Sharing Training Data among Different Activity Classes

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UbiComp'13 Adjunct, September 8–12, 2013, Zurich, Switzerland.
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ACM 978-1-4503-2215-7/13/09...$15.00.

http://dx.doi.org/10.1145/2494091.2495991

Abstract
We propose a new activity recognition system for the daily activity by using a generative/discriminative hybrid model that can learn an activity classification model with small quantities of training data by sharing training data among different activity classes. Many existing activity recognition studies employ a supervised machine learning approach and thus require an end user's labeled training data, this approach places a large burden on the user. In this study, we assume that a user wears sensors (accelerometers) on several parts of the body such as the wrist, waist, and thigh, and by sharing sensor data obtained from only selected accelerometers (e.g., only waist and thigh sensors) among two different activity classes based on a sensor data similarity measure, the quantities of training data can be increased. For further reduction of the burden on the user, we also adopt semi-supervised approach to train the classifier in our study.

Author Keywords
Activity recognition, Wearable sensors, Semi-supervised learning

ACM Classification Keywords
I.5.2 [PATTERN RECOGNITION]: Design Methodology.

General Terms

Algorithms, Design

Introduction

In order to address the activity recognition task, we construct an activity classification model that classifies a sensor data segment in an appropriate activity class. Many studies employ a supervised machine learning approach to construct (train) the classification model. However, because the supervised machine learning approach requires large quantities of training data labeled by an end user, this approach places a large burden on the user. So, constructing a classification model with small quantities of training data is one of the effective methods in reducing the end user's burden. However, it is difficult to correctly estimate parameters of the model with small quantities of training data. In this paper, we propose a new activity recognition model that can achieve the highly accurate recognition of activities with small quantities of training data by sharing training data among different activity classes. That is, when we train an activity class A_1, we use training data related to another activity class A_2 in addition to those of A_1 and vice versa. However, in a classification task, simply sharing training data among different two classes will only decrease the classification accuracy. The sharing makes it impossible for us to distinguish the activity classes because we train the two classes by using the same training data.

In our proposed approach, we assume that a user wears accelerometers on several parts of the body such as the hands, waist, and thigh, and we share sensor data obtained from only selected accelerometers (e.g., only waist and thigh sensors) among two different activity classes. Here, we select an accelerometer that produces similar sensor data related to the two activity classes because the sensor data are not useful for distinguishing the two classes. Assume that we try to recognize two activity classes: 'walk' and 'ascend stairs' activities. Also, assume that right hand sensor data related to the two activities are similar and right thigh sensor data are dissimilar. When we learn activity models of the two activities, we share training data obtained from only the right hand accelerometer among the two activity classes. To achieve such training data sharing, we design a new activity classification model. In addition, we incorporate semi-supervised learning approach to achieve further reduction of user's burden.

Related Work

Since many activity recognition approaches rely on machine learning techniques that require labeled training data, many studies have tried to reduce the effort needed to prepare the labeled training data which is required of an end user. For example, Stikic et al. [13] employ semi-supervised machine learning techniques such as self-training and co-training to reduce required quantity of labeled training data. Stikic et al. [13] also employ active learning techniques to reduce labeling costs and achieve highly accurate recognition. The recognition system proposed in [13] locates a sensor data segment that it finds hard to recognize, and then asks the end user to input the correct answer for the segment. Forster et al. [4] implement an adaptive gesture recognition system that employs brain decoded signals to detect recognition errors automatically, and re-trains the recognition model according to the detected errors. Huynh et al. [5] combine generative models and discriminative classifiers to reduce labeling effort. More specifically, they first obtain clusters of activities by employing a generative approach without any labels and then improve the recognition results of the generative models by employing a discriminative approach with small numbers of labels. On the other hand, we propose a new activity recognition framework that enables us to share training data obtained from particular accelerometers among different activity classes.

Several activity recognition studies attempt to construct an end user's activity model by employing other users' labeled data prepared in advance. Ohmura et al. [12] employ adaptation techniques such as maximum-likelihood linear regression (MLLR) and maximum a posteriori (MAP) to adapt user-independent activity models to an end user based on small quantities of end user sensor data. Krassnig et al. [8] model the activities of an end user simply by using labeled sensor data from other users of the same gender as the end user. Maekawa et al. [10] employ information about an end user's physical characteristics to automatically select training data obtained from other users that may be similar to the sensor data of the end user. Also, Lane et al. [9] finds appropriate training data obtained from other users by employing the similarities of physical characteristics, behavioral patterns, and sensor data between users. The above approaches that employ other users' data prepared in advance work based on the following assumptions.
(1) An end user uses the same type of accelerometer product as other users use. Also, the end user attaches accelerometers to the same positions as the other users attach. If not, an end user cannot obtain similar sensor data to those of the other users.
(2) The end user does not perform activities that are not included in training data obtained from other users. In other words, the existing approaches can recognize only activity classes that are included in training data from other users. That is, the approaches cannot recognize new activity classes that the end user intends to capture.
(3) The end user's physical characteristics (e.g., gender, height, and dominant hand) are similar to some of other users' characteristics. If not, sensor data obtained from the end user are very different from those of other users. When an end user collects training data by herself, she may not suffer from the above problems. So, we indicate that it is valuable to train an activity classification model with small quantities of training data obtained from an end user.

Proposed Method

We explain our method that permits us to model activities with sharing training data among different activity classes. The training data sharing gives us the following advantages.
(1) As we have mentioned before, when the different activities share training data of similar parts of the body, thus the quantities of the training data will be enhanced without adding new training data.
(2) Our approach also has another advantage that enables us to cover the wider variety of situations in the activities with less training data. For example, assume that the leg sensor data related to 'use PC' and 'write in notebook' are shared, and the two activities are acted while sitting. So the possible action of leg may be 'leg-crossing' or 'not-leg-crossing.' When the leg sensor's training data of 'write in notebook' contain the situation of leg-crossing while those of 'use PC' do not, and we share each other's leg sensor data, so the situations of leg-crossing in using PC are also covered. Thus, we can expand the coverage of the training data.

Basic idea

To achieve such training data sharing, we design a new activity classification model by taking the following problems into consideration.
-There are two reasons why it is difficult for the existing activity recognition systems to share sensor data of

particular sensors among different activity classes. (They are detailed in section *Related Work*.) (1) The existing activity recognition systems extract features from all sensors and then construct a feature vector concatenating the *all* extracted features. So, it is difficult for the systems to share training data related to particular sensors. (2) The systems learn a discriminative classifier by employing the constructed feature vectors. However, simply sharing training data among different two activity classes will only decrease the classification accuracy. In this study, we design a new activity recognition framework by employing a hybrid generative/discriminative approach. It is based on employing a generative model to learn a probability density function of sensor data obtained from each sensor (each part of the body) for each activity class. That is, we construct a generative model that shows movements of a part of the body for each activity class. For example, we construct a generative model of right hand sensor data related to the 'walk' activity class. By doing so, when we model movements of a part of the body for each activity class, we can train the model by using training data related to the other activity classes obtained from the same part of the body. With a probability density function of a generative model, the likelihood of the generative model for an unlabeled sensor data segment can be computed, e.g., the likelihood of the right hand model related to the 'walk' activity for an unlabeled sensor data segment. That is, we can compute a 'score' with which the sensor data segment is produced from the right hand model related to the 'walk' activity. After that, we learn a discriminative classifier that identifies activities by combining the outputs from the generative models prepared for the sensors (parts of the body) and activities. By doing so, we can recognize activities with sharing training data obtained from only particular sensors. As above, we attempt to share training data among different activity classes by employing the generative/discriminative hybrid model.

-In this study, we attempt to increase the quantities of training data that are used to estimate model parameters by sharing training data among different activity classes. However, by sharing training data among different classes, we may not be able to find clues as regards identifying the classes. For example, when right hand training data are shared among the 'walk' , 'ascend stairs' and 'descend stairs' activities, the above three activities cannot be distinguished by just using right hand sensor data. (This is because we learn the activities based on the assumption that right hand movements of the two activities are identical.) So, it is important to adequately select a part of the body whose sensor data to be shared. In this study, we propose three methods that select the part of the body, and evaluate the methods with real sensor data.

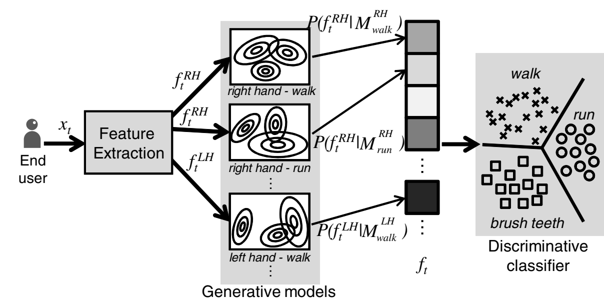

Figure 1: Architecture of our activity recognition method.

Overview

We attempt to share training data among different activity classes by employing a generative/discriminative hybrid model. Fig. 1 shows the overview of our method. Our proposed architecture is a two-tiered system. The first tier consists of generative models. Each generative model models movements of a part of the body for each activity class. The second tier includes a discriminative classifier that identifies activities by combining the outputs from the generative models.

Feature extraction

We first compute a feature vector, which is the input of the generative models, for each sliding time window x_t at time t. We extract features based on the FFT components of 64 sample time windows. As features, we use the mean, energy, and FFT components as described below. The mean can characterize the posture of parts of the body. The energy feature is calculated by summing the magnitudes of the squared discrete FFT components. Note that the DC component of the FFT coefficients is excluded from this summation. The energy can be used to distinguish low intensity activities such as standing from high intensity activities such as walking [14, 1, 11]. The FFT components allow us to distinguish between repetitive motions with similar energy values. We construct a feature vector that concatenates the above features for each part of the body at time t such as f_t^{RH} (RH: right hand) and f_t^{LH} (LH: left hand) as shown in Fig. 1.

Finding sensors to be shared

In the training phase, we find an accelerometer (a part of the body) that produces similar sensor data related to two different activity classes. We propose the following three approaches that compute sensor data similarity between different activities and investigate them in the evaluation section. Basically, we compute the dissimilarity of sensor data (training data) obtained from a same part of the body between two different activity classes, and we share the training data among the classes when the dissimilarity is small. The sharing will be done by comparing all pairs of activities.

Sensor data dissimilarity with GMMs

We compute the dissimilarity between two different activities related to sensor data from a part of the body (an accelerometer). We should compare sensor data segments of different lengths between different two activities. In this method, we learn the probability density function (PDF) related to a part of the body for each activity class by employing a Gaussian mixture model (GMM), e.g., GMM for the right hand related to the 'walk' activity. We obtain feature vectors of a part of the body corresponding to an activity class, and estimate parameters of the GMM by employing expectation maximization (EM) [3]. Then we compute the distance (dissimilarity) between the two GMMs. We can employ the Kullback-Leibler divergence to compute the distance between two Gaussians. However, it does not yield an analytic closed-form expression for GMMs.

In this study, we employ the Cauchy-Schwarz PDF divergence measure that yields an analytic closed-form expression for GMMs [7]. Let $M_1(f)$ and $M_2(f)$ denote two Gaussian mixtures: $M_1(f) = \sum_{n=1}^{N} \pi_n \mathcal{N}(f, \mu_n, \Sigma_n)$ and $M_2(f) = \sum_{m=1}^{M} \pi_m \mathcal{N}(f, \mu_m, \Sigma_m)$, where π_n, μ_n, and Σ_n are the mixture weight, the mean vector, and the covariance matrix of nth multivariate Gaussian distribution, respectively. The Cauchy-Schwarz PDF divergence measure [6] is given by: $D_{CS}(M_1, M_2) = -\log(\frac{\int M_1(x)M_2(x)dx}{\int M_1(x)^2 dx \int M_2(x)^2 dx})$. For more detail, see [7]. With this divergence, we can compute the dissimilarity (distance) between two different activities related to a part of the body.

Information gain of sensor data features
The above GMM-based method simply computes the dissimilarity of movements of a part of the body between two different activities, and then shares training data related to the part among the two activities. On the other hand, the main goal of this study is to recognize daily activities (i.e., classify a sensor data segment into an appropriate activity class). Therefore, we suggest that we should not share training data (feature vectors) from a sensor whose features are useful to distinguish the activities. Thus, this method employs information gain of a feature. The information gain is usually used to find distinguishable attributes (features) of instances. The information gain of an attribute increases the better the attribute classifies the instances. For more detail, see [15]. We then compute the sum of the information gain of features related to a sensor (a part of the body) according to two activity classes. The sum corresponds to the distance between the two activity classes related to the sensor.

Classification accuracy of sensor data features
This method employs a straightforward approach. When we can accurately classify training data obtained from a part of the body related to two activity classes, we should not share the training data of the sensor among the classes. This is because the training data help to distinguish the two classes. So, we compute the classification accuracy of the training data with a cross validation approach. Here, we simply employ a decision stump as a classifier. When the accuracy is low, we can share the training data since the data are not useful for distinguishing the activities. The accuracy corresponds to the distance between the two activity classes related to the sensor.

Training generative model
We employ a Gaussian mixture model to learn a probability density function of sensor data obtained from each sensor (each part of the body) for each activity class. For example, we construct a GMM for right hand sensor data related to the 'walk' activity class M^{RH}_{walk} as shown in Fig. 1. Here, when we model movements of a part of the body for each activity class, we train the model with sharing training data from the part of the body among activity classes whose distances computed by the above methods are smaller than a certain threshold. Note that, when we share training data from all parts of the body among two activity classes, we cannot distinguish the two activities. So, when a user wears N sensors, we share training data from $N-1$ sensors at most among two different activity classes.

Training discriminative model
With the GMM M^{RH}_{walk}, for example, we can compute the likelihood of M^{RH}_{walk} for f^{RH}_t as follows: $p(f^{RH}_t|M^{RH}_{walk}) = \sum_i \pi_i \mathcal{N}(f^{RH}_t, \mu_i, \Sigma_i)$, where π_i is the mixture weight of the ith Gaussian in M^{RH}_{walk}, and μ_i and Σ_i show the mean vector and covariance matrix of the Gaussian, respectively. We construct a feature vector f_t concatenating the likelihood of the models as shown in Fig. 1, and then train a discriminative model by using the feature vectors with labels. The SVM is employed as the discriminative model.

Semi-supervised learning
To further reduce the burden on the end user, we incorporate a semi-supervised learning approach into our recognition system. The semi-supervised learning method is based on the idea of being able to prepare large quantities of unlabeled data compared to the data with labels, and to train the model by utilizing both the

unlabeled data and labeled data. Because, data used in our study are obtained from daily activities, and obtaining unlabeled activity data is relatively easy. In this study, we employ the "Self-training"[2] method to perform the semi-supervised learning. The self-training is a learning method consisting of three steps described as follows. Step 1: Learning a activity model according to the procedure indicated from section *Feature extraction* to section *Classification accuracy of sensor data features* by using the labeled data. Step 2: Recognizing the unlabeled data (classifying a feature vector into) by using the learned classification model. Step 3: Learning a new activity model according to the procedure indicated from section *Feature extraction* to section *Classification accuracy of sensor data features* again by using the data that have been labeled at step 2, and the data already have been labeled.

Evaluation

Data set

We collected 48 hours of sensor data from 20 paid experimental participants. We collected sensor data with wireless sensor nodes equipped with three-axis acceleration sensors and sampling rates of 30 Hz. Each participant wore the sensor nodes on the wrists of both wrist, the waist, and the right thigh. Here, the most natural data would be acquired from the normal daily lives of the participants. However, obtaining sufficient samples of such data with correct annotations from large numbers of participants is very costly. Therefore, we collected the sensor data by using a semi-naturalistic collection protocol [1] that permits greater variability in participant behavior than laboratory data. In the protocol, the participants perform a random sequence of activities following instructions on a worksheet. Each participant completed ten sessions in total in our experimental environment. To annotate the collected data, a companion recorded the participants with a web camera during the experiment. The web camera was connected to a mobile computer carried by the companion. The sensor data from the four sensor nodes attached to the participant were also sent to the mobile computer. We describe in detail how several of the activities in Table 1 were performed. In activity J, we instructed the participants to enter several sentences on the computer keyboard. In activities K and L, we instructed the participants to write some sentences in a notebook and on a whiteboard, respectively. In activity M, each participant played pingpong with a worker in our laboratory. We obtained a total of 4960 labeled activities from the 20 participants.

A	stand	H	brush teeth
B	walk	I	wash dishes
C	run	J	use PC
D	sit	K	draw on whiteboard
E	ascend stairs	L	write in notebook
F	descend stairs	M	play pingpong
G	bicycle	N	vacuum

Table 1: Activities performed in our experiment.

Evaluation methodology

With our approach, we attempt to recognize activities with small quantities of training data. So, we evaluated our recognition approach with 'leave-n-sessions-out' cross validation, and changed n to evaluate the approach. We regarded n-sessions' data as test data and the remaining sessions' sensor data as training data, and we computed the classification accuracy of the test data. In this evaluation, we computed the classification performance with randomly selected n sessions and iterated the test ten times. (When n is 1, for example, we regard randomly selected one session as test data and compute the classification performance. We iterate it ten times.) We

evaluated the recognition (classification) performance of our method by using its error rate. The error rate is described as
$error\ rate = 1.0 - F\text{-}measure = 1.0 - \frac{2 \cdot precision \cdot recall}{precision + recall}$.
Precision and recall were calculated based on the results for the estimated class at each time slice. The smaller error rate gave a better classification performance. To validate the effectiveness of our proposed approach, we tested the following three methods.
$Naive$: This method does not perform the training data sharing. This method simply trains a discriminative classifier with feature vectors extracted from all body-worn sensors.
CS: This method performs the training data sharing with the Cauchy-Schwarz PDF divergence as described in section *Sensor data dissimilarity with GMMs*.
$Gain$: This method performs the training data sharing with the information gain as described in section *Information gain of sensor data feature*.
Acc: This method performs the training data sharing with the classification accuracies as described in section *Classification accuracy of sensor data features*.

	$Naive$	CS (3)	$Gain$ (4)	Acc (0.6)
stand	24.8	24.3	26.3	28.5
walk	8.8	7.8	8.6	8.4
run	11.7	6.1	6.6	6.8
sit	37.3	42.6	45.9	47.4
ascend stairs	35.3	35.6	45.1	52.0
descend stairs	31.4	49.5	46.5	45.9
bicycle	20.5	17.1	21.5	22.6
brush teeth	50.4	37.6	43.6	42.8
wash dishes	31.3	27.5	30.2	30.9
use PC	41.7	41.6	46.2	47.6
draw on whiteboard	41.7	24.5	30.8	29.3
write in notebook	48.1	47.4	57.5	58.3
play pingpong	39.6	38.9	39.3	40.2
vacuum	31.2	24.5	22.0	22.1
overall	28.4	24.5	26.9	27.2

Table 2: Error rates of recognition methods in percentages when # of training sessions was 1.

Results
Performance
Fig. 2 shows the error rate transition of the $Naive$ method described in section *Evaluation methodology* when we changed n (# of training sessions). As n increases, the error rate decreases. Because we could use sufficient quantities of training data when n was large, $Naive$ could correctly estimate model parameters. Fig. 2 also shows the error rate transitions of our three methods described in section *Evaluation methodology*. (CS: threshold was 3. $Gain$: threshold was 4. Acc: threshold was 0.6. As mentioned in section *Training generative model*, we share training data from the part of the body among activity classes whose dissimilarities computed by the above methods are smaller than a threshold. We mention the threshold later.) Also, Figs. 3, 4, and 5 show the error rate transitions of our three methods when we changed their thresholds. (The x-axis indicates the number of training sessions.) In addition, Table 2 shows the detailed recognition results of the recognition methods when n was 1.

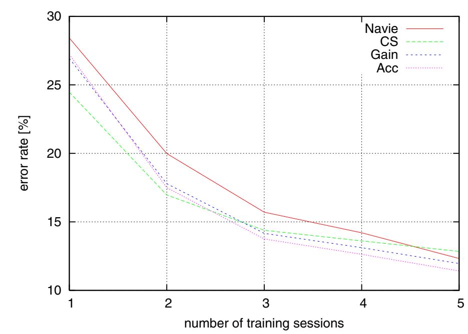

Figure 2: Transition of error rates of recognition methods.

When n was 1, our methods greatly outperformed the $Naive$ method. In particular, the CS method reduced the error rate by about 4% by sharing training data among

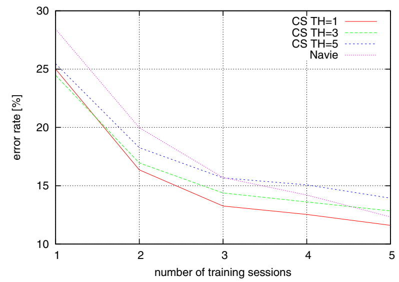

Figure 3: Transitions of error rates of CS method.

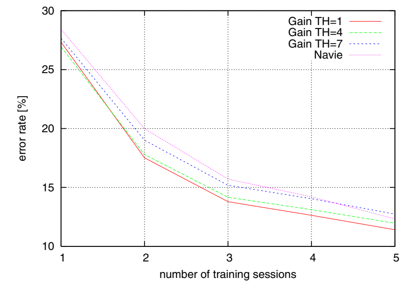

Figure 4: Transitions of error rates of $Gain$ method.

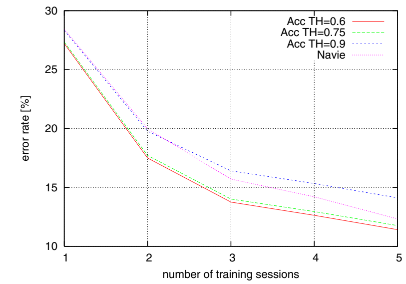

Figure 5: Transitions of error rates of Acc method.

different activity classes. That is, CS could reduce the error rate by about 4% without using any additional training data when we use only small quantities of training data. We achieved a 13.7% error reduction rate compared with the naive method ($\frac{28.4-24.5}{28.4} = 13.7\%$). On the other hand, when n was larger than 1, the error rate differences between $Naive$ and our methods became smaller. Because we used sufficient quantities of training data, $Naive$ could correctly estimate model parameters. As above, we confirmed that our methods can achieve high recognition accuracies when we employ only small quantities of training data.

Shared sensors

We investigate the results related to our methods in detail. We focus on Figs. 3, 4, and 5. When the threshold is large, our methods share training data among large numbers of activities. So, we can not be able to find clues as regards identifying the shared activities. On the other hand, when the threshold is small, our methods share training data among small numbers of activities. So, our method cannot correctly estimate model parameters. For example, Figs. 6, 7 and 8 illustrate how much training data were shared among different activity classes. (Averages over 20 participants when n was 1) The darker cell indicates that much more training data were shared among its corresponding activity classes. As shown in Fig. 6, much training data were shared between the 'brush teeth' and 'draw on whiteboard' activities. When n was 1, the error rate of $CS:3$ was the best. This may be because $CS:3$ shared adequate quantities of training data.

[Results of CS]

Here we use CS (TH: 3) as an example to draw the following analysis. First we focus on the activities from the 'bicycle' to 'vacuum,' large quantities of training data were shared among them, especially the waist sensing data appeared to be shared very frequently. As in this set of activity, waist movement is not very intense or is static, so the waist sensor data were widely shared. As shown in Table 2, the average error rate of the 'bicycle' to 'vacuum' activities decreased 5.7% compared with the naive method. In addition, the 'stand' activity and the activities having standing feature ('brush teeth,' 'wash dishes,' and

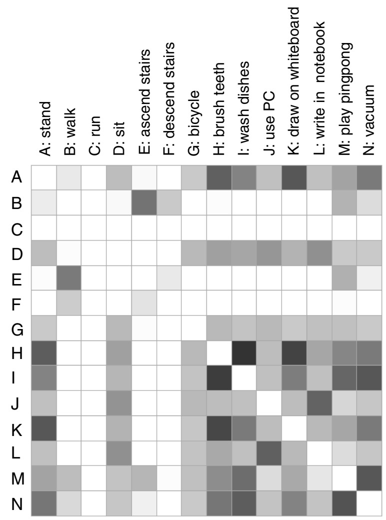

Figure 6: Matrix that illustrates how much training data were shared among different activity classes (CS: 3).

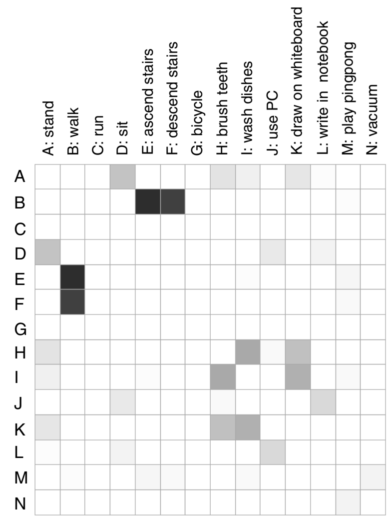

Figure 7: Matrix that illustrates how much training data were shared among different activity classes ($Gain$: 4).

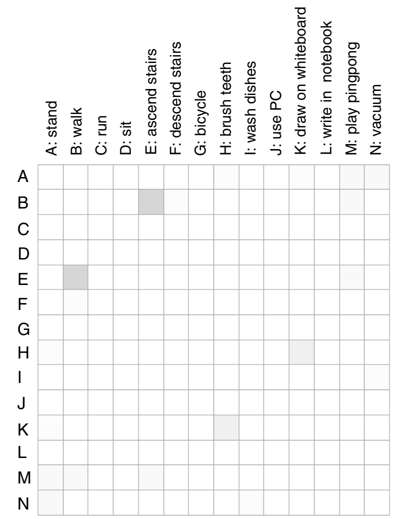

Figure 8: Matrix that illustrates how much training data were shared among different activity classes (Acc: 0.6).

'draw on whiteboard') shared each other's large quantities of training data. This situation indicates that our method worked as we wished. As shown in Table 2, the average error rate of these four activities ('stand,' 'brush teeth,' 'wash dishes,' and 'draw on whiteboard') was 8.6% smaller than that of the naive method. Similarly, the 'sit' activity and the activity group with sitting feature ('use PC' and 'write in notebook') also shared large quantities of training data related to the waist sensor.

On the other hand, the 'run' activity did not share any training data. Because, from a practical view, the movements of the various parts of the human body in the 'run' activity are extremely strenuous, so there is no other activity similar to the activity. Although the 'run' activity did not share any training data, the error rate of this activity was relatively low.

[Results of $Gain$ and Acc]

About the $Gain$ and Acc methods, we can obtain some findings from Figs. 7, 8, 9, and 10. Figs. 9 and 10 show the transitions of error rates of $Gain$ and Acc when we changed their threshold values. ($n = 1$) As shown in Figs. 7 and 8, less training data were shared when n was 1. Note that Figs. 7 and 8 show results when $Gain$ and Acc achieved the lowest error rates as shown in Figs. 9 and 10. The following reason can explain why we obtained the results shown in the figures. First of all, we have to admit the reality that our only one-session training data are not

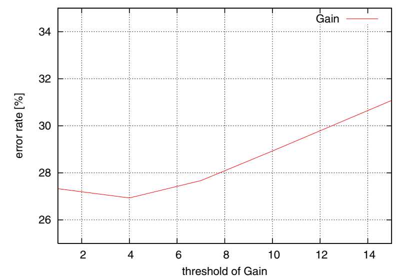

Figure 9: Transition of error rates of $Gain$ method when we changed threshold value. $(n = 1)$

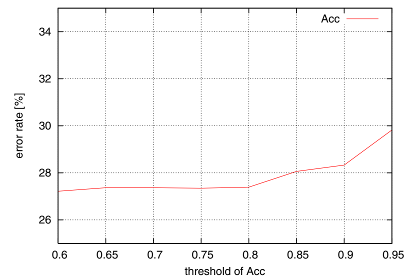

Figure 10: Transition of error rates of Acc method when we changed threshold value. $(n = 1)$

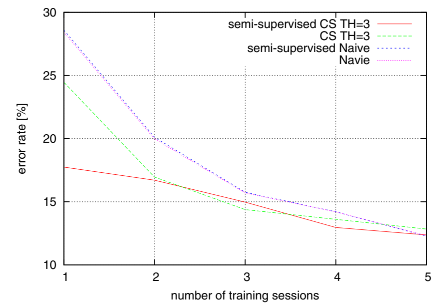

Figure 11: Transition of error rates of semi-supervised method.

able to cover very much situations of every activity. When Acc determines which sensor to be shared, it computes the classification accuracy of the training data related to each sensor with a cross validation approach. With the small quantities of one-session training data, we found that Acc could distinguish activities by using every sensor's data with very high accuracies (about 95%). So, Acc regarded that the distance related to every sensor's data among two activity classes was similar, and the method could not find which sensor should be shared. This overfitting problem caused by the small quantities of training data decreased the accuracies of Acc. We could find the similar situations as regards the $Gain$ method. Then we investigate the $Gain$ and Acc results when these methods shared training data with similar quantities as those of CS (TH: 3). In Figs. 9 and 10, we found the error rates of the $Gain$ and Acc methods increased with the increasing of their thresholds. Also, when the thresholds of $Gain$ and Acc reached 15 and 0.95, respectively, the total numbers of the shared sensors were similar with that of CS. However, their error rates were higher than that of CS. These results also indicate that $Gain$ and Acc could not adequately find sensors to be shared.

Result of semi-supervised learning method

Fig.11 shows the error rate transition of our recognition system with *semi-supervised learning* method described in section *Semi-supervised learning* when we changed n ($\#$ of training sessions). When n was 1, the error rate of the CS method with the semi-supervised learning process had a significant reduction (17.7%), and its reduction rate was 27.8% compared to the CS method without semi-supervised learning process, and 37.7% compared to the $Naive$ method.

As mentioned in section *Semi-supervised learning*, the semi-supervised learning method is effective under the situation where being able to prepare large quantities of unlabeled data compared to those of the data with labels. When n was 1, the ratio of labeled data to unlabeled data became the lowest (about 11%, one session's labeled data and nine sessions' unlabeled data), thus the effect of semi-supervised learning was signification. However, when

n is larger than 1, the effect of the semi-supervised learning became small. This may be because the ratio of labeled data to unlabeled data was large, and the semi-supervised learning did not contribute so much. For $Naive$ method, the effect of semi-supervised learning was small, so the error rate did not decreased so much. This may be because the recognition performance of $Naive$ method, which did not perform semi-supervised learning, was low. And the test data labeled by the method included many errors. The errors had negative effects on training the final generative and discriminative models .

Conclusion

In this paper we proposed a new activity recognition approach that permits us to share training data obtained from particular body-worn sensors among different activity classes. We investigated three methods by employing real sensor data obtained from twenty participants and confirmed that a method based on GMM dissimilarity achieved good accuracies. The method models sensor data from a sensor with a GMM for each activity class and computes sensor data dissimilarity between different activities by employing the Cauchy-Schwarz PDF divergence measure. We confirmed that the method could successfully compute sensor data dissimilarity between different activities. By incorporating the semi-supervised learning approach, we confirmed that it worked well on further reducing the burden of the effort on obtaining the labeled data. So, even when we have small quantities of training data, we can estimate model parameters with sufficient quantities of data by sharing training data among different activity classes.

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