Using LUPI to Improve Complex Activity Recognition

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Abstract Sensor-based activity recognition can recognize simple activities such as walking and running with high accuracy, but it is difficult to recognize complex activities such as nursing care activities and cooking activities. One solution is to use multiple sensors, which is unrealistic in real life. Recently, LUPI (Learning using Privileged Information) has been proposed, which enables training using additional information only in the training phase. In this paper, we used LUPI for improving the accuracy of complex activity recognition. In short, training is performed with multiple sensors during the training phase, and a single sensor is used during testing. We used four published datasets for evaluating our proposed method. As a result, our proposed method improves by up to 16% in F1-Score to 67% compared to the baseline method when we used random-split cross-validation of each subject.

1 Introduction

Human activity recognition (HAR) is a task of recognizing different types of activities from sensors or video data. This has become popular research in ubiquitous computing [1]. While simple activities such as walking, running, and sitting can be easy to recognize, complex activities such as nurse care activities and cooking activities are difficult to recognize [3, 6]. For this reason, a previous study proposed a

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method of HAR using multiple sensors [13]. While it is easy to collect training data with multiple sensors, they are rarely used in real-life environments. In this study, we employ LUPI(Learning using privileged information) [19] for HAR. LUPI is a learning paradigm based on the supposition that one may access additional information about the training samples, which is not available during testing. In classical supervised learning, the learner model is presented with the training tuple(x_i, y_i) and creates an optimization model f for predicting Y.

$$(x_i, y_i), \dots, (x_l, x_l), x_i \in X, y_i \in \{-1, 1\}$$

On the other hand, LUPI is presented with the training tuple(x_i, x_i^*, y_i) as shown below, and X^* can be used only during training.

$$(x_i, x_i^*, y_i), \dots, (x_l, y_l^*, x_l), x_i \in X, x_i^* \in X^*, y_i \in \{-1, 1\}$$

X^* is called privileged information(PI). In this study, we used sensors of different positions as PI. That is, we used multiple sensors during training and a single sensor during testing. The contributions of this study can be summarized as follows:

1. In sensor-based activity recognition, we show that the recognition accuracy is improved by using multiple sensors for complex activity recognition.
2. We compared the performance between LUPI and the baseline method using several situations(random-split cross-validation, leave-one-subject-out cross-validation).
3. LUPI is shown to be superior to the baseline method in a data set containing complex activities.

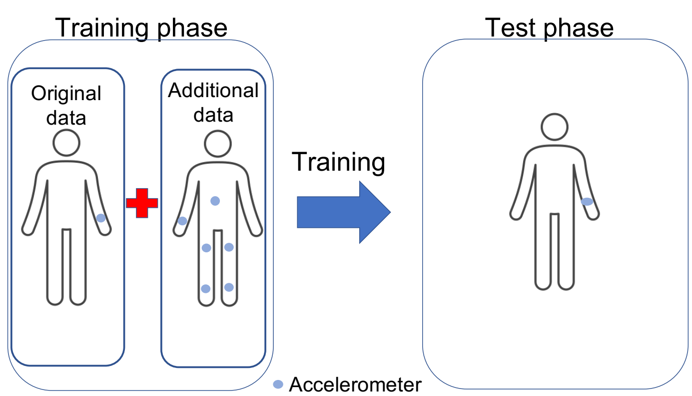


Fig. 1 Overview of the our proposed method. At the time of training, training is performed with original data (single sensor) and additional data (multiple sensors), and at the time of testing, only the original data (single sensor) is used.

2 Related work

Different learning paradigms have been used in activity recognition to improve performance in real-life settings. This section describes related work about Transfer Learning, Multi Model Learning, and Machine Learning using LUPI.

Transfer Learning: Sensor-based activity recognition affects recognition accuracy depending on sensor orientation and subject differences in the source and target domains. To address this issue, there are proposed HAR using transfer learning [15, 2]. In this study, we handle different sets of sensors in the source domain and the target domain. Then, we aim to improve the recognition accuracy of activity recognition of complex activities that are difficult to recognize with a single sensor.

Multi Modal Learning: In activity recognition using visual information, activity comprehension may fail due to occultation and appearance variation, but IMU sensors may be able to avoid them. For this reason, there are proposed HAR methods of combined multiple modalities such as sensor and visual information [7, 14]. Kong et al. [7] perform activity recognition using RGB Video, Key-points, acceleration, gyroscope, orientation, Wi-Fi, and pressure signal data. They succeeded in creating a highly robust model for different subjects, viewpoints, indoor environments, and sessions in training data and test data. In this study, different position sensors worn on the body are treated as multimodal data. In our problem setting, multiple sensors are used only during training, and only a single sensor is used during the test.

Machine Learning Using LUPI: There are many studies using LUPI [5, 20, 21, 18, 10]. Gauraha et al. [5] classify MNIST and discover drugs using SVM+ with LUPI implemented, and show that it can be recognized with higher accuracy than SVM. In addition, John et al. [10] proposed a method that makes the distribution of Dropout in CNN and RNN a function of privileged information, and showed that it can be recognized with higher accuracy in image recognition and machine translation than the baseline method. Michalis et al. [20, 21] use LUPI in the activity recognition of moving images and train the model by using voice, Pose, and attribute data in addition to the moving image only during training. These studies use visual data instead of sensor data as this study. Lago et al. [9] uses a similar problem setting for sensor-based activity recognition and improved recognition accuracy by performing feature learning using unsupervised machine learning by multiple sensors and then mapping a single sensor to the learned space. In this study, supervised learning is also used for additional information that can be used only during training.

3 Proposed Method

In this paper, we proposed a method for improved single activity recognition using LUPI. Fig.2 shows the overall proposed method. At the time of training, after feature extraction is performed from multiple sensors, the original data and additional data are trained using SVM+ [11] which is a LUPI classifier. In this study, we build the ensemble classifier that combines a LUPI classifier(SVM+) and a baseline model(SVM) trained using only a single sensor. Note that, at the time of testing, the data added during training is not used. In this section, we describe the proposed method in detail.

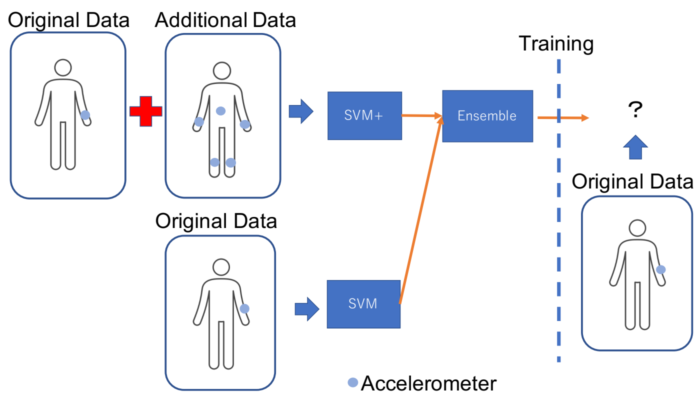


Fig. 2 The overall proposed method. We used SVM+ as a LUPI classifier. Then, we build an ensemble classifier using SVM and SVM+.

3.1 LUPI classifier(SVM Plus)

We describe difference between SVM and SVM+ [11]. Both classifiers are finding some $\omega \in X$ and $b \in R$ to built according to the following rules

$$f(x) = sgn[\langle \omega, x_i \rangle + b].$$

The SVM learning method(non-separable SVM) to find ω and b to solving the following optimization problem:

$$\min \frac{1}{2}\langle \omega, \omega \rangle + C\sum_{i=1}^{m} \xi_i$$

$$s.t.\ \ y_i[\langle \omega, x_i \rangle] \geq 1 - \xi_i,\ \ i = 1, \ldots, m.$$

where C is some regularization parameter that needs to tune. And, if the slacks ξ_i are all equal to zero then we call the set of given examples separable. On other hand, SVM+ has modified the SVM formulation as follows in order to consider privileged information X^*.

$$\min \frac{1}{2}[\langle \omega, \omega \rangle + \gamma \langle \omega^*, \omega^* \rangle] + C\sum_{i=1}^{m}[\langle \omega^*, x^* \rangle + b^*]$$

Table 1 Datasets used for the evaluation

Dataset (Activity type)	No. of sensors	No. of subjects	No. of classes	No. of windows
OPP HL [17] (complex activities)	5 IMUs	4	6	1745
Cooking dataset [8] (complex activities)	5 IMUs	7	16	1780
PAMAP [16] (simple activities)	3 IMUs	5	12	2569
OPP Locomotion [17] (simple activities)	5 IMUs	4	6	5461

$$s.t. \;\; y_i[\langle \omega, x_i \rangle + b] \geq 1 - [\langle \omega^*, x_i^* \rangle + b^*], \;\; i = 1, \ldots, m.$$
$$[\langle \omega^*, \; x_i^* \rangle + b^*] \geq 0, \;\; i = 1, \ldots, m.$$

where $\omega^* \in X^*$ and $b^* \in R$. In this problem, C and γ are hyper parameters to be tuned. The difference between SVM+ and SVM is that it uses privileged information to estimate the slack variables. Given the training tuple (x, x^*, y), SVM+ maps x to the feature space Z and x^* to a separate feature space Z^*. Then, slack variables are estimated by $\xi = \langle \omega^*, x^* \rangle + b^*$.

3.2 Ensemble Classifier

In this study, we combined SVM and SVM+ model to achieve better performance. We apply ensemble averaging [4] for the combination. For this, we first train the SVM using (x, y). Then we train the SVM+ using (x, x^*, y). Finally, we combined their model using ensemble averaging.

4 Experimental Evaluation

In this section, we describe datasets and evaluation method used for this experiment. The goal of the experiments is to compare the performance of the baseline method and the proposed method single sensor activity recognition in several situations.

4.1 Dataset

We used four datasets for evaluating our proposed method. Some important aspects of the data are summarized in Table 1. These datasets contain multiple sensor data from different placement.

4.1.1 Cooking Dataset

The Cooking Dataset [8] consists of the following main dietary activities:(i) Prepare a soup (ii) Set table. (iii) Eat meal. (iv) Clean up and put away utensils. More detailed behaviors are labeled for each dietary activity. In this study, we used the accelerometer of the IMU sensor for evaluation and we use windows of 1 second with no overlapping.

4.1.2 Opportunity Dataset

The opportunity Dataset [17] contains morning routine behaviors collected by four subjects. Activities are labeled with different types of locomotion, gestures, and high-level activities. In this study, we used high-level activities (OPP HL), which include complex activities such as Relaxing, Coffee (prepare and drink), Sandwich (prepare and eat), Early-morning (check objects in the room), and cleanup, and locomotion activities (OPP Loc) which include Stand, Walk, Sit, and Lie. As with the Cooking Dataset, the accelerometer of the IMU sensor was used for this data set as well. we used a 1-second time window for simple activities and a 10-second time window for complex activities.

4.1.3 PAMAP Dataset

The Physical Activity Monitoring Dataset [16] is a benchmark data set for monitoring physical activities. This dataset contains the activities of lie, sit, stand, walk, run, cycle, Nordic walk, iron, vacuum clean, rope jump, ascend, and descend stairs. Also, not all subjects performed all activities, so some subjects were not included in the evaluation data in this study. We also used a 5 second time window for this dataset.

4.2 Implementation and Evaluation Metrics

For the implementation, we used Python and Scikit-Learn. And we extracted max, min, average, and standard deviation of each segment for each axis. For evaluation protocol, we used a random-split cross-validation(each subject and entire data) and leave-one-subject-out cross-validation (user-independent models). As evaluation metrics, we used F1-Score to compare the performance between our proposed method and the baseline method.

4.3 Result

We present the results of the evaluation. We first show the results of comparing activity recognition performance between a single sensor and multiple sensors (Section 4.3.1). Then, we show results of our proposed method using three cross-validations namely random-split cross-validation using each subject (Section 4.3.2), random-split cross-validation using entire dataset (Section 4.3.3), and leave-one-subject-out cross-validation (Section 4.3.4).

4.3.1 Measuring The Gap between Single-Sensor and Multi-Sensor Activity Recognition Performance

Fig.3 and 4 show the results of comparing the recognition accuracy of activity recognition using a single sensor and the accuracy using multiple sensors for the four datasets. We used SVM after the feature extraction, use Leave-one-subject-out cross-validation for evaluation. As we can see, recognition accuracy is higher when multiple sensors are used in most cases. Especially in the case of complex activities of the Cooking dataset and Opportunity dataset (Fig.4(a) and 4(b)), it can be seen that the recognition accuracy is relatively high when using multiple sensors. This experiment validates the hypothesis that using multiple sensors improves the accuracy of activity recognition. Therefore, multiple sensors can be used as additional information during training.

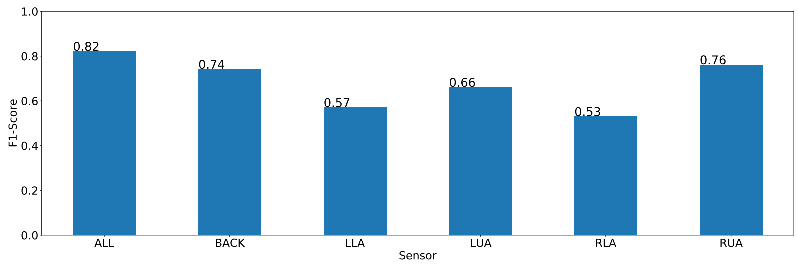
4.3.2 Validation Results Using Additional Information During Training (Random-Split Cross-Validation of Each Subject)

Fig.5 shows the results showing the average value of F1-score using random-split cross-validation of each subject. Since the number of labels for one subject was small and it was impossible to properly divide it into training data and test data, the cooking dataset was excluded from this validation.

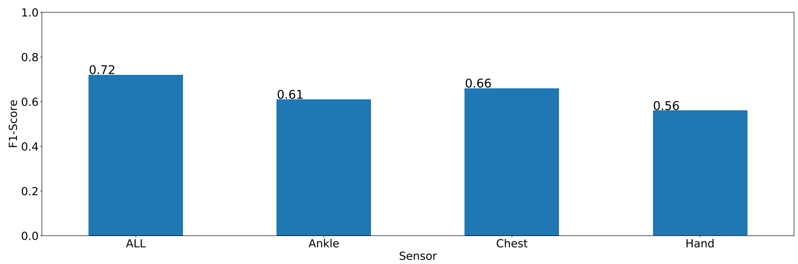
Fig.5(a) shows the results using the PAMAP dataset. This dataset can use 5 subjects and 3 IMU sensors. Therefore, we validated 15 cases combinations of subjects and sensors in total. From the figure, it can be seen that the average value of F1-Score is improved compared to the baseline method in all cases.

Fig.5(b) shows the validation results using simple activities data set in the Opportunity data set. This dataset can use 4 subjects and 5 IMU sensors. Therefore, we validated 20 cases combinations of subjects and sensors in total. From the figure, it can be seen that the average value of F1-Score is improved in 2 out of 5 cases compared to the baseline method.

Fig.5(c) shows the validation results when using the complex activities dataset of the Opportunity dataset. This dataset can use 4 subjects and 5 IMU sensors. Therefore, we validated 20 cases combinations of subjects and sensors in total. From

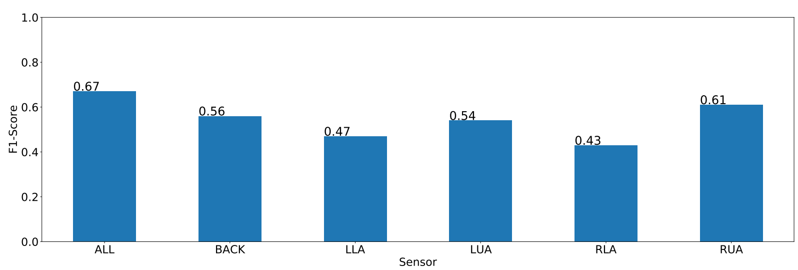


(a) Opportunity dataset

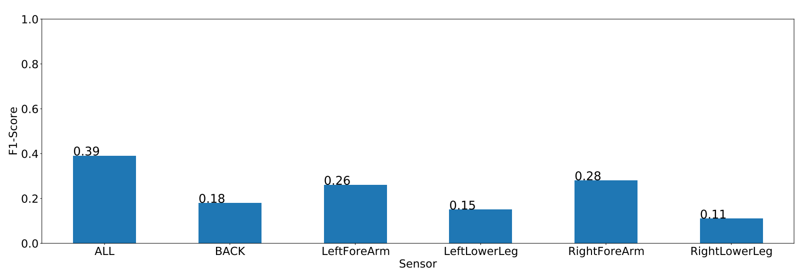


(b) PAMAP dataset

Fig. 3 Comparison of recognition accuracy of activity recognition with a single sensor and multiple sensors (simple activity). "ALL" used multiple sensors, others used a single sensor.



(a) Opportunity dataset

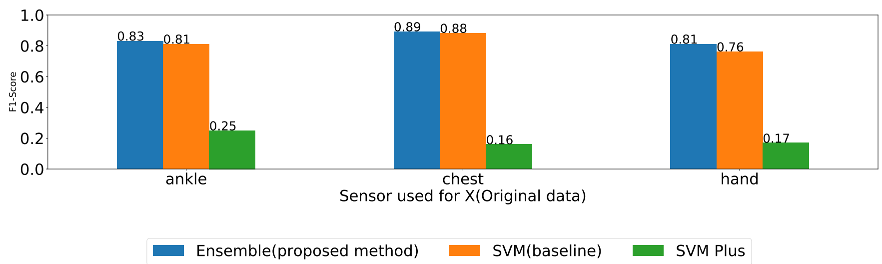


(b) Cooking dataset

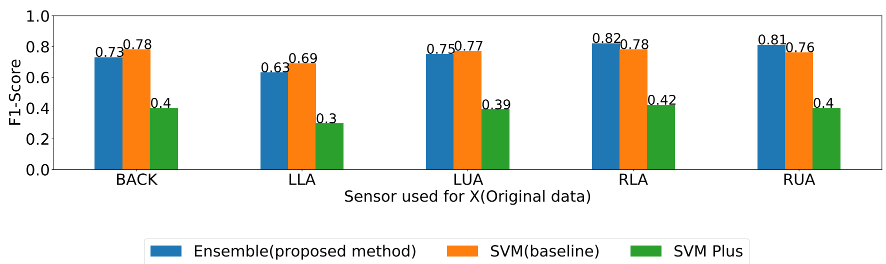
Fig. 4 Comparison of recognition accuracy of activity recognition with a single sensor and multiple sensors (complex activity) "ALL" used multiple sensors, others used a single sensor.

this figure, it can be seen that the average value of the F1-score is improved compared to the baseline method in each case.

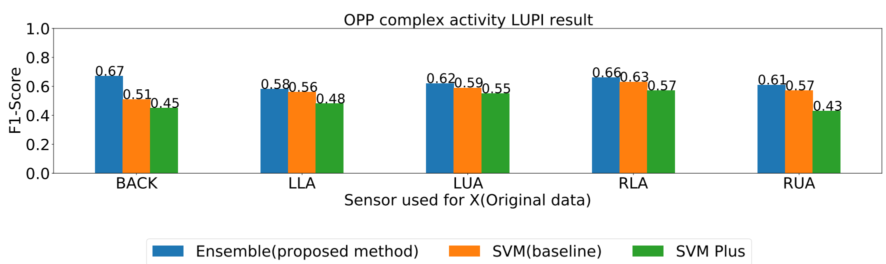
Table 2 shows the number of improvements and the number of deteriorations between SVM (baseline) and ensemble for each dataset in this validation. From the table, it can be seen that the number of improvements is greater than the number of deteriorations in all datasets. In addition, it can be seen that the F1-Score of the complex activity type dataset is improved compared to the simple activity type dataset.



(a) PAMAP Dataset



(b) Opportunity Dataset(simple activate)



(c) Opportunity Dataset(complex activities)

Fig. 5 The validation result of the each subject using random-split cross-validation (train:80% test:20%)

Table 2 The total number of improvements and degradations between SVM (baseline) and ensemble was validated using random-split cross-validation of each subject using three datasets.

	total number of cases	number of improvements	number of deteriorations
PAMAP	15	14	1
OPP HL	20	18	2
OPP Locomotion	20	11	9

4.3.3 Validation Results Using Additional Information During Training (Random-Split Cross-Validation of The Entire Data)

Fig.6, 7 show that the results of validation by randomly setting 80% of the training data and 20% of the test data for each dataset.

Fig.6(a) shows that results of using a simple activities dataset in the Opportunity data set are shown. This dataset contains 5 sensors, we validated 5 cases in total. The figure shows that the F1-Score was improved compared to the baseline method in 3 out of 5 cases.

Fig.6(b) shows the results of validation using the PAMAP dataset. This dataset contains 3 sensors, we validated 3 cases in total. From the figure, the F1-Score was improved compared to the baseline method (SVM) when hand and ankle are used for X.

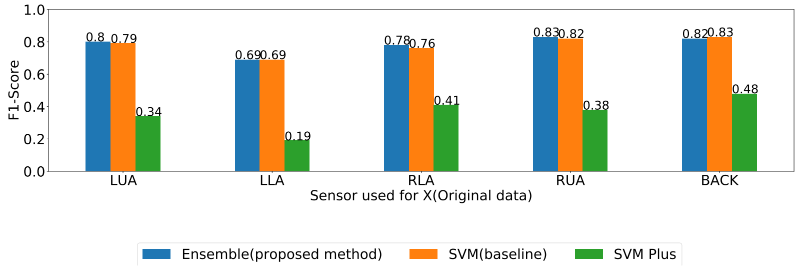
Fig.7(a) shows the results when using a dataset of complex activities in the Opportunity dataset. This dataset contains 5 sensors, we validated 5 cases in total. From the figure, it can be seen that the F1-Score was improved compared to the baseline method in 4 out of 5 cases.

Fig.7(b) shows the validation results using the Cooking dataset. From this figure, it can be seen that the F1-Score was improved compared to the baseline method(SVM) in all cases.

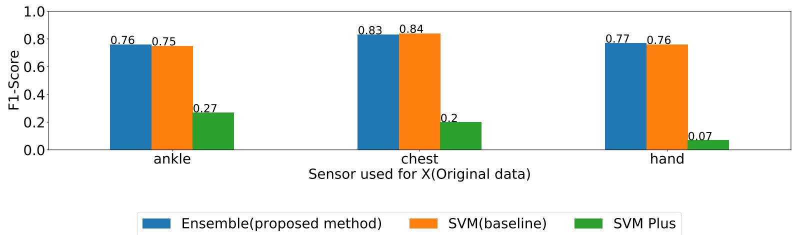
Table 3 shows the number of improvements and the number of deteriorations between SVM (baseline) and ensemble for each dataset in this validation. From the table, the number of improvements is greater than the number of deteriorations in all datasets

Table 3 The total number of improvements and degradations between SVM (baseline) and ensemble was validated using random cross-validation using four datasets.

	total number of cases	number of improvements	number of deteriorations
Cooking	5	5	0
PAMAP	3	2	1
OPP HL	5	4	1
OPP Locomotion	5	3	2

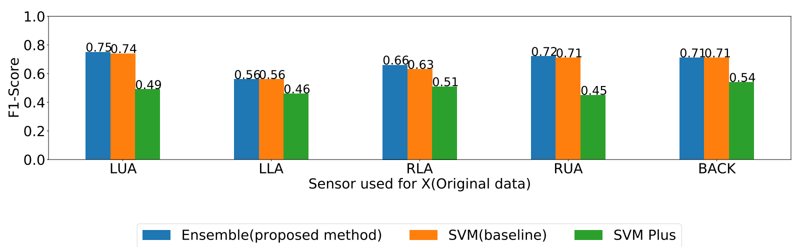


(a) Opportunity Dataset

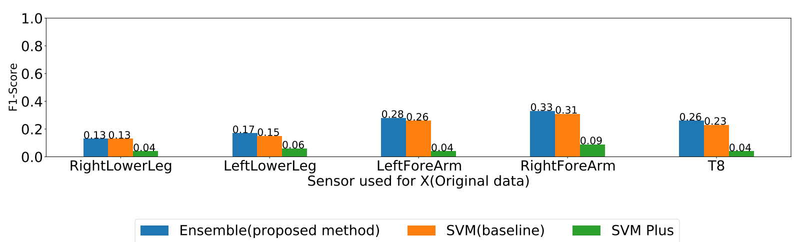


(b) PAMAP Dataset

Fig. 6 The validation result of the entire dataset(simple activities) using random cross-validation (train:80% test:20%)



(a) Opportunity dataset



(b) Cooking dataset

Fig. 7 The validation result of the entire dataset (complex activities) using random cross-validation (train:80% test:20%)

Table 4 The total number of improvements and degradations between SVM (baseline) and ensemble was validated using leave-one-subject-out cross-validation using four datasets.

	total number of cases	number of improvements	number of deteriorations
Cooking	35	15	20
PAMAP	15	8	7
OPP HL	20	9	11
OPP Locomotion	20	13	7

4.3.4 Validation Results Using Additional Information During Training (Leave-One-Subject-Out Cross-Validation)

Fig. 8 and 9 show the results of leave-one-subject-out cross-validation. These figures show the average value of the F1-score when cross-validation was performed.

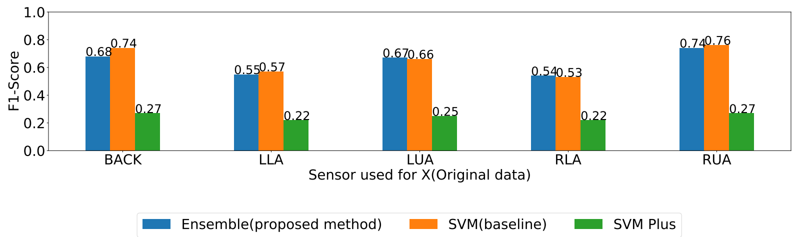
Fig.8(a) shows the results when a simple activities dataset in the Opportunity dataset is used. This dataset can use 4 subjects and 5 IMU sensors. Therefore, we validated 20 cases combinations of subjects and sensors in total (4 cross-validation patterns $\times$ 5 combination patterns of X and X^*). The figure shows that the average value of F1-Score is improved in 2 out of 5 cases compared to the baseline method.

Fig.8(b) shows the results of validation using the PAMAP dataset. This dataset can use 5 subjects and 3 IMU sensors. Therefore, we validated 15 cases combinations of subjects and sensors in total (5 cross-validation patterns $\times$ 3 combination patterns of X and X^*). The figure shows that the average value of F1-Score is improved in 2 out of 3 cases compared to the baseline method.

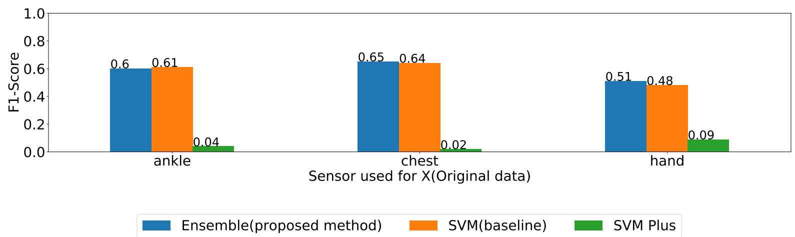
Fig.9(a) shows the results of using the complex activities data set in the Opportunity data set. This dataset can use 4 subjects and 5 IMU sensors. Therefore, we validated 20 cases combinations of subjects and sensors in total (5 cross-validation patterns $\times$ 3 combination patterns of X and X^*). The figure shows that the average value of F1-Score is improved in 2 out of 5 cases compared to the baseline method.

Fig.9(b) shows the results of validation using the Cooking dataset. This dataset can use 7 subjects and 5 IMU sensors. Therefore, we validated 35 cases combinations of subjects and sensors in total (7 cross-validation patterns $\times$ 5 combination patterns of X and X^*). From the figure, it can be seen that the average value of F1-Score is improved in recognition accuracy in 1 case out of 5 cases compared to the baseline method.

Table 4 shows the number of improvements and the number of deteriorations between SVM(baseline) and ensemble for each data set in this validation. From the table, it can be seen that the number of deteriorations is higher than the number of improvements, except for the datasets of complex activities types of PAMAP and Opportunity dataset.

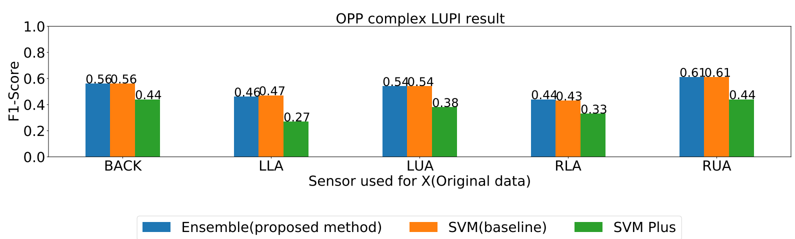


(a) Opportunity dataset

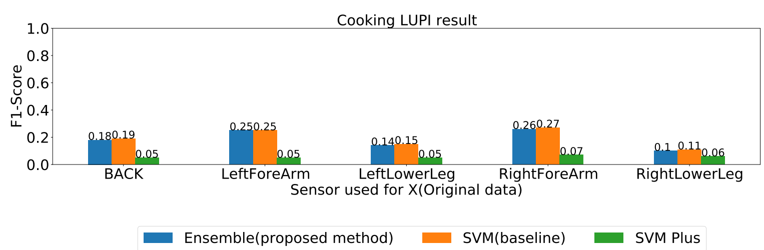


(b) PAMAP dataset

Fig. 8 The validation result using Leave-subject-out cross-validation(simple activities)



(a) Opportunity dataset



(b) Cooking dataset

Fig. 9 The validation result using Leave-subject-out cross-validation (complex activities)

5 Discussion

In this section, we consider the following based on the results of the previous section.

- Improvement of recognition accuracy by using additional Training information
- Deterioration of recognition accuracy due to the use of additional Training information

5.1 Improvement of Recognition Accuracy by Using Additional Learning Information

From the results of the Table 3, it can be said that the recognition accuracy can be improved when training with additional information that can be used only during training. In particular, as we can see, it is effective for the datasets containing complex activities such as the Opportunity dataset(Fig.7(a)) and the Cooking dataset (Fig.7(b)).

5.2 Deterioration of Recognition Accuracy Due to The Use of Additional Training Information

From the Table 4, it was found that when the subjects are different between the training data and the test data, there are more cases of deterioration than improvement. Therefore, in order to apply this method to such cases, it is necessary to consider the difference in the features of each subject. In addition, it can be said that the recognition accuracy of SVM+ is lower than that of the baseline method as a whole, which is the cause of the low recognition accuracy even when combined as an ensemble. As a feature of SVM+, additional information is assume trained as accurate information, so even if it is not accurate information, it is treated as correct information, which is thought to have led to a decrease in recognition accuracy. Furthermore, the previous research [12] studies sensor-based activity recognition using SVM+. But, the same IMU sensor information has been used. In short, the accelerometer sensor is used as original data, the gyroscope sensor is used as additional data.

6 Conclusion

In this paper, in order to improve the accuracy of complex activity recognition, we employ ensemble learning which combined baseline (SVM) and LUPI (SVM+) classifier. We used four published datasets for evaluating our proposed method using random-split cross-validation and leave-one-subject-out cross-validation. As a result, the proposed method improved by up to 16% in F1-Score to 67% compared to baseline method when we used random-split cross-validation of each subject. However, when we used leave-one-subject-out cross-validation, the recognition accuracy is worse than the baseline method. In addition, it is different features between sensor positions and affects recognition accuracy. Another major reason is that SVM + has lower accuracy than SVM. Unfortunately, our work does not show a benefit of LUPI, with the performance of SMV+ significantly lower than the baseline SVM. The performance of the ensemble is slightly higher than SVM. While this might indicate that a combination of classical SVM and SVM with LUPI could lead to better ensembles, it does not rule out that the improvement observed comes from using an ensemble at all. In order to elucidate this question, other ensembles should be assessed (e.g. SVM and KNN). Based on the above, As future work, we would like to study the following:

- Examining methods for extracting common features from different sensors.
- Examining feature extraction methods that do not depend on the subject.
- Comparing ensemble learning with other classifiers to use in combination with SVM+.

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