Context-Aware Method for Human Activity Recognition Based On a Real-Time Environment

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Abstract: Sensor-based human activity recognition is getting popular in various applications. In this paper, context-aware method for human activity recognition, based on a real-time sensor data stream coming from a minimum number of sensors placed in the environment. Well proposed method is being developed and will be validated in real life environment.

Keywords: context-aware, real-time, feature extraction, neural networks

I. INTRODUCTION

With the advance and prevalence of low-cost low-power sensors, computing devices and wireless communication networks, pervasive computing has evolved from a vision to an achievable and deployable computing paradigm. Human activity recognition is a key task in ambient intelligence applications to achieve proper ambient assisted living. There has been remarkable progress in this domain, but some challenges still remain to obtain robust methods. Our goal in this work is to provide a system that allows the modeling and recognition of a set of complex activities in real life scenarios involving interaction with the environment [1][2]. Human activity recognition approach can be based on the use of emerging sensor network technologies for activity monitoring. [3] Human activity recognition process involves provide sensors, gathering and processing sensor data, make computational models and finally develop reasoning algorithms. Most of the current work is assuming that learning data sets and test data sets have both been gathered within the same context and in most cases recorded in labs environment, perform poorly when tested in real life scenarios and when activity to be recognized is performed by a person that is not the one who performed activities based on which the activity model has been built in the first place. The major drawback is that most developed methods do not support activity recognition in real-time, but instead require all sensor data which represents a specific activity to be recorded before activity recognition can take place. [4][5] We can build context aware method that becomes independent of the hardware, simultaneously making the hardware architecture simple, low-cost and therefore widely accessible. Low-cost sensor technologies and wireless communication networks has pushed the research focus to high-level information integration, context processing, and activity recognition and inference. Physical activity recognition is becoming increasingly popular in various domains such as context-aware computing, mobile computing, and wireless sensor networks and others. Our aim to use of minimum number of low-cost sensors for data gathering, we performed real-time activity recognition and classification entirely on the server side based on raw sensor data, without any additional data pre-processing on sensor nodes themselves[6][7].

II. RELATED WORK

Current approaches to reason on human activities are categorized as:

[8][9]*Sensor-based activity recognition* exploits the emerging sensor network technologies to monitor an actor's behaviour along with their environment. In this case there are sensors attached to humans. Data from the sensors are collected and analyzed using data mining or machine learning algorithms to build activity models and perform activity recognition. In this case, they're recognized activities included human physical movements: walking, running, sitting down/up as in. Most of wearable sensors are not very suitable for real applications due to their size or battery life [10][11]. In sensor-based approach, can use either wearable sensors or object-attached sensors. The most used machine learning is the Hidden Markov Model– a graphical oriented method to characterize real world observations in terms of state models. Another good alternative is the Conditional Random Field model, which is an un-directed graphical method which allows the dependencies between observations and the use of incomplete information about the probability distribution of a certain observable. The sensor data which are collected are usually analysed using data mining and machine learning techniques to build activity models and perform further means of pattern recognition. In this approach, sensors can be attached to either an actor under observation or objects that constitute the environment. Sensors attached to humans, i.e., wearable sensors often use inertial measurement units (e.g. accelerometers, gyroscopes, magnetometers), vital sign processing devices (heart rate, temperature) and RFID tags to gather an actor's behavioural information.

[12][13] *Activity recognition* in smart homes is a very active research subject. Here, we are particularly interested in approaches which use low level data, as opposed to image-based techniques. Approaches based on machine learning are naturally very popular in this field, most of which are supervised learning approaches. Activity recognition became an important research issue related to the successful realization of intelligent pervasive environments. It is the process by which an actor's behavior and his or her environment are monitored and analyzed to infer the activities. Activity recognition consists of activity modeling, behavior and environment monitoring, data processing and pattern recognition [14][15][16]. Activity recognition systems typically have three main components: - A low-level sensing module that continuously gathers relevant information about activities using microphones, accelerometers, light sensors, and so on - A feature processing and selection module that processes the raw sensor data into features that help discriminate between activities - A classification module that uses the features to infer what activity an individual or group of individuals is engaged - In, for example, walking, cooking, or having a conversation [17][18][19]. Activity recognition based on wearable sensors has been extensively used in the

recognition of human physical movements. Activities such as walking, running, sitting down/up, climbing or physical exercises, are generally characterised by a distinct, often periodic, motion pattern. The wearable sensor based approach is effective and also relatively inexpensive for data acquisition and activity recognition for certain types of human activities, mainly human physical movements [20][21].

[22][3] *Context-Aware Reasoning for Activity Recognition*
One important task of our system, which is also typical of similar types of systems having been frequently reported in the literature, is to identify the activities of a person in the environment such as "sleeping", "watching TV", "cooking", etc. [23] In addition to being able to identify an activity, we are also interested in the time and location of where the activity is carried out. By specializing the ontological classes in the modules of the SmartHome ontology, we can provide the representational basis for the context inference process. However, in order to continuously capture changes (either in the form of activities or other events) in the environment, a stream reasoning process is required. By stream reasoning, we mean a logical reasoning process applied upon data streams in real time to be able to recognize the current situation of the environment. Since context awareness is assumed to be in real time, the stream reasoning process should be stable, as well as efficient, specifically in dealing with unknown situations that are likely to happen in a smart environment due to either the lack of observations or sensor failures [24][25]. In many context awareness applications, the reasoning process is deductive, which relies on monotonic logic and specify conditions under which events may occur. However, in order to keep the performance of the reasoner suitable for real-time monitoring, deductive models usually provide less declarative language than models relying on non-monotonic logic. Non-monotonic reasoning is based on belief revision, which allows a new hypothesis or observation to contradict the previously-inferred beliefs. Due to the inherent uncertainty of sensor data, hypotheses in the form of sensor observations are not always complete. In particular, interpretation of sensor data about the environment evolves over time. Since non-monotonic reasoning is known to be efficient in dealing with incomplete data, in this work, we have applied answer set logic as a non-monotonic logic for sensor data [18].

III. PROPOSED METHOD

The Proposed Method is based to give cost effective sensor network in the real world activities.
Here we are using the minimum number of sensors for gathering and processing the data in a well manner. The method involves the following steps:

1. **Gathering Data:** Sensor is attached to various wearable or non wearable devices to collect the data for further processing. In-house, they will attach to the doors for gather data. Here we need Wi-Fi system to send the information to desktop about the various activities. In the case of doors, Sensors Collect the information about the open, close, lock and unlock door activities are collected.
2. **Extracting Features:** Feature extraction done by the Neural Networks, a powerful tool for feature representation, which can learn features and build a classifier by itself based solely on sensor data. This approach has already proven to be successful both for feature extraction and activity recognition based on sensor data.
3. **Recognizing activities:** Data set can be developed to building and testing the classifiers for activity recognition. Subset of the collected data set will be selected as a training data set, while the remaining subset will be selected as the test data set. Neural Networks use to aim for feature extraction and building the classifiers will give best results when it comes to activity recognition/classification.

IV. CONCLUSION

In this paper, we can developed the context-aware method for human activity recognition, that is totally based on a real-time data stream gathering from a minimum number of sensors placed in the environment in which activity is performed. Such types of methods are cost effective and robust in the real world environment.

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