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Activity Recognition Method for Home-Based Elderly Care Service Based on Random Forest and Activity Similarity

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ABSTRACT In home-based elderly care service, how to precisely recognize activities is a key issue in the design and implementation of context-aware service for elderly people. Existing research works reveal that those approaches ignore the characteristics of activity diversity, and similarity and the features of activities of elderly people at home, so recognition accuracy of those approaches are not high enough for real-life applications. Thus, in this paper, we first study the types of activities in home-based elderly care service. Then, we propose a two-stage elderly home activity recognition method based on random forest and activity similarity. The method uses improved random forest to obtain a preliminary result in the first stage. Then, the correlation between activity, location, and time is employed to judge the rationality of the result. The similarity of activities is further used to correct the results in the second stage. We set up a series of experiments to evaluate the effectiveness and efficiency of our approach.

INDEX TERMS Activity recognition, activity similarity, context awareness, home-based care service, random forest.

I. INTRODUCTION

Providing intelligent home-based care services for the elderly through advanced IT technologies such as Internet of Things(IoT), service computing, and cloud computing is the main way for governments to solve the problem of population aging. How to accurately and actively sense the service context in order to provide better and faster services is the core issue in the design and implementation of context-aware service(CAS) for elderly people. In the elements of service context, the activity recognition is the most important one, and is the basis of the follow-up requirement analysis and service design. Most of activity related data can be obtained by sensors, however, in most cases it is hard or even impossible to directly judge the exact activity. Therefore, activity recognition has seen a tremendous growth in the last decade playing a major role in the field of pervasive computing and context-aware service. It has myriad of real-life applications primarily dealing with human-centric problems like healthcare and elder care.

Activity recognition can be seen as an important branch of pattern recognition. Many research attempts with data mining and machine learning techniques have been undergoing to accurately detect human activities. Decision tree, support vector machine, naive Bayes, hidden Markov model, etc. have been widely used and made great achievements [1], [4]. However, there are still problems in existing research. On one hand, most studies do not pay attention to the characteristics of activity diversity and similarity. The activity diversity means that different users act differently when doing the same activity, and even the same activity of the same user may also be different due to factors such as stress, fatigue, emotional state, and environmental factors. At the same time, multiple activities have similarities and are easily confused. These are important factors that affect the accuracy of recognition. On the other hand, the activities of elderly people at home have some special features: the activity area is limited, mainly in bedroom, living room, toilet, and kitchen; only a small number of typical activities often happen; smartphones which are the most frequently adopted sensing devices often are not carried at home. These features are very helpful in improving recognition accuracy. Unfortunately, they are ignored in most research.

Therefore, in this paper, we propose a two-stage elderly home activity recognition method based on random forest and activity similarity. In the first stage, we use improved random forest algorithm to obtain a preliminary activity recognition result. In the second stage, we consider the correlation between activity, location, and time to judge the rationality of preliminary result. Then the result is corrected by activity similarity matrix.

The remainder of this paper is organized as follows: In Section II, we introduce some related works. In Section III, we introduce the methodology framework and mathematical definition. In Section IV, we elaborate the elderly activity recognition algorithm based on random forest and activity similarity matrix. In Section V, the focus is on the evaluation of our method compared with others. Section VI summarizes the paper.

II. RELATED WORK

Solving the daily safety and nursing problems of the elderly is an important purpose and application field of activity recognition research. Reference [2] proposed a hierarchical activity recognitionsystem to identify abnormal activities (such as chest pain, headache, vomiting, syncope, etc.) in the lives of elderly people living alone. Through an automatic periodic monitoring system to ensure the safety of the elderly and improve the quality of life of the elderly people living alone as well as reduce the cost of health care. Reference [3] focused on recognizing daily activities recognition of the elderly to help doctors or family members to understand the regularity of their activities and the amount of exercise, and improve the accuracy of doctors' health evaluation to formulate more appropriate rehabilitation strategies. Reference [6] designed a wearable fall recognition and alarm system using a 3-axis accelerometer and a gyroscope to monitor the activities of the elderly and timely use the mobile phone to alarm. The system can support to quickly carry out the rescue work after the fall. Reference [5] proposed a gait-assisted system based on a wearable projector. When the elderly walk, the system recognizes the gait posture and projects the expected position on the ground, which can effectively and inexpensively help the elderly to walk.

In the research of activity recognition approaches, traditional approaches are mainly divided into two categories according to the representation of activities based on sensor data: logic based and probability based. In the logic based approaches, each activity to be monitored has an explicit rule encoding which is the range of allowed values for the relevant parameters. Most logic-based systems use decision trees to classify data by gradually narrowing the range of activities that can be represented [8]. In the probability-based approaches, each activity is represented by a model and classified by comparing the probability distance metrics using sensor data in the stored model. Most solutions based on this kind approaches use hidden Markov models [5], [7] or Gaussian mixture models [9], [10].

In recent years, deep learning has received extensive attention and has also been applied to the field of activity recognition. Deep learning allows a large amount of data to be calculated by multiple hidden layers to obtain a multi-level abstract data representation. This learning method is in line with the mechanism of human perception of the world. Therefore, when the training samples are enough, the features learned through the deep network often have certain semantic features and are suitable for activity recognition [11]. Among the approaches, CNN(Convolutional Neural Network) [12]–[15] and RNN(Recurrent Neural Network) [16], [17] have improved the accuracy of traditional approaches due to the deep representation of spatial and temporal relationships of activity. However, it cannot be ignored that the deep learning-based activity recognition approaches require huge data for training, and the training speed is slow, it needs to be further studied when applied to real scenes.

III. PROBLEM FORMULATION

A. ELDERLY HOME ACTIVITY RECOGNITION

The main goal in this paper is to infer the most possible activities of elderly according to the data obtained through sensors. Taking into account the limited and typical nature of the daily basic activities of the elderly at home, the activities of elderly we mainly recognize are summarized into 5 categories and 12 kinds as shown in Table 1.

TABLE 1. List of typical elderly home behaviors.

Action	Behavior
Washing(A1)	Combing hair(B1), Brushing teeth
Moving(A2)	getting up(B3), Lying down(B4), Sitting down(B5), Standing up(B6),Walking(B7)
eating(A3)	Drinking water(B8), Eating with chopsticks(B9), Eating with a spoon(B10)
cooking(A4)	Pouring oil/water into pan(B11)
Calling(A5)	Making a phone Call(B12)

It can be seen from Table 1 that these daily activities of the elderly cannot directly obtained by sensors. It is necessary to infer activities based on collected sensor data. In the current activity recognition research, it is mainly based on data sources such as video, pictures and mobile phone data. Considering the possibility, feasibility, and convenience of information acquisition in practice, we adopts the activity triaxial acceleration which is easy to obtain in practice as the input data source for activity recognition.

B. METHODOLOGY FRAMEWORK

Recognizing activities through data is a typical classification problem. In machine learning, random forests, decision tree, support vector machine, Bayesian network and other methods are often used to deal with this problem. In these methods, random forest is an integrated learning algorithm that uses multiple weak models to combine strong models. Its algorithm accuracy is better than other algorithms on most datasets. Random forests method can also balance the error for unbalanced data. The activities of elderly at home have obvious imbalances, for example, lying and sitting are more, yet brushing teeth, combing hair, etc. are significantly less. Therefore, the method we proposed is based on random forests to produce the preliminary recognition result.

Because random forests are not enable to ensure activities can be completely and correctly recognized, and misjudgment may occur, such as recognizing wake-up activity as going to toilet, it is necessary to identify and correct misjudgment of activities. In fact, on the one hand, many elderly people's home activities are related to locations and time, such as getting up in the bedroom in the morning and cooking in the kitchen at the time of cooking. On the other hand, there is a certain degree of similarity between activities, such as the activity of brushing teeth and the activity of combing hair, which is caused by the similarity of human wrist movement. Therefore, our solution is using the relevance of activity, location, and time to determine whether the location and time where and when an activity happens is reasonable. If it is unreasonable, we will find the most reasonable similar activity as result according to similarity between activities. We proposed a two-level elderly home activity recognition method based on random forest and activity similarity (AR-RFAS for short). The model of AR-RFAS is as follows:

$$H = \begin{cases} F(x) & F(x) \in H_{LT} \\ \max\limits_{j} AcCorr_{[F(x)][j]} & F(x) \notin H_{LT} \end{cases} \tag{1}$$

where x is the input triaxial acceleration, $F(x)$ is the activity obtained by the random forests algorithm, and H_{LT} is the activity set of the current location and time. If $F(x)$ is in H_{LT}, the result activity H is $F(x)$. Otherwise, the similarity $AcCorr$ between activities in H_{LT} and $F(x)$ is further calculated. Finally, the activity with the greatest similarity is obtained as the result H.

The relevance between location,time, and activity can be predefined and the location data in recognition can also be easily obtained through sensors. So in IV, we will focus on the activity recognition method based on random forest and the calculation of the activity similarity matrix.

IV. PROPOSED METHODOLOGY

A. ELDERLY ACTIVITY RECOGNITION BASED ON RANDOM FOREST

The random forest algorithm used in this paper exploits the Bagging parallel algorithm idea, which can effectively resist differences and prejudice. The calculation process is as follows: firstly, the training sample set is constructed by randomly extracting N samples from the dataset; then each training sample generates a decision tree by means of random splitting attributes; finally, the N decision trees constitute a forest, and the final classification result is determined by the voting of the classification results of the N decision trees. The random forest classifier is shown in Fig. 1.

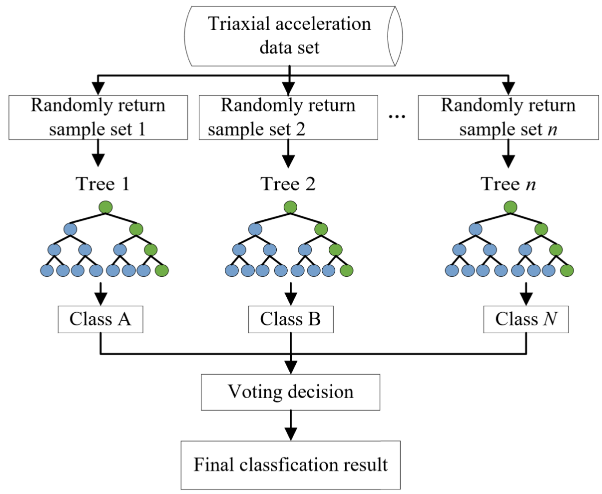

FIGURE 1. **Random forest classifier.**

Among them, the random attribute selection is introduced in the decision tree training process, and when the split attribute is selected, the ordinary decision selects the optimal attribute among all the attributes of the current node. When the decision tree in the random forest selects an attribute, a candidate attribute set is randomly selected from all the attributes, and the optimal attribute is selected from the candidate attribute set. Through k-round training, the algorithm obtains a sequence of classification models:

$$\{f_1(x), f_2(x), \ldots, f_k(x)\} \tag{2}$$

A classification model is composed of the sequence of (2). The final classification result of the model is produced by a simple majority voting method, namely:

$$F(x) = arg \max_{y} \sum_{i=1}^{k} I(f_i(x) = y) \tag{3}$$

In (3), $F(x)$ denotes a combined classification model; $f_i(x)$ is a single decision tree classification model; x denotes an input variable (XYZ three-axis acceleration); y denotes an output variable (elderly combing, brushing, walking and other activities); $I(x)$ is the indicator function.

Random forests randomly construct different training sets, and different training sets produce different decision trees. By combining the decision results of decision trees, the model classification ability is improved.

B. ACTIVITY SIMILARITY MATRIX

In the field of home care service, some elderly activities have certain similarities. For example, the activity of brushing teeth and the activity of combing hair are similar, and the activities such as combing hair, getting up, lying down, standing up, and making a phone call are related. This correlation is caused by the similarity of human wrist movement. The random forest approach proved to be the most effective one in calculating activity similarity. In reference [18], random forest algorithm is used on the standard benchmark dataset HMP of such problem. The confusion recognition matrix of the elderly activity recognition is obtained through a large number of experiments, and then the confusion matrix is analyzed and the activity similarity value is calculated. The detailed calculation formula is: assuming that there are n activities, the definition of the similarity between activity i

and activity j is as follows:

$$AcCorr_{i,j} = \frac{p[i][j]}{\sum_{k=1}^{n} p[i][k]} \tag{4}$$

In (4), $\sum_{k=1}^{n} p[i][k]$ denotes the number of times judged as the activity j in all experiments, and $p[i][j]$ denotes that the activity is judged to be the activity i, but the activity actually performed by the user is j.

Based on (4), the activity similarity matrix is $ACMatrix = [c_{ij}]_{m\times n}$, where $c_{ij} = AcCorr[i][j]$. The value of the activity similarity matrix is shown in Fig. 2.

C. AR-RFAS ALGORITHM

As described in III-B, the core idea of AR-RFAS is firstly obtaining the preliminary recognition results by using the random forest algorithm, and then using the activity similarity matrix to correct the errors in first step to enhance the recognition result. The algorithm of AR-RFAS is shown in Algorithm 1.

Firstly, we collect the original sensor data, process the collected data, set a smooth window, calibrate labels, select and extract features, generate test sets and training sets. Secondly, we put the training set into the random forest model, determine the activity of the elderly by voting based on random forest activity recognition model. Thirdly, based on this preliminary result, we can judge the correctness of the activity according to the location and time information of the elderly. If the activity is wrong, the activity set associated with the location and time is screened out, and the activity is further corrected according to the activity similarity matrix. For example, the result is brushing teeth, but the location of the elderly is detected as the bedroom, according to the relationship between the location and activity, brushing teeth is not associated with bedroom. Activities associated with bedroom includes lying in bed, getting up, walking and so on. The activity similarity matrix shows that the activity is related to the activity getting up in the bedroom, so the result is corrected to getting up.

Algorithm 1 Elderly Activity Recognition Algorithm Based on Random Forest and Activity Similarity

Input: dataset $data(<x, y>)$, the number of trees in random forests T, minimum sample α, minimum information gain β
Output: elderly activity h

begin
  $data \leftarrow$ sensor data
  $windows \leftarrow 30$ /*Set a smooth window*/
  $datacomps \leftarrow inputfileSlide()$
  $initTraining()$ /*Data preprocessing*/
  $addFeature()$ /*Calculate eigenvalues*/
  for $t \leftarrow 1$ **to** T **do**
    $k \leftarrow poisson(\lambda)$ /*The times of random sampling with return*/
    if $k > 0$ **then**
      for $u \leftarrow 1$ **to** k **do**
        $j \leftarrow findLeaf(x)$
        $updateNode(j, <x, y>)$
        if $|r_j| > \alpha$ and $\exists s \in s : \Delta l(r_j, s) > \beta$ **then**
          $s_j \leftarrow argmaxs \in s\Delta l(r_j, s)$
          $createLeftChild(p_{jls})$ /*Establish left subtree*/
          $createRightChild(p_{jrs})$ /*Establish right subtree*/
        end
      end
    else
      $estimate\ oobe \leftarrow updateOOBE(<x, y>)$ /*The decision tree is established completed*/
    end
  end
  $h \leftarrow buildClassifier()$ /*Multiple decision trees constitute random forests, and voting to generate profit activity.*/
  $x \leftarrow acLocTimRelation(h, location)$ /* Get location and time correlation*/
  if $x < 1$ **then** $h \leftarrow locTimAcRelation(h)$
  return h /*Correct recognition based on correlation of activity, location, and time*/
end

V. EXPERIMENT AND ANALYSIS

A. DATASETS AND EXPERIMENT ENVIRONMENT

Most of the existing studies use three-axis accelerometer sensors provided by smartphones to obtain data. However, because smartphones have the disadvantages of unfixed position, uncertain carrying time, and inability to ensure that the elderly always carry them, the sensors on mobile phones are not suitable for the elderly. In this paper, we use wrist-type three axis accelerometer (i.e. wristband), which has the characteristics of small size, light weight, convenient carrying. It is more feasible than mobile phones. The data collected are the acceleration values of X, Y, and Z axes. The dataset used in this paper is the public dataset HMP [18] which consists of 979 trials covering the 12 actions listed in Table 1 and the activity data of 16 volunteers (11 men and 5 women, aged between 19 and 81 years old). Since there is no specific annotation for the elderly data, all data are used. Each experimental file records three-axis acceleration values once to perform an activity. There are a total of 729,476 records.

In the process of statistical feature extraction, according to the data characteristics generated by the three-axis accelerometer, we apply the feature extraction method to process the data. For each dimension time series of data in sliding window, statistical-based features are extracted, including maximum, minimum, mean, standard deviation, quartile-Q1, quartile-Q2, quartile-Q3, mode, range, mean, mid-range, etc.

	brush teeth	comb hair	drink water	pour oil	have meal	walking	get up	lie down	stand up	sit down	call up
brush teeth	0.9866	0.01	0	0	0	0	0.0033	0	0	0	0
comb hair	0	0.9505	0	0	0	0	0	0	0	0	0.0099
drink water	0	0	0.9872	0	0	0	0	0	0	0	0.0085
drain oil	0.0269	0	0	0.9624	0	0	0	0	0	0	0.0054
have a meal	0	0	0	0	0.9858	0	0	0.0095	0.0024	0	0.0024
walking	0.0051	0.0026	0	0	0	0.9668	0.0026	0.0128	0.0102	0	0
get up	0	0.0116	0	0	0	0	0.9767	0.0116	0	0	0
lie down	0	0	0	0	0	0	0	1	0	0	0
stand up	0.0397	0.0265	0	0	0	0	0	0.0199	0.9139	0	0
sit down	0	0.0065	0	0	0	0	0	0.0065	0.0065	0.98064516	0
call up	0	0	0	0	0	0	0	0	0	0	0.9939

FIGURE 2. Matrix of activity similarity.

These features can be used to describe the characteristics of the activities studied in this paper. The features generated from the multi-dimensional data are combined as new data segment representation so as to classify the activity of the elderly.

The cross-validation method of training set and test set is used to ensure the correctness of the algorithm. The k-fold cross-validation is used to analyze the data, which is mainly applied in the case of insufficient sample data. The dataset is randomly divided into k parts, one of which is taken as test set, and the remaining $k-1$ data is taken as training set. We set $k = 10$ in this paper.

During the experiment, four datasets with different sizes, i.e. DS_1, DS_2, DS_3, and DS_4, were generated from the original dataset. The sizes of DS_1, DS_2, DS_3, and DS_4 are one fourth of the original dataset, two quarters of the original dataset, three quarters of the original dataset, and equal to the original dataset, respectively. We conducted experiments on these four datasets. The performance of the proposed algorithm is analyzed from two perspectives: the influence of feature number on the algorithm and the degree of improvement of algorithm performance by activity similarity method. Then our algorithm was compared with the algorithm proposed in reference [18] on the same dataset to analyze the performance of our algorithm, and compared with other machine learning algorithms to verify the superiority of the random forest algorithm.

B. EVALUATION INDICATOR

We use the three performance evaluation indicators of accuracy rate, kappa coefficient and root mean squared error(RMSE) to evaluate the activity recognition algorithm of the elderly based on random forest.

Accuracy rate is the ratio of the number of correct classifications to the total number of instances, which is the most widely used performance evaluation indicator. The formula is shown in (5).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{5}$$

where TP represents samples belonging to positive categories being classified into positive categories. TN represents samples belonging to negative categories being classified into negative categories. FP represents samples belonging to negative categories being classified into positive categories. FN represents samples belonging to positive categories being classified into negative categories.

Kappa coefficient is used to consistency checking based on confusion matrix. Its formula is as follows:

$$k = \frac{p_0 - p_e}{1 - p_e}, \quad p_0 = \frac{s}{n},$$
$$p_e = \frac{a_1 \times b_1 + a_2 \times b_2 + \cdots + a_n \times b_n}{n \times n} \tag{6}$$

where n is the total number of categories and s is the correct number of classifications. p_0 is the sum of the number of correctly classified samples for each category divided by the total number of samples, i.e., the overall classification accuracy. $a_1, a_2, \cdots, a_n$ are the numbers of real samples for each category. $b_1, b_2, \cdots, b_n$ are the numbers of predicted samples for each category.

RMSE is widely used to measure the accuracy of classification. The smaller the value is, the better the performance is. The formula is as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}} \tag{7}$$

C. RESULT ANALYSIS

In the first experiment, we compare Random Forest(RF) method with other related classification methods in order to prove the advantages of RF in activity recognition problem. RF is compared with Multi-layer Perceptron(MLP), J48 in decision tree, Naive Bayesian(NB), Bayesian Network(BN), and Sequence Minimal Optimization(SMO). Each algorithm was run 50 times in a 10-fold cross validation manner. The average value of each method in the three value of accuracy rate, kappa coefficient and RMSE is calculated as the average comprehensive accuracy. The average comprehensive

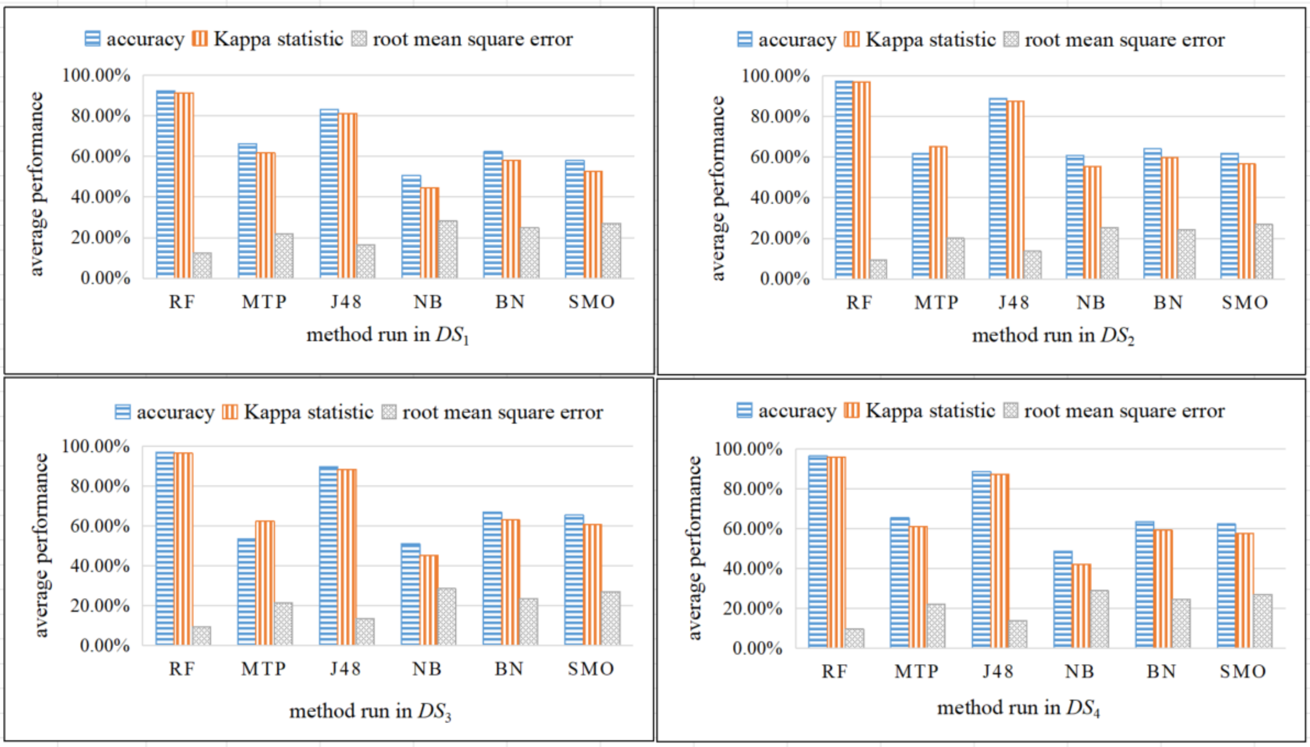

FIGURE 3. Average comprehensive accuracy comparisons of different machine learning methods on datasets with different sizes.

accuracy comparisons of different machine learning methods on datasets with different sizes is shown in Fig.3.

It can be seen from Fig.3 that under all datasets, the accuracy of activity recognition of the elderly in random forest is the highest, the kappa coefficient is also the highest, and the root mean square error is the lowest. The advantage of random forest is mainly reflected in that it is an Ensemble Learning method which combines the results of multiple decision trees to determine the reasoning results. Therefore, we choose the random forest method as the initial method to identify the activity of the elderly.

In the second experiment, we analyze the influence of features on the accuracy of algorithm. In machine learning, feature selection is very important. We chose the characteristics based on statistics. The candidate features include maximum, minimum, average, standard deviation, quartile-Q1, quartile-Q2, quartil-Q3, mode, extremum value difference, average number, medium range, coefficient of variation, variance, skewness, kurtosis, etc. We run AR-RFAS with different combinations of features on the four datasets to obtain the average accuracy of the algorithm based on random forests. The accuracy of AR-RFAS for different characteristics is shown in Fig. 4 and the running time of the algorithm for different characteristics is shown in Fig. 5.

It can be seen from Fig. 4 that as the number of features increases, the accuracy of the algorithm gradually increases. When the number of features reaches 11, the accuracy reaches the peak value. When the number of selected features continues to increase, there is no significant change of the

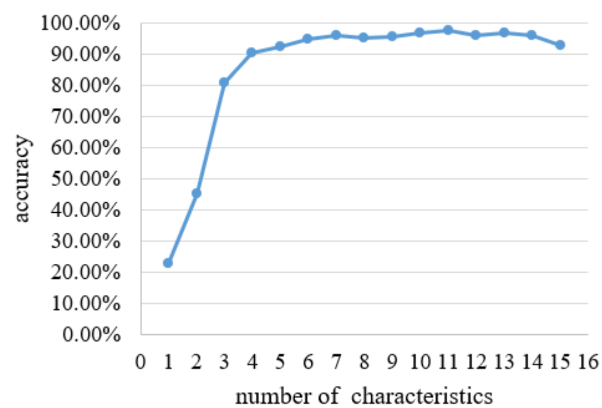

FIGURE 4. Accuracy of AR-RFAS for different characteristics.

accuracy. However, as shown in Fig. 5, the running time of the algorithm increases with the number of features significantly. Therefore, selecting the appropriate feature number and feature combination can not only guarantee the accuracy, but also reduce the time-consuming of the algorithm. In this paper, we set the number of features to 11.

After preprocessing the dataset and extracting the features, in the third experiment, model training was conducted with the training set, and then the algorithm was tested with the test set. The accuracy rate of the algorithm on dataset DS_1 is 92.31%, and its confusion matrix is shown in Fig. 6. As shown in Fig. 6, the activity of lying down is easy to be judged

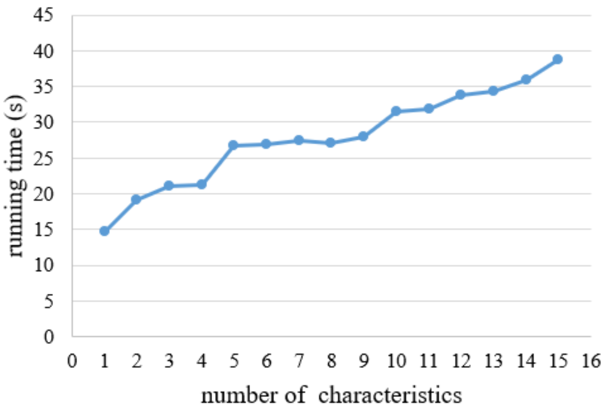

FIGURE 5. Running time of AR-RFAS for different characteristics.

a	b	c	d	e	f	g	h	i	j	k	<-- classified as
146	1	2	0	0	0	4	0	3	1	0	a = brush_teeth
1	78	0	0	2	0	0	0	0	3	0	b = use_telephone
0	2	99	0	0	0	0	0	0	0	0	c = comb_hair
0	0	0	188	0	0	0	0	1	0	0	d = walk
0	0	0	0	112	2	0	0	0	1	0	e = drink_glass
0	0	0	0	9	194	0	0	0	5	0	f = eat_meat
0	0	0	0	0	0	72	0	0	0	0	g = standup_chair
1	0	1	7	0	1	8	21	3	0	1	h = getup_bed
0	0	1	2	0	0	0	0	72	1	0	i = liedown_bed
0	0	0	0	4	1	0	0	0	82	2	j = cook
0	0	1	3	0	3	13	0	2	1	53	k = sitdown_chair

FIGURE 6. Confusion matrix of activity recognition of the elderly.

as other activities, such as combing hair and walking. The activity of brushing teeth can easily be inferred to combing, getting up, sitting down and so on.

In order to accurately correct the identified activity and reduce the false judgment, the correlation values of location and activity were set by analyzing the confusion matrix of random forests according to the correlation between location and activity. Based on the values, the activity of the elderly was verified through behavioral similarity. By running the algorithm 50 times on DS_1 and averaging the accuracy rate of each activity recognition, the comparison of the accuracy rate of each activity between AR-RFAS and the random forest algorithm without using activity similarity is shown in Fig. 7. The average accuracy rate in the result of two-layer algorithm is 95.59%, much better than the result 92.31% of random forest algorithm without using activity similarity. In the random forest algorithm, the activity recognition accuracy of brushing, walking, drinking, pouring water, lying down, and eating is high, and the recognition accuracy rate of sitting down and getting up is relatively low. The random forest algorithm has different accuracy for each activity recognition. After the activity similarity is adopted, by the test of the correlation between location, time and activity, and the correction activity through activity similarity, the recognition accuracy can generally be improved, especially the activity of getting up which is easy to be recognized as other activities.

We analyzed the accuracy of AR-RFAS on different size datasets. AR-RFAS is run several times on each of the four datasets, and the average accuracy of the algorithm is shown

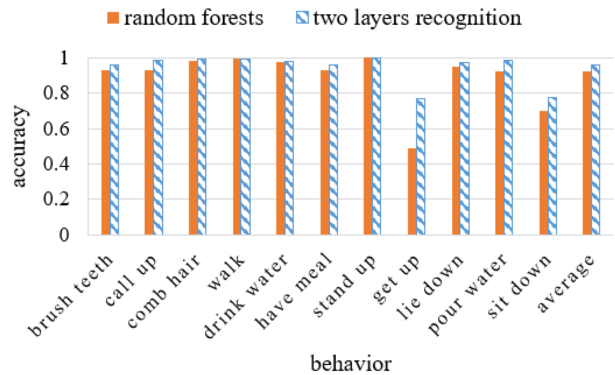

FIGURE 7. Comparison between random forest algorithm and two-layer activity recognition.

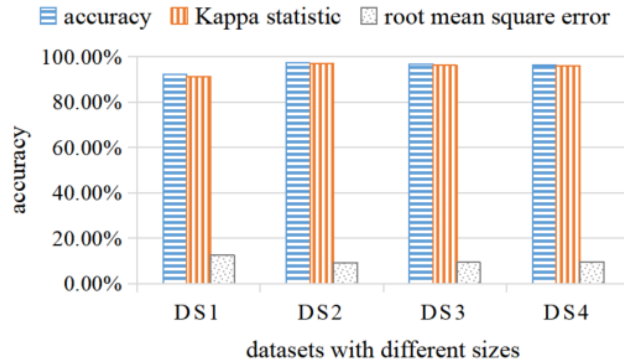

FIGURE 8. Recognition accuracy on different size datasets.

in Fig. 8. As the data size increases, the accuracy is increasing, but after the data size reaches a certain level, the accuracy of the data does not increase any more.

In the last experiment, AR-RFAS is compared with the related method. Dyana, an ADL data collector, proposed a framework for recognizing activities which relies on Gaussian mixture regression to build an activity model, specifically based on Mahalanobis distance using GMM(Gaussian Mixture Model) and GMR(Gaussian Mixture Regression) modeling features to achieve simple runtime recognition [19]. The method recognized seven human activities. The comparison between AR-RFAS and the Mahalanobis-distance-based algorithm is shown in Fig. 9. In Fig. 9, AR-RFAS has a higher accuracy than the Mahalanobis-distance-based algorithm, and can recognize more activities. There are three possible reasons. First, AR-RFAS adopts multiple statistical characteristic values, which can better reflect the meaning expressed by the data than a single value. Second, the random forest method integrates multiple models to judge activity by voting, which is better than the single mathematical model. Third, we further correct the activity recognition result by using the similarity of activities, which can eliminate the situation that some activities has lower recognition accuracy

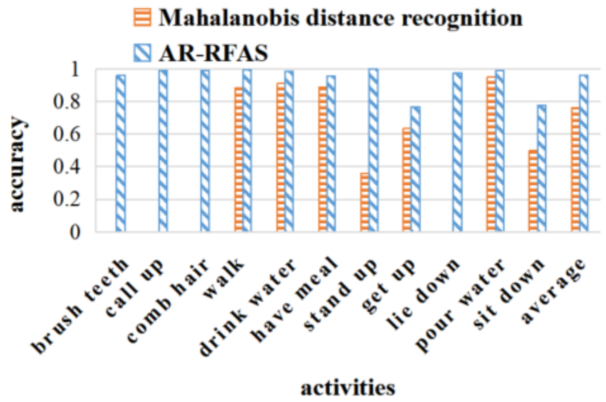

FIGURE 9. Comparison between AR-RFAS and Mahalanobis-distance-based algorithm.

rate. This method further improves the overall accuracy of AR-RFAS.

VI. CONCLUSION AND FUTURE WORK

In this paper, we first analysis the typical activities of elderly home care service. Then we propose a two-stage elderly home activity recognition method based on random forest and activity similarity. The method first uses improved random forest to obtain a preliminary result. Then the correlation between activity, location, and time is employed to judge the rationality of the result. Last, the similarity of activities is further used to correct the results. We set up a series of experiments to evaluate the effectiveness and efficiency of our approach.

The future work will focus on the extension of the problem model which will increase the type and scale of acquired sensor data to further improve the recognition accuracy and application range. Meanwhile, trying to apply the method into the realization of context-aware service and active service for elderly people.

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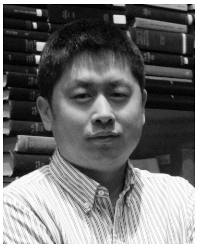

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