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A Dynamic Time Warping-Based Method for Similarity Evaluation Between Smart Homes

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Abstract. Evaluating the similarity of smart homes is the basis for selecting the most suitable daily activity recognition model for migration and a key step in achieving model transfer in heterogeneous smart home environments. In this paper, we propose an improved DTW-based method for calculating the similarity of smart homes, which is used to select source smart homes that are similar to the target smart home. Firstly, the method standardizes the sensor mapping space and the daily activity space. Then the spatial features of the sensors are combined to calculate the similarity between the source smart home and the target smart home using an improved Dynamic Time Warping (DTW) algorithm. As a result, the set of candidates with similar source smart homes is obtained. Finally, fine-tuning is performed to evaluate the model transfer effect of similar source smart homes. The experimental results show that the daily activity recognition model selected by the proposed method can obtain the optimal transfer effect.

Keywords. smart home, daily activity recognition, dynamic time warping

1. Introduction

Smart homes are designed to detect the daily activities of residents through non-invasive sensors deployed in smart homes. Daily activity recognition enables early diagnosis of residents' cognitive health conditions, such as mild cognitive impairment and Alzheimer's disease, facilitating timely medical interventions for affected individuals.

Diagnosing cognitive impairments is challenging and requires long-term tracking of residents' daily trajectories to identify abnormal patterns. On the other hand, the global population of individuals with Alzheimer's disease is estimated to be around 47 million and is projected to reach 132 million by 2050. The caregiving costs for global cognitive impairment patients amount to a staggering $800 billion, posing a significant burden on countries worldwide. Research on daily activity recognition based on smart homes can contribute to the early detection of residents' cognitive impairments, enabling individuals to take effective measures for early prevention or slowing down the progression of the disease, thus reducing society's caregiving costs.

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Therefore, the research on the resident's daily activity recognition in smart homes holds profound economic and societal significance

2. Related Work

Cook et al. identified the variations in smart homes, residents' habits of daily activities, and the diversity in the spatial distribution of daily activity categories as the root causes of challenges in transferring daily activity recognition models [1]. Overcoming these differences has become a primary concern in addressing the transferability of daily activity recognition models.

Currently, research on the transfer of daily activity recognition models is still in the exploratory stage and lacks influential research outcomes. And precision and recall on public datasets remain relatively low. The limited research achievements in this area can be summarized in the following three aspects:

(1) Mapping of daily activity categories between the source and target smart homes

Hu et al. conducted a web search to find relevant web pages by using daily activity categories as keywords. By assigning weights to different pages and calculating the similarity of web pages, they determined the similarity of daily activity categories between the source and target smart homes. Finally, a similarity threshold was used to annotate the daily activities in the target smart home [2].

(2) Mapping of daily activity features between the source and target smart homes

Samarah et al. proposed a fog computing-based framework for daily activity recognition, where the mapping of daily activity features was achieved by calculating the similarity of sensor environments between the source and target smart homes [3]. Chiang et al. argue that the key to daily activity recognition in heterogeneous smart home environments lies in the representation of daily activity features and the feature alignment strategy between the source smart home and the target smart home. Based on this perspective, they proposed a mapping algorithm for daily activity feature decomposition, combination, and alignment for daily activity recognition [4].

(3) Transfer of daily activity recognition models

Wemlinger et al. initially defined a semantic feature space model shared between the source and target smart homes [5]. They calculated the parameters of the semantic feature space based on the distribution of daily activity samples in both homes [6]. Subsequently, they applied a model-based transfer learning method for daily activity recognition using this feature space [7]. Hu et al. proposed a transfer learning-based approach for daily activity recognition. Their method involved computing the sensor probability distributions for each daily activity in the source and target smart homes. The labels of the nearest daily activities in the source smart home were assigned as the labels for the target smart home's daily activities. This method relaxed the assumptions of the same feature space, label space, and underlying distribution and facilitated model transfer across different daily activity recognition tasks [8].

3. The Proposed Approach

When the daily activity recognition model built in the source smart home is transferred to the target smart home, there are usually multiple daily activity recognition models built based on the source smart home that can be used as candidate models for transferring to the target smart home [9]. How to select the most suitable one from multiple candidate daily activity recognition models to transfer is the primary problem of transferring daily activity recognition models in heterogeneous smart home environments. Since the daily activity recognition model is generated based on the sensor event streams triggered by daily activities in the smart home, calculating the similarity of sensor distributions and sensor event streams in the smart homes becomes crucial for selecting the most appropriate model for transfer. The more similar the sensor distributions and sensor event streams are, the better the transfer effect will be. Otherwise, it may lead to a negative transfer. Combining the spatial characteristics of smart homes, this chapter proposes a method to calculate the similarity of smart homes based on the improved DTW and Fine-Tune algorithms, as shown in Figure 1.

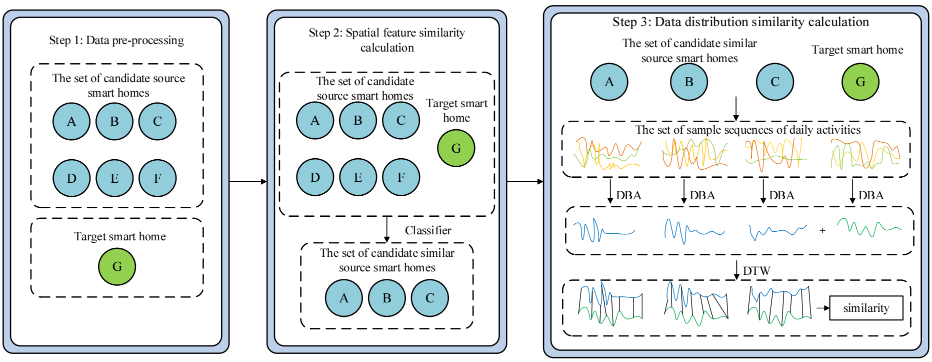

Figure 1. Smart home similarity calculation method

3.1 Data Preprocessing

The first step in data preprocessing is to map multiple sensors of the same type and in the same location from different smart homes to a single sensor.

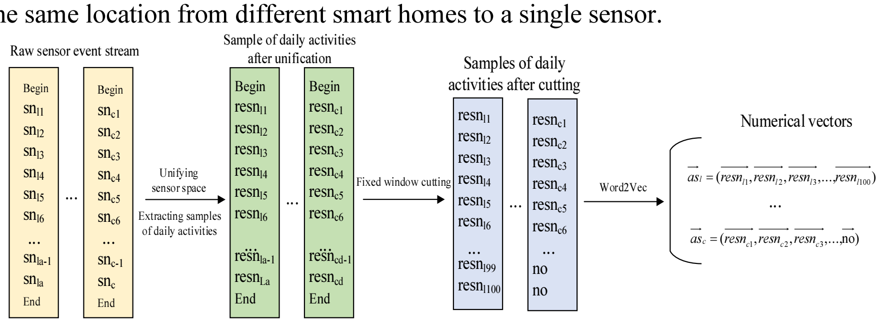

Figure 2. Data processing flow chart

After unifying the sensor space, the sensor event streams are segmented using a segmentation method based on instances of daily activities. Then, the extracted sequences of sensor names are used as samples for daily activities. Since the cut daily activity samples are of different lengths, a fixed window size is set in this paper, to ensure that each input daily activity sample is of the same length to facilitate network training. If a daily activity sample is smaller than the fixed window size, it is padded with the word “no”. After that, the Word2Vec algorithm is applied to convert the daily activity samples into numerical vectors. The entire data processing flow is illustrated in Figure 2. Here, "sn" represents the original sensor names, "resn" denotes the renamed sensor names after sensor mapping, "$\overrightarrow{resn}$" represents the numerical vectors of "resn", and "$\overrightarrow{as}$" represents the numerical vectors of daily activity samples, composed of multiple numerical vectors of sensor names triggered by the daily activity [10].

3.2 Smart Home Similarity Calculation Based on Spatial Features

The method for calculating smart home similarity based on spatial features is shown in Algorithm 1. We let $SH = \{sh_1, sh_2, ..., sh_n\}$ be a set of smart homes. For $sh \in SH$, $sh.FA$ represents its functional area set, and $sh.SC$ is the sensor category set of sh. $SH.FS = sh_1.FA \cup sh_2.FA \cup \ldots \cup sh_n.FA \times sh_1.SC \cup sh_2.SC \cup \ldots \cup sh_n.\ SC$ represents the feature space of the smart home set. Given a set of source smart homes, $SH = \{sh_1, sh_2, ..., sh_n\}$, and a target smart home sh^*, the sensors of each smart home are divided into several categories according to the feature space of $SH \cup \{sh^*\}$. Then, the number of sensors belonging to the same category in each smart home, denoted as q, is calculated. Based on this, the $sh.L$ feature vector is calculated, which consists of the number of sensors under all categories in a particular smart home environment. The feature vectors of the source smart home are used for training a classifier, which yields the classification of the feature vector for the target smart home. Afterward, the source smart homes corresponding to the classified label are removed from the SH set for the next classification. The source smart homes that belong to the top three classifications are selected as the candidate set of similar source smart homes for the target smart home.

Algorithm 1 Similar source smart home selection algorithm based on spatial features

Input: $SH=\{sh_1, sh_2, \ldots, sh_n\}$, the set of source smart home
sh^*, Target Smart Home
Output: $sh^\# \in SH$, candidate similar source smart homes for the target domain

$sh^\# \leftarrow \varnothing$
for each sh **in** $SH \cup \{sh^*\}$
  $sh.L \leftarrow \varnothing$
  for each f **in** $SH \cup \{sh^*\}.FS$
    $q \leftarrow getQuantity(sh, f)$
    $sh.L \leftarrow sh.L \cup \{(f, q)\}$
  end for
end for
for each sh **in** SH
  if $similarity(sh.L, sh^*.L)$ **then** //Classification
    $sh^\# \leftarrow sh$
    $delete(sh, SH)$
  end if
end for
return $sh^\#$

3.3 Smart Home Similarity Calculation based on Improved DTW Algorithm

After obtaining three candidate source smart homes that are similar to the target smart home based on spatial features, we propose an improved DTW algorithm to further calculate the similarity of the data distribution in the daily activity sample sets between the candidate source smart homes and the target smart home. The aim is to identify the most similar source smart home in the candidate set to the target smart home in terms of data distribution. The higher the similarity of data distribution between two smart homes is, the more transferable components there are, and the daily activity recognition model trained on the source smart home with similar data distribution is also the most suitable for the target smart home.[11]

The schematic diagram of the improved DTW algorithm is shown in Figure 3 and consists of two steps: DTW Barycenter Averaging (DBA) compression [12] and DTW distance calculation [13].

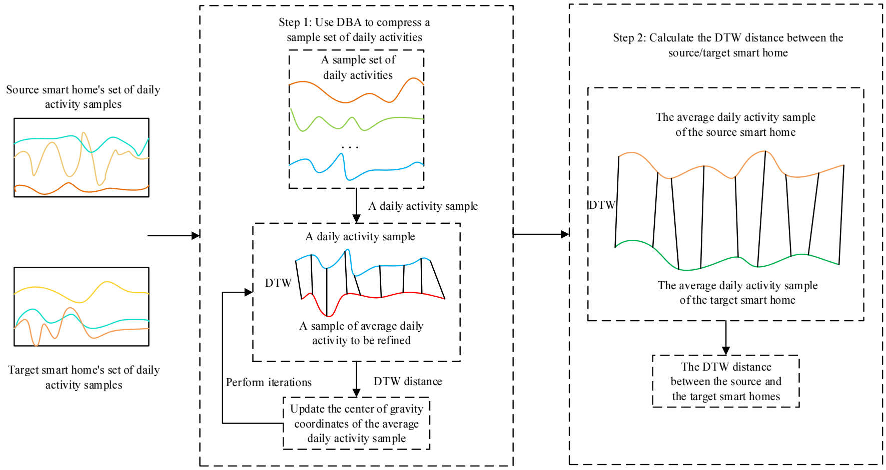

Figure 3. Smart home similarity calculation based on the improved DTW algorithm

Firstly, since the DTW algorithm is primarily used for distance calculation between two time series and is not suitable for computing distances between sets of daily activity samples, we employ the DBA method to calculate the average sequences of the candidate source smart home's and target smart home's daily activity sample sets, respectively. Based on this method, multiple daily activity samples are compressed into one average daily activity sample. The DBA algorithm is an iterative process that performs the following two steps in each iteration:

(1) We calculate the DTW distance between each daily activity sample and the refined temporary average daily activity sample to determine the relationship between the coordinates of the average daily activity sample and the coordinates of the daily activity sample set.

(2) In the first step, each coordinate of the average daily activity sample is updated to the coordinates of the center of gravity associated with it.

Next, the compressed average daily activity samples of the source smart home and the target smart home are denoted as $seq_1 = \{x_0, x_1, \ldots, x_{a-1}, x_a\}$ and $seq_2 = \{y_0, y_1, \ldots, y_{b-1}, y_b\}$ respectively. The DTW method is used to calculate the pairwise distance between them. A smaller distance indicates higher similarity, while a larger distance indicates lower similarity. In addition, the DTW method used in this study is an optimized approach that handles distance calculation for periodic sequences better, especially when two-time series have common subsequences. The optimized DTW algorithm mainly consists of the following three steps:

In the first step, we calculate the original DTW distance, denoted as DTW_1, between the average daily activity samples of the source smart home and the target smart home. The main idea of DTW is to compute the shortest distance path between two average daily activity samples using dynamic programming, which measures the similarity between them. Calculating the DTW distance requires satisfying the following three conditions:

(1) Boundary Constraint: The selected path must start from the bottom left corner and end at the top right corner, meaning that the starting and ending points of the two average daily activity samples should correspond to each other.

(2) Continuity: Each data point in the average daily activity samples has a corresponding data point.

(3) Monotonicity: The data points of all average daily activity samples should not cross-correspond with each other.

To calculate the DTW distance for the given source and target smart home average daily activity samples seq_1 and seq_2, the cumulative average daily activity sample distance matrix D needs to be computed. For the leftmost column of the matrix, the cumulative distance calculation is performed as shown in Equation (1); for the bottom row of the matrix, the cumulative distance calculation is performed as shown in Equation (2); for the remaining values in the matrix, the cumulative distance calculation is performed as shown in Equation (3); when i=0 and j=0, the matrix value is calculated, as shown in Equation (4). An example of DTW alignment is shown in Figure 4.

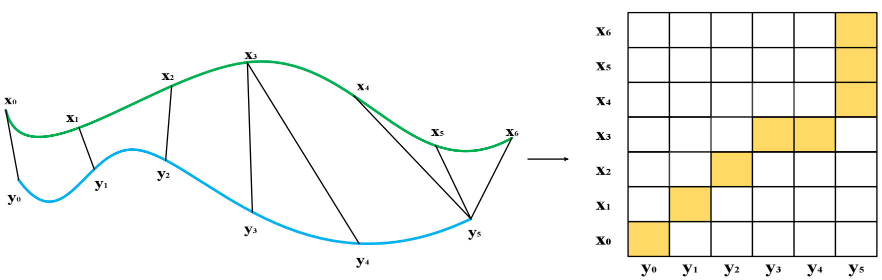

Figure 4. Diagram of an example of DTW alignment

$$D[i,0] = |x_i - y_0|^2 + D[i-1,0] \tag{1}$$

$$D[0,j] = |x_0 - y_j|^2 + D[0,j-1] \tag{2}$$

$$D[i,j] = |x_i - y_j|^2 + min(D[i-1,j], D[i,j-1], D[i-1,j-1]) \tag{3}$$

$$D[0,0] = |x_0 - y_0|^2 \tag{4}$$

$$DTW_1(seq_1, seq_2) = D[a,b] = |x_a - y_b|^2 + min(D[a-1,b], D[a,b-1], D[a-1,b-1]) \tag{5}$$

$$\alpha = 1 - \frac{L \times L}{Len(seq_1) \times Len(seq_2)} \tag{6}$$

$$DTW_2(seq_1, seq_2) = \alpha \times DTW_1(seq_1, seq_2) \tag{7}$$

The process of calculating the DTW distance starts from the first data point of both average daily activity samples and continues until the last data point. The alignment of each data point is determined using the minimum value decision method, which transforms the calculation of DTW distance into a calculation of subsequence distance for the average daily activity samples. The original DTW calculation equation is shown in Equation (5).

In the second step, the lengths of seq_1 and seq_2, as well as the length of the longest common subsequence, denoted as $Len(seq_1)$, $Len(seq_2)$, and L, respectively, are obtained. A penalty factor α is calculated, using the penalty factor equation shown in Equation (6).

In the third step, α is multiplied by the original DTW distance to obtain the optimized DTW distance between the average daily activity samples of the source smart home and the target smart home. This optimized DTW distance is denoted as DTW_2, and the equation for DTW_2 is shown in Equation (7).

4. Results

4.1 Dataset Introduction

The datasets used in this experiment are the HH101 to HH109 datasets provided by CASAS [14]. Among them, the HH101, HH102, and HH103 datasets are selected as the target smart homes. All datasets except for the target smart homes are considered as candidate source smart homes, from which the top three candidates with similarity are chosen for knowledge transfer.

4.2 Smart Home Similarity Calculation

When HH101 is chosen as the target smart home, the HH102 to HH109 datasets are considered as the candidate source smart home collection. When HH102 is chosen as the target smart home, the HH101, HH103 to HH109 datasets are considered as the candidate source smart home collection. When HH103 is chosen as the target smart home, the HH101, HH102, and HH104 to HH109 datasets are considered as the candidate source smart home collection.

We employ two classifiers, K-Nearest Neighbor (KNN) and Naive Bayes (NB), to calculate the spatial feature similarity between the candidate source smart homes and the target smart home. The top three candidate source smart home datasets that exhibit the most similar sensor spatial distribution to the target smart home are selected. The KNN classifier is chosen for its mature theory and high accuracy, while the NB classifier performs well in training with small-scale data.

Next, the DTW method is employed along with the DBA method to calculate the data distribution similarity. Firstly, the DBA method is used to compress the collection of daily activity sample sequences into a single vector representation, enabling time series similarity measurement. Then, the DTW method is used to calculate the distance between vectors, and the candidate source smart home datasets are sorted in ascending order based on the distances. The top three source smart home datasets are selected as the candidate similar source smart home set for the target smart home.

4.3 Experimental setup and results analysis

During the fine-tuning process, similar source smart homes are used as the training set, and 20% of the data from the target smart home is randomly selected as the fine-tuning training set, while the remaining 80% of the data from the target smart home is used as the testing set. Additionally, the KNN classifier and NB classifier are separately used to calculate the spatial feature similarity, enhancing the generalizability of this method. Finally, the top three source smart homes ranked by similarity to the target smart home are used for knowledge transfer, and the patterns of dataset similarity and transfer effects are obtained.

When the DTW distance difference is less than 1, as shown in experiments 1 to 3 when KNN is used as the classifier, HH101 is the target smart home, and HH105, HH102, and HH103 are selected as the transfer source smart homes. The DTW distance differences range from 0.52 to 0.95. The accuracy is almost equal, with slight anomalies in accuracy when HH102 and HH103 are the source smart homes. However, this phenomenon is reasonable as it occurs when the DTW distances are close, and it confirms the conclusion of this study, which is that the similarity between datasets can reflect the transfer effects of source smart homes to some extent. Similar situations can be observed in experiments 13 to 14. When NB is used as the classifier, HH102 is the target smart home, and HH109 and HH105 are selected as the transfer source smart homes. The DTW distance difference is 0.27, and the accuracy difference is only 0.40%. There are slight anomalies in precision and F1-score, with differences of 0.45% and 1.24% respectively. The transfer effects are not significantly different. In experiments 7 to 8 (same as experiments 16 to 17), when KNN (NB) is used as the classifier, HH103 is the target smart home, and HH101 and HH102 are selected as the transfer source smart homes. The DTW distance difference is 0.56. There is a slight anomaly in the recall, with a difference of 0.48%, while the other indicators follow the negative correlation pattern.

Additionally, in most cases where the target smart home is the same, the most similar source smart home (the one with the smallest DTW distance among the candidate similar source smart homes) and the least similar source smart home (the one with the largest DTW distance) have DTW distance differences greater than 1, resulting in significantly different transfer effects. As shown in experiments 7 and 9 (same as experiments 16 and 18), when KNN (DB) is used as the classifier, HH103 is the target smart home, and HH101 and HH105 are selected as the transfer source smart homes, the DTW distance difference is 1.62, with an accuracy difference of 6.37%, precision difference of 8.85%, recall difference of 8.07%, and F1-score difference of 9.32%. Similarly, in experiments 10 and 12, when NB is used as the classifier, HH101 is the target smart home, and HH109 and HH102 are selected as the transfer source smart homes, the DTW distance difference is 5.55, with an accuracy difference of 3.56%, precision difference of 5.54%, recall difference of 3.95%, and F1-score difference of 4.74%. In experiments 13 and 15, when NB is used as the classifier, HH102 is the target smart home, and HH109 and HH106 are selected as the transfer source smart homes. The DTW distance difference is 3.14, with an accuracy difference of 3.20%, precision difference of 10.61%, recall difference of 2.91%, and F1-score difference of 4.29%.

From the overall analysis of the experimental results, the proposed similarity calculation method for smart homes allows the selection of source smart homes with better transfer effects from a large number of datasets for fine-tuning. The study provides distance metrics, and most of the data sets are consistent with the pattern that DTW distance is negatively correlated with migration effects. Moreover, when the target smart home is the same, a DTW distance difference greater than 1 leads to more pronounced differences in transfer effects.

5. Conclusions

We propose a smart home similarity calculation method based on an improved DTW and fine-tuning. The method first finds the first three candidate source smart homes with similar spatial characteristics by the spatial characteristics of the sensor layout in the smart home. Then, an improved DTW algorithm is used to calculate the similarity between the daily activity sample sets of the target smart home and the candidate source smart homes. Subsequently, a fine-tuning approach is employed to evaluate the transfer effects of the selected candidate similar source smart homes' models. Finally, experimental results in Table1 and Table2 demonstrate that the daily activity recognition models selected using the smart home similarity calculation method achieve optimal transfer effects in the task of daily activity recognition for the target smart home.

Table 1. Results of the experiments based on the KNN classifier

Number	Target	Source	Accuracy	Precision	Recall	F1-score	DTW
Experiment 1	HH101	HH105	**0.7060**	**0.6158**	**0.6081**	**0.5962**	**11.80**
Experiment 2	HH101	HH102	0.7024	0.6047	0.5791	0.5780	12.23
Experiment 3	HH101	HH103	0.7042	0.5803	0.5616	0.5488	12.75
Experiment 4	HH102	HH101	**0.8299**	**0.6047**	**0.6102**	**0.6000**	**12.23**
Experiment 5	HH102	HH103	0.7900	0.5773	0.5643	0.5611	13.30
Experiment 6	HH102	HH105	0.7480	0.5553	0.5015	0.5116	16.02
Experiment 7	HH103	HH101	**0.7539**	**0.6848**	**0.6583**	**0.6678**	**12.75**
Experiment 8	HH103	HH102	0.7380	0.6596	0.6631	0.6458	13.31
Experiment 9	HH103	HH105	0.6902	0.5963	0.5776	0.5746	14.37

Table 2. Results of the experiments based on the NB classifier

Number	Target	Source	Accuracy	Precision	Recall	F1-score	DTW
Experiment I0	HH101	HH109	**0.7380**	**0.6601**	**0.6186**	**0.6254**	**6.68**
Experiment 11	HH101	HH105	0.7060	0.6158	0.6081	0.5962	11.80
Experiment 12	HH101	HH102	0.7024	0.6047	0.5791	0.5780	12.23
Experiment 13	HH102	HH109	**0.7520**	**0.5508**	**0.5053**	**0.4992**	**15.76**
Experiment 14	HH102	HH105	0.7480	0.5553	0.5015	0.5116	16.03
Experiment 15	HH102	HH106	0.7200	0.4447	0.4762	0.4563	18.90
Experiment 16	HH103	HH101	**0.7539**	**0.6848**	**0.6583**	**0.6678**	**12.75**
Experiment 17	HH103	HH102	0.7380	0.6596	0.6631	0.6458	13.31
Experiment 18	HH103	HH105	0.6902	0.5963	0.5776	0.5746	14.37

References

[1] Cook D, Feuz K D, Krishnan N C. Transfer learning for activity recognition: a survey[J]. Knowledge and Information Systems, 2013, 36(3): 537-556.

[2] Hu D H, Zheng V W, Yang Q. Cross-domain activity recognition via transfer learning[J]. Pervasive and Mobile Computing, 2011, 7(3): 344-358.

[3] Samarah S, Zamil M G H, Rawashdeh M, et al. Transferring activity recognition models in FOG computing architecture[J]. Journal of Parallel and Distributed Computing, 2018, 122: 122-130.

[4] Chiang Y T, Lu C H, Hsu J Y. A feature-based knowledge transfer framework for cross-environment activity recognition toward smart home applications[J]. IEEE Transactions on Human-Machine Systems, 2017, 47(3): 310-322.

[5] Feuz K D, Cook D J. Transfer learning across feature-rich heterogeneous feature spaces via feature-space remapping (FSR)[J]. ACM transactions on intelligent systems and technology (TIST), 2015, 6(1): 1-27.

[6] Chiang Y, Hsu J Y. Knowledge transfer in activity recognition using sensor profile[C]. 2012 9th International Conference on Ubiquitous Intelligence and Computing and 9th International Conference on Autonomic and Trusted Computing, Japan: Fukuoka, 2012: 180-187.

[7] Wemlinger Z E, Holder L B. Cross-environment activity recognition using a shared semantic vocabulary[J]. Pervasive and Mobile Computing, 2018, 51: 150-159.

[8] Hu D, Yang Q. Transfer learning for activity recognition via sensor mapping[C]. Proceedings of the Twenty-Second International Joint Conference on Artificial Intelligence, Spain: Barcelona, 2011: 1962.

[9] Azkune G, Almeida A, Agirre E. Cross-environment activity recognition using word embeddings for sensor and activity representation[J]. Neurocomputing, 2020, 418: 280-290.

[10] Ye J, Dobson S, Zambonelli F. XLearn: Learning activity labels across heterogeneous datasets[J]. ACM Transactions on Intelligent Systems and Technology (TIST), 2020, 11(2): 1-28.

[11] Ye J. SLearn: Shared learning human activity labels across multiple datasets[C]. 2018 IEEE International Conference on Pervasive Computing and Communications (PerCom), Greece: Athens, 2018: 1-10.

[12] Petitjean F, Ketterlin A, Gancarski P. A global averaging method for dynamic time warping, with applications to clustering[J]. Pattern Recognition, 2011, 44(3): 678-693.

[13] Sakoe H, Chiba S. Dynamic programming algorithm optimization for spoken word recognition[J]. IEEE Transactions on Acoustics, Speech and Signal Processing, 1978, 26(1): 43-49.

[14] Cook D J, Crandall A S, Thomas B L, et al. CASAS: A Smart Home in a Box[J]. Computer, 2013, 46(7): 62-69.