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Research article

A daily activity feature extraction approach based on time series of sensor events

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Abstract: Activity recognition benefits the lives of residents in a smart home on a daily basis. One of the aims of this technology is to achieve good performance in activity recognition. The extraction and selection of the daily activity feature have a significant effect on this performance. However, commonly used extraction of daily activity features have limited the performance of daily activity recognition. Based on the nature of the time series of sensor events caused by daily activities, this paper presents a novel extraction approach for daily activity feature. First, time tuples are extracted from sensor events to form a time series. Subsequently, several common statistic formulas are proposed to form the space of daily activity features. Finally, a feature selection algorithm is employed to generate final daily activity features. To evaluate the proposed approach, two distinct datasets are adopted for activity recognition based on four different classifiers. The results of the experiment reveal that the proposed approach is an improvement over the commonly used approach.

Keywords: daily activity recognition; feature extraction; smart home; time series

1. Introduction

Smart homes aim to provide a comfortable, convenient, and efficient living environment and effectively alleviate the impact of the functional decline [1,2]. Besides, smart home is also designed to improve energy management [3–5]. The premise of achieving the goal is to accurately recognize daily activities, which take place in smart homes. To achieve good activity recognition performance, several approaches have been proposed. Existing approaches focus on different stages of the process of activity recognition [6]. Some approaches focus on stages such as, segmenting sensor event streams [7–10], extracting and selecting daily activity features [11–15], and developing recognition models [16–19]. In this paper, the proposed approach focuses on extracting and selecting daily activity features.

The primary task of extracting and selecting daily activity features is to establish a feature space and generate a sample space. Daily activity features are divided into temporal and sensor features. Temporal features include the start time, end time, and duration of the daily activity. For the sensor features, while some approaches take all smart home sensors as the feature space, others take the sets or sequences of frequency sensors as the feature space. For a given sensor feature and daily activity, most of the approaches take the frequency activated in the daily activity as the value of the sensor feature. The existing common practice for extracting daily activity features is discretizing sensor event streams. This widespread practice leads to the character loss of the time series of sensor event streams and limits the improvement of activity recognition performance.

To utilize the character of the time series of sensor event streams to improve activity recognition performance, this paper proposes a novel approach for extracting daily activity features. As compared with existing approaches, the proposed approach achieves better activity recognition performance. The main contributions of this paper are as follows.

(1) An algorithm that serves to extract time series data from sensor event streams is proposed.

(2) Several common statistic formulas are proposed to establish an initial feature space.

(3) A feature selection algorithm is employed to generate final daily activity features.

(4) The proposed approach is evaluated on two common datasets. The experiment results show that the proposed approach achieves better performance than previous approaches for solving daily activity features.

The rest of this paper is arranged as follows: First, related work is introduced; the proposed approach is then introduced; the proposed approach is validated and results discussed. Finally, we summarize our findings.

2. Related work

Approaches for activity recognition in smart homes can be divided into knowledge-driven and data-driven approaches. For knowledge-driven approaches, an activity model is developed as a reusable context model, which associates objects, space, and time with activities. The knowledge driven model is semantically clear and follows an agreed indication. Logic language and ontology are the two most common models representing domain knowledge [20–26]. After the knowledge model is established, logical reasoning is employed to perform activity recognition. Knowledge-driven approaches are robust but face limitations in the case of uncertain data.

Data-driven approaches adopt data mining and machine learning techniques to develop the activity recognition model. Conventional classification algorithms e. g. Naive Bayesian (NB) [27–30], Hidden Markov Model (HMM) [31,32], Dynamic Bayesian Network (DBN) [33], Support Vector Machine (SVM) [34], Conditional Random Field (CRF) [35], and Recursive Neural Network (RNN) [36] have been widely used in activity recognition tasks. Besides conventional classification algorithms, some specialized algorithms were invented. Wan et al. proposed a novel activity recognition model called COBRA. COBRA mixed the combined sliding window with a logistic regression model for near-real-time activity recognition [37]. To deal with the problem of class imbalance and improve the performance of the model, Medina-Quero et al. developed an integrated classifier based on long short-term memory (LSTM) to recognize daily activities [38].

Besides classification algorithms, the fine features of daily activities are equally vital to activity recognition performance. Daily activity features can be divided into temporal and sensor features. The temporal features space usually includes the time when a daily activity starts, its duration, and when it ends. The sensor features space is generated directly or indirectly from the set of initial sensors. Liu et al. take the set of initial sensors as the sensor features space and a sensor as a daily activity feature [39]. Because the relationship between sensors is lost when a sensor is taken as a daily activity feature, daily activities which activate similar sensors are hard to differentiate. To improve activity recognition performance, the frequent items mining method [40], frequent periodic pattern mining method [41], and activity modelling based on a low-dimensional feature space [42] were proposed. In addition, Wen et al. and Nasreen et al. used the association rules mining method to mine frequent sensor combinations, to conduct activity modelling for the low-dimensional feature space [43,44]. Twomey proposed an unsupervised method to learn the topology structure of sensors in a smart home and mined effective combinations of sensor events as daily behaviour characteristics, according to the topology structure [45]. Yatbaz et al. [46] used a Scanpath Trend Analysis (STA) method to set a priority for sensors to obtain sensor combinations that represent daily activity features, to improve the evaluation standard of the model. Compared to the approach where a sensor is taken as a daily activity feature, these approaches consume more computing resources, even if activity recognition performance is slightly improved.

For sensor features, truth value, frequency, and density of the activated sensors are the most common eigenvalues [47]. In addition, the term frequency-inverse document frequency (TF-IDF) formula [8], mutual information formula [48], deep learning technology [49], and differential representation between different activities were employed to compute these eigenvalues [50]. However, these above mentioned strategies for estimating the eigenvalues generate only shallow features, which are far from adequate when describing the nature of the time series of sensor event streams. This paper performs an in-depth feature mining on the time series data, which can preserve the essential information of the time itself. Consequently, the proposed approach can be extended to promote the user activity recognition model.

3. The proposed approach

In a smart home, different types of non-invasive sensors e.g. infrared motion sensors, and temperature sensors, are deployed in different parts of the house. When residents carry on daily activities *e.g.* sleeping, and bathing, corresponding sensor readings are generated accordingly. Figure 1 shows a sequence of sensors triggered by cooking breakfast as a daily activity. Each line denotes a sensor event. Each activated sensor is recorded as a sensor event *se*, denoted as a four tuple; $se = (D, T, I, R)$. D and T are the date and the time when the *se* is generated, respectively; I is the identification of the activated sensor, and R is the sensor reading. For example, the sensor event shown in line 1 is generated at 07:58:39.655022 on 2011-06-15. The activated sensor is M007 with a reading ON.

1.	2011-06-15	07:58:39.655022	M007	ON
2.	2011-06-15	07:58:39.788219	LS005	15
3.	2011-06-15	07:58:39.82442	BATV005	9480
4.	2011-06-15	07:58:39.856593	M005	OFF
5.	2011-06-15	07:58:42.465461	M007	OFF
6.	2011-06-15	07:58:45.585184	D005	OPEN
7.	2011-06-15	07:58:45.794425	M008	ON
8.	……			
9.	2011-06-15	08:02:51.985144	M007	OFF

Figure 1. Sequence of activated sensors by daily activity, cooking breakfast.

3.1. Feature category

Based on the nature time series of sensor events, 6 categories of common daily activity features are proposed in form of statistic formulas. Each statistic formula corresponds to a given time series. Throughout this section, T=<t_1, t_2, …, t_n> denotes a time series, where t_i is the *ith* time value of a given time series.

(1) **Mean:** $\mu(T)$ returns the mean of T. $\mu(T)$ is defined in formula (1).

$$\mu(T) = \frac{\sum t_i}{n} \tag{1}$$

(2) **Standard Deviation:** $\sigma(T)$ returns the standard deviation of T. $\sigma(T)$ is defined in formula (2).

$$\sigma(T) = \sqrt{\frac{\sum (t_i - \mu)^2}{n-1}} \tag{2}$$

(3) **Skewness:** $Skew(T)$ returns the skewness of T. $Skew(T)$ is defined in formula (3).

$$Skew(T) = \frac{\mu^3}{\sigma^3} \tag{3}$$

(4) **Slope:** $Slope(T)$ returns the slope of the linear least-squares regression for the values of T. $Slope(T)$ is defined in formula (4).

$$Slope(T) = slope(llsr(T)) \tag{4}$$

Where *llsr* returns the linear least-squares regression for the values of T.

(5) **Wave:** $Wave(T)$ returns the number of troughs and peaks and of T. $Wave(T)$ is defined in formula (5).

$$Wave(T) = peaks(T) + troughs(T) \tag{5}$$

Where *peaks* returns the number of peaks of *T*. *troughs* returns the number of troughs of *T.*

(6) **Wavelet Transform Coefficients:** For two specified parameters *w* and $t \in T$, *CWTC*(*t*,*w*) returns continuous wavelet transform coefficients. *CWTC*(*t,w*) is defined in formula (6). *cwt*(*t*,*w*) returns a continuous wavelet transform for the ricker wavelet of the wavelet function.

$$CWTC(t,w) = wavelettransformcoefficients(t,w,cwt(t,w)) \tag{6.1}$$

$$cwt(t,w) = \frac{2}{\sqrt{3 \cdot w} \cdot \pi^{\frac{1}{4}}}(1 - \frac{t^2}{w^2})exp(-\frac{t^2}{2 \cdot w^2}) \tag{6.2}$$

Where *w* is the width parameter in the wavelet transform function, which is 2 in the experiment.

3.2. Feature extraction

For a sequence of sensor events activated by a daily activity, time series data which is input to each feature category. Feature space is generated by Algorithm 1. Algorithm 1 can be divided into two stages. In the first stage (lines 4–12), the identification and times of each activated sensor are extracted. Activated times form time series data. In the second stage (lines 13–22), features are extracted using feature formulas with extracted time series data.

3.3. Feature selection

One drawback to the features of daily activity is the high dimension of feature set. To obtain the strong ability features and eliminate the weak ability ones, we need to use feature selection technique to optimize feature subset. In this paper, the SDSFS algorithm [51] is used to evaluate the activity recognition capability of these features.

In the initial phase, each agent is assigned to combine the features subset in their respective search spaces (all possible combinations of the features). Each agent will use an independent random split to divide the dataset into training and testing subsets according to a ratio of 4:1. The hypothesis is a binary string that represents the feature subset within the subset size. In the string, if the bit is 1, it contains its corresponding feature, if 0, it is not.

In the test phase, these activities of the agent are determined according to the average F-score of multiple classifiers in their fitness function, where the agent selects another random agent and compares them. If the F-score of the selected agent is more than that of the random agent, then the selected agent is set to active, otherwise it is set to inactive. The agents will repeat this process to determine their respective states. After that, the diffusion phase would ideally begin.

In the diffusion phase, both inactive and active agents choose other agents. If the randomly selected agent is active, it will offset the hypothesis (the feature subset) , which will be shared with an inactive agent. Instead, the selected agents choose the new random hypothesis (the feature subset) from its search space (all feature combinations in the subset size). For offsetting, one of the features is randomly removed (by changing 1 to 0) with another randomly added one (by changing 0 to 1). This keeps the size of the subset. Besides, when the active agent picks another active agent that maintains a similar hypothesis, the selected agent will be set to inactive and assigned to a random hypothesis. This frees up all agents and increases diversity. Algorithm 2 is repeatedly executed until the maximum number of iterations (*numIterations*) is reached.

Algorithm 1. *featureExtraction*

```
Input:  S, deployed sensor identifications in smart house
        Φ, set of the proposed feature categories
        E, a sequence of sensor events activated by a daily activity a
Output: F
F←∅;
TS←∅;
IS←∅; // set of sensor identifications activated by a
while(true)
    e←getNextSensorEvent(E); //Get next sensor event e in E.
    (t, s)←extractTime&Sensor(e)//Extract T and I of e.
    TS←TS∪{(T, I)};
    IS←IS∪{I};
    if(e is last traversed sensor event in E) then
        break;
    end if
end for
for each I in S
    for each φ in Φ
      if I∈IS then
          T_I← {T|(T,I)∈TS};
          F←F∪{(I, φ(T_I))};
      else
          F←F∪{(I, 0)};
      end if
    end for
end for
return F
```

Algorithm 2. *Description of SDSFS algorithm*

Input: *numIterations*, the number of iterations

numAgents , the number of agents

Output: Optimal feature subset

```
//Initialisation phase
Assign numAgents agents to random hypotheses with inactive states, each agent represents a set of features.
while less than numIterations do
    //Evaluation phase
    for each agent in agents
        Evaluate the fitness value;
        Find the maximum fitness value;
    end for
    //Test phase
    for each agent in agents
        if Agent's fitness > random agent's fitness then
            Set agent as active;
        end if
    end for
    //Diffusion phase
    for each agent in agents
        if agent is inactive then
            Select a random agent;
            if selected agent is active then
                Copy its hypothesis & offset it;
                Evaluate the fitness value;
            else
                Pick a random hypothesis;
                Evaluate the fitness value;
            end if
        end if
    end for
end for
return Optimal feature subset
```

4. Evaluation

Activity recognition performance depends on the daily activity feature. We use two common datasets “Cairo” and “Tulum2009” to evaluate the approaches for solving activity recognition performance of daily activity features. “Cairo” and “Tulum2009” are provided by the Washington State University [52]. The involved sensors and daily activities are listed in Table 1.

Table 1. Involved sensors and daily activities.

Dataset	Residents and pets	Sensor Categories	Number of sensors	Activity Categories	Number of Activity instances	Measurement Time
“Cairo”	2 residents and 1 pet	“Motion sensors” (M001–M027)	27	“Night_wandering”	67	57 days
				“Bed_to_toilet”	30	
				“R1_wake”	53	
				“R2_wake”	52	
				“R2_take_medicine”	44	
				“Breakfast”	48	
				“Leave_home”	69	
		“Temperature sensors ” (T001–T005)	5	“Lunch”	37	
				“Dinner”	42	
				“R2_sleep”	52	
				“R1_sleep”	50	
				“R1_work_in_office”	46	
				“Laundry”	10	
“tulum2009”	2 residents	“Motion sensors” (M001–M018)	18	“Cook_Breakfast”	80	84 days
				“R1_Eat_Breakfast”	66	
				“Cook_Lunch”	71	
				“Leave_Home”	75	
				“Watch_TV”	528	
		“Temperature sensors ” (T001–T002)	2	“R1_Snack”	491	
				“Enter_Home”	73	
				“Group_Meeting”	11	
				“R2_Eat_Breakfast”	47	
				“Wash_Dishes”	71	

4.1. Experiment setup

For daily activity feature solving approaches, we use Jupyter Notebook to carry out experimental comparison of four methods. First, the proposed method is called "SR" , and the second is called "FR". FR is an extraction approach of daily activity feature. For FR method, frequency of activated sensor is extracted as daily activity feature. “FR” and its variants have been be used most extensively as daily activity feature. Feature spaces of the approach are composed of “st”, “et”, “du” and sensor features [53]. The other two are the combination of SR and FR with SDSFS algorithm respectively, called "SR+FS" and "FR+FS". FR+FS (FR+FS) means that SDSFS is employed to select features of daily activity after features are extracted.

For a given daily activity, the values of *st*, *et*, and *du* refer to the start time, end time, and duration of the daily activity, respectively. Sensor features, each of which corresponds to a sensor are mapped to all deployed sensors in the smart home. For FR, the value of a sensor feature is the frequency that activates the corresponding sensor in the given daily activity. For the SDSFS algorithm, the parameters involved are listed in Table 2.

For data-driven approaches, activity recognition is usually treated as a classification problem. Without loss of generality, Logistic Regression (LR), Naive Bayesian (NB), Decision Tree (DT) and LSTM are used to evaluate the proposed approach. The parameters involved are listed in Table 3. The rest of the parameters are default. A leave-one-day-out cross validation is taken to evaluate the proposed approach. The performance indicators used are the Recall, Precision, and F-score, which are defined in formula (7), (8) and (9), respectively, where Q is the number of activity labels; TP_i is the number of true positives; FP_i is the number of false positives; FN_i is the number of false negatives; TN_i is the number of true negatives.

$$Recall = \frac{\sum_{i=1}^{Q} \frac{TP_i}{TP_i + FN_i}}{Q} \tag{7}$$

$$Precision = \frac{\sum_{i=1}^{Q} \frac{TP_i}{TP_i + FP_i}}{Q} \tag{8}$$

$$F\text{-}score = \frac{2*Precision*Recall}{Precision + Recall} \tag{9}$$

Table 2. Parameter Interpretation of SDSFS algorithm.

Configuration Name	Parameter Interpretation
the number of iterations	*numIterations*←150
the number of agents	*numAgents*←30
the minimum number of features included in an agent	*lowerLim*←5
the maximum number of features included in an agent	*upperLim*←30

Table 3. Parameter Settings of Classifiers.

Classifiers Name	Parameter Name	Parameter Settings
LR	regularization intensity, random number seed	C←1.0, *random_state*←2018
DT	random number seed	*random_state*←2018
NB	/	/
LSTM	The number of units	16
	Gradient descent algorithm	AdamOptimizar
	Learning rate	1e-3
	Batch size	100
	Epoch number	100

4.2. Results

Recall, Precision, and F-measure are listed in Tables 4–9 and Figures 3,5.

(1) Results on Dataset "Cairo"

After feature selection, the scores of each agent are shown in Figure 2. FR+FS and SR+FS have the highest average F-score in the 14th and 3rd agents respectively. Based on the above results, we conduct the following experiments using the features in the best agents respectively.

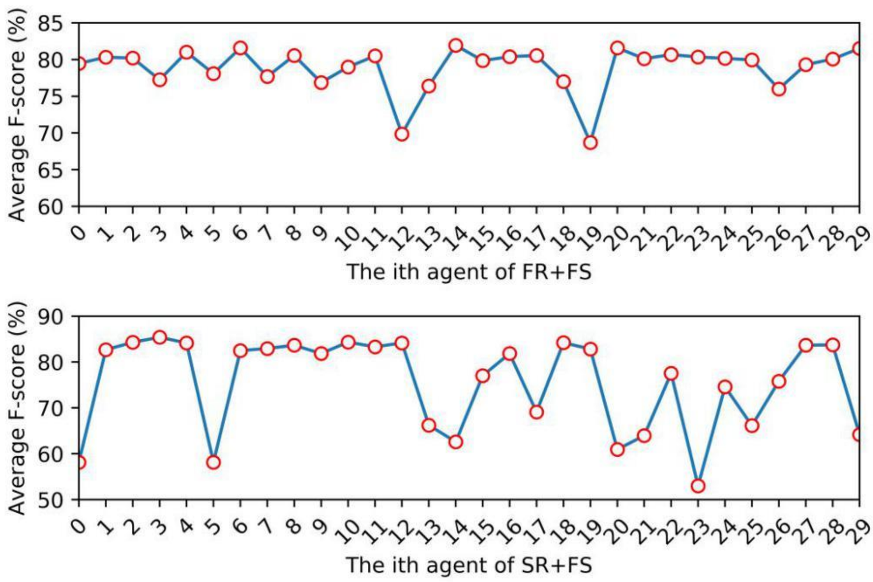

Figure 2. The average F-score of the extracted features in each agent.

The Precision obtained using SR+FS is higher than that obtained using the other three methods for all classifiers. The Recall and F-score obtained using SR+FS are higher than those obtained using FR, SR and FR+FS for LR and NB. The highest Precision (89.511%), Recall (87.114%) and F-score (87.529%) are obtained using SR+FS for DT. Besides, the first three classifiers, their average Precision value obtained using SR+FS improves by at least 2.883% compared with the performance of other tests. And the average Recall value of the SR+FS is 83.555%. There is 1.346% improvement over the best outcomes of the first three methods. Similarly, the average F-score of the SR+FS achieves at least 7.574%, 13.459% and 2.024% improvements over other benchmark methods. Finally, SR also beats FR in every metric of the LSTM.

Table 4. Precision of activity recognition in different classifiers of “Cairo”. The best-performing tests by the metric are shown in underline.

Approaches	LR	NB	DT	LSTM
FR	79.263%	72.207%	84.346%	81.021%
SR	70.900%	70.775%	79.358%	88.152%
FR + FS	83.112%	81.334%	87.379%	/
SR + FS	<u>87.006%</u>	<u>83.958%</u>	<u>89.511%</u>	/

Table 5. Recall of activity recognition in different classifiers of “Cairo”. The best-performing tests by the metric are shown in underline.

Approaches	LR	NB	DT	LSTM
FR	74.776%	70.225%	85.018%	75.2693%
SR	66.043%	68.411%	78.236%	88.268%
FR + FS	81.310%	79.023%	86.295%	/
SR + FS	<u>82.918%</u>	<u>80.634%</u>	<u>87.114%</u>	/

Table 6. F-score of activity recognition in different classifiers of “Cairo”. The best-performing tests by the metric are shown in underline.

Approaches	LR	NB	DT	LSTM
FR	75.603%	69.265%	84.280%	76.321%
SR	66.254%	67.167%	78.074%	87.748%
FR + FS	81.021%	78.589%	86.189%	/
SR + FS	<u>84.133%</u>	<u>80.214%</u>	<u>87.529%</u>	/

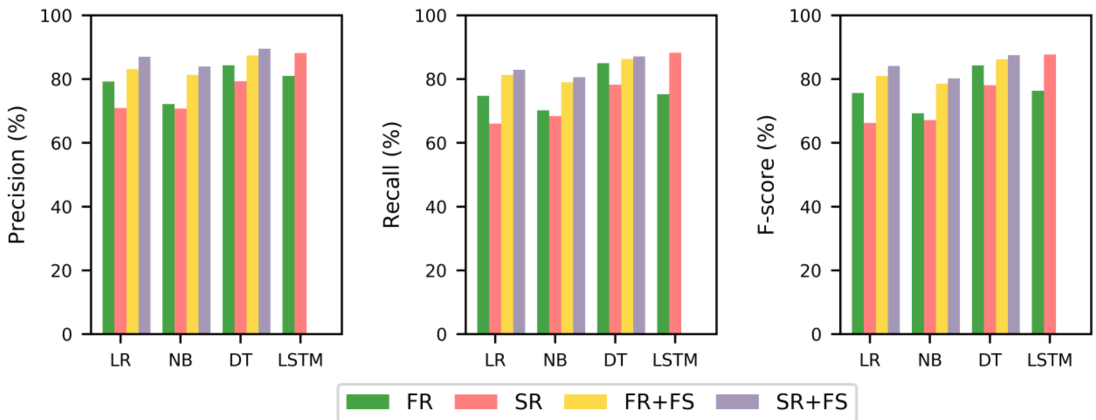

Figure 3. Performance comparison of the different daily activity feature solving approaches on three classifiers.

(2) Results on Dataset "Tulum2009"

After feature selection, the scores of each agent are shown in Figure 4. FR+FS and SR+FS have the highest average F-score in the 5th and 22nd agents respectively. Based on the above results, we conduct the following experiments using the features in the best agents respectively.

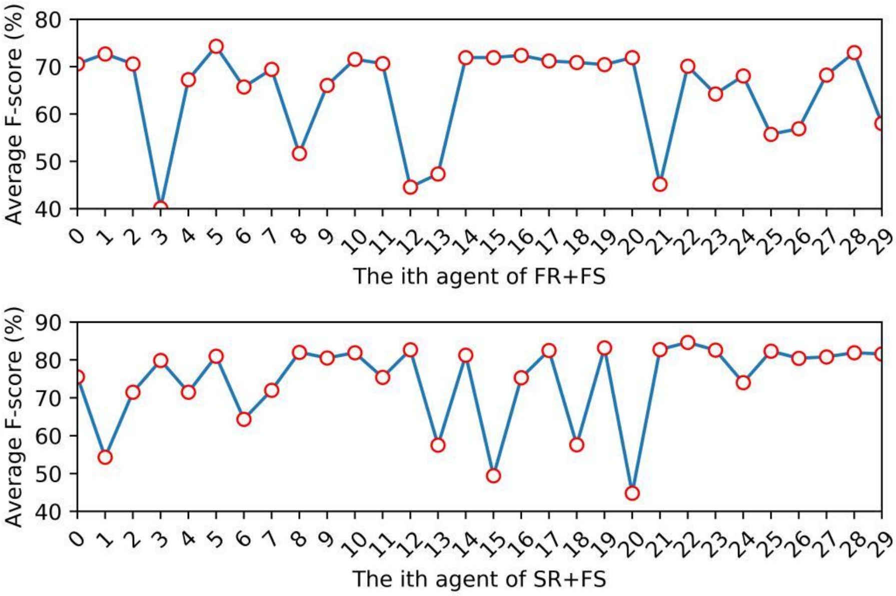

Figure 4. The average F-score of the extracted features in each agent.

The dataset also gets the same result pattern. The Precision obtained using SR+FS is also higher than that obtained using the other three methods for all classifiers. The Recall and F-score obtained using SR+FS are higher than those obtained using FR, SR and FR+FS for LR and NB. Although SR+FS lags behind FR + FS in the Precision of DT. Besides, the first three classifiers, their average Precision value obtained using SR+FS improves by at least 7.919% compared with the performance of other tests. Besides, the average Recall value of the SR+FS is 86.148%. There is 9.948% improvement over the best outcomes of the first three methods. Similarly, the average F-score of the SR+FS achieves at least 16.862%, 10.192% and 12.614% improvements over other benchmark methods. Finally, SR also beats FR in every metric of the LSTM.

Table 7. Precision of activity recognition in different classifiers of "Tulum2009". The best-performing tests by the metric are shown in underline.

Approaches	LR	NB	DT	LSTM
FR	72.627%	58.688%	84.993%	85.907%
SR	77.075%	73.139%	80.689%	88.8%
FR + FS	81.864%	65.650%	<u>86.122%</u>	/
SR + FS	<u>90.844%</u>	<u>81.221%</u>	85.329%	/

Table 8. Recall of activity recognition in different classifiers of "Tulum2009". The best-performing tests by the metric are shown in underline.

Approaches	LR	NB	DT	LSTM
FR	64.540%	72.008%	79.591%	76.256%
SR	74.478%	75.513%	78.609%	86.716%
FR + FS	65.519%	75.564%	81.985%	/
SR + FS	<u>86.101%</u>	<u>87.574%</u>	<u>84.771%</u>	/

Table 9. F-score of activity recognition in different classifiers of "Tulum2009". The best-performing tests by the metric are shown in underline.

Approaches	LR	NB	DT	LSTM
FR	65.912%	58.368%	81.628%	80%
SR	75.543%	71.112%	79.265%	86.909%
FR + FS	68.535%	66.448%	83.669%	/
SR + FS	<u>88.205%</u>	<u>83.562%</u>	<u>84.727%</u>	/

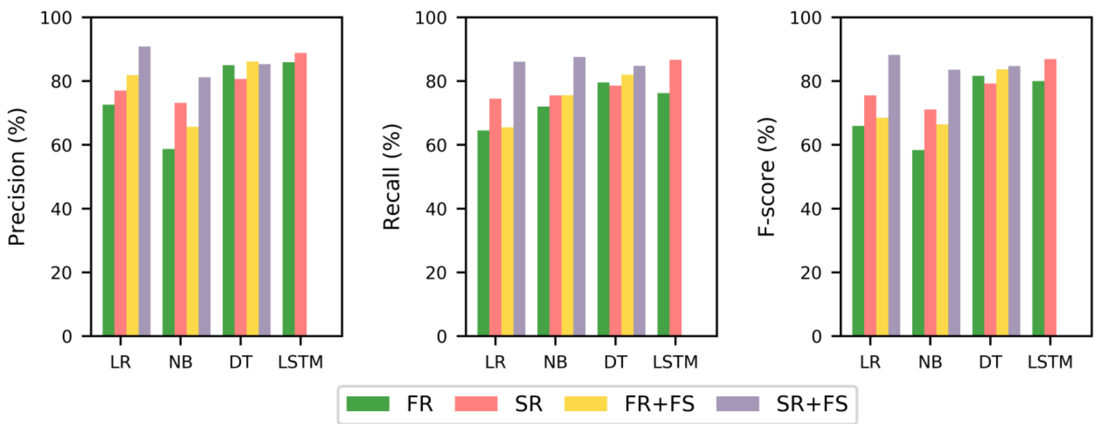

Figure 5. Performance comparison of the different daily activity feature solving approaches on three classifiers.

4.3. Discussion

We discuss few crucial observations from our experiments. As shown in Figures 3,5, SR+FS performs better than the other three groups. First, this gain may be due to feature selection. There are inevitably redundant features in the original data. These features are not sensitive to the classification label, but they can disturb the classifier's correct judgment of the sample. Therefore, the performance of SR is low in some classifiers.

In addition, it may be that the traditional method only counts the frequency of the sensor and loses the time information of the sensor. In contrast, our method extracts the trigger time of the sensor in the activity in turn, and then carries out feature calculation. Such different feature computing methods increase the diversity of features. In this way, the frequency information and the time information of the time series data are retained.

We note that there are imbalances of categories in daily activities, but this paper does not do the corresponding processing when modeling. Excessive differences between categories may make the model biased towards more categories, which may affect the performance evaluation of the model to some extent. Consequentially, it may be worthwhile to perform further studies to determine how such problems impact performance, especially in smart home environment.

5. Conclusion

Daily activity features have a significant influence on activity recognition performance. To improve activity recognition performance, we proposed a statistic representation of daily activity features based on the time series nature of sensor event streams. We utilized four classifiers to compare the proposed approach with approaches based on the frequency and truth of sensor events on two common datasets. The results showed that the proposed approach can significantly improve activity recognition performance.

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Conflict of interest

The authors declare no conflicts of interest.

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