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Activity Recognition in Smart Homes using Clustering based Classification

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***Abstract*—Activity recognition in smart homes plays an important role in healthcare by maintaining the well being of elderly and patients through remote monitoring and assisted technologies. In this paper, we propose a two level classification approach for activity recognition by utilizing the information obtained from the sensors deployed in a smart home. In order to separate the similar activities from the non similar activities, we group the homogeneous activities using the Lloyd's clustering algorithm. For the classification of non-separated activities within each cluster, we apply a computationally less expensive learning algorithm Evidence Theoretic K-Nearest Neighbor, which performs better in uncertain conditions and noisy data. The approach enables us to achieve improved recognition accuracy particularly for overlapping activities. A comparison of the proposed approach with the existing activity recognition approaches is presented on two publicly available smart home datasets. The proposed approach demonstrates better recognition rate compared to the existing methods.**

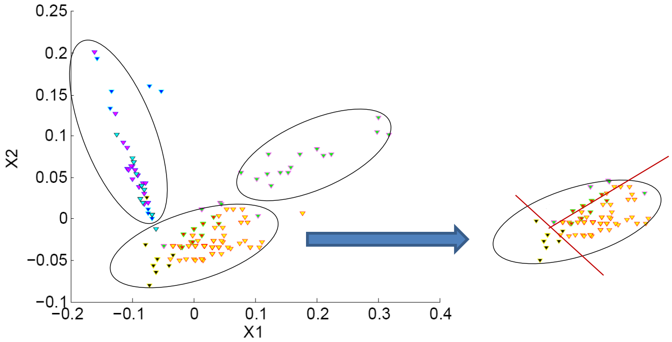


Fig. 1. An example of Activity Recognition by Clustering based Classification (AR-CbC). The axes X_1 and X_2 show the first two principal components of features. Similar activity instances are grouped into one cluster. A learning method is applied for classification within each cluster that separates the overlapping activities.

I. Introduction

Advances in pervasive computing such as development of affordable and unobtrusive wireless sensors along with efficient data processing techniques have resulted in the development of unprecedented, cost effective and technologically driven healthcare solutions [1], [2]. One such example is assisted living in smart homes with the sensors deployed to gather information about the user and its context. The obtained information is exploited to monitor the functional ability of the resident [3]. In order to live independently, a smart home resident should be able to complete the basic activities such as grooming, eating, taking medication or meal preparation. Automated recognition of these activities is an important step towards independent living [3]. Activity recognition in smart homes has a number of prospective applications such as providing a safe environment for people with physical or cognitive impairments by timely indication of changes in their daily routine and by ensuring immediate medical aid when required [1].

The obtained sensor data of a user and its interactions within the environment is segmented according to the activity descriptions known as activity instances. The detected activity instances are used to train an activity recognition model. The trained models are then used to classify and assign a label to a new activity instance. Activities can be recognized by using techniques such as Hidden Markov Model (HMM) [1], Ontology [2], Conditional Random Fields (CRF) [4], Naive Bayes (NB) classifier [5], Decision Trees (DT) [6], Probabilistic Neural Networks (PNN) [7], Support Vector Machines (SVM) [8] and Nearest Neighbors classifier [9]. Mis-classifications in the activity recognition may occur due to unreliable sensor information. Also activities performed at the same location and involving similar objects share common features and thus can be overlapping [10], such as kitchen activities: preparing breakfast, lunch and dinner. In addition, activities can be performed depending on a user's preferences or lifestyle, which may not follow predefined order of sequences or steps. It is therefore important to address both inter and intra-class activity variations [1], since next level of decisions such as long term analysis [7] may depend on the outcome of these recognition systems.

In this paper, we propose an Activity Recognition approach by Clustering based Classification (AR-CbC). Figure 1 shows an example of clustering the similar activities and the classification within each cluster. The proposed approach is effective in improving the recognition accuracy by learning the fine grained differences in the similar activities. In the proposed approach, the features are extracted from pre-segmented activity instances. We identify the most significant features by applying Principle Component Analysis (PCA), which reduces the feature dimensions by removing the redundant feature components. Activity instances are then clustered using Lloyd's clustering algorithm. Finally, in order to separate activity instances of different classes grouped in one cluster, we apply the learning method Evidence Theoretic K-Nearest Neighbors (ET-KNN) that combines KNN with the Dampster Shafer Theory (DST) of evidence. The approach is evaluated using two publicly available smart home datasets: Aruba and Kasteren. The results show a better performance compared to the existing approaches on the defined evaluation measures.

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

II. RELATED WORK

Activity recognition approaches developed in the past differ from each other in the sensing modalities, applied techniques and the operating environments. Some approaches are based on wearable sensors (accelerometers, gyroscope) and are developed to recognize the physical activities such as sitting, standing, walking or falling [6], [9]. In contrast, the activity recognition approaches based on ambient or environment interactive sensors (reed switches, motion, pressure and analog sensors) examine the more complex activities such as meal preparation, eating, grooming and sleeping [1], [2], [8], [11]. NB classifier is used to develop an activity recognition approach by exploiting the information of user interaction with multiple objects in a home obtained through switch state sensors [5]. A two layered hierarchical organization approach based on Switching Hidden Semi Markov Model (S-HSMM) and discrete coxian distribution is developed to recognize the daily activities and to identify the anomalies [12]. One layer represents the events and their duration, while the other layer corresponds to the higher level activities. An unsupervised approach mines the discontinuous frequent patterns and groups the similar patterns into clusters, HMM is then applied to recognize the activities [1]. HMM is compared with CRF to recognize the daily activities [4]. HMM requires a large amount of training data and unlike CRF, HMM may not be able to capture long range dependencies of sensor observations due to its strong independence assumption.

A knowledge driven activity recognition approach uses Ontological modeling, domain knowledge and semantic reasoning [2]. The information of activated sensors is combined to form an activity description, which is fed into the reasoning engine to infer the activity class against the activity models and profiles. PCA is used to extract significant features and a multi-class method one-versus-one SVM is applied for the classification of activities [8]. Based on self adaptive neural network, growing self organizing maps is applied to recognize the activities in a smart home [13]. Next, PNN and K-means clustering are applied to monitor the daily routine of smart home occupants and to identify anomalies [7]. An active learning approach for recognition in the presence of overlapping activities (AALO) first performs location based frequent item set mining to find the activity patterns and then DBSCAN clustering is applied to form the activity clusters [10]. In [11], the temporal information of domain knowledge is incorporated in the DST of evidence, where the start time and duration of the activity is used in the Evidence Decision Network (EDN) for the recognition. However, incorporating the temporal information such as activity start time, duration or definition of absolute intervals for the execution of an activity makes the approach restricted to a particular user's way of working and thus may not represent a more general scenario. Also variations in the duration of activities performed makes temporal information less relevant.

TABLE I. COMPARATIVE SUMMARY OF STATE-OF-THE-ART METHODS FOR ACTIVITY RECOGNITION. ALL FEATURES - MEAN NO EXPLICIT FEATURE SELECTION. KEY: PCA - PRINCIPAL COMPONENT ANALYSIS, HMM - HIDDEN MARKOV MODEL, CRF - CONDITIONAL RANDOM FIELDS, PNN - PROBABILISTIC NEURAL NETWORKS, SVM - SUPPORT VECTOR MACHINE, ET-KNN - EVIDENCE-THEORETIC K-NEAREST NEIGHBOR.

		[3]	[5]	[2]	[4]	[6]	[8]	[10]	[1]	[14]	[11]	[7]	AR-CbC
Feature Selection	All Features	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	
	PCA						✓						✓
Association Approaches	Naive Bayes	✓	✓										
	Ontology			✓									
	Decision Tree					✓							
	K-means Clust								✓				✓
	DBScan Clust							✓					
	HMM	✓			✓				✓				
	CRF	✓			✓								
	Itemset mining							✓					
	Web mining									✓			
	DST										✓		
	PNN											✓	
	SVM						✓						
	ET-KNN												✓

To conclude this section, Table I summarizes and compares the activity recognition approaches in the state of the art.

III. ACTIVITY RECOGNITION

Let $\mathbf{A} = \{A_1, ..., A_k, ..., A_K\}$ be a set of K activity classes and $\mathbf{I}_k = \{I_{1k}, ..., I_{jk}, ..., I_{Jk}\}$ be a set of J activity instances of A_k in the training data observed by R binary sensors installed at different locations in a smart home. We propose a two level activity recognition approach in which we perform the activity clustering from the extracted features and then the assignment is performed within each cluster. Figure 2 shows the block diagram of the proposed approach.

Each activity instance I_{jk} is represented by a set $\mathbf{F}_{jk} = \left\{f_{jk}^r\right\}_{r=1}^{R}$ of R features. Each feature f_{jk}^r represents the number of times a sensor is activated during the activity. In the training set containing $N = J \times K$ pre-segmented activity instances I_{jk}, each f_{jk}^r in the feature set is normalized such that $0 \leq \hat{f}_{jk}^r \leq 1$ given as

$$\hat{\mathbf{F}}_{jk} = \left\{\hat{f}_{jk}^r\right\}_{r=1}^{R} = \left\{\frac{f_{jk}^r - \min_{j,k} f_{jk}^r}{\max_{j,k} f_{jk}^r - \min_{j,k} f_{jk}^r}\right\}. \quad (1)$$

In order to select the most significant features, we apply PCA and select the principal components representing 99% of the data. PCA results in finding the discriminating features between different activity classes. In the next step, activities are grouped based on similarities between the feature sets. We apply the Lloyd's k-mean clustering algorithm [15] for the grouping. The algorithm aims at minimizing the error objective

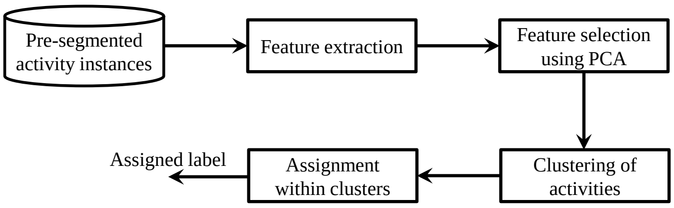


Fig. 2. Block diagram of the proposed activity recognition approach.

function

$$\Psi = \sum_{\kappa=1}^{\kappa} \sum_{i=1}^{N} ||I_i^{(\kappa)} - C_\kappa||^2, \quad (2)$$

where I_i is i^{th} activity instance without the class information and C_κ is the κ^{th} cluster center. We have κ clusters, where κ is initially set to the number of classes, however after the clustering, empty clusters are removed. Objective function measures the distance of the activity instances from their respective cluster centers.

Once the clusters of the overlapping activity classes are obtained, we apply ET-KNN [16] within each cluster to recognize the activities. Since K-Nearest Neighbor (KNN) works by classifying the activity instances based on their nearest training samples in the feature space, a new activity instance X in the feature space is assigned to the Activity class A_k, if it has the minimum distance D(.) from A_k

$$D_{min} = min\left\{D(X, P_l)\right\}, l \in \hat{K}, \quad (3)$$

where P_l are the reference patterns of each activity class A_k and $\hat{K}$ are the total number of P_l in a cluster. Euclidean distance is usually calculated.

ET-KNN [17] extends KNN to address the issue of uncertainty in data. ET-KNN is based on DST of evidence [18], where each neighboring pattern is considered as an evidence supporting the hypothesis of the class membership. Consider a classification problem, where a pattern (new activity instance) X has to be assigned to one of the $\hat{K}$ activity classes in a cluster. We compare X with $\hat{K}$ reference patterns: $P_1, P_2, ..., P_{\hat{K}}$. Each pattern P_l is supposed to have a degree of membership μ_k^l to each class A_k with $\sum_{l=1}^{\hat{K}} \mu_k^l = 1$. From the degree of membership we perform the Basic Belief Assignment (BBA) for each pattern in the cluster and aggregate using Dempster's rule of combination [18]. The parameters are optimized by the error minimizing function as in [16]. The label of the activity class with the maximum belief of membership is assigned to X.

IV. Evaluation and Discussion

The proposed approach (AR-CbC) is evaluated on two smart home datasets: Aruba and Kasteren. The performance measures for the comparisons are Precision, Recall, F1score and Accuracy, using True Positives (TP), False Positives (FP) and False Negatives (FN). Results are compared with the learning classifiers ET-KNN, KNN and PNN in [7], [9], [17]. Activity based comparisons of AR-CbC with two existing approaches [11] and [10] are performed using Kasteren dataset.

TABLE II. Summary of datasets used in the evaluation.

Datasets	Activity classes	Activity instances	Name of activities
Aruba	11	6477	Bed to Toilet, Eating, Enter Home, House Keeping, Leave Home, Meal Preparation, Relax, Resperate, Sleeping, Wash Dishes and Work.
$Kasteren_7$	7	245	Breakfast, Dinner, Drink, Leave Home, Showering, Sleeping and Toileting.
$Kasteren_{10}$	10	272	Breakfast, Dinner, Drink, Dish Washing, Leave Home, Toileting, Snack, Showering, Sleeping and Washing Machine.

A. Evaluation measures

Precision indicates the presence of correctly recognized instances in all the recognized instances of an activity class as

$$Precision = \frac{TP}{TP + FP} \times 100. \quad (4)$$

Recall is the percentage of correctly labeled instances from the total instances of that class

$$Recall = \frac{TP}{TP + FN} \times 100. \quad (5)$$

Recall is the ability of a classifier to return most of the correct labels out of the total correct labels. *F1score* combines the precision and recall and returns a single measurement that is the weighted average of precision and recall of the system given as

$$F1score = \frac{2 \times Precision \times Recall}{Precision + Recall}. \quad (6)$$

F1score returns a value in the range $[0\ ,\ 1]$. A value closer or equal to 1 shows the best performance, while a value of 0 indicates the worst performance. Finally, the recognition *Accuracy* of the system for all the activity instances is measured as

$$Accuracy = \frac{TP}{N}, \quad (7)$$

where N is the total number of instances.

B. Datasets

Table II shows the summary of publicly available smart home datasets: Aruba [19] and Kasteren [4] used in the evaluation. The information of the user and its interaction with the multiple objects within the environment is gathered using the binary sensors: contact switch sensors, motion sensors, absent/present status of item and door open/close status of cabinet sensors. Kasteren dataset has been used as sets of 7 and 10 activities in the state of the art. For the evaluation and comparisons we use both $Kasteren_7$ and $Kasteren_{10}$ datasets. In Aruba dataset 11 types of activities are performed. Total number of instances in datasets $Kasteren_7$ (245) and $Kasteren_{10}$ (272) are far less than Aruba (6477) dataset. Some of the activities are performed in the same location and share same sensors, such as 'Breakfast', 'Dinner' and 'Drink' in Kasteren dataset, while 'Meal preparation' and 'Wash Dishes' in Aruba dataset, which may result in less discriminative information and highlight less inter-class variations.

We apply three fold cross validation on the Aruba, $Kasteren_7$ and $Kasteren_{10}$ datasets. In order to compare

TABLE III. COMPARISON OF AR-CBC WITH ET-KNN [17], KNN [9] AND PNN [7] FOR ARUBA, $Kasteren_7$ AND $Kasteren_{10}$ SMART HOME DATASETS.

Datasets	Folds	Approach	Precision (%)	Recall (%)	F1score $[0, 1]$	Accuracy (%)
Aruba	Three folds	**AR-CbC**	**79.65**	**76.46**	**0.75**	**91.40**
		ET-KNN	74.27	75.42	0.71	90.17
		KNN	72.39	73.11	0.70	90.07
		PNN	76.48	68.98	0.69	88.62
$Kasteren_7$	Three fold	**AR-CbC**	**91.76**	**90.48**	**0.90**	**94.71**
		ET-KNN	89.89	87.77	0.87	92.27
		KNN	89.95	82.82	0.84	89.80
		PNN	90.28	84.52	0.85	91.43
	One day out	**AR-CbC**	**96.26**	**95.07**	**0.95**	**96.33**
		ET-KNN	93.41	89.66	0.90	93.06
		KNN	88.25	83.66	0.84	90.20
		PNN	86.55	84.80	0.84	92.24
$Kasteren_{10}$	Three fold	**AR-CbC**	90.29	**89.88**	**0.89**	**93.36**
		ET-KNN	**90.70**	84.31	0.85	90.04
		KNN	90.50	83.30	0.84	89.31
		PNN	87.92	81.35	0.82	90.03
	One day out	**AR-CbC**	**88.80**	**90.07**	**0.88**	**93.00**
		ET-KNN	83.62	83.32	0.82	90.77
		KNN	85.98	83.18	0.82	89.31
		PNN	81.33	78.62	0.78	89.29

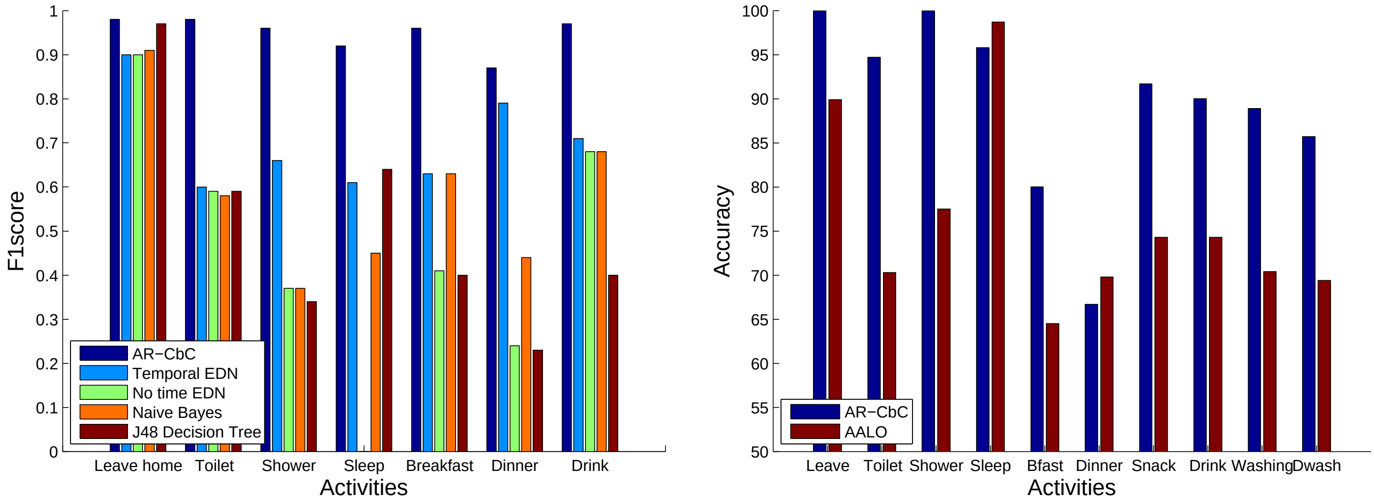
with the existing approaches, leave one day out cross validation is applied on $Kasteren_7$ and $Kasteren_{10}$ datasets. Experiments are carried out using Matlab version 7.11 on a 3.3 Ghz dual core desktop system with 4 GB of RAM.

C. Analysis and discussion

Table III shows the comparison of AR-CbC with ET-KNN, KNN and PNN classification approaches for Aruba, $Kasteren_7$ and $Kasteren_{10}$ datasets. AR-CbC shows better performance for all evaluation measures. In Aruba, the higher precision and recall rates of 79.65% and 76.46% by AR-CbC shows the effectiveness of proposed approach in the correct recognition of the activity instances. F1scores of AR-CbC, ET-KNN, KNN and PNN are 0.75, 0.71, 0.70, and 0.69. The high value of F1score confirms the improved performance in both precision and recall compared to other classifiers. Finally, the accuracy of AR-CbC is 91.40%, that is 1.23%, 1.33% and 2.78% higher than that of ET-KNN, KNN and PNN respectively. In $Kasteren_7$ dataset, we obtain the results for both three fold and leave one day out cross validation. AR-CbC shows an overall better performance than ET-KNN, KNN and PNN classification approaches. In the results of leave one day out cross validation, AR-CbC achieved the precision and recall values of 96.26% and 95.07%, which are respectively 2.85% and 5.41% higher than ET-KNN, 8.01% and 11.41% higher than KNN, while 9.71% and 10.27% higher than PNN. The performance of KNN and PNN classification approaches remain comparable to each other. The high F1score of AR-CbC indicates its better performance in the correct labeling of activity instances. Similarly, for three fold cross validation results of $Kasteren_7$ dataset, AR-CbC outperformed the ET-KNN, KNN and PNN classifiers in the accurate identification of the activity instances. For $Kasteren_{10}$ dataset, in the case of three fold cross validation, AR-CbC obtained a high F1score (0.89) and accuracy (93.36%), which shows its effectiveness in the correct classification of activity instances to one of the predefined activity classes. For leave one day out cross validation, F1score of AR-CbC is 0.88. The accuracy of AR-CbC is 93%, which is 2.23%, 3.69% and 3.71% higher than ET-KNN, KNN and PNN approaches. The above results show that AR-CbC obtained better performance on both three fold and leave one day cross validation in comparison to the ET-KNN, KNN and PNN approaches.

Figure 3(a) shows the comparison of AR-CbC with [11] using $Kasteren_7$ dataset by applying leave one day out cross validation. The evaluation measure used is F1score. AR-CbC shows higher F1score on all the activities in comparison to Evidence Decision Network (EDN), No time EDN, Naive Bayes (NB) and J48 Decision Tree (DT) with an overall accuracy of 96%. In Fig. 3(b) AR-CbC is compared with AALO [10] using $Kasteren_{10}$ dataset and the evaluation measure accuracy. It can be observed that AR-CbC achieved a higher accuracy in the activities of 'Leave Home', 'Toilet', 'Shower', 'Breakfast', 'Snack', 'Drink', 'Washing machine' and 'Dish Washing' compared to AALO. The slightly less accuracy is observed in the 'Sleep' and 'Dinner' activities. AR-CbC obtains an overall improved performance than the existing approaches and is more effective in the accurate recognition of both separated and overlapping activities. We further analyze the performance of AR-CbC using the confusion matrix of the performed activities in Aruba and $Kasteren_7$ datasets.

Table IV shows the confusion matrix of activities in Aruba dataset. It can be observed that almost all the activities are recognized with high accuracy. Two activities: 'Leave Home' and 'Wash Dishes' are confused. The 86% of instances of



(a) F1score comparison using $Kasteren_7$ dataset

(b) Accuracy comparison using $Kasteren_{10}$ dataset

Fig. 3. Using leave one day out cross validation, AR-CbC is compared with (a) Temporal EDN [11], No time EDN [11], Naive Bayes and J48 Decision Tree, and (b) Active learning recognition approach in presence of overlapping activities (AALO) [10].

TABLE IV. CONFUSION MATRIX OF AR-CBC ON ARUBA DATASET. ROWS REPRESENT THE ACTUAL ACTIVITIES AND COLUMNS REPRESENT THE PREDICTED ACTIVITIES.

Activities	Toilet	Eat	Enter	H-keep	Leave	Mealprep	Relax	Resperate	Sleep	W-dishes	Work
Toilet	99.40	0	0	0	0	0	0.60	0	0	0	0
Eat	0	94.20	0	0.40	0	2.30	3.10	0	0	0	0
Enter	0	0	95.80	0	3.5	0.70	0	0	0	0	0
H-keep	0	0	0	90.90	0	3.00	6.10	0	0	0	0
Leave	0	0	86.80	0	11.6	1.20	0	0.20	0	0	0
Meal prep.	0	0	0	0	0	96.80	0.60	0	0	2.30	0
Relax	0	0.20	0	0.20	0	1.30	97.60	0	0.30	0	0.10
Resperate	0	0.40	0	0	0	0	0	66.70	0	0	33.30
Sleep	0	0.30	0	0.20	0	0	1.5	0	98.30	0	0
W-dishes	0	0	0	0	0	90.80	0	0	0	9.20	0
Work	0	0	0.60	0	0	0.60	1.80	0.60	0	0	96.50

TABLE V. CONFUSION MATRIX OF AR-CBC ON $Kasteren_7$ DATASET FOR ALL ACTIVITIES. THE ROWS REPRESENT THE ACTUAL ACTIVITIES AND COLUMNS REPRESENT THE PREDICTED ACTIVITIES.

(a) Three fold cross validation

Activities	Leave	Toilet	Shower	Sleep	Breakfast	Dinner	Drink
Leave	97.10	0	0	2.90	0	0	0
Toilet	0	97.40	2.60	0	0	0	0
Shower	0	0	100.00	0	0	0	0
Sleep	0	8.30	0	91.70	0	0	0
Breakfast	0	0	0	0	80.00	20.00	0
Dinner	0	0	0	0	30.00	70.00	0
Drink	0	0	0	5.00	10.00	0	85.00

(b) Leave one day out cross validation

Activities	Leave	Toilet	Shower	Sleep	Breakfast	Dinner	Drink
Leave	97.10	0	0	2.90	0	0	0
Toilet	0	97.40	1.80	0.90	0	0	0
Shower	0	0	100.00	0	0	0	0
Sleep	0	4.20	0	95.80	0	0	0
Breakfast	0	0	0	0	100.00	0	0
Dinner	0	0	0	0	20.00	80.00	0
Drink	0	0	0	5.00	0	0	95.00

’Leave Home’ are identified as ’Enter Home’ activity due to the reason that the same exit door is used in both activities resulting in the activation of same sensor in both cases. In ’Wash Dishes’ 90% of activity instances are recognized as ’Meal preparation’, which could be due to the reason that ’Wash Dishes’ can be a sub-activity in ’Meal preparation’. The ’Resperate’ activity is recognized with 66% accuracy, while its remaining instances are identified as ’Work’ activity. The ’Resperate’ activity involves operating of a device to lower the blood pressure and therefore 33% of ’Resperate’ activity instances are identified as ’Work’ activity.

Table V presents the confusion matrices of activities in $Kasteren_7$ dataset using three fold and leave one day out cross validation. It can be noted from the results that almost all activities are identified with high recognition accuracy. The meal preparation activities of ’Breakfast’, ’Dinner’ and ’Drink’ share their errors with each other (Table V(a)). ’Breakfast’ activity sends 20% of errors to the ’Dinner’ activity, while the ’Dinner’ transfers 30% of errors to the ’Breakfast’ activity. Similarly, 10% of instances of ’Drink’ activity are erroneously identified as ’Breakfast’. The sharing of errors between each other in the meal preparation activities is due to the same location and use of similar features.

From the detailed analysis of the results of proposed approach in comparison with the existing methods, it can be concluded that AR-CbC proves to be more effective and reliable in the recognition of activity instances.

V. Conclusion

We proposed a robust activity recognition approach that identifies the performed activities of daily livings. The approach combines the classification with the clustering to improve the recognition accuracy in the case of similar activities with less inter class variations. The approach shows a recognition accuracy of up to 91%, 96% and 93%, respectively in Aruba and $Kasteren_7$ and $Kasteren_{10}$ datasets. In the future, we aim at exploiting the additional information like semantic reasoning and temporal information for activity inference.

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