Integration of discriminative and generative models for activity recognition in smart homes

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Abstract

Activity recognition in smart homes enables the remote monitoring of elderly and patients. In healthcare systems, reliability of a recognition model is of high importance. Limited amount of training data and imbalanced number of activity instances result in over-fitting thus making recognition models inconsistent. In this paper, we propose an activity recognition approach that integrates the Distance Minimization (DM) and Probability Estimation (PE) approaches to improve the reliability of recognitions. DM uses distances of instances from the mean representation of each activity class for label assignment. DM is useful in avoiding decision biasing towards the activity class with majority instances; however, DM can result in over-fitting. PE on the other hand has good generalization abilities. PE measures the probability of correct assignments from the obtained distances, while it requires a large amount of data for training. We apply data oversampling to improve the representation of classes with less number of instances. Support Vector Machine (SVM) is applied to combine the outputs of both DM and PE, since SVM performs better with imbalanced data and further improves the generalization ability of the approach. The proposed approach is evaluated using five publicly available smart home datasets. The results demonstrate better performance of the proposed approach compared to the state-of-the-art activity recognition approaches.

Keywords: Activity recognition, Smart homes, Assisted living, Pervasive healthcare, Distance minimization, Probability estimation, Support vector machine

1. Introduction

Recognition of activities performed by a smart home resident is a fundamental task in assisted living and requires a high accuracy due to its use in healthcare services, such as remote monitoring of patients and elderly, and to assess their functional abilities [1, 2, 3]. Activity recognition supports independent stay of elderly in their own homes and ensures immediate medical aid as required [4, 5]. Early identification of health deterioration can also be possible through the long term analysis of recognized activities [1, 5]. Smart homes are equipped with sensors to record the events, such as interaction of the resident with objects and the environment. The sequence of events together defines an activity, such as eating, sleeping, meal preparation, or appropriate usage of medicines [4]. Challenges in activity recognition arise due to high intra-class variations, where varying sequences of events lead to the same activity; high inter-subject variations, where same activity is performed differently by different users; and less inter-class variations, where different activities are performed at the same location, such as preparing breakfast, lunch or dinner, [3, 5]. In addition, limited amount of training data, variation in frequency of execution of activities and sensor errors may also affect the performance of recognition approaches.

Activity recognition can be performed either by discriminative approaches, such as K-nearest neighbor (KNN) [6, 7], Artificial Neural Networks (ANN) [8], Support Vector Machine (SVM) [9] Distance Learning (DL) [5] and Conditional Random Fields (CRF) [10]; or generative approaches, such as Naive Bayes (NB) [11], Hidden Markov

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Model (HMM) [3, 10] and Dynamic Bayesian Networks (DBN) [12]. *Discriminative approaches* map the feature space to activity labels by learning the data boundaries [13]. Discriminative models are computationally efficient, capture the fine details in the data and remain robust in prediction of class labels. Discriminative approaches have the capability of tuning the parameters for the task at hand, however, these approaches can suffer from over-fitting [14]. On the other hand, *generative approaches* improve the generalization ability by modeling the underlying distribution of classes from the obtained feature space. Generative models are flexible, since they learn the structure and the relationship between the classes by exploiting the prior knowledge for the given task such as Markov assumptions, prior distributions and probabilistic reasoning, although the parameters are not optimized. Generative approaches perform well with uncertainty in the data; however, require a large amount of data for reasonable estimations [13, 14]. We provide a hybrid model for activity recognition, which minimizes the limitation of both discriminative and generative approaches.

In this paper, we propose an activity recognition approach for smart homes by integrating Distance Minimization (DM) and Probability Estimation (PE). The approach exploits the capabilities of both discriminative and generative models. We combine a discriminative model, obtained by measuring inter-class feature distances from the mean representations of each class, with a generative model that measures the actual distribution of the obtained distances by curve fitting. In the case of activities with fewer instances, we use an over-sampling technique to improve the data representation of minority classes. Outputs of both models, the obtained distances and their estimated probabilities, are fused using the learning method multi-class SVM (one-versus-one), which is computationally efficient in the case of multiple classes, and a better choice in the case of imbalance number of activity instances [9]. The validation of the proposed approach using five smart home datasets through a comprehensive evaluation metrics demonstrates an improved performance in correct recognition of activities compared to existing approaches.

The rest of the paper is organized as follows: Sec. 2 discusses the related work on activity recognition. In Sec. 3, we discuss the proposed activity recognition approach. The datasets and experimental analysis are presented in Sec. 4. Finally, Sec. 5 draws conclusions.

2. Related work

Data obtained from ambient or environment interactive sensors, such as reed switches, pressure, motion, analog and binary sensors, is used for recognition of general activities performed in a smart home, such as preparing meal, eating, sleeping. Activity recognition approaches are generally classified into data driven and knowledge driven approaches. Data driven approaches can be further categorized into discriminative and generative recognition approaches. This paper is mainly focused on data driven approaches.

In generative approaches, NB classifier is used for activity recognition, which assigns the label of activity class with the highest probability corresponding to the sequence of activated sensor values [11]. Hierarchical-HMM (HHMM) is applied for activity recognition, where the number of events corresponding to each activity in the top layer is fixed [15]. HHMM remains more effective than Hidden Semi Markov Model (HSMM) and HMM. An extension to this approach applies HHMM using variable number of events for each activity to represent different levels of complexity (HHMM-VS) [16]. Incorporation of temporal reasoning with HMM can improve the recognition accuracy [17]. Long range dependencies in sequential algorithms are obtained by pattern mining, which finds the patterns indicating time segments during the execution of an activity. A probabilistic model is learned to represent the distribution of pattern matches along sequences in an activity, which is integrated with HSMM for recognition of activities (AR-SPM) [18]. In an unsupervised approach, the discontinuous frequent patterns are extracted and similar patterns are grouped in the clusters, while the boosted HMM is applied to learn from the clusters [3]. An incremental learning approach using DBN is applied to recognize activities by reconfiguring the previously learned models to adapt the variations within the activities [19]. The recognition performance and effectiveness of Dempster Shafer Theory (DST) of evidence and DBN approaches are compared for activity classification [12], where DST is suitable for uncertainty in the data, while DBN performance depends upon the quality and reliability of the input data. The capabilities of both generative (HMM) and discriminative (CRF) models are also evaluated for activity recognition [10].

In discriminative approaches, Principal Component Analysis (PCA) identifies the discriminative features, while multi-class SVM (one-versus-one) is used for activity classification [9]. Inter-class distance based approach is applied to select the best features, while three learning approaches ANN, HMM and NB are used for recognition, among all, ANN performs better [20]. CRF is undirected graphical model to label the sequential data and has been applied for classification of activities [21]. The representative patterns of activities can be selected by pattern mining and sequence alignment methods, the patterns are then matched with the observed sequences of events for activity recognition [22]. Activity patterns can be identified in each location using frequent item set mining, while density based clustering is applied to form activity clusters [23]. Pattern mining is applied to extract the frequent patterns and Latent Dirichlet Allocation (LDA) is used to cluster the co-occurring sequential patterns, (ADR-SPLDA) [4]. Two variants of LDA obtained by replacing the multinomial distribution, LDAGaussian and LDAPoissonvon-Mises, can be used for classification of activities [24]. In a clustering based classification approach, homogeneous activities are grouped into clusters, while learning is applied within each cluster independently to learn the fine-grained differences between the activities [7]. Information gain is used to select feature subsets, while data balancing is applied to improve the representation of minority classes and Evidence-theoretic K-Nearest Neighbor (ET-KNN) is used for recognition of activities [25]. The comparison of five learning classifiers is performed under different challenges in [26], where SVM demonstrates to be the most robust classifier in activity recognition. Activity recognition can also be improved by separating activities from anomalies, where Support Vectors Data Descriptors (a variant of SVM) has been used for the classification of normal and anomalous behavior patterns of the elderly [27]. In an activity recognition approach with self-verification of assignments (ARSH-SV), correct/incorrect assignments are learned for label assignment using SVM, while the confidence of assigned label is estimated by measuring the distribution of underlying data through sub-clustering within each activity class [5]. In an online activity recognition approach, evolving neuro-fuzzy classifiers have been used to reflect the changes in the execution of activities [28]. Activity recognition can also be used for the behavior analysis of the smart home resident. HMM is applied to identify the repetitive patterns for behavior modeling, while atypical trends in the behavior are recognized through deviations in the distribution of events in the activities [29]. In [8], Probabilistic Neural Network (PNN) is applied to recognize the activities, while clustering based on the frequency of executed activities per day is used to monitor the daily routine of a smart home occupant and to identify the anomalies. A behavior modeling approach is developed by using Recurrent Neural Network and temporal information of a smart home occupant [1]. In an activity recognition approach to identify changes in behavior, different machine learning and statistical methods have been used to identify anomalies in different contexts and the outputs of all models are combined using a fuzzy rule based model to get the final decision [30].

Knowledge driven, evidence based and other hybrid approaches have also been applied for recognition of activities. In a knowledge driven approach, ontological modeling and semantic reasoning are applied for classification of activities [2]. A hybrid approach combines the ontological and temporal knowledge representation for activity modeling [31]. Partially observable Markov decision process models are built using the user interaction information within the context for activity recognition [32]. Temporal reasoning can be incorporated in ontology to recognize the daily activities [33]. Clustering can be used to define initial incomplete models through knowledge engineering, which are then used to represent an activity and to aggregate new events, and variations in the activity pattern are learned to get the complete model for activities [34]. Recognition approaches based on belief theory are also applied, such as Evidence Decision Network (EDN) approach [35], where the temporal information of domain knowledge i.e start time and duration of the activity is incorporated in the DST. An extension of this work is discussed in [36], where a data fusion approach based on DST is developed to include the temporal evidence of the occurrence of events. An evidential approach (EFA-AR) exploits the combination rule of DST to support conflict resolution by combining the sensor information with common-sense knowledge [37]. Experience Sampling for activity annotation and weakly supervised learning methods, multi-instance learning and graph structure, are also applied [38]. In multi-instance learning, the activity data is grouped into bags-of-activities and the labels are assigned to bags instead of activity instances, and the goal is to determine the labels of instances belonging to particular activity provided by the bag's label. In graph structure, the labels are propagated to the unlabeled neighboring activity instances through feature similarity and time proximity [38].

In this work, we combine both discriminative and generative models to minimize their limitations. A learning model is used for the integration, thus reducing the uncertainty in their decisions while improving the recognition performance and the generalization ability.

3. Activity recognition

Let $\mathbf{A} = \{A_k\}_{k=1}^{K}$ be a set of K activity classes and $\mathbf{I}_k = \{I_{jk}\}_{j=1}^{J}$ be a set of J activity instances of A_k performed in a smart home. Let R binary sensors be deployed at different locations/objects to monitor the activities. Each activity

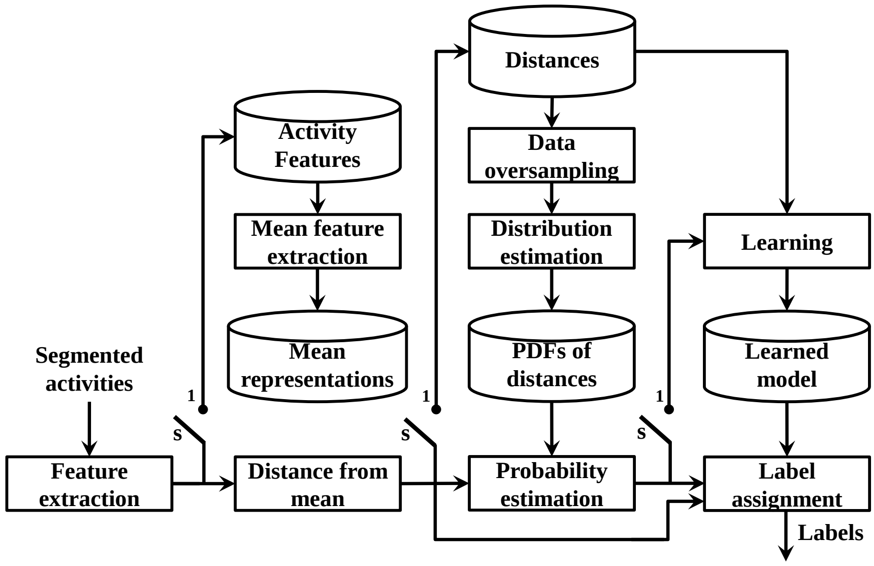


Figure 1: Block diagram of the proposed activity recognition approach. Switch $s = 1$ is training.

instance I_{jk} is represented by a feature set $\mathbf{F}_{jk} = \{f^r_{jk}\}^R_{r=1}$ of R features. Each feature f^r_{jk} represents the number of times a sensor is activated during an activity. Fig. 1 shows the block diagram of the proposed learning approach to integrate DM and PE for activity recognition. DM, PE and their integration strategy are discussed in the next subsections.

3.1. Distance from means

We obtain K sets of mean feature representation $\mathbf{M}_k = \{m^r_k\}^R_{r=1}$, where m^r_k is the mean of the same type of features extracted from all instances $\{I_{jk}\}^J_{j=1}$ of A_k given as

$$m^r_k = \frac{1}{J}\sum_{j=1}^{J} f^r_{jk}. \tag{1}$$

Each activity class A_k is represented by an M_k [5]. For each activity instance I_{jk}, we obtain a distance vector $\mathbf{D}_{jk} = \{D^{\hat{k}}_{jk}\}^K_{\hat{k}=1}$ containing K distances each between its feature set $\mathbf{F}_{jk}$ and mean set $M_{\hat{k}}$, where $\hat{k} = 1 \dots K$, given as

$$D^{\hat{k}}_{jk} = ||\mathbf{F}_{jk} - \mathbf{M}_{\hat{k}}||_2. \tag{2}$$

Label assignment at this stage can be performed using DM as

$$k^* \;=\; arg_{\hat{k}}min\; D^{\hat{k}}_{jk}, \tag{3}$$

where k^* is the index of the activity class whose mean has the minimum distance from I_{jk}, the label of the selected class is represented by L_{k^*}. The obtained M_k from A_k having fewer number of activity instances may not be a good representative of that class and results in overfitting of data. Furthermore, the sensor errors, such as missed activations or faulty readings in some activity instances can result in uncertainty in data [2].

For each activity class A_k, we obtain a $K \times J$ distance matrix $\mathbf{\Delta}_k$, where each column of $\mathbf{\Delta}_k$ is $\mathbf{D}_{jk}$, while the k^{th} row represented as $\chi_k = \{D^k_{jk}\}^J_{j=1}$ has the distances of J instances of A_k from its mean M_k. We exploit χ_k to estimate the probability of assignment of correct label.

3.2. Probability estimation

We analyze the distances in χ_k to estimate their distribution. In order to obtain a better data representation in the case of fewer number of instances per activity class, we generate more related samples of χ_k using oversampling technique SMOTE [39, 40]. SMOTE generates synthetic examples by adding to the sample under consideration, an obtained difference between the sample and its nearest neighbor. We obtain the set $\mathbf{V_k}$ containing new samples $\hat{\chi}_k$ along with the original χ_k as

$$\mathbf{V}_k = \{\chi_k, \hat{\chi}_k\}. \tag{4}$$

The combined set $\mathbf{V}_k$ is used for the analysis. We normalize the histogram of $\mathbf{V}_k$ to obtain its corresponding Probability Density Function (PDF) (Fig. 2). The PDF obtained for each class is characterized by curve fitting the existing parametric distribution models [41]. We select the nearest model to the PDF by applying Bayesian Information Criterion [42]. The selected model T_k with its parameters is stored, which approximates the PDF of distances between the instances of the same class and its class mean. For K activity classes we have $\mathbf{T} = \{T_k\}_{k=1}^{K}$ models.

We measure the probability $P(L_{\hat{k}}|D_{jk}^{\hat{k}})$ of instance I_{jk} belonging to $A_{\hat{k}}$ for the given distance $D_{jk}^{\hat{k}}$ and the distribution model $T_{\hat{k}}$ (Eq. 2).

$$P(L_{\hat{k}}|D_{jk}^{\hat{k}}) = G(D_{jk}^{\hat{k}}, T_{\hat{k}}), \tag{5}$$

where $G(.,.)$ takes as input the distance $D_{jk}^{\hat{k}}$ and the selected model $T_{\hat{k}}$ and returns the probability of the activity instance belonging to the class $A_{\hat{k}}$. Since for each activity instance we have a set $\mathbf{D}_{jk}$ containing K distances, we obtain the set $\mathbf{P}_{jk} = \{P_{jk}^{\hat{k}}\}_{\hat{k}=1}^{K}$ containing K probabilities, where each $P_{jk}^{\hat{k}}$ is the probability of I_{jk} belonging to $A_{\hat{k}}$. $\mathbf{D}_{jk}$ and $\mathbf{P}_{jk}$ are combined by concatenation as a set $\mathbf{\Gamma}_{jk}$ to represent each I_{jk} as

$$\mathbf{\Gamma}_{jk} = \{\mathbf{D}_{jk}, \mathbf{P}_{jk}\}. \tag{6}$$

$\mathbf{\Gamma}_{jk}$ along with its class label L_k are given as input to the multi-class SVM for learning.

3.3. Activity classification using SVM

We use the learning method SVM for the activity classification. SVM finds the most optimal hyperplane to discriminate the data points of two classes with maximum margin [43, 44].

Consider N training pairs $(\mathbf{\Gamma}_i, L_i)$, where for simplicity $jk = i$, $\mathbf{\Gamma}_i$ is $2R$ dimensional feature vector and L_i is the class label. The optimal hyperplane for non-separable patterns is obtained by solving the following optimization problem

$$\psi(w, \xi) = \frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i, \tag{7}$$

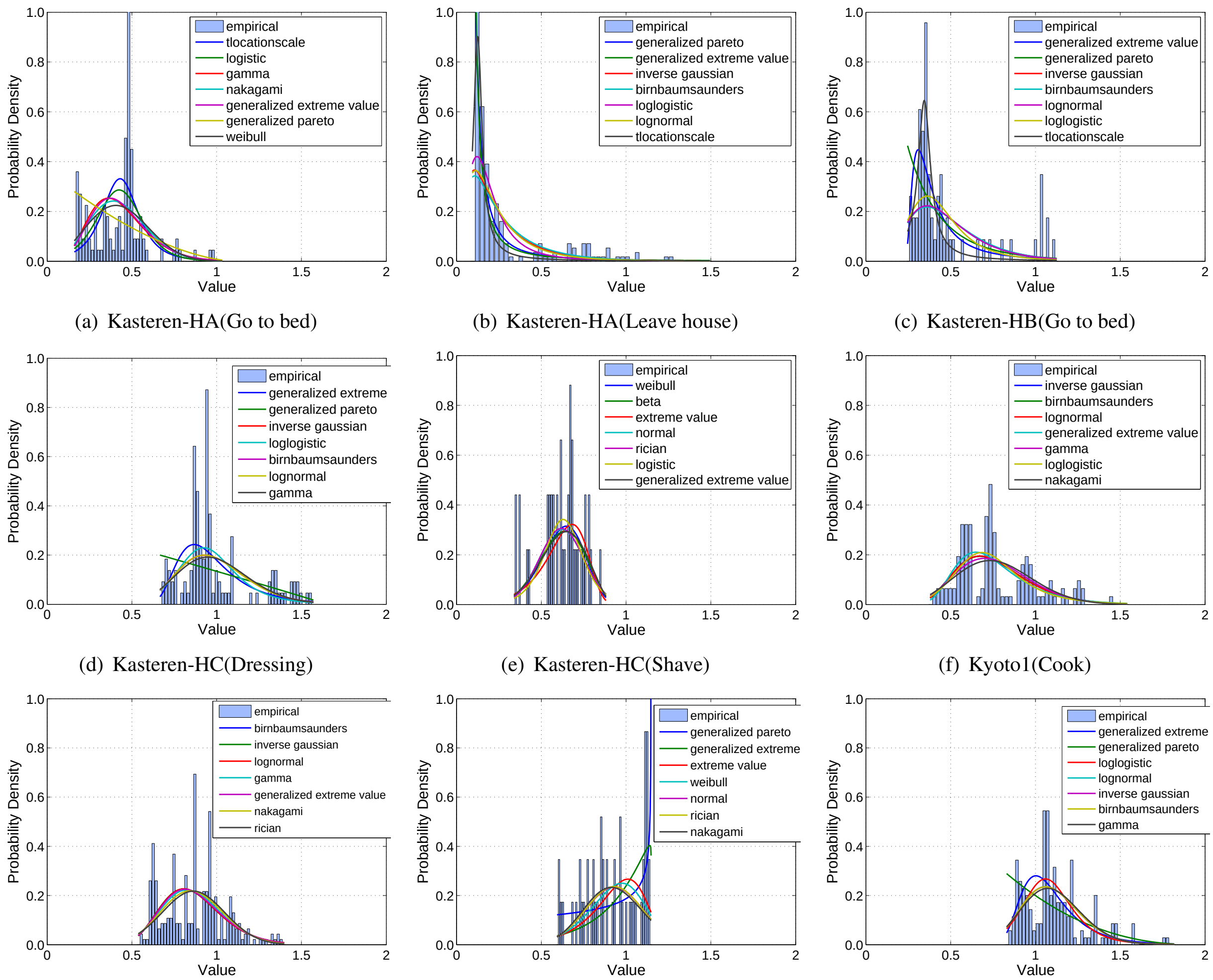
subject to the condition $L_i(w^T \psi(\mathbf{\Gamma}_i) + bias) \geq 1 - \xi_i, \xi_i \geq 0$, where C is the penalty parameter of error term $\sum_{i=1}^{N} \xi_i$. It represents the cost of constraint violation of data points on the wrong side of decision boundary, and $\psi(\mathbf{\Gamma})$ is the non-linear mapping. The weight vector w minimizes the cost function term $w^T w$. The non-linear input data is mapped to higher dimension through a mapping function $\psi(\mathbf{\Gamma})$ such that $\psi : R^N \rightarrow F^M, M >> N$. Each point in the new feature space is defined by a kernel function $K(\mathbf{\Gamma}_i, \mathbf{\Gamma}_j) = \psi(\mathbf{\Gamma}_i).\psi(\mathbf{\Gamma}_j)$. The non-linear decision surface S can now be constructed by a new function $f(\mathbf{\Gamma})$ as:

$$f(\mathbf{\Gamma}) = \sum_{i=1}^{N_s} \alpha_i L_i K(\mathbf{\Gamma}_i, \mathbf{\Gamma}) + bias = \sum_{i=1}^{N_s} \alpha_i L_i \psi(\mathbf{\Gamma_i}).\psi(\mathbf{\Gamma}) + bias, \tag{8}$$

where the coefficient $\alpha_i > 0$ is the Lagrange multiplier in an optimization problem. A pattern vector $\mathbf{\Gamma}_i$ corresponding to $\alpha_i > 0$ is called a support vector. N_s is the number of support vectors. The $f(\mathbf{\Gamma})$ is independent of the dimension of the feature space. In this work, Radial Basis Function and Polynomial kernels are used, receptively, given as:

$$\begin{aligned} K(\mathbf{\Gamma}_i, \mathbf{\Gamma}_j) &= exp(-\left\|\mathbf{\Gamma}_i - \mathbf{\Gamma}_j\right\|^2 / (2\sigma)^2) \\ &and \\ K(\mathbf{\Gamma}_i, \mathbf{\Gamma}_j) &= (\mathbf{\Gamma}_i^T \mathbf{\Gamma}_j + 1)^{\rho}, \end{aligned} \tag{9}$$

where σ shows the width of the Gaussian function and ρ is the power of the Polynomial function. For multi-class classification, we used SVM (one-versus-one) to build the classifiers using all the pairwise combination of N classes.



(a) Kasteren-HA(Go to bed) (b) Kasteren-HA(Leave house) (c) Kasteren-HB(Go to bed)

(d) Kasteren-HC(Dressing) (e) Kasteren-HC(Shave) (f) Kyoto1(Cook)

(g) Kyoto7(R1 groom) (h) Kyoto7(R1 work at dining room table) (i) Kyoto7(R2 prepare lunch)

Figure 2: Examples of distributions of obtained distances of instances from the mean of their activity class. Legends are stored in the order of the nearest distribution to the data obtained using curve fitting. Curve fitting on distributions are generated using matlab library at link: http://uk.mathworks.com/matlabcentral/fileexchange/34943-fit-all-valid-parametric-probability-distributions-to-data (last accessed Feb. 2015).

In case of imbalanced dataset, multi-class SVM (one-versus-one) is a preferable choice, as fewer classifiers would be distorted. In addition, constructing the set of classifiers would be easy and less time-consuming [9].

Let ϕ be a newly detected activity instance. We extract the normalized feature set $\mathbf{F}_{(\phi)}$. From $\mathbf{F}_{(\phi)}$, we obtain the distance vector $\mathbf{D}_{(\phi)}$ using Eq.2 and the probability vector $\mathbf{P}_{(\phi)}$ using Eq.5. The two vectors are concatenated and given as input to the obtained learned SVM model for label assignment. Using the distance and probability vectors, we generate an activity pattern with highest probability and minimum distance to be classified. The model returns the label L_{k^*} of the newly detected activity instance.

4. Evaluation and Discussion

We evaluate the proposed activity recognition approach through comprehensive evaluation metrics containing four measures: Precision, Recall, F1score and Accuracy [5]. Five publicly available smart home datasets from two smart home projects are used in the evaluation. The results are compared with two baseline approaches: distance minimization (DM) and probability estimation (PE), and two learning approaches: ET-KNN [7, 45] and PNN [8, 46].

Next, we compare the results with existing state-of-the-art recognition approaches ADR-SPLDA [4], AR-SPM [18], HHMM-VS [16], EFA-AR, Murphy rule and Dempster-Shafer rule [37], Temporal EDN, No time EDN [35, 47], CL-AR and J48-DT [48]. Furthermore, we present the activity level performance analysis though F1-scores and confusion matrices. Leave one day out cross validation is applied for the evaluation, where a single day data is used for testing and the remaining for training, and the process is repeated for all days.

4.1. Evaluation measures

Four measures for the evaluation using true positives (TP), false positives (FP) and false negatives (FN) are given as:

$$Precision = \frac{TP}{TP + FP} \times 100, \tag{10}$$

$$Recall = \frac{TP}{TP + FN} \times 100, \tag{11}$$

$$F1score = \frac{2 \times Precision \times Recall}{Precision + Recall}, \tag{12}$$

$$Accuracy = \frac{TP}{N}, \tag{13}$$

where N is the total number of instances. F1score and accuracy return values between [0 , 1], where a value near to 1 shows the best performance, and near to 0 indicates the worst performance.

4.2. Datasets

Table 1 shows the summary of five publicly available smart homes datasets, from Kasteren [49, 50] and CASAS [51] smart home projects, used in the evaluation. The selected datasets includes the challenges of overlapping of features among activity instances of different classes, availability of fewer instances for learning, number of participants in each home, and variations in the performance of the same activity by different users.

Kasteren smart home project includes three smart homes datasets; namely, *Kasteren-HA*, *Kasteren-HB* and *Kasteren-HC*. In each smart home, activities are performed by a single resident, where 7, 10 and 15 types of different activities are respectively, performed in three houses. Total number of activity instances are 245, 135 and 257, respectively. The information regarding three different houses is collected through several wireless sensor networks equipped with various binary sensors; for example, reed switches, pressure mats, mercury contacts and passive infrared. The annotation of the activities is achieved by using either handwritten dairy or bluetooth handset.

We select two smart home datasets from CASAS project: *Kyoto1* and *Kyoto7*. In comparison to Kasteren, the selected CASAS datasets comprise of multiple residents, which result in high inter-subject variations. Sensor network comprises of motion and other utility sensors, such as absent/present status of item and door open/close status of cabinet sensors. Moreover, analog sensors are used to measure the temperature and water usage. The annotation is achieved by using 3D visualization tool and residents diaries. In *Kyoto1* dataset, 5 types of activities are performed by 20 participants. Each activity is performed once by each participant one after the other. The number of activity instances are 120. *Kyoto7* contains activity instances performed by two residents living together and performing activities independently without cooperation. *Kyoto7* comprises of 14 types of activities with 499 instances.

4.3. Comparison with existing approaches

Table 2 shows the performance of proposed approach compared with DM, PE, ET-KNN and PNN, using defined performance evaluation metrics applied on the results obtained from five datasets.

In Kasteren datasets, some of the activities, such as *Prepare breakfast*, *Prepare dinner*, *Get snack* and *Get drink*, or *Brush teeth* and *Take shower* are performed in the same location and therefore share same sensors, which result in less inter-class variations. In *Kasteren-HA*, proposed approach achieves precision, and recall of 93.94% and 94.23%. Similarly, F1score and accuracy of proposed approach is 0.93 and 95.19%, which is also better than the two learning based approaches ET-KNN and PNN. DM shows lesser performance in comparison to ET-KNN and PNN due to less inter-class variations, while performance of PE is affected by the availability of less number of activity instance, i.e only 245. In *Kasteren-HB*, proposed approach outperforms rest of the classification approaches. Precision, recall

Table 1: The summary of five smart home datasets used in the evaluation of proposed approach. Key: R1 - Resident 1, R2 - Resident 2.

S.no	Datasets	Description	Participants	Activity classes	Activity instances	Name of activities
1	Kasteren-HA	Kasteren	1	7	245	Leave house, Use toilet, Take shower, Go to bed, Prepare breakfast, Prepare dinner and Get drink.
2	Kasteren-HB	Kasteren	1	10	135	Leave house, Use toilet, Take shower, Brush teeth, Go to bed, Dressing, Prepare meal, Get drink, Washing machine and Eat.
3	Kasteren-HC	Kasteren	1	15	257	Leave house, Eat, Use toilet downstairs, Take shower, Brush teeth, Use toilet upstairs, Shave, Go to bed, Dressing, Take medication, Prepare breakfast, Prepare lunch, Prepare dinner, Get snack and Get drink.
4	Kyoto1	ADL Activities	20	5	120	Clean, Cook, Eat, Phone call, and Wash hands.
5	Kyoto7	Daily life, Spring 2009	2	14	499	R1 bed to toilet, R1 prepare breakfast, R1 groom, R1 sleep, R1 work at computer, R1 work at dining room table, R2 bed to toilet, R2 prepare breakfast, R2 groom, R2 prepare dinner, R2 prepare lunch, R2 sleep, R2 watch tv and R2 work at computer.

and accuracy of proposed approach are 77.96%, 79.05% and 78.56%, respectively. Higher values of precision, recall and accuracy shows the effectiveness of proposed approach in correct assignment of activity instances to the target class in the case of less inter-class variations and limited number of instances, i.e, only 135, for ten activity class. Similarly, F1score (0.73) of proposed approach remains higher than that of DM (0.58), PE (0.50), ET-KNN (0.67) and PNN (0.67) classification approaches. In *Kasteren-HC*, proposed approach obtains the highest accuracy of 64.93%. Precision and recall of proposed approach are 60.17% and 60.92%, respectively, which are 6.36% and 4.61% higher than DM, 9.78% and 11.22% higher than PE, 2.24%, 2.59% higher than ET-KNN, and 6.16% and 3.19% higher than PNN. The F1score also remains higher in comparison to other approaches.

In CASAS datasets, both *Kyoto1* and *Kyoto7* datasets have high intra-class and inter-subject variations, however, in *Kyoto1*, each activity class is discriminative enough and well separated. In *Kyoto1*, proposed approach shows better performance with the F1score of 0.98 and accuracy of 98.21%. The performance of ET-KNN and PNN remains comparable to each other with an F1score of 0.93. In *Kyoto7*, precision, recall and accuracy of proposed approach are 77.33%, 80.43% and 81.03%, respectively, and remain higher than other approaches. The F1score of proposed approach (0.78) also remains better than DM (0.73), PE (0.53), ET-KNN (0.68) and PNN (0.67). In both Kasteren and CASAS datasets, PE shows less performance due to less number of activity instances available for training.

Table 3 shows performance comparison of the proposed approach with existing activity recognition approaches: ADR-SPLDA [4], AR-SPM [18], HHMM-VS [16], EFA-AR, Murphy rule and Dempster-Shafer rule [37], Temporal EDN and No time EDN [35, 47] and CL-AR and J48-DT [48]. We measure accuracy and F1score, while applying the cross validations same as mentioned in the compared approaches. Proposed approach shows a better accuracy than ADR-SPLDA [4] in the two datasets. In *Kasteren-HA*, it shows an improvement of 13% with an accuracy of 95.19%, while in *Kyoto1*, it achieves an accuracy of 98.21% in comparison to 81.78% of ADR-SPLDA. In the case of imbalanced class data, where some activities are executed more frequently than others, a high accuracy may represent the assignment of correct labels to the class with the majority of instances. However, F1score solves this limitation by incorporating both precision and recall and thus is more reliable. The Kasteren-HA, Kasteren-HB and Kasteren-HC are imbalanced datasets including overlapping activities with less number of activity instances, particularly Kasteren-HB comprises of ten activities with 135 activity instances. The proposed approach has the highest F1score in, *Kasteren-HA* (0.93), *Kasteren-HB* (0.73), and *Kasteren-HC* (0.59), compared to existing approaches. Similarly in *Kyoto7*, F1score of proposed approach is higher (0.78) than AR-SPM (0.73), which demonstrates that the approach remains least affected in the case of high intra-class and inter-subject variations, and less inter-class variations.

4.4. *Activity level performance analysis*

Fig. 3 presents the activity level performance comparison using F1score. Fig. 3(a) shows the comparison of proposed approach with AR-SPM [18], Temporal EDN, No time EDN, NB and J48-DT [47] on *Kasteren-HA* dataset. The proposed approach attains high F1score in all seven activities compared to EDN, no time EDN, NB and J48-DT. In comparison with AR-SPM [18], for five activities F1score remain higher, while remain comparable the two activities, *Go to bed* and *Leave house*. The proposed approach is further compared with AR-SPM in other three datasets. In *Kasteren-HB* dataset [Fig. 3(b)], proposed approach obtains better F1score than AR-SPM in eight activities, and comparable in two activities of *Go to bed* and *Get drink*. In *Kasteren-HC* dataset [Fig. 3(c)], proposed approach achieves a higher F1score than AR-SPM in nine activities, comparable in two activities of *Eat* and *Shave*, while

Table 2: Performance evaluation metrics on five smart home datasets for proposed approach and the existing approaches: DM, PE, ET-KNN [7, 45] and PNN [8, 46] using leave one day out cross validation. Feature sets comprising of obtained distances and their estimated probabilities are given as input to the learning classifiers. Precision, Recall and Accuracy are in percentages (%), The range of F1score is between [0 , 1]. The highest values in the performance evaluation metrics are highlighted in bold.

S.no	Datasets	Classifiers	Precision(%)	Recall(%)	F1score	Accuracy(%)
1	Kasteren-HA	Proposed approach	**93.94**	**94.23**	**0.93**	**95.19**
		DM	88.62	89.41	0.88	91.70
		PE	66.37	66.40	0.64	69.66
		ET-KNN	92.97	91.30	0.91	93.55
		PNN	92.88	91.30	0.91	93.50
2	Kasteren-HB	Proposed approach	**77.96**	**79.05**	**0.73**	**78.56**
		DM	63.17	60.19	0.58	58.92
		PE	51.91	52.97	0.50	52.65
		ET-KNN	67.37	70.07	0.67	69.89
		PNN	67.94	70.88	0.67	69.42
3	Kasteren-HC	Proposed approach	**60.17**	**60.92**	**0.59**	**64.93**
		DM	53.81	56.31	0.52	58.04
		PE	50.39	49.70	0.48	52.33
		ET-KNN	57.93	58.33	0.56	60.33
		PNN	54.01	57.73	0.54	59.59
4	Kyoto1	Proposed approach	**98.75**	**98.21**	**0.98**	**98.21**
		DM	96.06	96.15	0.95	96.15
		PE	87.14	87.18	0.85	87.18
		ET-KNN	93.21	94.62	0.93	94.62
		PNN	92.64	93.85	0.93	93.85
5	Kyoto7	Proposed approach	**77.33**	**80.43**	**0.78**	**81.03**
		DM	72.85	78.37	0.73	78.01
		PE	52.08	57.06	0.53	57.36
		ET-KNN	67.18	72.36	0.68	73.51
		PNN	66.01	70.86	0.67	71.90

comparatively lesser in four activities of *Leave house*, *Go to bed*, *Take medication* and *Get snack*. In *Kyoto7* [Fig. 3(d)], proposed approach achieves better F1score in eleven activities and comparable in two activities of *R2 prepare breakfast* and *R2 groom*, while show relatively less performance in *R1 prepare breakfast* than AR-SPM.

Table 4(a) presents the confusion matrix of activities in *Kasteren-HA* dataset. The proposed approach correctly recognizes most of the activity classes with an overall accuracy of more than 95%. The *Prepare breakfast* and *Prepare dinner* activities share 10% of their instances among each other due to being performed at the same location. Table 4(b) shows the confusion matrix of activities in *Kasteren-HB* dataset. The proposed approach has high recognition performance for activities other than kitchen activities *Get drink*, *Wash dishes* and *Eat*. The reason for less recognition accuracy in kitchen activities is the usage of similar features and same location as well as less amount of activity instances. 28% of *Get drink* activity instances are correctly recognized, while 57% goes into *Eat* and 14% are confused with *Prepare meal* activities. Similarly, *Wash dishes* transfers 33% of errors to *Brush teeth* and 16% to *Eat* activities. In *Eat* activity, only 12% of instances are accurately identified due to the least number of instances (8) are available for training. Table 4(c) shows the confusion matrix of activities in *Kasteren-HC* dataset. The activities with few number of instances do not perform well, such as shave and Get snack each comprises of 7 instances, while *Prepare lunch* and *Prepare dinner* contains 8 and 11 activity instances, respectively. *Take medication* activity could not be recognized due to least number of activity instances i.e, only 3. Some of the activities transfer their errors to the other similar activities, such as *Shave* activity, 28% of instances are identified correctly, while 57% and 14% instances are confused with *Brush teeth* and *Take shower* activities, respectively. Similarly, another example of overlapping activities is *Prepare dinner*, where 45% activity instances are accurately assigned labels, while its 36% instances are erroneously recognized as *Prepare lunch* and it transfer its 9% errors to both each of the *Prepare breakfast* and *Eat* activities. The other similar classes such as *get drink*, *Eat*, *Prepare lunch* and *Get snack* shows similar trend of sharing errors among each other.

Table 5(a) shows the confusion matrix of *Kyoto1* dataset. All the activities are correctly recognized. In *Eat* activity, 95% instances are correctly identified, while 4% of instances are erroneously identified as *Wash hands*, since it comes

Table 3: Comparison of existing approaches with proposed approach. Accuracy is in percentage(%) and the range of F1score is between $[0, 1]$. The highest values are highlighted in bold.

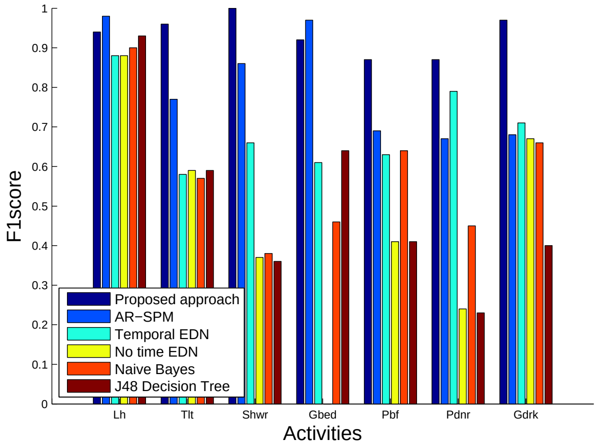
Evaluation measure	Cross validation	Dataset	Approach	
Accuracy	1 day out	Kyoto1	**Proposed approach**	**98.21**
			ADR-SPLDA(SPL=2) [4]	92.49
			ADR-SPLDA(SPL=3) [4]	79.44
		Kasteren-HA	**Proposed approach**	**95.19**
			ADR-SPLDA(SPL=2) [4]	80.67
			ADR-SPLDA(SPL=3) [4]	81.78
F1score	1 day out	Kyoto7	**Proposed approach**	**0.78**
			AR-SPM(C+CP) [18]	0.73
		Kasteren-HA	**Proposed approach**	**0.93**
			AR-SPM(C+LP) [18]	0.81
			HHMM-VS(AIC) [16]	0.70
			EFA-AR [37]	0.77
			Murphy rule [37]	0.68
			Dempster-Shafer rule [37]	0.54
			Temporal EDN [47]	0.70
			No time EDN [47]	0.45
		Kasteren-HB	**Proposed approach**	**0.73**
			AR-SPM(C+LP) [18]	0.52
			HHMM-VS(AIC) [16]	0.55
		Kasteren-HC	**Proposed approach**	**0.59**
			AR-SPM(C+LP) [18]	0.51
			HHMM-VS(Intuitive) [18]	0.50
	Ten-fold	Kasteren-HA	**Proposed approach**	**0.90**
			CL-AR [48]	0.87
			J48-DT [48]	0.79

next in sequence to *Eat*. Overall, the proposed approach achieves an accuracy of 95% or above in the recognition of all activities. Table 5(b) shows the confusion matrix of activities in *Kyoto7* dataset. The meal preparation activities are sharing their errors among each other. An example of this is *R1 prepare breakfast* activity with 41% instances correctly identified, while 14% are incorrectly recognized as both *R2 prepare breakfast* and *R2 prepare dinner* and 26% instances are erroneously identified as *R2 prepare lunch* activity. In *R2 prepare breakfast* activity, 55% of instances are correctly recognized, while it sends its 20% errors to *R2 prepare dinner* and 13% errors to *R2 prepare lunch* activity class. For the remaining, the proposed approach recognized the activities with high accuracy.

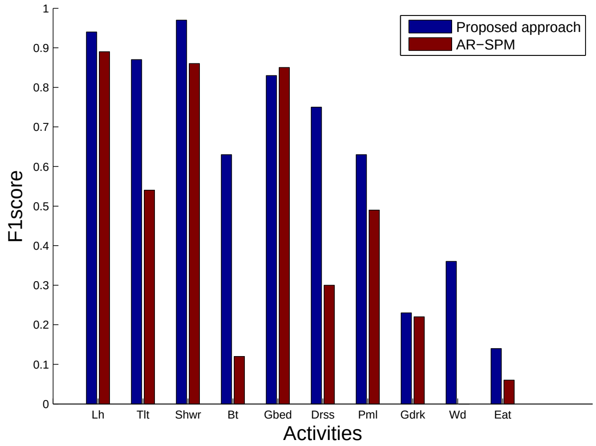
From the detailed analysis of the results of proposed approach in comparison with existing methods, it can be concluded that proposed approach proves to be more effective and reliable in correct classification of activities in case of limited amount of training data, variations in the activity patterns and in the frequency of execution of activities, compared to other approaches. The PM approach shows the least results in all the datasets, since in order to obtain the actual distribution, a large amount of data is required. However, most of the activities in Kasteren and CASAS datasets have fewer instances, while increasing the instances of minority classes through oversampling does not always capture all the intra-class variations leading to a decreasing performance trend.

5. Conclusions

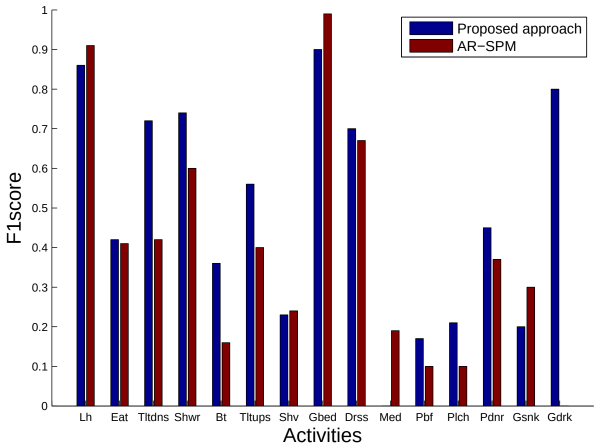
We proposed an activity recognition approach for smart homes that combines DM with PE to improve the reliability of classifications. DM approach is non-biased towards majority classes and also robust in learning activity classes with fewer instances and with less inter-class and high intra-class variations; however, DM can lead to over-fitting. PE is effective in providing better generalization, while it requires a large amount of training data. Both DM and PE in the individual capacity remained less effective. However, when DM is combined with PE, a significant improvement in the performance can be attained. Both DM and PE approaches are combined through SVM to minimize their limitations and to improve the recognition performance. The evaluation of the proposed approach using five publicly available smart home datasets demonstrates a better performance compared to existing approaches. Future work includes automated segmentation of data through trained detectors before classification.



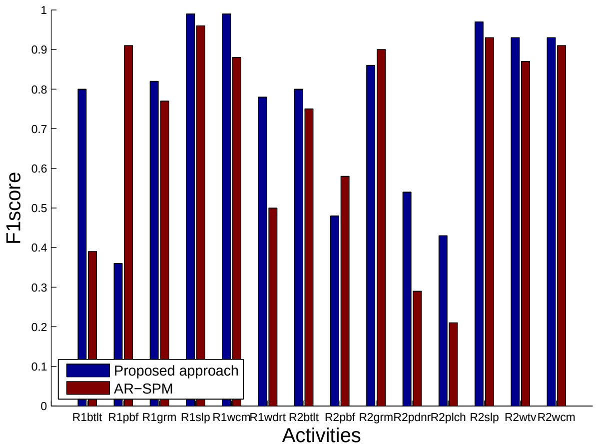
(a) Kasteren-HA dataset



(b) Kasteren-HB dataset



(c) Kasteren-HC dataset



(d) Kyoto7 dataset

Figure 3: Activity level performance comparison of proposed approach with existing methods through F1score using 'leave one day' out cross validation: (a) AR-SPM (C+LP) [18] Temporal EDN, No time EDN, NB and J48-DT [47] on Kasteren-HA (b) AR-SPM (C+LP) [18] on Kasteren-HB (c) AR-SPM (C+LP) [18] on Kasteren-HC (d) AR-SPM (C+CP) [18] on Kyoto7 datasets. Key (Kasteren): Lh - Leave House, Tlt - Use toilet, Shwr - Take Shower, Gbed - Go to bed, Pbf - Prepare breakfast, Pdnr - Prepare dinner, Gdrk - Get drink, Bt - Brush teeth, Drss - Dressing, Pml - Prepare Meal, Eat - Eat, Wd - Wash dishes, Tltdns - Use toilet downstairs, Tltups - Use toilet upstairs, Shv - Shave, Med Take medication. Key (Kyoto7): R1btlt - R1 bed to toilet, R1pbf - R1 prepare breakfast, R1grm - R1 groom, R1slp - R1 sleep, R1wcmp - R1 work at computer, R1wdrt - R1 work at dining room table, R2btlt - R2 bed to toilet, R2pbf - R2 prepare breakfast, R2grm - R2 groom, R2pdnr - R2 prepare dinner, R2plch - R2 prepare lunch, R2slp - R2 sleep, R2wtv - R2 watch tv, R2wcmp - R2 work at computer.

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Table 4: Confusion matrices of activities in Kasteren datasets using leave one day out cross validation, (a) Kasteren-HA (b) Kasteren-HB (c) Kasteren-HC. Rows represent the actual and columns represent the predicted activities. Key: Lh - Leave House, Tlt - Use toilet, Shwr - Take Shower, Gbed - Go to bed, Pbf - Prepare breakfast, Pdnr - Prepare dinner, Gdrk - Get drink, Bt - Brush teeth, Drss - Dressing, Pml - Prepare Meal, Eat - Eat, Wd - Wash dishes, Tltdns - Use toilet downstairs, Tltups - Use toilet upstairs, Shv - Shave, Med - Take medication.

(a) Kasteren-HA

Activities	Lh	Tlt	Shwr	Gbed	Pbf	Pdnr	Gdrk
Lh	97.10	0	0	2.90	0	0	0
Tlt	0	97.30	1.80	0.90	0	0	0
Shwr	0	0	100	0	0	0	0
Gbed	0	4.30	0	95.70	0	0	0
Pbf	0	0	0	0	90.00	10.00	0
Pdnr	0	0	0	0	10.00	90.00	0
Gdrk	5.30	0	0	0	0	0	94.70

(b) Kasteren-HB

Activities	Lh	Tlt	Shwr	Bt	Gbed	Drss	Pml	Gdrk	Wd	Eat
Lh	95.70	0	0	4.30	0	0	0	0	0	0
Tlt	0	81.00	3.80	3.80	0	3.80	3.80	0	3.80	0
Shwr	0	0	100.00	0	0	0	0	0	0	0
Bt	7.70	0	0	69.20	0	0	0	0	15.40	7.70
Gbed	0	0	0	0	84.60	7.70	0	0	7.70	0
Drss	7.70	7.70	0	15.40	0	69.20	0	0	0	0
Pml	0	6.70	0	0	0	0	53.30	26.70	0	13.30
Gdrk	0	0	0	0	0	0	14.30	28.60	0	57.10
Wd	0	0	0	33.30	0	0	0	0	50.00	16.70
Eat	0	0	0	12.50	0	25	12.50	25.00	12.50	12.50

(c) Kasteren-HC

Activities	Lh	Eat	Tltdns	Shwr	Bt	Tltups	Shv	Gbed	Drss	Med	Pbf	Plch	Pdnr	Gsnk	Gdrk
Lh	84.80	6.50	6.50	0	0	0	0	0	2.20	0	0	0	0	0	0
Eat	7.70	57.70	3.90	0	0	0	0	0	0	0	7.70	0	11.50	11.50	0
Tltdns	8.00	4.00	76.00	0	0	0	0	4.00	0	0	4.00	0	0	0	4.00
Shwr	0	0	0	78.60	7.10	14.30	0	0	0	0	0	0	0	0	0
Bt	0	8.00	0	8.00	40.00	12.00	12.00	8.00	0	0	0	4.00	4.00	0	4.00
TltUps	0	11.10	0	3.70	3.70	66.70	3.70	0	3.70	3.70	3.70	0	0	0	0
Shv	0	0	0	14.30	57.10	0	28.60	0	0	0	0	0	0	0	0
Gbed	0	0	0	0	0	0	0	94.70	0	0	0	0	5.30	0	0
Drss	0	4.80	4.80	0	4.80	9.40	0	0	71.40	0	4.80	0	0	0	0
Med	0	0	0	0	66.70	33.30	0	0	0	0	0	0	0	0	0
Pbf	0	30.00	0	0	0	10.00	0	0	10.00	0	20.00	10.00	20.00	0	0
Plch	0	0	0	0	12.50	0	0	0	0	0	25.00	25.00	12.50	12.50	12.50
Pdnr	0	9.00	0	0	0	0	0	0	0	0	9.10	36.40	45.50	0	0
Gsnk	0	28.50	0	0	0	0	0	0	0	0	0	14.30	14.30	14.30	28.60
Gdrk	0	0	12.50	0	12.50	0	0	0	0	0	0	0	0	0	75.00

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Table 5: Confusion matrices of activities in CASAS datasets using leave one day out cross validation, (a) Kyoto1 (b) Kyoto7. Rows represent the actual and columns represent the predicted activities. Key: R1btlt - R1 bed to toilet, R1pbf - R1 prepare breakfast, R1grm - R1 groom, R1slp - R1 sleep, R1wcmp - R1 work at computer, R1wdrt - R1 work at dining room table, R2btlt - R2 bed to toilet, R2pbf - R2 prepare breakfast, R2grm - R2 groom, R2pdnr - R2 prepare dinner, R2plch - R2 prepare lunch, R2slp - R2 sleep, R2wtv - R2 watch tv, R2wcmp - R2 work at computer.

(a) kyoto1

Activities	Clean	Cook	Eat	Phone Call	Wash Hands
Clean	95.80	0	4.20	0	0
Cook	0	100	0	0	0
Eat	0	0	95.80	0	4.20
Phone Call	0	0	0	100	0
Wash Hands	0	4.20	0	0	95.80

(b) Kyoto7

Activities	R1btlt	R1pbf	R1grm	R1slp	R1wcmp	R1wdrt	R2btlt	R2pbf	R2grm	R2pdnr	R2plch	R2slp	R2wtv	R2wcmp
R1btlt	82.40	2.90	11.80	0	0	0	2.90	0	0	0	0	0	0	0
R1pbf	0	41.20	0	0	0	0	2.90	14.70	0	14.70	26.50	0	0	0
R1grm	11.10	0	84.50	0	0	0	2.20	0	2.20	0	0	0	0	0
R1slp	0	0	0	100.00	0	0	0	0	0	0	0	0	0	0
R1wcmp	0	1.70	0	0	98.30	0	0	0	0	0	0	0	0	0
R1wdrt	0	0	0	0	0	77.80	0	0	0	0	0	0	11.1	11.1
R2btlt	2.60	0	0	0	0	0	87.20	0	7.70	0	0	0	0	2.50
R2pbf	0	10.30	0	0	0	0	0	55.20	0	20.70	13.80	0	0	0
R2grm	2.50	0	2.50	0	0	0	7.50	2.50	82.50	0	2.50	0	0	0
R2pdnr	0	16.70	0	0	0	0	0	13.90	0	58.30	11.10	0	0	0
R2plch	0	27.60	0	0	0	0	0	6.90	0	17.20	48.30	0	0	0
R2slp	0	0	0	2.90	0	0	0	0	0	0	0	97.10	0	0
R2wtv	0	0	0	0	0	6.50	0	0	0	0	0	0	93.50	0
R2wcmp	0	0	0	0	2.20	0	2.20	0	0	0	0	0	0	95.60

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