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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.

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 [1–3]. 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 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,

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they 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 combined using the learning method multi-class SVM (one-versus-one), which is computationally efficient in the case of multiple classes, and a better choice for imbalance number of activity instances. 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: Section 2 discusses the related work on activity recognition. In Section 3, we discuss the proposed activity recognition approach. The datasets and experimental analysis are presented in Section 4. Finally, Section 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 integrating pattern mining with HSMM for recognition of activities (AR-SPM) [18]. In an unsupervised approach, the discontinuous frequent patterns are extracted and similar patterns are grouped into clusters, while the boosted HMM is applied to learn from those 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]. An inter-class distance based approach is applied to select the best features, while three learning approaches, ANN, HMM and NB, are used for recognition [20]. Among these, ANN performs better. 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 [22]. These patterns are then matched with the observed sequences of events for activity recognition. 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 also performed under different challenges [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, 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 a 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 a behavior analysis approach, 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 [34]. Variations in the activity pattern are learned to get the complete model for activities. Recognition approaches based on belief theory are also applied, such as Evidence Decision Network (EDN) approach [35], where the