frank, E.: Data Mining: Practical machine learning tools and techniques. Morgan Kaufmann, San Francisco (2004)