Adaptive Multi-state Pipe Framework Based on Set Pair Analysis

Leixin Shi, Hongji Xu, Beibei Zhang, Xiaojie Sun, Juan Li, and Shidi Fan

Abstract—**Human Activity Recognition (HAR) is one of the main research fields in pattern recognition. In recent years, machine learning and deep learning have played important roles in Artificial Intelligence (AI) fields, and are proven to be very successful in classification tasks of HAR. However, there are two drawbacks of the mainstream frameworks: 1) all inputs are processed with the same parameters, which would cause the framework to incorrectly assign an unrealistic label to the object; 2) these frameworks lack generality in different application scenarios. In this paper, an adaptive multi-state pipe framework based on Set Pair Analysis (SPA) is presented, where pipes are mainly divided into three kinds of types: main pipe, sub-pipe and fusion pipe. In the main pipe, the input of classification tasks is preprocessed by SPA to obtain the Membership Belief Matrix (MBM). The sub-pipe shunt processing is performed according to the membership belief. The results are merged through the fusion pipe in the end. To test the performance of the proposed framework, we attempt to find the best configuration set that yields the optimal performance and evaluate the effectiveness of the new approach on the popular benchmark dataset WISDM. Experimental results demonstrate that the proposed framework can get the good performance by achieving a result of 1.4% test error.**

Index Terms—**Human Activity Recognition (HAR), Membership Belief Matrix (MBM), multi-state pipe framework, Set Pair Analysis (SPA).**

I. Introduction

Human Activity Recognition (HAR) is an important area in pattern recognition and its research can be traced back to the 1990s [1]. There are two main ways to acquire human activities, i.e., using cameras and wearable sensors [2]. With the rapid development of microelectronics and the Internet of Things (IoT), wearable sensors allow people to interact with devices. Many scholars have made great achievements in using various advanced algorithms to classify and process perceived activity information [3]-[5]. However, there are two drawbacks of the mainstream frameworks: most of them fail to use a divide-and-conquer-based method for different activities and lack generality in different application scenarios.

In this paper, a novel framework is presented for HAR, which utilizes a divide-and-conquer-based method based on Set Pair Analysis (SPA). SPA is a theoretical tool for dealing with uncertainties proposed by K. Q. Zhao [6]. The main idea is that there are two connected sets A and B to form the set pair $H(A, B)$ in a specific problem, which is used to analyze the certainty and uncertainty of the two sets [7]. In the proposed framework, the sample data is pre-classified by K-Nearest Neighbor (KNN), and the results are processed by SPA to obtain the Membership Belief Matrix (MBM). The Membership Belief (MB) is determined by the threshold method for the selection of sub-pipes. Finally, the results are output through the fusion pipe. During the feedback phase, this paper traverses the optimal solution for finding MB to further improve activity recognition performance.

The rest of this paper is organized as follows. The related outline of SPA is introduced in Section II. The details of the proposed framework are described in Section III. The experimental results are showed and analyzed in Section IV. Finally, the conclusions and some future works are described in Section V.

II. Related Works

Some related concepts about existing frameworks of HAR and SPA are reviewed in this section briefly.

A. Framework of HAR

With the development of hardware processing ability and Artificial Intelligence (AI), the framework of HAR is constantly optimized. The articles [8]-[11] used various methods of machine learning to identify human behaviors and analyzed the performance of various methods. I. Cleland *et al.* [12] and K. Altun *et al.* [13] compared the performances of various machine learning classification methods, and the results indicated that Bayesian Decision Making (BDM) generally can get the highest correct classification rate with relatively small computational cost. The above frameworks are only suitable for dealing with low complexity applications. J. B. Yang *et al.* [14] proposed a system feature learning method of HAR which used a deep Convolutional Neural Network (CNN) to automate feature learning from the raw inputs in a systematic way. F. J. Ordez *et al.* [15] proposed a general deep activity recognition framework based on convolution and Long Short-term Memory (LSTM) cycle units. In order to improve the shortcomings of the current frameworks, i.e., their failure to take the important spatial hierarchies between features into account, the concept of capsule was first proposed in 2011 by

G. Hinton [16] and achieved state-of-the-art accuracy on the dataset MNIST in 2017 [17]. T. Turan *et al*. [18] monitored

infant's emotional cry in domestic environments using the capsule network architecture.
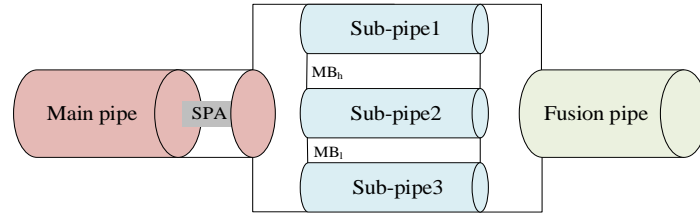

Fig. 1. The structure of the adaptive multi-state pipe framework based on SPA.

However, the above frameworks perform the same processing for all kinds of data, resulting in an inability to distinguish behavior. H. Cho *et al*. [19] applied a divide-and-conquer approach and built a two-stage activity recognition process, where the abstract activities, i.e., dynamic and static activities, were first recognized using a 2-class classifier, and then the individual activities were recognized using two 3-class classifiers. This framework effectively compensates for the shortcomings of the previous frameworks, but still has shortcomings in generality.

B. Set Pair Analysis

SPA is a theoretical tool for dealing with uncertainty problems. The basic idea is that in the context of a specific problem, there are two connected sets A, B forming a set pair $H(A, B)$ [20].

The two sets A and B are quantitatively described by the identical, contradictory and discrepant analysis according to their characteristics. The set pair $H(A, B)$ has M features, including the identical features, contradictory features and other features. For a specific problem, assuming that the number of identical features is S, and then the identity degree of two sets is S/M; the number of contradictory features is P, and then the contradictory degree is P/M; the number of other features is $F = M - S - P$, and then the discrepancy degree is F/M. The connection degree of sets A and B can be expressed as:

$$\mu_{(A-B)} = \frac{S}{M} + \frac{F}{M}I + \frac{P}{M}J, \tag{1}$$

where I is the coefficient of discrepancy degree and J is the coefficient of contradictory degree, $I \in [-1,1]$, and the value of J is -1 usually. We set $a = S/M$, $b = F/M$, $c = P/M$, and the range of them is $[0,1]$. Then, equation (1) can be rewritten as:

$$\mu_{(A-B)} = a + bI + cJ, \tag{2}$$

where $a + b + c = 1$.

The proximity of two vectors v_1 and v_2 .can be represented by:

$$cos\theta_{12} = \frac{(v_1, v_2)}{\|v_1\|_2 \cdot \|v_2\|_2} \tag{3}$$

where (v_1, v_2) is the inner product of the two vectors v_1 and v_2, and $\|v_1\|_2 \cdot \|v_2\|_2$ is the 2-norm product of them.

III. ADAPTIVE MULTI-STATE PIPE FRAMEWORK BASED ON SPA

Differentiation of confusing activities is still a difficult problem in HAR. A novel adaptive multi-state pipe framework based on SPA is proposed to effectively identify confusing activities.

A. Proposed Relational Degree of Evidences

Fig. 1 shows the basic flowchart of the proposed framework, which is mainly composed of main pipe, sub-pipes and fusion pipe. In the main pipe, the training information is processed by the KNN [21] algorithm to obtain the confusion matrix of each predicted value and actual value, and then the SPA algorithm is used to obtain the Belief Matrix (BM). When the test information enters the main pipe again, the MBM is obtained by multiplying the membership with the previous BM, and then the corresponding sub-pipes are selected by the upper and the lower limits of the credibility to classify the information. Finally, the results in each sub-pipe are output through the fusion pipe.

B. Procedure of the Proposed Method

As shown in Fig. 2, the flowchart of the adaptive multi-state pipe framework based on SPA is as follows:

- Step 1: Activity information is collected through intelligent hardware as input to this framework.
- Step 2: The proposed framework pre-processes the data and detect whether the information is uncertain by using a preset threshold. If there exists uncertainty, the system will execute uncertainty elimination and information standardization, otherwise it will directly execute information standardization. There are three main types of data standardization.

1) Standardization of category-type features using one-hot coding.
2) Standardization of numerical features using normalization.
3) Standardization of ordered features using ordered numerical coding.

After the original data eliminates uncertainty, activity information will have higher credibility. Normalization unifies the scalar to $[0,1]$, which is convenient for calculation and may help the system to find the global optimal solution.

- Step3: Enter the appeal results into the main pipe of the framework, and use KNN for classification processing to

get the confusion matrix. The columns of confusion matrix represent the predicted categories of data and the sum of data in each column is the number predicted as a category. The rows represent the real categories of data, and the sum of data in each row is the number of data instances of one category. The diagonal of the confusion matrix represents the same number of instances as the actual prediction, that is, the prediction is correct. The confusion matrix of the main pipe is showed in Table I, where n represents the number of activity types, and $Number_{ij}$ represents the number that input activity i is identified as output activity j.
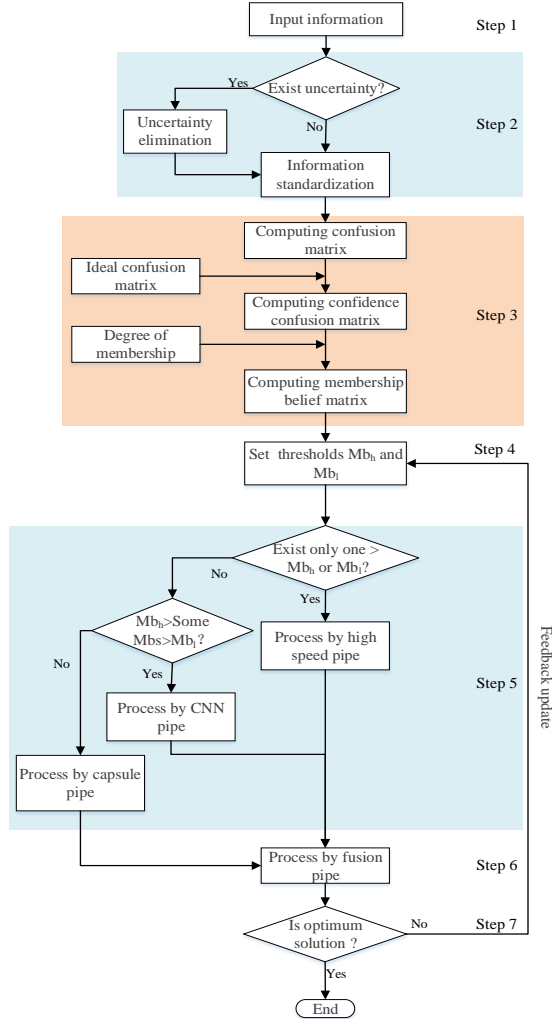

Fig. 2. The flowchart of the adaptive multi-state pipe framework based on SPA.

TABLE I: THE CONFUSION MATRIX OF MAIN PIPE

	Activity 1	Activity 2	...	Activity n
Activity 1	$Number_{11}$	$Number_{12}$	...	$Number_{1n}$
Activity 2	$Number_{21}$	$Number_{22}$	...	$Number_{2n}$
...	...	...	...	...
Activity n	$Number_{n1}$	$Number_{n2}$	...	$Number_{nn}$

According to the confusion matrix, we can find the membership degree of each predicted activity for the actual activity and express as:

$$v_i = [\frac{Number_{1i}}{sum(col_i)}, \frac{Number_{2i}}{sum(col_i)}, ..., \frac{Number_{ji}}{sum(col_i)}, ..., \frac{Number_{ni}}{sum(col_i)}]^T$$
$$= [p_{1i}, p_{2i}, ..., p_{ji}, ..., p_{ni}]^T, \qquad (4)$$

where p_{ji} represents the proportion of actual behavior j in predicted behavior i, $\sum_{k=1}^{n} p_{ki} = 1$ and $i \in [1,n]$. Then $[v_1, v_2, ..., v_i, ..., v_n]$ means the confusion matrix and $sum(col_i)$ is the sum of elements in its column i.

TABLE II: THE MEMBERSHIP MATRIX OF MAIN PIPE

v_1	v_2	...	v_n
p_{11}	p_{12}	...	p_{1n}
p_{21}	p_{22}	...	p_{2n}
...	...	...	...
p_{n1}	p_{n2}	...	p_{nn}

Table II shows the Membership Matrix (MM) of the main pipe. The ideal membership matrix is a unit matrix, i.e., $\mathbf{E} = [e_1, e_2, ..., e_j, ..., e_n]$, where $e_j = [0,0,...,1,...,0]^T$. The proximity procedure between the element of actual MM and that of ideal MM is shown as:

$$cos\theta_{ij} = \frac{(v_i, e_j)}{||v_i||_2 \cdot ||e_j||_2} = \frac{p_{ji}}{||v_i||_2}, \qquad (5)$$

where $(v_i, e_j) = \sum_{k=1}^{n} p_{ki}e_{jk}$ represents the inner product of v_i and e_j, $||v_i||_2 = \sqrt{\sum_{k=1}^{n} p_{ki}^2}$ represents the 2-norm of the vector v_i. $cos\theta_{ij}$ indicates the proximity of the ideal membership degree of the i-th predicted activity and the j-th predicted activity. The value of $cos\theta_{ij}$ is between 0 and 1.

Table III shows the BM of the main pipe, and it indicates that the prediction credibility is 100% when the element value is 1.

TABLE III: THE BELIEF MATRIX OF MAIN PIPE

$cos\theta_{11}$	$cos\theta_{12}$	...	$cos\theta_{1n}$
$cos\theta_{21}$	$cos\theta_{22}$	...	$cos\theta_{2n}$
...	...	...	...
$cos\theta_{i1}$	$cos\theta_{i2}$	...	$cos\theta_{in}$
...	...	...	...
$cos\theta_{n1}$	$cos\theta_{n2}$	...	$cos\theta_{nn}$

The membership degree of test information $\mathbf{p} = [p_1, p_2, ..., p_i, ..., p_n]^T$ is obtained through the KNN algorithm of the main pipe, where p_i represents the probability that the predicted activity belongs to activity i. The membership of the test information and the reliability matrix BM of the main pipe are multiplied respectively to obtain the MBM, which is shown as:

$$MBM = \begin{vmatrix} p_1 cos\theta_{11}, p_2 cos\theta_{12}, ..., p_i cos\theta_{1i}, ..., p_n cos\theta_{1n} \\ p_1 cos\theta_{21}, p_2 cos\theta_{22}, ..., p_i cos\theta_{2i}, ..., p_n cos\theta_{2n} \\ \vdots \\ p_1 cos\theta_{i1}, p_2 cos\theta_{i2}, ..., p_i cos\theta_{ii}, ..., p_n cos\theta_{in} \\ \vdots \\ p_1 cos\theta_{n1}, p_2 cos\theta_{n2}, ..., p_i cos\theta_{ni}, ..., p_n cos\theta_{nn} \end{vmatrix}, \qquad (6)$$

● Step4: Define a new concept of credibility MB for sub-pipe selection as $MB_{ij} = p_i cos\theta_{ij}$. The sub-pipe shunt processing is performed according to the upper limit (MB_h) and the lower limit (MB_l) of the threshold.

$$MB_h = 0.8 \times \left(\frac{0.8}{\sqrt{0.8^2 + (1-0.8)^2}}\right) = 0.776$$

$$MB_l = 0.6 \times \left(\frac{0.6}{\sqrt{0.6^2 + (1-0.6)^2}}\right) = 0.498 \qquad (7)$$

where the membership degree corresponding to MB_h is initialized to 0.8 and the membership degree of test data is 0.8. The one corresponding to MB_l is initialized to 0.6 and the membership degree of test data is 0.6. Initial values of them are determined by simulations, MB_h and MB_l are then equal to 0.776 and 0.498, respectively.

TABLE IV: ALGORITHM IMPLEMENTATION FOR FINDING OPTIMAL PARAMETERS

Algorithm 1 Find the best combination of MB_h and MB_l

```
for (i=0.1; i<=1; i=i+0.1)
{
    for (j=0.1; j<i; j=j+0.1)
    {
        acctotal.append(now_acc);
        if(now_acc>oldacc)
        {
            MBh = i;
            MBl = j;
        }
    }
}
Return MBh, MBl
```

- Step5: The sub-pipes are divided into high-speed sub-pipe, CNN sub-pipe, and capsule sub-pipe. If the classification result of main pipe is accurate, the data passes through the high-speed sub-pipe. Otherwise the sub-pipe using CNN or capsule is used for secondary classification.
- Step6: The processed data is sequentially merged through the fusion pipe.
- Step7: Traverse the sub-pipeline between MB_h and MB_l in 0.1 step to find the best solution. The results adjust step 4 as feedback. The algorithm implementation to find the optimal MB_h and MB_l is shown in Table IV.

IV. EXPERIMENTS AND EVALUATION

The experiments are performed on a PC equipped with Intel Core i7-8700 + 16G RAM + NVIDIA GeForce GTX 1080 Ti, and run on windows system through Pycharm + Anaconda (Python 3.6.5) + CUDA 9.0 + Cudnn + Tensorflow-gpu 1.8.

In order to demonstrate the efficiency of the proposed framework, the experiments are performed on the public dataset WISDM. The dataset collects 36 people's activities through sensors in smartphones, including the following six activities: walking, standing, going upstairs, going downstairs, sitting and jogging. The whole data is divided into 75% training data and 25% testing data. We analyze how MB_h and MB_l of the proposed framework affect the classification results, and confirm the optimal configuration of parameters. Finally, we show the performance of the proposed framework by comparing with some other state-of-the-art frameworks, including CNN and a two-stage learning of multiple 1D CNN model.

A. Optimal Configuration of MB

Fig. 3 shows the comparison of the accuracy of different thresholds of the adaptive multi-state pipe framework based on SPA. The abscissa represents MB_l, the legend represents MB_h, and the ordinate represents the accuracy of different thresholds of the proposed framework. After several simulations we find out that the recognition rate of the framework is optimal when the probability coefficient corresponding to MB_h is 0.8 and the one corresponding to MB_l is 0.6. In different application scenarios, the optimal parameters may be different.
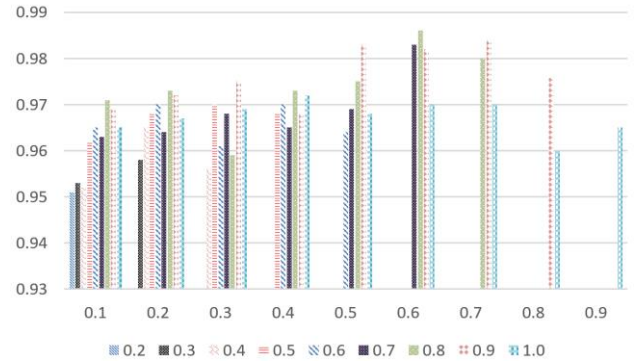

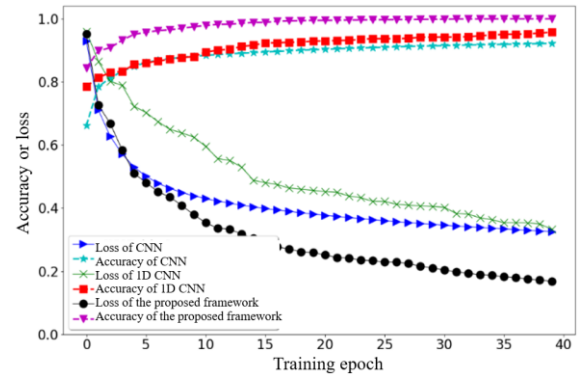Fig. 3. Comparison of the accuracy of different thresholds of the adaptive multi-state pipe framework based on SPA.

Fig. 4. The accuracy and loss of CNN, 1D CNN and the adaptive multi-state pipe framework based on SPA.

B. Comparison with the State-of-the-Art Frameworks

In terms of the performance of the proposed framework, we compare it with some other state-of-the-art frameworks of HAR. Fig. 4 shows the accuracy and loss of CNN, 1D CNN and the proposed framework. We can see that when the loss tends to converge, the recognition accuracy of the proposed framework is 98.6% (i.e., the test error is 1.4%). During the training process, the recognition accuracy of the proposed framework is always higher than that of CNN or 1D CNN.

Table V shows comparison of the accuracy of the above three frameworks, we can see that the proposed framework's testing recognition rate is optimal, which is about 7.9% higher than that of CNN and 2.2% higher than that of 1D CNN.

Fig. 5 shows the accuracy of each activity with the

proposed framework. It can be seen that the proposed framework has relatively high recognition accuracy for each activity. Fig. 6 shows the accuracy of each activity of CNN, 1D CNN and the proposed framework，respectively. It can be seen that the recognition accuracy of jogging, walking and standing are very high. However, like most other classifiers, CNN and 1D CNN fail in distinguishing between very similar activities like going upstairs and going downstairs. The proposed adaptive multi-state pipe framework based on SPA can handle these activities more effective and get the best performance.

TABLE V: THE COMPARISON OF THREE FRAMEWORKS

Framework	Training Accuracy	Testing Accuracy
CNN	92.3%	90.7%
1D CNN	98.6%	96.4%
The proposed framework	99.9%	98.6%

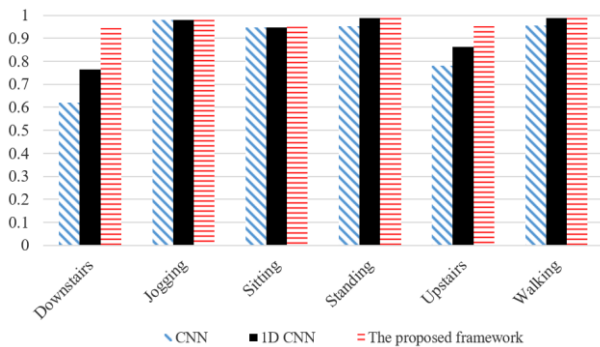|	Accuracy	Downstairs	Jogging	Sitting	Standing	Upstairs	Walking
	Downstairs	0.945	0.017	0.000	0.000	0.017	0.021
	Jogging	0.009	0.979	0.000	0.000	0.007	0.005
True	Sitting	0.000	0.000	0.947	0.045	0.008	0.000
Label	Standing	0.000	0.003	0.000	0.988	0.006	0.003
	Upstairs	0.013	0.013	0.001	0.003	0.952	0.018
	Walking	0.005	0.001	0.000	0.000	0.006	0.988

Fig. 5. The accuracy of each activity.

Fig. 6. The accuracy of each activity of CNN, 1D CNN and the adaptive multi-state pipe framework based on SPA.

V. CONCLUSION

In this paper, an adaptive multi-state pipe framework based on SPA is proposed, which provides an effective and feasible method for the differentiation of confusing activities. In the experiments, the optimal configuration of parameters is confirmed by analyzing the impact of several key parameters on the proposed framework. To demonstrate the strength of the proposed framework, it is compared with two state-of-the-art frameworks on the raw time series of the WISDM dataset. The experimental results demonstrate that the proposed framework's recognition accuracy is 98.6% on the dataset WISDM, which is about 7.9% higher than CNN and 2.2% higher than 1D CNN. Therefore, it can be used in both highly confused and general situations, and the fusing results are more effective compared with some other typical frameworks. Future works will consider combining capsule and LSTM to identify the characteristics of human activity.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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