Sensor Based Smart Home System

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Abstract- In the first instance it aims to it provide an overview addressing the state-of-the-art in the area of activity recognition in Smart homes. Smart homes are augmented residential environments equipped with sensors, actuators and devices. In early method, they used data-driven approaches only for sensor data in this paper introduces a knowledge-driven approach to real-time, continuous activity recognition and describe the underlying ontology-based recognition process. We analyze the characteristics of smart homes and Activities of Daily Living (ADL) upon which we built both context and ADL ontologies.we will concern ourselves with one type of stochastic signal model is hidden markov model for recognition process.

Index Terms- Smart homes, ADL, activity recognition, ontology

I. INTRODUCTION

A convergence of technologies in machine learning and pervasive computing as well as the increased accessibility of robust sensors and actuators has caused interest in the development of smart environments to emerge. Furthermore, researchers are recognizing that smart environments can assist with valuable functions such as remote health monitoring and intervention.

The need for the development of such technologies is underscored by the aging of the population, the cost of formal health care, and the importance that individuals place on remaining independent in their own homes.

To function independently at home, individuals need to be able to complete Activities of Daily Living (ADLs) such as eating, dressing, cooking, drinking, and taking medicine.

Automating the recognition of activities is an important step toward monitoring the functional health of a smart home resident. When surveyed about assistive technologies, family caregivers of Alzheimer's patients ranked activity identification and tracking at the top of their list of needs.

In response to this recognized need, researchers have designed a variety of approaches to model and recognize activities. The generally accepted approach is to model and recognize those activities that are frequently used to measure the functional health of an individual.

However, a number of difficulties arise with this approach. First, there is an assumption that each

Third, to track a predefined list of activities, a significant amount of training data must be labeled and made available to the machine learning algorithm.

Because individuals perform activities differently due to physical, mental, cultural, and lifestyle differences, sample data need to be collected and labeled for each individual before the learned model can be used reliably to track the individual's activities and functional well-being.

Unfortunately, collecting and labeling such sensor data collected in a smart environment is an extremely time-consuming task. If the individual is asked to participate by keeping track of their own activities over a period of time, the process is additionally obtrusive, laborious, and prone to self-report error.

II. METHODOLOGY

In this paper, we introduce an unsupervised method of discovering activities in a smart environment that addresses the above issues. We implement our approach in the context of the CASAS Smart Home project by using sensor data that are collected in the CASAS smart apartment testbed.

The unsupervised nature of our model provides a more automated approach for activity recognition than is offered by previous approaches, which take a supervised approach and annotate the available data for training. Compared to traditional methods for activity recognition which solely utilize HMM or other models for recognizing labeled activities, our approach first "discovers" interesting patterns of activity, and then, recognizes these discovered activities to provide a more automated approach.

We introduce a unique mining method for discovering activity patterns, along with a clustering step to group discovered patterns into activity definitions.

For the recognition step, we create a boosted version of a hidden Markov model (HMM) to represent the activities and their variations, and to recognize those activities when they occur in the smart environment.
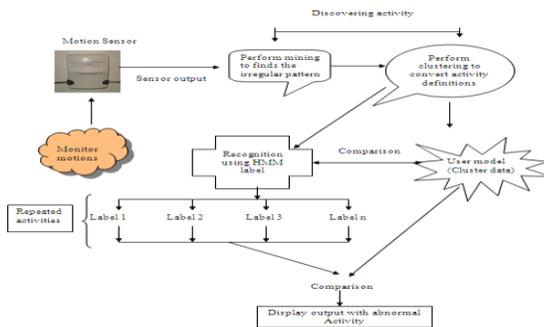
III. RESULTS

A. Figure

Fig. 1. Recognition activities in a smart environment

References

Activity recognition approaches can be generally classified into two categories. The first is based on the use of visual sensing facilities, [1]. Camera-based surveillance systems, to monitor an actor's behavior and environmental changes. The approaches in this category exploit computer vision techniques to analyze visual observations for pattern recognition. [2].

The second category is based on the use of emerging sensor network technologies for activity monitoring. The sensor data are analyzed using data mining and machine learning techniques to build activity models, which are then used as the basis of activity recognition. In these approaches, sensors can be attached to an actor under observation-namely wearable sensors, or objects that constitute the activity environment-namely dense sensing. [3].Wearable sensors often use inertial measurement units and RFID tags to gather an actor's behavioral information. This approach is effective for recognizing physical movements such as physical exercises. In contrast, dense sensing infers activities by monitoring human-object interactions through the usage of low power and low-cost sensors.

Abbreviations and Acronyms

- ADL - Activities of Daily Living

- HMM - Hidden Markov model

- RFID - Radio-Frequency Identification

E. Algorithm and techniques

Activity discovery method performs **frequent sequence mining** using DVSM to discover frequent patterns, and then, groups the similar discovered patterns into clusters. We use DVSM to find sequence patterns from discontinuous instances that might also exhibit varied-order events. As an example, DVSM can extract the pattern ha; bi from instances fb; x; c; ag;

fa; b; qg, and fa; u; bg, despite the fact that the events are discontinuous and have varied orders.

It should be noted that our algorithm is also able to find continuous patterns by considering them as patterns with no discontinuity. Our approach is different from frequent item set mining because we consider the order of items as they occur in the data. Unlike many other sequence mining algorithms, we report a general pattern that comprises all frequent variations of a single pattern that occur in the input data set D. For general pattern a, we denote the variation of the pattern as ai, and we call the variation that occurs most often among all variations of the prevalent variation, ap. We also refer to each single component of a pattern as an event (such as a in the pattern ha; bi).

CHAMELEON uses k-nearest neighbor graph approach to represent its objects. This graph captures the concept of neighborhood dynamically and results in more natural clusters. The neighborhood is defined narrowly in a dense region, whereas it is defined more widely in a sparse region.

IV. CONCLUSION

Activity recognition is becoming an increasingly important determinant to the success of context-aware personalized pervasive applications. Synergistic research efforts in various scientific disciplines, e.g., computer vision, artificial intelligence, sensor networks and wireless communication. To this end, we introduced an ontology-based approach to activity recognition in this paper. The approach makes use of ontologies for modeling, representation and inference in the lifecycle of activity recognition, ranging from sensor, objects and activities to reasoning and recognition.

We have described the algorithms of activity recognition making full use of the reasoning power of semantic modeling and representation. Compared with traditional approaches, ontological ADL models are flexible and can be easily created, customized, deployed and scaled up. Description reasoning can provide advanced features such as exploitation of domain knowledge, progressive activity recognition and multiple levels of recognition.

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