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Research article

Optimal search mapping among sensors in heterogeneous smart homes

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Abstract: There are huge differences in the layouts and numbers of sensors in different smart home environments. Daily activities performed by residents trigger a variety of sensor event streams. Solving the problem of sensor mapping is an important prerequisite for the transfer of activity features in smart homes. However, it is common practice among most of the existing approaches that only sensor profile information or the ontological relationship between sensor location and furniture attachment are used for sensor mapping. The rough mapping seriously restricts the performance of daily activity recognition. This paper presents a mapping approach based on the optimal search for sensors. To begin with, a source smart home that is similar to the target one is selected. Thereafter, sensors in both source and target smart homes are grouped by sensor profile information. In addition, sensor mapping space is built. Furthermore, a small amount of data collected from the target smart home is used to evaluate each instance in sensor mapping space. In conclusion, Deep Adversarial Transfer Network is employed to perform daily activity recognition among heterogeneous smart homes. Testing is conducted using the public CASAC data set. The results have revealed that the proposed approach achieves a 7–10% improvement in accuracy, 5–11% improvement in precision, and 6–11% improvement in F1 score, compared with the existing methods.

Keywords: daily activity recognition; smart home; sensor mapping

1. Introduction

Smart homes are designed to maintain personal independence and enhance their sense of well-being for residents. It is one of the basic functions of smart homes to recognize daily activities, e.g., sleeping, cooking. To recognize daily activities, smart homes are equipped with ambient sensors [1]. These sensors are activated continuously when daily activities are carried out [2]. It is a challenging subject to recognize daily activities from activated sensor events. Thus, daily activity recognition has been discussed widely.

Approaches for daily activity recognition can be divided into two categories: data-driven approaches and knowledge-driven approaches. Data-driven approaches include supervised and unsupervised learning approaches. Supervised learning methods require a large amount of labeled data [3]. Labeling data is a time-consuming and error-prone task [4]. The goal of the research gradually shifted to reducing data labeling and maximizing the use of knowledge to solve similar problems [5]. To save these problems, transferring trained models of daily activity recognition from one smart home to another becomes a promising study [6].

Sensors are important features for daily activity recognition, whether based on wearable sensor environments or smart home environments [7]. Sensor flow is closely related to activity features [8]. On the one hand, recent studies based on activity recognition for wearable sensors has shown an emphasis on sensor data. Tang et al. increased the expressiveness of sensor features to recognize activity by using the idea of hierarchical-split (HS) [9]. Meanwhile, Huang et al. improved the method of normalizing mixed sensor features by proposing a method called Channel Equalization. They used the execution of whitening or de-correlation operations to reactivate these channels that were suppressed by normalization [10]. In addition, Cheng et al. used conditionally parametrized convolution for real-time HAR on mobile and wearable devices to improve the efficiency of computing sensor features [11]. On the other hand, sensor features are also important for the field of activity recognition in smart homes. There are different house configurations and sensor equipment in different smart homes [12]. Sensor equipment in the same house can be altered over time. Therefore, it is one of the primary tasks to map sensors in heterogeneous smart homes. After this, transfer learning methods can be used to recognize and transfer the features of daily activities between different residents [13]. However, it is common practice among most of existing approaches that only sensor profile information or the ontological relationship between sensor location and furniture attachment are used for sensor mapping. The rough mapping seriously restricts the performance of daily activity recognition. Intuitively, superior sensor mapping brings more promising results of daily activity recognition in heterogeneous smart homes. To achieve superior existing sensor mapping, this paper presents an optimal search based on a sensor mapping strategy.

The study of sensor mapping methods is often neglected in more existing approaches, and most of them use the sensor profile information, or the ontological relationship between sensor location and furniture attachment to calculate its similarity, then obtain a rough mapping.

The main contributions of this paper can be summarized as follows.

1) In order to find the most similar one from multiple sources of the smart homes, we propose a similarity algorithm for solving the similarity between smart homes.

2) We propose a sensor mapping algorithm to achieve superior sensor mapping.

3) We employ DANN to transfer the trained daily activity recognition model.

4) We evaluate the proposed approach on public datasets.

The rest of this paper is organized as follows: Section 2 summarizes the knowledge-driven and data-driven activity recognition methods based on heterogeneous environments. Section 3 displays the concrete implementation of the method. Section 4 analyzes the experimental setup, evaluation methods and results. Section 5 is a summary of the article.

2. Related work

There are two categories of approaches for daily activity recognition in heterogeneous smart homes. The first is the knowledge-driven approach. For the knowledge-driven approach, reasoning is performed to recognize daily activities based on a shared knowledge model (e.g., ontology). The other is the data-driven approach, which adjusts learned model by the sensor events stream collected from the source smart homes to recognize daily activities in target smart homes. Transfer learning is widely used for daily activity model evolution.

2.1. Knowledge-driven approaches

Ye et al. proposed a knowledge-driven ensemble learning technique called Slearn [14]. It is based on semantic mapping to migrate knowledge between multiple datasets. Then, they improved on it and proposed the method named XLearn [15]. Firstly, ontologies are used to perform sensor space and daily activity space mapping. Then, a part of daily activities are identified based on clustering, and the remaining daily activities are recognized based on ensemble learning. Ye et al. also proposed a knowledge model to represent shared daily activities in smart homes [16]. The knowledge model is applied to achieve computationally efficient feature space remapping and uncertainty inference, which leads to an effective classifier fusion and further improves activity recognition accuracy. Marjan et al. proposed a framework called E-care@home [17]. Semantic interpretation of events and context awareness are achieved by integrating measurement data collected from heterogeneous smart homes into an ontology. Stream inference is performed based on an incremental answer set solver to recognize daily activities. Wemlinger and Holder proposed a method called SCEAR [18]. Firstly, an initial common ontology of semantic feature space is established. Then, the raw sensor data is transformed into common conceptual features to revise the initial ontology. The reasoning is conducted to recognize daily activities based on smart home ontology.

2.2. Data-driven approaches

A feature-based knowledge transfer framework was proposed by Chiang et al. [19]. The framework uses transfer learning to mitigate the constraint that training, and testing datasets are required to be highly similar in distribution. The framework can outperform non-transfer learning models by 8% in terms of accuracy, and greatly reduces the task of labeling the target domain. In addition, Chiang and Hsu used sensor profiles to encode activities and further measured the feature similarity between datasets [20]. Graph matching algorithm is applied to automatically compute the appropriate mapping of features based on similarity measures. Zhen et al. used web search to access similarity functions that are used to evaluate the similarity between the daily activities of the source smart home and the target smart home [21]. By the learned similarity metric, the collected data from a smart home are interpreted as the data in another smart home with a different confidence level. Feuz and Cook proposed a novel heterogeneous transfer learning technique named Feature Space Remapping (FSR) [22]. The features of the source and target domains are linked by constructing meta-features and using integrated learning for activity classification. And they also proposed a heterogeneous transfer learning for AR based on heuristic search techniques [23]. Azkune et al. proposed two data-driven daily activity recognition systems, SEMINAR-u and SEMINAR-s, to address the two cases of the presence of labeled and unlabeled daily activities in the source domain respectively [24]. Word embeddings were used to establish a common semantic feature domain for different domain sensors and daily activities mapping. Hu et al. supposed that the feature space of sensors is the same among smart homes [25]. Initially, keywords related to daily activities are retrieved using a web search engine. Then, being used as the weight of daily activity feature in the source domain, the similarity between daily activities is solved by applying the maximum mean difference (MMD). Finally, pseudo-training datasets are of the target domain. The feature mapping from the source domain to the target domain is completed. Hu and Yang proposed a transfer learning framework [26]. This framework transforms the sensor readings into the same feature space by KL-divergence and Dynamic Time Warping. Daily activity labels of the source domain are used to label the daily activities of the target domain by the sensor distribution. After that, the Google similarity distance metric is applied to find labels of target domain that are the most similar to the labels of the source domain. Myagmar et al. proposed a novel heterogeneous transfer learning algorithm called Heterogeneous Daily Living Activity Learning (HDLAL) [27]. HDLAL processes data from two domains into a derivation space on account of the maximum mean difference. Then, domain-invariant feature representation space from the cross-domain data distribution is derived. An ensemble classification algorithm is operated to train a multi-label classifier in a new feature space. Finally, the projection data is used to predict the labels of the target domain. In unsupervised domain adaptation, Sanabria et al. integrated bidirectional generative adversarial networks (Bi-GAN) and kernel mean matching (KMM) to identify feature transfer between two heterogeneous domains for daily activity recognition [28].

3. The proposed approach

In this section, we will illustrate how to select a source domain that is similar to the target one, and how to find the optimal mapping of sensors in different smart home environments.

3.1. Source smart home selection

To demonstrate the process of selecting the similar source domains, necessary definitions are given below.

Definition 1. Let $SH = \{sh_1, sh_2, \ldots, sh_n\}$ be a set of smart homes. For any $sh \in SH$, let $sh.FA$ be set of function areas of sh and let $sh.SC$ be set of sensor categories of sh. $SH.FS = sh_1.FA \cup sh_2.FA \cup \ldots \cup sh_n.FA \times sh_1.SC \cup sh_2.SC \cup \ldots \cup sh_n.SC$ is said to be feature space of SH.

Definition 2. Let $SS = \{ss_1, ss_2, \ldots, ss_j\}$, $TS = \{ts_1, ts_2, \ldots, ts_m\}$ be a set of sensors of a source smart home and a target smart home, respectively. ss_k denotes the k-th sensor in the source domain, $1 \le k \le j$. And ts_h denotes the h-th sensor in the target domain, $1 \le h \le m$.

Since sensors are activated continuously when daily activities are carried out, they are regarded as important space features of daily activity. Location, category and number of sensors vary from one smart home to another. For instance, there are 20 pressure sensors and 10 light sensors in a smart home sh_1. Whereas there are 10 pressure sensors and 8 light sensors in smart home sh_2. Some pressure sensors are installed in the bedroom and others are installed in the living room in sh_1. All pressure sensors are installed in the shower room in sh_2. When the same daily activity is carried out in two smart home sh_1 and sh_2, two corresponding sensor streams ss_1 and ss_2 are generated. Intuitively, the more similar in location, category and number of sensors of the two smart homes are, the more similar the activated sensor events streams are. Thus, ss_1 can be used approximately to recognize the daily activity, which is carried out in sh_2, and vice versa. From the perspective of daily activity recognition, two smart homes are shown to be similar if locations, categories and number of them are similar to each other.

Hence, it is an important premise for cross-environment daily activity recognition to find the most similar one from multiple source smart homes.

Algorithm 1 is used to find the source smart home which is the most similar to the target one. Given a set of source smart homes $SH = \{sh_1, sh_2, \ldots, sh_n\}$ and a target smart home sh^*, divide sensors of each smart home into several classes by feature space of $SH \cup \{sh^*\}$. Count the number q of sensors which belong to same class for each smart home. And $sh.L$ denotes a feature vector consisting of the numbers of sensors under all categories in a given smart home environment. Solve similarities between each $sh \in SH$ and sh^* and select the source smart home $sh^\#$, which is most similar to sh^*. A source domain's similarity is the number of classifiers that select this source domain. And th is the maximum similarity. Figure 1 shows a sample.

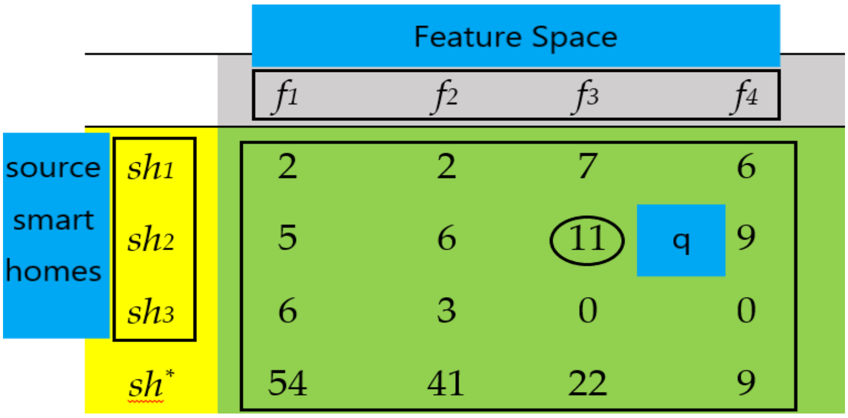

Figure 1. A sample of source smart home selection.

Algorithm 1.

```
Input: SH = {sh1, sh2, …, shn}, set of source smart homes
       sh*, target smart home
Output: sh# ∈ SH, most similar to sh*
sh# ← ∅
for each sh in SH ∪ {sh*}
    sh.L ← ∅
    for each f in SH ∪ {sh*}. FS
        q ← get Quantity (sh, f)
        sh.L ← sh.L ∪ {(f, q)}
    end for
end for
th ← 0
for each sh in SH
    if max (similarity (sh.L, sh*.L)) then
        Th ← similarity (sh.L, sh*.L)
        sh# ← sh
    end if
end for
return sh#
```

3.2. Sensors division

Firstly, sensors of selected source smart and target smart home are merged. Then, merged sensors are divided into different parts by certain category (e.g., motion) of sensors and function area (e.g., bedroom) in which they located. Values of "category" and "function area" are used as label of part. Figure 2 shows a sample of the sensors division. There are 7 sensors in the selected source smart and target smart home, respectively. c_fa1, c_fa2 and c_fa3 are three different values of "category" and "function area". All sensors are divided into three parts ($\{ss_1, ss_2\}$, $\{ts_1, ts_2\}$), ($\{ss_3, ss_4\}$, $\{ts_3, ts_4, ts_5\}$) and ($\{ss_5, ss_6, ss_7\}$, $\{ts_6, ts_7\}$).

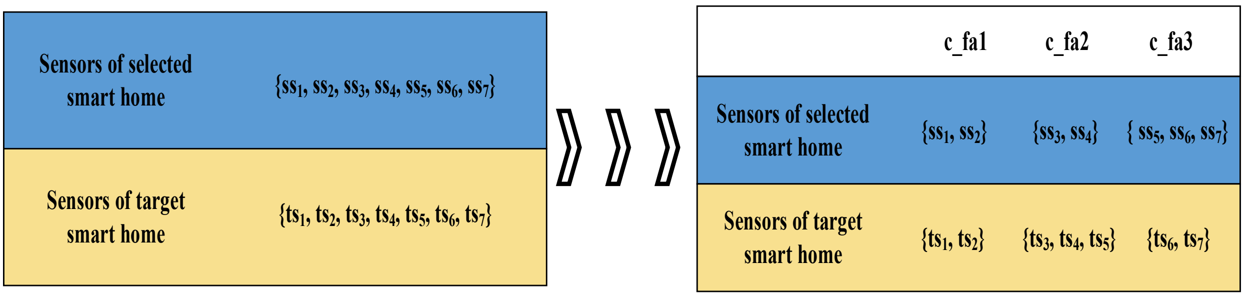

Figure 2. A sample of sensors division.

3.3. Sensors mapping

To show the process of sensors mapping, necessary terms are defined as follow.

Definition 3. Let $SP = \{(SS^{\#}, TS^{\#}) \mid SS^{\#} \subseteq SS, TS^{\#} \subseteq TS\}$ be sensors division for SS and TS. For a part $p \in SP$, $CM_p = \{(ss, ts) \mid ss \in SS^{\#} \wedge ts \in TS^{\#}\}$ is said to be a candidate mapping of p if $\forall$ (ss_1, ts), $(ss_2, ts) \in CM_p$, $ss_1 = ss_2$ holds.

Definition 4. $se = (d, t, sn, sv, ar)$ is called a sensor event, where sn is the sensor name, d is the date when sn was activated, t is the time when sn was activated, sv is the value of sn when sn was activated, and ar is the daily activity occurring when sn was activated.

Definition 5. Given n sensor events $se_1, se_2, \ldots, se_n$, $< se_1, se_2, \ldots, se_n >$ is said to be a sensor events stream. If $\forall 1 \leq i \leq n\text{-}1$, se_{i+1} is always followed by se_i in chronological order.

Table 1 shows a fragment of sensor events stream which is activated by daily activity "Relax".

For a part $p \in SP$, there is usually more than one candidate mapping. Algorithm 2 is used to find optimal sensors mapping from all candidate mappings for each part of SP. To begin with, a handful of sensors event stream TD^* which is collected from target smart home TD are extracted as samples to evaluate performance of sensor mapping. For each candidate mapping CM_p of p, sensors of all sensor events of TD^* are replaced with the sensors used in source smart home by the mapping relations of CM_p. Table 2 shows an instance of sensors mapping with the assumption of CM_p = {(M008, M003), (M009, M004), (LS004, LS002), (LS008, LS005), (LS008, LS006)}. A handful of sensor event streams are collected from the target smart home which is activated by daily activity "Sleep". Sensor names of column sn^* are generated after the column sn are replaced. Next, sensors event stream collected from selected source smart home SD is used as training set, and TD^* is used as test set. A classifier is employed to evaluate the performance of the sensors mapping based on accuracy. The candidate sensors mapping with the best metrics are selected as the final sensors mapping.

Table 1. A fragment of sensor events stream.

d	t	sn	sv	ar
2012/8/25	15/01	M008	OFF	Relax
2012/8/25	15/01	M009	ON	
2012/8/25	15/01	M008	OFF	
2012/8/25	15/02	M009	ON	
2012/8/25	15/03	LS008	25	
2012/8/25	15/05	LS004	31	
2012/8/25	15/06	LS003	3	
2012/8/25	15/07	LS016	8	
2012/8/25	15/07	LS004	8	
2012/8/25	15/09	LS008	24	
2012/8/25	15/09	M008	OFF	

Algorithm 2.

```
Input: SP, sensors division for SS and TS
       SD, sensors event stream collected from selected source smart home
       TD, sensors event stream collected from target smart home
Output: SM, optimal sensors mapping
TD* ← handful (TD) // Extract a handful of sensor events stream from TD.
for each p in SP
    opt_q ← 0
    opt_CM ← ∅
    for each CM_p in p
        for each (ss, ts) in CM_p
            replace (ss, ts, TD) // Replace ts of TD with ss.
        end for
        q ← evaluate (SD, TD*) // Use some classifier to solve performance of CM_p on SD and TD*.
        if (q > opt_q) then
            opt_q ← q
            opt_CM ← CM_p
        end if
    end for
    SM ← SM ∪ {opt_CM}
end for
return SM
```

Table 2. A handful of sensor events stream collected from target smart home.

d	t	sn	sn*	sv	ar
2012/9/5	13/07	M004	M009	OFF	Sleep
2012/9/5	13/08	M003	M008	ON	
2012/9/5	13/08	M004	M009	ON	

Continued on next page

d	t	sn	sn*	sv	ar
2012/9/5	13/12	M003	M008	OFF	Sleep
2012/9/5	13/13	LS006	LS008	5	
2012/9/5	13/15	LS002	LS004	42	
2012/9/5	13/15	LS005	LS008	62	

4. Results and evaluation

4.1. Smart homes and collected datasets

Center for Advanced Studies in Adaptive Systems (CASAS) of Washington State University is well-known for their research on the daily activity recognition in smart homes. CASAS published multiple collected datasets from different smart homes [29]. In this paper, four smart homes HH101, HH105, HH109 and HH110 and corresponding collected datasets are employed to evaluate the proposed approach. Room layouts and sensor locations of these smart homes are shown in Table 3. Every smart home is divided into seven parts. They are the Kitchen, Dining, Parlor, Porch, Toilet, Bedroom and Porch_toilet, respectively. Installed sensors can be divided into six categories, the "temperature sensor (T)", "infrared motion sensor (M)", "wide area infrared motion sensor (MA)", "light sensor (LS)", "Light Switch Sensor (L)" and "Door Switch Sensor (D)", respectively. LS and T will output real values when triggered, and the M, MA, D and L will output boolean when triggered. In Table 3, each data item denotes the number of sensors which belong to some categories and are installed in some parts for some sensor categories in different smart homes. For the underlined data item 4, 3, 2, 2, these numbers mean that there are 4, 3, 2, 2 sensors which belong to M category and are installed in Kitchen of HH101, HH105, HH109 and HH110, respectively. Ten categories of daily activity, the "Bed_Toilet_Transition", "Cook", "Dress", "Eat", "Med", "Personal_Hygiene", "Relax", "Sleep", "Sleep_Out_Of_Bed", "Toilet", are used to evaluate the proposed approach. Please note that "Cook_Lunch", "Cook_Breakfast" and "Cook_Dinner" are merged into one daily activity, "Cook". And "Eat", "Eat_Lunch", "Eat_Breakfast" and "Eat_Dinner" are merged into the "Eat". In addition, "Take_Medicine", "Morning_Meds" and "Evening_Meds" are merged into the "Med".

Table 3. Sensor layouts of selected smart homes.

		Kitchen	Dining	Parlor	Porch	Toilet	Bedroom	Porch_t-oilet
HH101, HH105, HH109, HH110	M	4, 3, 2, 2	1, 2, 1, 1	3, 2, 4, 4	1, 1, 1, 1	0, 0, 0, 0	2, 3, 3, 2	1, 2, 2, 1
	MA	1, 1, 1, 1	0, 1, 0, 0	1, 1, 1, 1	0, 0, 0, 0	1, 1, 1, 1	1, 1, 1, 1	0, 0, 0, 0
	D	0, 2, 0, 2	0, 0, 0, 0	1, 1, 1, 1	1, 1, 1, 1	1, 1, 1, 1	0, 0, 0, 0	0, 0, 0, 0
	T	0, 1, 0, 1	0, 0, 0, 0	3, 1, 1, 1	1, 1, 1, 1	1, 2, 1, 1	0, 0, 0, 0	0, 0, 0, 0
	L	0, 2, 0, 2	0, 0, 0, 1	0, 1, 0, 1	0, 0, 0, 1	0, 2, 0, 0	0, 1, 0, 1	0, 0, 0, 0
	LS	5, 4, 3, 3	1, 3, 1, 1	4, 3, 5, 5	1, 1, 1, 1	1, 1, 1, 1	3, 4, 4, 3	1, 2, 2, 1

4.2. Metrics

Daily activity recognition is a classification task. Hence, the evaluation metrics used are accuracy, precision and F1-score, which are shown in Eqs (1)–(3), respectively. The recall is shown in Eq (4). *TP* is the number of the true positives which are correctly classified based on the proposed approach, whereas *FP* is the number of false positives which are incorrectly classified based on the approach. *TN* is the number of correctly classified true negatives based on the proposed method, while *FN* is the number of false negatives which are incorrectly classified.

$$\mathrm{Accuracy} = \mathrm{TP} + \mathrm{TN}/(\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}) \tag{1}$$

$$\mathrm{Precision} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FP}) \tag{2}$$

$$\mathrm{F1} - \mathrm{score} = 2 * \mathrm{Precision} * \mathrm{Recall}/(\mathrm{Precision} + \mathrm{Recall}) \tag{3}$$

$$\mathrm{Recall} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FN}) \tag{4}$$

4.3. Results

4.3.1. Similarities between source smart homes and target smart home

HH109 is used as target smart home and HH101, HH105 and HH110 are used as source smart homes. The similarity between source smart home and target smart home is solved as a classification task. K-Nearest Neighbor (KNN), Random forest (RF), Decision Tree (DT) and Naive Bayes (NB) are used for similarity solution. The results are shown in Table 4. Since HH101 is the most similar to HH109 on KNN, RF and DT, it is selected as most similar source smart home.

Table 4. Similarities between HH109 and HH101, HH105, HH110.

Target Smart Home	Source Smart Homes	KNN	RF	DT	NB
HH109	HH101	√	√	√	
	HH105				√
	HH110				

4.3.2. Optimal mapping of sensors

Data collected from HH109 in six different dates are independently used for the sensor mapping. DANN is employed to evaluate candidate sensors mappings. Parameters of DANN are shown in Table 5. Sensors installed in HH101 and HH109 are divided into 23 parts which are shown in Table 6. Accuracy obtained from DANN is used as the evaluation criterion for each part. The one with the highest accuracy is selected as the optimal sensor mapping, as shown in Table 7.

Table 5. Parameters of the DANN network.

Learning_rate	Momentum_rate	Batch_size	Epoch	Optimizer
0.001	0.9	64	100	Momentum optimizer

Table 6. Division for sensors from HH101 and HH109.

	HH101	HH109
Part1	LS011	LS016, LS011
Part2	M011	M016, M011
Part3	LS005, LS008, LS010, LS013	LS002, LS003, LS004, LS005, LS006
Part4	M009, M012	M012, M014, M015
Part5	LS015	LS017
Part6	MA016	MA009
Part7	MA015	MA017
Part8	M001	M001
Part9	T102	T102
Part10	LS009, LS012, LS014	LS012, LS013, LS014, LS015
Part11	D001	D001
Part12	T101, T104, T105	T101
Part13	MA014	MA013
Part14	M005, M008, M010	M002, M003, M004, M006
Part15	LS002, LS003, LS006, LS007, LS016	LS008, LS010, LS009
Part16	T103	T103
Part17	D003	D003
Part18	D002	D002
Part19	LS001	LS001
Part20	LS004	LS007
Part21	MA013	MA005
Part22	M002, M003, M006, M007	M008, M010
Part23	M004	M007

4.3.3. Data pre-processing

For each activated sensor *s* of an instance of daily activity, *s* is represented in pattern of FA_C_N, where FA is the name of function area in which *s* is installed, C is the category of *s*, N is the sensor serial number at this area and category. For example of the sensor event "2012/8/25 15/01 M008 OFF" shown in Table 1, sensor M008 of is represented in bedroom_M_2, where M008 is installed in bedroom. Further, sensor events stream corresponding to an instance of daily activity is represented as a string vector. The string vector is transformed into a digital vector using word2vec algorithm. After the sensor events streams of all instances of daily activity are represented in digital vectors, these digital vectors from source smart home are used to train DANN. The results are shown in Table 8. And iteration processes for each date are shown in Figures 3–5. It is shown that no matter which date is selected, a favorable performance of daily activity recognition has been achieved.

Table 7. Optimal mapping for each division in different samples space.

D^*	Date 1	Date 2	Date 3	Date 4	Date 5	Date 6
Part1	{(LS011, LS016), (LS011, LS011)}	{(LS011, LS016), (LS011, LS011)}	{(LS011, LS016), (LS011, LS011)}	{(LS011, LS016), (LS011, LS011)}	{(LS011, LS016), (LS011, LS011)}	{(LS011, LS016), (LS011, LS011)}
Part2	{(M011, M016), (M011, M011)}	{(M011, M016), (M011, M011)}	{(M011, M016), (M011, M011)}	{(M011, M016), (M011, M011)}	{(M011, M016), (M011, M011)}	{(M011, M016), (M011, M011)}
Part3	{(LS008, LS002), (LS010, LS003), (LS008, LS004), (LS010, LS005) (LS013, LS006)}	{(LS013, LS002), (LS008, LS003), (LS013, LS004), (LS010, LS005) (LS005, LS006)}	{(LS010, LS002), (LS008, LS003), (LS008, LS004), (LS010, LS005) (LS008, LS006)}	{(LS005, LS002), (LS008, LS003), (LS008, LS004), (LS010, LS005) (LS013, LS006)}	{(LS008, LS002), (LS010, LS003), (LS013, LS004), (LS010, LS005) (LS010, LS006)}	{(LS008, LS002), (LS005, LS003), (LS010, LS004), (LS010, LS005) (LS010, LS006)}
Part4	{(M012, M012), (M010, M014), (M012, M015)}	{(M009, M012), (M009, M014), (M012, M015)}	{(M012, M012), (M012, M014), (M012, M015)}	{(M012, M012), (M009, M014), (M012, M015)}	{(M012, M012), (M009, M014), (M012, M015)}	{(M009, M012), (M009, M014), (M009, M015)}
Part5	{(LS015, LS017)}	{(LS015, LS017)}	{(LS015, LS017)}	{(LS015, LS017)}	{(LS015, LS017)}	{(LS015, LS017)}
Part6	{(MA016, MA009)}	{(MA016, MA009)}	{(MA016, MA009)}	{(MA016, MA009)}	{(MA016, MA009)}	{(MA016, MA009)}
Part7	{(MA015, MA017)}	{(MA015, MA017)}	{(MA015, MA017)}	{(MA015, MA017)}	{(MA015, MA017)}	{(MA015, MA017)}
Part8	{(M001, M001)}	{(M001, M001)}	{(M001, M001)}	{(M001, M001)}	{(M001, M001)}	{(M001, M001)}
Part9	{(T102, T102)}	{(T102, T102)}	{(T102, T102)}	{(T102, T102)}	{(T102, T102)}	{(T102, T102)}
Part10	{(LS009, LS012), (LS009, LS013), (LS012, LS014), (LS014, LS015)}	{(LS009, LS012), (LS009, LS013), (LS012, LS014), (LS014, LS015)}	{(LS009, LS012), (LS012, LS013), (LS009, LS014), (LS014, LS015)}	{(LS012, LS012), (LS014, LS013), (LS014, LS014), (LS014, LS015)}	{(LS009, LS012), (LS009, LS013), (LS014, LS014), (LS012, LS015)}	{(LS012, LS012), (LS014, LS013), (LS014, LS014), (LS012, LS015)}
Part11	{(D001, D001)}	{(D001, D001)}	{(D001, D001)}	{(D001, D001)}	{(D001, D001)}	{(D001, D001)}
Part12	{(T105, T101)}	{(T105, T101)}	{(T105, T101)}	{(T105, T101)}	{(T101, T101)}	{(T105, T101)}
Part13	{(MA014, MA013)}	{(MA014, MA013)}	{(MA014, MA013)}	{(MA014, MA013)}	{(MA014, MA013)}	{(MA014, MA013)}

Continued on next page

D^*	Date 1	Date 2	Date 3	Date 4	Date 5	Date 6
Part14	{(M008, M002), (M005, M003), (M010, M004), (M005, M006)}	{(M010, M002), (M010, M003), (M010, M004), (M008, M006)}	{(M005, M002), (M005, M003), (M010, M004), (M005, M006)}	{(M010, M002), (M010, M003), (M010, M004), (M010, M006)}	{(M005, M002), (M010, M003), (M008, M004), (M008, M006)}	{(M008, M002), (M008, M003), (M005, M004), (M008, M006)}
Part15	{(LS003, LS008), (LS006, LS010), (LS007, LS009)}	{(LS007, LS008), (LS006, LS010), (LS003, LS009)}	{(LS003, LS008), (LS016, LS010), (LS008, LS009)}	{(LS003, LS008), (LS006, LS010), (LS007, LS009)}	{(LS003, LS008), (LS002, LS010), (LS007, LS009)}	{(LS002, LS008), (LS016, LS010), (LS006, LS009)}
Part16	{(T103, T103)}	{(T103, T103)}	{(T103, T103)}	{(T103, T103)}	{(T103, T103)}	{(T103, T103)}
Part17	{(D003, D003)}	{(D003, D003)}	{(D003, D003)}	{(D003, D003)}	{(D003, D003)}	{(D003, D003)}
Part18	{(D002, D002)}	{(D002, D002)}	{(D002, D002)}	{(D002, D002)}	{(D002, D002)}	{(D002, D002)}
Part19	{(LS001, LS001)}	{(LS001, LS001)}	{(LS001, LS001)}	{(LS001, LS001)}	{(LS001, LS001)}	{(LS001, LS001)}
Part20	{(LS004, LS007)}	{(LS004, LS007)}	{(LS004, LS007)}	{(LS004, LS007)}	{(LS004, LS007)}	{(LS004, LS007)}
Part21	{(MA013, MA005)}	{(MA013, MA005)}	{(MA013, MA005)}	{(MA013, MA005)}	{(MA013, MA005)}	{(MA013, MA005)}
Part22	{(M006, M008), (M007, M010)}	{(M003, M008), (M007, M010)}	{(M002, M008), (M007, M010)}	{(M003, M008), (M002, M010)}	{(M002, M008), (M006, M010)}	{(M003, M008), (M007, M010)}
Part23	{(M004, M007)}	{(M004, M007)}	{(M004, M007)}	{(M004, M007)}	{(M004, M007)}	{(M004, M007)}

Table 8. Results of daily activity recognition.

D^*	Accuracy	Precision	F1-score
Date 1	83.89%	78.14%	80.47%
Date 2	81.70%	76.88%	76.31%
Date 3	83.56%	77.88%	79.65%
Date 4	80.31%	68.83%	73.57%
Date 5	81.02%	78.58%	78.87%
Date 6	80.40%	69.07%	73.56%

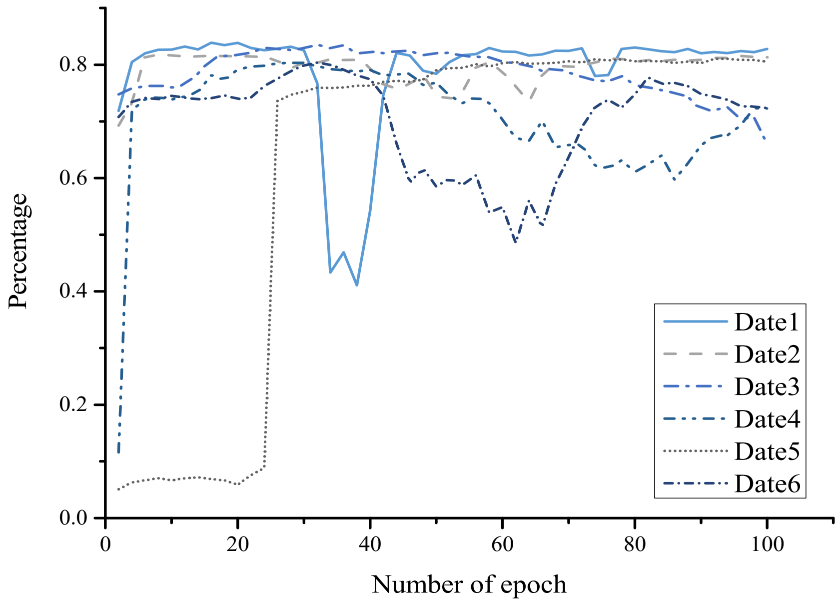

Figure 3. The accuracy of daily activity recognition which vary from 1st epoch to 100th epoch based on six dates.

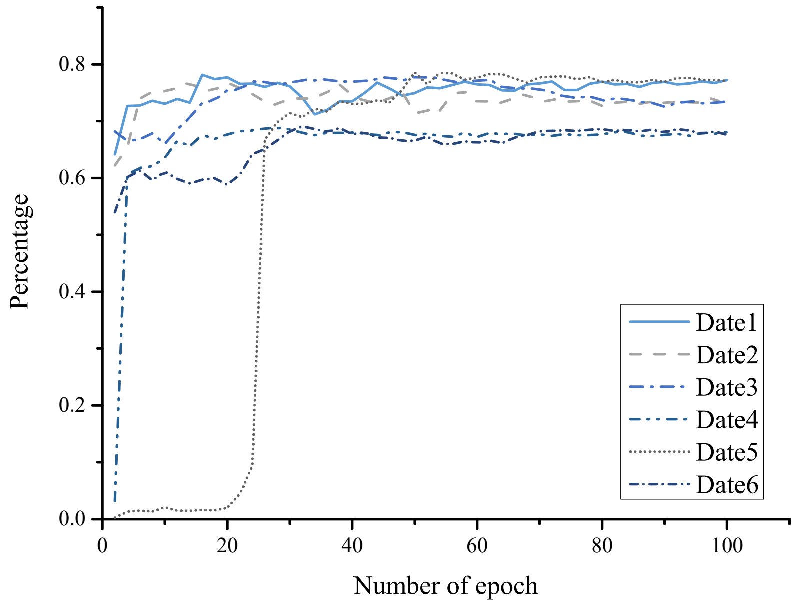

Figure 4. The precision of daily activity recognition which vary from 1st epoch to 100th epoch based on six dates.

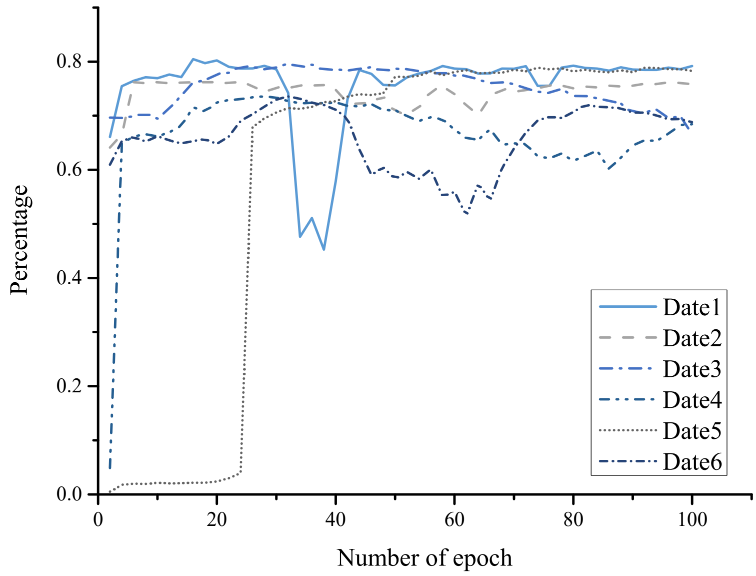

Figure 5. The F1-score of daily activity recognition which vary from 1st epoch to 100th epoch based on six dates.

4.4. Evaluation

4.4.1. Performance comparison among different source smart homes

Among HH101, HH105 and HH110, HH101 is most similar to HH109. We employ DANN to evaluate the performances of daily activity recognition using HH101 and HH105 as training sets, respectively. As shown in Figures 6–8, the performance of daily activity recognition based on the data from HH101 as training set is better than that from HH105 as training set. The experiment results demonstrate the effectiveness of Algorithm 1.

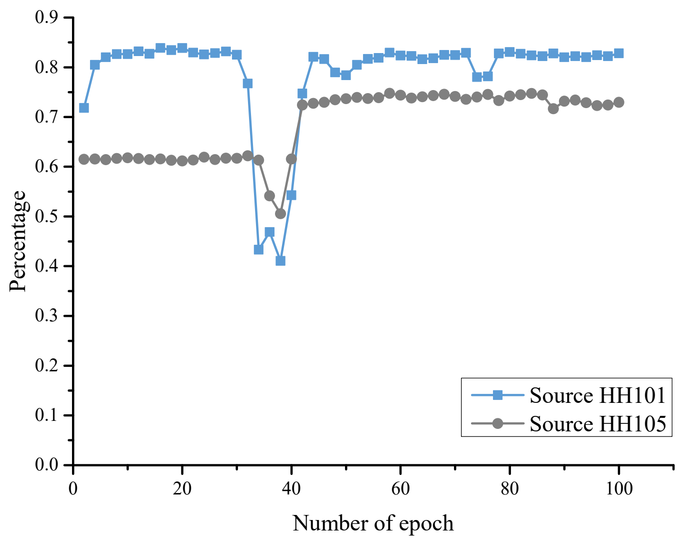

Figure 6. The accuracy of daily activity recognition using data collected from HH101 and HH105 as training set, respectively.

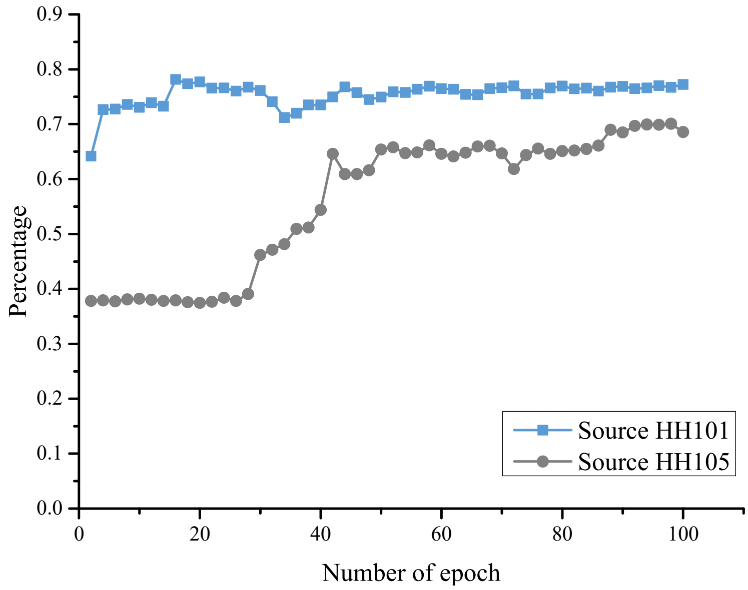

Figure 7. The precision of daily activity recognition using data collected from HH101 and HH105 as training set, respectively.

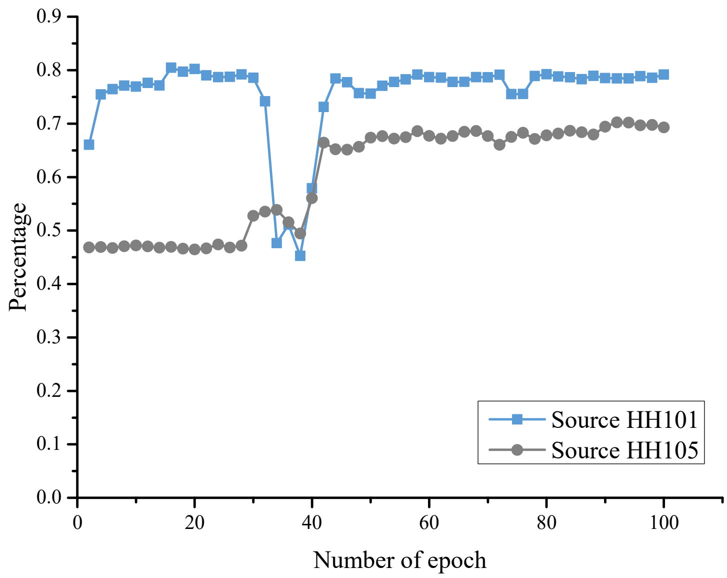

Figure 8. The F1-score of daily activity recognition using data collected from HH101 and HH105 as training set, respectively.

4.4.2. Performance comparison between the proposed method and state-of-the-art methods

We compared the proposed method within two state-of-the-art methods, which are the ontology sensor mapping method and the word embedding mapping method [15,24]. The results are shown in Figures 9–11. The proposed method is superior to the word embedding mapping method and the ontology sensor mapping method. It is shown that the proposed method of the precise sensor mapping is more advantageous.

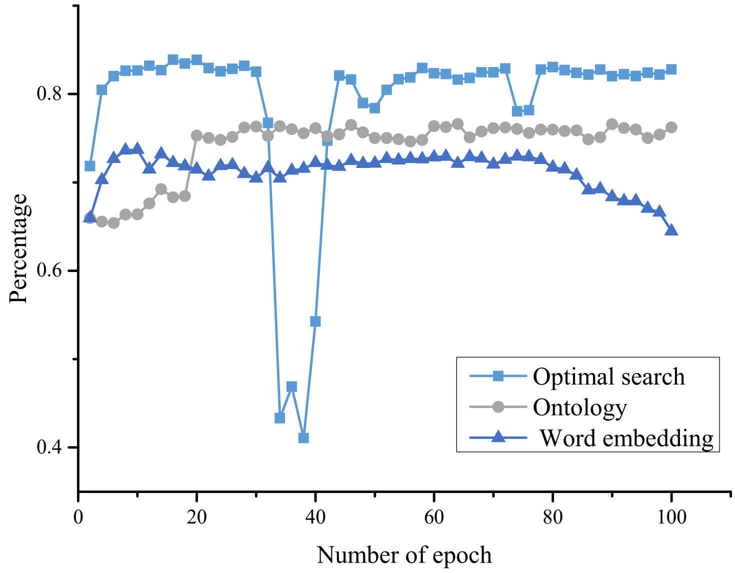

Figure 9. The accuracy of daily activity recognition using different sensor mapping methods.

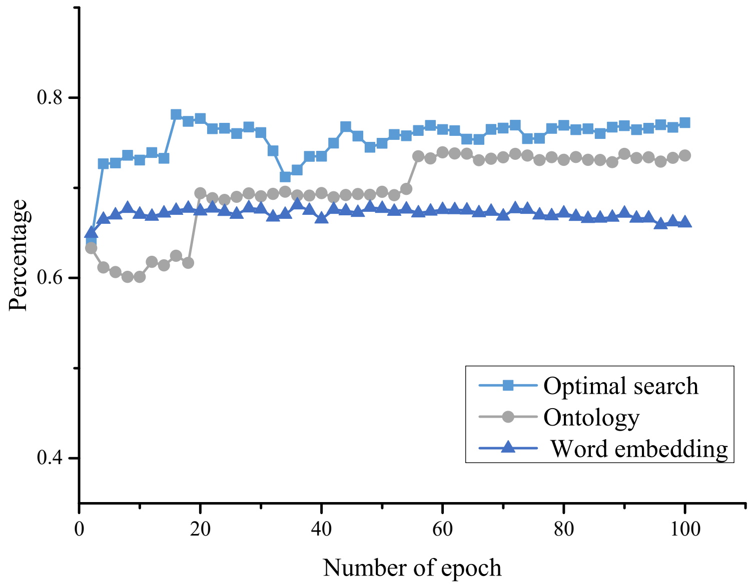

Figure 10. The precision of daily activity recognition using different sensor mapping methods.

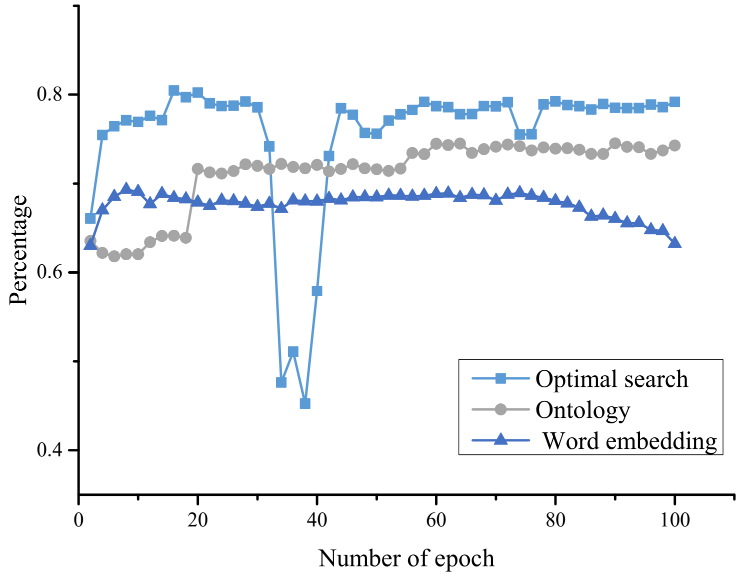

Figure 11. The F1-score of daily activity recognition using different sensor mapping methods.

4.4.3. Performance comparison between the proposed method and rough sensor mapping

Rough sensor mapping consists of two sensors which are respectively installed in source smart home and target smart home, the two sensors are mapped when locations and categories of them are the same. The results are shown in Figures 12–14. Owing to precise sensor mapping, which generates more distinguished features of daily activity, the proposed method is also superior to rough sensor mapping.

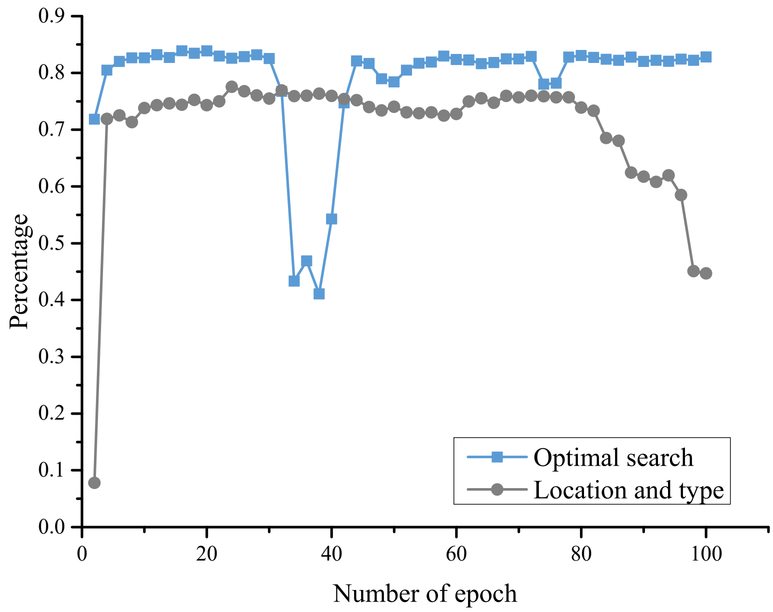

Figure 12. The accuracy of daily activity recognition using the proposed method and rough sensors mapping method.

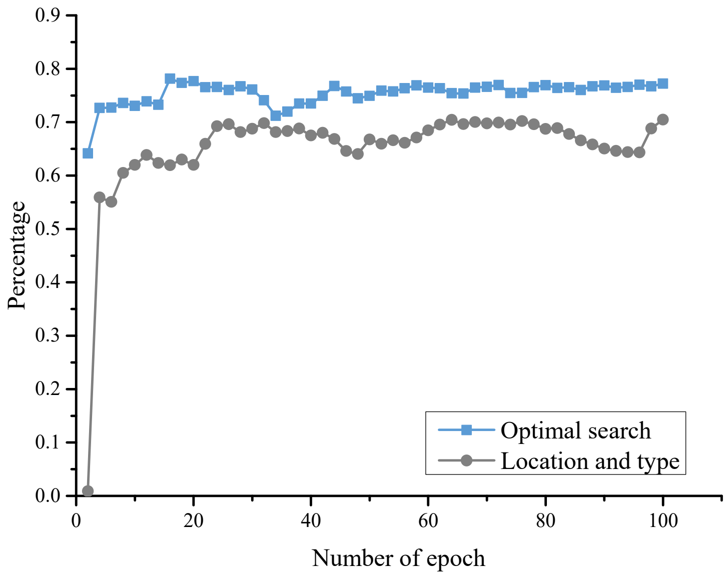

Figure 13. The precision of daily activity recognition using the proposed method and rough sensors mapping method.

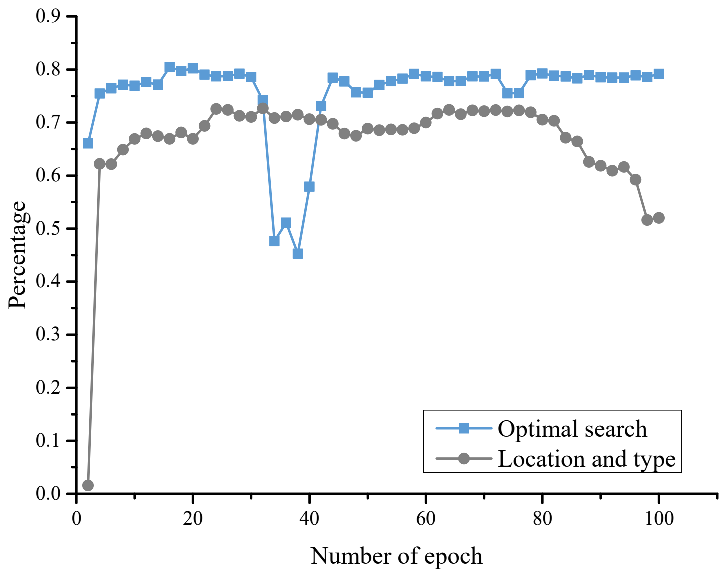

Figure 14. The F1-score of daily activity recognition using the proposed method and rough sensors mapping method.

5. Conclusions

The performance of daily activity recognition in cross-environment mainly depends on the sensor mapping between heterogeneous smart homes. This paper presents a novel approach to discovering the optimal sensor mapping by iteratively evaluating each candidate sensor mapping between the most similar source smart home and target smart home. Two public datasets involving sensor data on ten daily activities are investigated to validate the proposed approach, and the results have proven its excellent performance.

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Conflict of interest

The authors declare there is no conflict of interest.

References

1. W. Wang, C. Miao, Activity recognition in new smart home environments, in *Proceedings of the 3rd International Workshop on Multimedia for Personal Health and Health Care*, Seoul, South Korea, (2018), 29–37. https://doi.org/10.1145/3264996.3265001
2. D. Roggen, K. Foerster, A. Calatroni, G. Troster, The adARC pattern analysis architecture for adaptive human activity recognition systems, *J. Ambient Intell. Hum. Comput.*, **4** (2013), 169–186. https://doi.org/10.1007/s12652-011-0064-0
3. T. Van Kasteren, G. Englebienne, B. J. Krose, Recognizing activities in multiple contexts using transfer learning, in *AAAI Fall Symposium: Ai in Eldercare: New Solutions to Old Problems*, (2008), 142–149.
4. P. Rashidi, D. J. Cook, Activity knowledge transfer in smart environments, *Pervasive Mob. Comput.*, **7** (2011), 331–343. https://doi.org/10.1016/j.pmcj.2011.02.007
5. T. Van Kasteren, G. Englebienne, B. J. Krose, Transferring knowledge of activity recognition across sensor networks, in *International Conference on Pervasive Computing*, Springer, Berlin, Heidelberg, **6030** (2010), 283–300. https://doi.org/10.1007/978-3-642-12654-3_17
6. D. Cook, K. D. Feuz, N. C. Krishnan, Transfer learning for activity recognition: A survey, *Knowl. Inf. Syst.*, **36** (2013), 537–556. https://doi.org/10.1007/s10115-013-0665-3
7. D. J. Cook, Learning setting-generalized activity models for smart spaces, *IEEE Intell. Syst.*, **27** (2012), 32–38. https://doi.org/10.1109/MIS.2010.112
8. S. J. Pan, Y. Yang, A survey on transfer learning, *IEEE Trans. Knowl. Data Eng.*, **22** (2009), 1345–1359. https://doi.org/10.1109/TKDE.2009.191.
9. Y. Tang, L. Zhang, F. Min, J. He, Multiscale deep feature learning for human activity recognition using wearable sensors, *IEEE Trans. Ind. Electron.*, **70** (2022), 2106–2116. https://doi.org/10.1109/TIE.2022.3161812
10. W. Huang, L. Zhang, H. Wu, F. Min, A. Song, Channel-Equalization-HAR: a light-weight convolutional neural network for wearable sensor based human activity recognition, *IEEE Trans. Mobile Comput.*, **2022** (2022). https://doi.org/10.1109/TMC.2022.3174816
11. X. Cheng, L. Zhang, Y. Tang, Y. Liu, H. Wu, J. He, Real-time human activity recognition using conditionally parametrized convolutions on mobile and wearable devices, *IEEE Sens. J.*, **22** (2022), 5889–5901. https://doi.org/10.1109/JSEN.2022.3149337
12. S. Sonia, R. D. Baruah, Transfer learning in smart home scenario, in *2020 International Joint Conference on Neural Networks (IJCNN)*, IEEE, Glasgow, UK, (2020), 1–8. https://doi.org/10.1109/IJCNN48605.2020.9206923

13. P. Rashidi, D. J. Cook, Transferring learned activities in smart environments, in *Intelligent Environments*, IOS Press, (2009), 185–192. https://doi.org/10.3233/978-1-60750-034-6-185
14. J. Ye, SLearn: Shared learning human activity labels across multiple datasets, in *2018 IEEE International Conference on Pervasive Computing and Communications (PerCom)*, *IEEE*, Athens, Greece, (2018), 1–10. https://doi.org/10.1109/PERCOM.2018.8444594
15. J. Ye, S. Dobson, F. Zambonelli, XLearn: Learning activity labels across heterogeneous datasets, *ACM Trans. Intell. Syst. Technol.*, **11** (2020), 1–28. https://doi.org/10.1145/3368272
16. J. Ye, Shared learning activity labels across heterogeneous, *J. Ambient Intell. Smart Environ.*, **13** (2021), 77–94. https://doi.org/10.3233/AIS-210590
17. M. Alirezaie, J. Renoux, U. Köckemann, A. Kristoffersson, L. Karlsson, E. Blomqvist, et al., An ontology-based context-aware system for smart homes: E-care@home, *Sensors*, **17** (2017), 1586. https://doi.org/10.3390/s17071586
18. Z. E. Wemlinger, L. B. Holder, Cross-environment activity recognition using a shared semantic vocabulary, *Pervasive Mob. Comput.*, **51** (2018), 150–159. https://doi.org/10.1016/j.pmcj.2018.10.004
19. Y. T. Chiang, C. H. Lu, J. Y. J. Hsu, A feature-based knowledge transfer framework for cross-environment activity recognition toward smart home applications, *IEEE Trans. Hum.-Mach. Syst.*, **47** (2017), 310–322. https://doi.org/10.1109/THMS.2016.2641679
20. Y. T. Chiang, J. Y. J. Hsu, Knowledge transfer in activity recognition using sensor profile, in *2012 9th International Conference on Ubiquitous Intelligence and Computing and 9th International Conference on Autonomic and Trusted Computing*, *IEEE*, Fukuoka, Japan, (2012), 180–187. https://doi.org/10.1109/UIC-ATC.2012.78
21. V. W. Zheng, D. H. Hu, Q. Yang, Cross-domain activity recognition, in *Proceedings of the 11th international conference on Ubiquitous computing*, ACM, Orlando, USA, (2009), 61–70. https://doi.org/10.1145/1620545.1620554
22. K. D. Feuz, D. J. Cook, Transfer learning across feature-rich heterogeneous feature spaces via feature-space remapping (FSR), *ACM Trans. Intell. Syst. Technol.*, **6** (2015), 1–27. https://doi.org/10.1145/2629528
23. K. D. Feuz, D. J. Cook, Heterogeneous transfer learning for activity recognition using heuristic search techniques, *Int. J. Pervasive Comput. Commun.*, **10** (2014), 393–418. https://doi.org/10.1108/ijpcc-03-2014-0020
24. G. Azkune, A. Almeida, E. Agirre, Cross-environment activity recognition using word embeddings for sensor and activity representation, *Neurocomputing*, **418** (2020), 280–290. https://doi.org/10.1016/j.neucom.2020.08.044
25. D. H. Hu, V. W. Zheng, Y. Qiang, Cross-domain activity recognition via transfer learning, *Pervasive Mob. Comput.*, **7** (2011), 344–358. https://doi.org/10.1016/j.pmcj.2010.11.005
26. D. H. Hu, Q. Yang, Transfer learning for activity recognition via sensor mapping, in *Twenty-second international joint conference on artificial intelligence*, AAAI, (2011), 1962–1967. https://doi.org/10.5591/978-1-57735-516-8/IJCAI11-328
27. B. Myagmar, J. Li, S. Kimura, Heterogeneous daily living activity learning through domain invariant feature subspace, *IEEE Trans. Big Data*, **7** (2020), 922–929. https://doi.org/10.1109/TBDATA.2020.2977626

28. A. R. Sanabria, F. Zambonelli, J. Ye, Unsupervised domain adaptation in activity recognition: a Gan-based approach, *IEEE Access*, **9** (2021), 19421–19438. https://doi.org/10.1109/ACCESS.2021.3053704
29. D. J. Cook, A. S. Crandall, B. L. Thomas, N.C. Krishnan, CASAS: A smart home in a box, *Computer*, **46** (2012), 62–69. https://doi.org/10.1109/MC.2012.328