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Activity recognition in smart homes with self verification of assignments

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ABSTRACT

Activity recognition in smart homes provides valuable benefits in the field of health and elderly care by remote monitoring of patients. In health care, capabilities of both performing the correct recognition and reducing the wrong assignments are of high importance. The novelty of the proposed activity recognition approach lies in being able to assign a category to the incoming activity, while measuring the confidence score of the assigned category that reduces the false positives in the assignments. Multiple sensors deployed at different locations of a smart home are used for activity observations. For multi-class activity classification, we propose a binary solution using support vector machines, which simplifies the problem to correct/incorrect assignments. We obtain the confidence score of each assignment by estimating the activity distribution within each class such that the assignments with low confidence are separated for further investigation by a human operator. The proposed approach is evaluated using a comprehensive performance evaluation metrics. Experimental results obtained from nine publicly available smart home datasets demonstrate a better performance of the proposed approach compared to the state of the art.

1. Introduction

The development of effective, long term and technologically driven solutions in health care improves the living standards of the elderly and people with chronic physical (low mobility level) and cognitive (Alzheimers disease) impairments [1–3]. In the recent years, different strategies such as telemedicine or telemonitoring have been applied for remote observations [4]. With the further advancements in technology, the concept of a smart home equipped with sensors and actuators that enables people to live independently at home under a continuous monitoring, has got more attention [4,5]. Activity recognition is a fundamental task in smart homes through which the performed activities such as hand washing, meal preparation, eating, sleeping, appropriate usage of medicines and prescribed physical exercises, can be identified and tracked. A long term analysis of the performed activities can provide important information to doctors about their patient's medical condition that is helpful in the timely prevention of many associated risks.

Low level observations of user and the context information, such as location and human-object interactions, are gathered through multiple non-intrusive sensors within the environment. The obtained sensor data is partitioned into multiple segments in order to map them to the activity descriptions known as activity segmentation, where a segment is a consecutive sequence of time instants during which an activity is performed [6]. Activity segmentation is performed using different techniques, sliding windows [7], relative weighting of objects in adjacent activities [8] or pattern mining [9], just to name a few. Segmented activity instances are classified in activity classes using different learning models such as Hidden Markov Model (HMM) [10], Conditional Random Fields (CRF) [11], Naive Bayes (NB) [12], Support Vector Machine (SVM) [13], Artificial Neural Network (ANN) [14,15], and Decision Tree (DT) [16]. In activity classification, a false assignment could occur due to the unreliable nature of sensor data [17], incorrect execution of an activity [18], similar activities due to overlapping in features [19] or inability of a learning algorithm to assign the correct label [20]. In health care systems, the reliability of activity recognition models is extremely important, therefore along with the correct recognition of activities, a model should also be capable of detecting and avoiding false assignments [20]. Most of the activity recognition approaches while focusing on the segmentation and recognition may ignore false assignments

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[10,13,21]. Additionally the existing approaches that exploit the temporal pattern for recognition assume that the activities follow a certain predefined sequence of events, however a fixed sequence may not always be the case, since a single activity can be performed in different ways by different users [22]. The variation in activity instances may also be observed even in the case of single user repeating the activity a number of times. Therefore, it is also important to consider intra-class and inter-subject differences along with inter-class differences.

In this paper, we propose an intelligent approach namely, *Activity Recognition in Smart Homes with the capability of Self Verification* (ARSH-SV) to recognize the pre-segmented activities of daily life. The proposed approach is able to measure the reliability of the assigned label using a confidence score thus highlighting the activities recognized with less confidence. ARSH-SV exploits the properties of both learning and statistical methods. The activity recognition is performed by learning the differences between the correct and incorrect assignments. Since the correct assignments are far less than the incorrect assignments and each activity class has varying number of activity instances, we apply the learning method SVM. SVM has a better generalization ability for imbalance problems due to considering only the support vectors and is also computationally efficient. We find the confidence score of the assigned label by finding the underlying distribution of the data through sub-clustering within each activity class. In the case of clusters with limited number of instances, the resampling method bootstrap is applied to improve the data representation in the training. The validation of the approach using nine smart homes datasets and through a comprehensive performance metrics shows that compared to the existing approaches, ARSH-SV improves the activity recognition by successfully reducing the false assignments.

The rest of the paper is organized as follows: Section 2 discusses the related work on activity recognition. In Section 3, the proposed approach is presented. Next, we discuss the datasets used, the evaluation criteria and the analysis of results in Section 4. Finally, Section 5 draws conclusions.

2. Related work

Activities of daily life can be categorized into (i) physical activities such as sitting, standing, walking, running or falling, and (ii) general activities such as cooking, eating, sleeping, cleaning or grooming. The sensing technology to capture human activity observations is based on either wearable sensors mainly used in physical activities, such as accelerometer and gyroscope [16], or environment interactive sensors used in general activities monitoring, such as light, temperature, motion, pressure and binary contact switch sensors [11]. While the proposed approach is focused more on the general activities category, for a review of the state of the art we also briefly discuss the existing approaches applied for physical activities.

In physical activities, the information through wearable sensors such as movement patterns extracted from acceleration data [1] obtained from accelerometers are exploited. DT is applied to classify twenty physical activities [16]. An ANN based approach [14] using acceleration features first separates the static (standing, sitting) and dynamic (walking, running) activities and then classifies the activities in each class, where Principal Component Analysis (PCA) is used to obtain the well performing features. ANN is also compared with auto generated and domain knowledge based DTs for activity classification, where auto generated DT shows better accuracy while ANN suffers from over fitting [23]. DT is then combined with ANN in a hybrid classifier model for activity recognition, which merges the prior knowledge of activities with the non-linear classification properties of ANN [24]. Probabilistic Neural Network (PNN) and Fuzzy Clustering based incremental learning method can also be applied for activity recognition [25]. The three classifiers: DT, ANN and SVM, are learned for activity recognition [26], where SVM shows a stable performance compared to others. Finally, an interesting approach on eye movement based activity recognition applies SVM in order to classify six static activities such as browsing a web and reading a printed paper [27].

General activities are recognized by gathering the location information and the user interactions with multiple objects within the environment [10,28–30]. A dense sensing platform is used, such as contact switch sensors to monitor the opening and closing of doors, motion sensors to detect the user presence at a particular location, or pressure sensors to indicate the usage of objects, bed or sofa [12,31,32]. Switch sensors deployed in multiple objects in a home such as doors, windows, cupboards and refrigerator, can be used in the NB classifier based recognition approaches [12,30], where NB identifies the activity corresponding to the sensor values with the highest probability. PNN classifier [15,33] derived from Bayesian and Fisher discriminant analysis (FDA) can be applied to estimate the likelihood of a sample being part of a learned activity class. A cluster based classification approach [34] groups the similar activities into clusters, while learning is performed within each cluster. The Evidence Theoretic KNN (ET-KNN) is applied to recognize the activities [34,35], where neighborhood of each pattern to be classified is considered as an evidence supporting certain hypothesis associated with the class membership of that pattern. The class with the maximum supporting evidence is assigned to the pattern, while the parameters are optimized by the error minimizing function in [36]. In order to exploit the semantic information of domain knowledge, sensor data and activities, context lattices are applied for activity recognition (CL-AR) [37]. HMM is applied and compared with CRF [11] and in order to get a more generalized activity recognition approach, NB, HMM and CRF are compared for activities within a dataset and by combining the common activities of multiple datasets with different environmental settings [30]. HMM requires a large set of training samples and unlike CRF it may not be able to capture long range dependencies of observations [19]. Long range dependencies between the observations within activity segments can be modeled by integrating sequential pattern mining, used to characterize the time spans during an activity execution, with Hidden Semi-Markov Model (HSMM) for the activity recognition (AR-SPM) [6]. Switching-HSMM defines two layers to recognize the daily activities and to identify anomalies [32]. In Hierarchical-HMM (HHMM) two layers are defined [38], where one layer presents the activities, while the second corresponds to the clusters of actions in an activity. HHMM proves to be more effective than HSMM and HMM.

Activities can be recognized by Frequent Pattern (FP) mining followed by the Emerging Pattern (EP): a discriminative pattern used for classification between patterns of activities [39,40]. Discontinuous FPs are mined to cluster similar activity patterns into groups and then HMM is applied for the recognition [10]. FP mining is used to find the repetitive patterns and Latent Dirichlet Allocation is applied to cluster the co-occurring sequential patterns in order to recognize the activities (ADR-SPLDA) [21]. The pattern mining and sequence alignment methods can be used to select the representative patterns of activities, which are then matched with the observed sequences to recognize the activities [41]. The Inter-transaction Association Rule (IAR) mining finds the frequent events, while anomalies are identified by using emergent IAR that highlights the abrupt changing points in the dataset [42]. An Active Learning approach in the presence of Overlapping activities (AALO) performs location based frequent item set mining