Mobile Activity Recognition Using Contextual Reasoning and Ubiquitous Data Stream Processing
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Abstract Activity recognition has become one of the emerging applications in the area of ubiquitous computing. This research aims at leveraging ubiquitous data stream mining and context reasoning for mobile activity recognition. The novel system allows dynamic adaptation and personalisation of the learning model to reflect the realistic activity changes emerged over time. Sensors fusion to attain a context aware activity recognition is also a key contribution in this project.

Keywords: Activity recognition, context, adaptation, personalisation, stream learning, holistic approach.

1 Introduction

The availability of real time sensory information through mobile sensors led to emerging research into "Mobile activity recognition". This focuses on inferring the current activities of mobile users by leveraging the rich sensory data that is available on today’s smart phone and rich information sources. The state of the mobile activity recognition research has focused on traditional classificatory learning techniques. Data is collected and labelled by users. Then, labelled data is used to build and train the classifier learning model. When the model is ready, it is deployed on a mobile device to predict activities from the sensory data. Wide range of classification models have been used for activity recognition such as Decision Tree, Naive Bayesian and Support Vector Machine [8, 5, 3]. This project is the first mobile activity recognition project that has the following key innovations of leveraging ubiquitous data stream mining and context reasoning for mobile activity recognition. The proposed system manages the learning of new evolving data from sensory information on board the mobile device itself using mobile data stream learning. The novel approach incorporates data from sensors on mobile phone, environmental sensors and any other contextual data that is available from external sources. Moreover, it allows dynamic adaptation and personalisation of the learning model to reflect the realistic activity changes emerged over time. This paper is organised as follows. Section 2 presents research issues in activity recognition. In section 3, the proposed system of ubiquitous data stream processing for contextual mobile activity recognition systems is devised. In section 4, the evaluation strategy is described . The paper is concluded in section 5.

2 Research Issues

Mobile activity recognition has become a stimulating field of study and there are still a number of open research problems worth further consideration.

- Mobile on-board activity recognition
  Personal mobile devices such as smart mobile phones provide a promising basis for determining user activity in an automated manner on a large scale [6]. The reasons for this are manifold. Personal mobile devices are self-contained with a variety of on-board sensor and do not require additional infrastructure support. The new generations of smart phones are designed to support complex tasks with high memory and processing capabilities. Moreover, since the devices are carried by their users continuously, the device’s context is tightly correlated to the user’s context [4]. Processing and predicting activities locally on today’s smart phones with high capabilities is reasonable. Performing the three processes of sensing, analysis and prediction of data on board preserves user privacy as there is no need to disclose user information by sending data to server or desktop machine.
• Model adaptation and refinement
In real life application, activities that user performing are changing over time. Therefore, the set of activities represented in the model has to be updated to reflect the change in the real performed activities. That includes adding new recognised activity and also ignoring other abandon activities. Model adaptation is a key criterion of the robustness of any activity recognition system. There is no notion of adaptation/refinement of the classifier models in the literature. Models do not include activities that may emerge over a period of time (post the data collection) or changes in user’s patterns, which are both completely realistic in the context of mobile user. The adaptation process aims to update the recognition model overtime to reflect changes in real life user’s activities at real time.

• Model personalisation
It can easily be seen that models that are built for general activity recognition would need to be tuned and personalised when deployed on user’s phone. Personalisation of learning model had a little focus in literature [10, 7]. The way people performing activities are different from one to another. Typical walking for one user is considered as jogging for another. Therefore, the significant of personalising the training model at real time became crucial in activity recognition in order to improve the recognition accuracy for a specific user. Personalisation is the process of tuning the general model to represent user’s personalised way of performing different activities. Unlike the adaptation process, personalisation updates the current existing model without changing the core activity types. Therefore, the personalisation process only ‘tunes’ current activities for a specific user at real time without adding or deleting any of the existing model activities.

• Sensors fusion
In today’s highly digitised world, it can be easily seen that, any holistic approach for mobile activity recognition should be inclusive to on board mobile sensors, body sensors, and physical and virtual sensors in the environment, as well as other rich sources of context that may be available or accessible. Diverse sensors available in the environment can provide another horizon of information when combined with information provided from mobile phone sensors. Integration of data streams from different sources as mobile sensors, environmental sensors, web data and domain knowledge... etc represents a comprehensive picture of the situation and the context of the performed activity.

• Context aware activity recognition
The automatic recognition of contextual activities is a non-trivial process. The context or situation and the kind of performed activity are commonly closely tied. It is often the case that some activities cannot be happened when the specific context information available at the same time. For example, an activity cannot be classified as running if the subject is in the middle of lake or at traffic jam. The combination of accelerometer data and a stream of location estimates from the GPS can recognise both the activity as well as the mode of transportation of a user and therefore help enhancing the overall accuracy.
3 **StreamAR**: Data Stream Mining Approach for Context Activity Recognition on Mobile Phone

### 3.1 Project Contribution

In this project, we aim to propose, develop and evaluate sophisticated mobile activity recognition technology that is tailored and adapted to infer the high level activities of mobile users. The project has the following innovations:

- Stream mining of mobile sensory data for activity recognition. Therefore, attain a real time adaptation and personalisation of the recognition system to cope with the evolving data streams.
- Understanding the high level situation in which an activity is occurring through integrating the mobile activity recognition system into a context aware framework.

### 3.2 StreamAR Operation

*StreamAR* is designed to receive data streaming from different sources and identify the contextual activity performed in real time. As illustrated in Figure 1, data is processed and analysed concurrently in two layers; context interpreter component layer and stream mining layer.

**Context interpreter component layer**: In this layer, The context interpreter component receives data streams and classifies the context activity performed by mobile user. The general learning model is built offline from sensory data of different users. The context model has the ability to extract knowledge from the offline built learning model and integrate it with other available data sources. Environmental sensors and on-body sensors -that are available and accessible- incorporated with the context interpreter component in additional to other information sources as domain knowledge, GPS or web data in order to detect the contextual activity.

**Stream learning layer**: Streaming techniques is deployed on high speed sensory data for real time analysis and detection of model changes. While sensory data is processed by the contextual interpreter component, the stream learning unit analyses the sensory data for change and novelty detection. The refinements of the model can be either updating/ personalising existing activities or changing the whole model to add new activities or delete existing. Therefore, this layer is designed to implement dynamic personalisation and adaptation of the learning model. The training model is updated with the refined one and that reflects the identification of the contextual activity second by second.
3.3 Methodology

- **Context interpreter component**
  In the first stage, the system collects data from mobile users. This stage is identical to the current mobile activity recognition systems. Data is used to train the learning model for recognising future activities. In traditional mobile activity recognition, the offline built model is deployed on mobile device for then recognising activities based on incoming sensors readings. In contrast, the proposed approach is recognising activities in more comprehensive and realistic way. We plan to extract knowledge from the training model and incorporate it with the context interpreter component inference engine. Then, we integrate the knowledge obtained through learning and induction process with other available information sources into a context reasoning interpreter component on the mobile phone.

  **Developed technique:**
  Enhanced context spaces Theory-based Reasoning Architecture (ECSTRA) ([2]) provides the basic framework for the context interpreter component in StreamAR system. ECSTAR provides a solution to reason about the context from the level of sensor data to the high level situation awareness. This framework has principally been developed for dealing with contextual information from sensors in real time and computationally capable of reasoning in real time. The context interpreter component uses ECSTAR as a base framework with modifications and extensions to extract knowledge from learning models and implement a holistic approach for contextual activity recognition.

- **Stream Mining Unit**
  The next step is to apply data stream mining techniques for mobile sensory data. This step aims to make a dynamic adaptation and personalisation of the offline built general training model in real time. The mobile data stream mining techniques perform effective continuous learning to refine and personalise the model.

  **Developed technique:**
  None of the developed stream learning techniques have been deployed for activity recognition on mobile devices. Therefore, we plan to develop a novel stream mining technique that can recognise changes occurring in data streams and refine the training model accordingly. The novel stream technique is based on deployment of hybrid similarity measures in order to detect changes in data streams. We have proposed, developed and evaluated recently a novel cluster-based K best neighbor classification method for traditional data mining based on three different similarity measures namely distance, density and gravity [1]. Applying the aforementioned similarity measures for static classification purpose shows superiority over the use of individual ones, and enhances the classification accuracy. Moving to the streaming settings, we plan to develop a stream learning approach of the hybrid similarity measures technique for change detection of sensory data to refine and adapt learning model. The system aims to assign weights for different activities based on user specific frequency of each performed activities which allows close monitoring of activity patterns.

- **Mobile Deployment**
  One of the most important stages in this project is the deployment of the different components on the mobile device. We plan to deploy the context interpreter component to the user mobile phone while using the phone as the sensing platform. All processing, analysis and recognition should be implemented locally on board including the refinement and personalisation as well as the real time recognition.
4 Evaluation Strategy

4.1 Benchmark activity recognition dataset

Activity recognition is an exciting ground for the development of robust machine learning techniques, as applications in this field typically require dealing with high-dimensional, multi-modal streams of data. However, unlike other applications, there is lack of established benchmarking problems for activity recognition. In the recently started European research project [9] the OPPORTUNITY dataset has been recorded to recognize complex activities from accelerometer sensors in addition to highly rich environmental sensors. The labelled data has information about both the user activities like (Sitting, walking and running) streaming form accelerometer sensors and gestures like (open door, close door and open drawer) provided from environmental sensors.

We plan to use the OPPORTUNITY data set and similar recent datasets in a dynamic way to simulate the change in detected activity and therefore test the adaptation capability of the novel technique. This dataset provides a platform to test StreamAR and compare its performance to existing activity recognition systems.

4.2 Research evaluation

Different measures will be deployed to evaluate the performance of the proposed approach. The criteria are as follow:

- **Accuracy**: The algorithms is developed to integrate sensors and other available information sources in order to predict the contextual activity based on sensory data. The context interpreter component performs a probabilistic recognition of each data stream/data source. Combination of probabilistic measures results a global probabilistic accuracy of the final contextual recognised activity. This accuracy is used to compare the proposed technique with other traditional activity recognition systems. The accuracy test is performed on simulated desktop environment at the first step. Then the accuracy will be tested with the algorithm deployed on mobile phone.

- **Adaptability**: One key contribution of the proposed technique is the ability to adapt with different changes that typically happened in user activities. The system adaptation includes:
  - Recognising new activities that the system has not trained on.
  - Removing abandon activities that user is no longer performing.
  - Tuning the model of specific user.

The adaptability of the system is measured by testing the three above points with real life dynamic dataset. We aim to change the dataset automatically to test cases when new activities emerged or old one abandoned. Personalisation of the model for a specific user is tested by measuring the accuracy of the model when deploying on diverse users with different activities patterns.

- **Running time**: The running time of the system that combines both the stream learning unit and context interpreter component is measured when deployed on both desktop and mobile phone.

- **Resources management**: As the system will be deployed on the mobile phone, monitoring the available resources and managing them accordingly is a crucial task. The usage of battery, memory and mobile CPU will be measured to test the system performance.
5 Conclusion

In this paper, we have proposed our novel system that combines stream learning and context aware approach for mobile activity recognition. Research issues in mobile activity recognition and contribution of this system to fill the research gaps have been explained in this paper.

References


