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Adaptive mobile activity recognition system with evolving data streams

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ABSTRACT

Mobile activity recognition focuses on inferring current user activities by leveraging sensory data available on today's sensor rich mobile phones. Supervised learning with static models has been applied pervasively for mobile activity recognition. In this paper, we propose a novel phone-based dynamic recognition framework with evolving data streams for activity recognition. The novel framework incorporates incremental and active learning for real-time recognition and adaptation in streaming settings. While stream evolves, we refine, enhance and personalise the learning model in order to accommodate the natural drift in a given data stream. Extensive experimental results using real activity recognition data have evidenced that the novel dynamic approach shows improved performance of recognising activities especially across different users.

1. Introduction

Data stream mining has unique characteristics that make it more challenging than static data mining. In typical streaming settings, data has an infinite length; therefore, traditional mining techniques that require several passes on data cannot be applied in a streaming environment. *Concept-drift* nature of streaming data makes it hard to predict and classify new incoming data. The prior knowledge of data eventually becomes outdated while stream evolves. Thus, the classificatory model has to be continuously updated and refined to cope with changes occurring naturally in data stream. There are many emerging applications in which data streams play an important and natural role, one of these is activity recognition. Activity recognition aims to provide accurate and opportune information on people's activities and behaviour. Activity recognition has become an emerging field in the areas of pervasive sensory data processing and ubiquitous computing because of its important proactive and preventing applications. The increased interest in the field of human activity recognition contributes to numerous domains, such as health care [18,32] surveillance and security [26,11], personal-informatics [32,5] and just-in-time systems [13,25].

Activity recognition (*AR*) has been widely studied with different approaches and from different perspectives. The state of the art in activity recognition research has focused on traditional classificatory learning techniques. First, data is collected and annotated by domain experts. Then, labelled data is deployed to build and train the classifier learning model. When the model is ready, the recognition system is used to predict activities from the sensory data. A wide range of classification models has been deployed for activity recognition such as Decision Trees, Naive Bayes and Support Vector Machines. The premise underlying machine learning in activity recognition is that new activities can be recognised using prior knowledge of previously collected data representing different activities. State-of-the-art activity recognition systems rely strongly on prior knowledge, ignoring post deployment essential adaptation and refinement that are naturally occurring in a dynamic streaming environment. Moreover, personalisation of model to suit a particular user had little focus in the research area. Typically, walking for one user may well be running for another, therefore tuning the general model to recognise a given user's personalised activities is crucial for building a robust activity recognition system. Thus, it became crucial to handle the emerging change of activities resulted from the modification of users' activities patterns or personalisation of user's activities while stream evolves.

In this paper, we aim to build a personalised and adaptive framework for activity recognition that incrementally learns from evolving data stream. The developed framework deals with high speed, multi-dimensional streaming data to learn, model, recognise personalised user's activities. The novel approach extends the

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state-of-the-art in activity recognition with the following contributions:

- *Dynamic incremental learning from evolving data stream*: To handle concept drift in data stream, we introduced a novel incremental automatic learning from unlabelled data to refine and adapt the learning model to the most changes in the data stream in real time.
- *Effective active learning with lowest cost*: Manual labelling of data stream is usually impractical, costly and time consuming. Therefore, we propose a novel active learning approach that asks to label only a small amount of the most uncertain data in the stream for a dynamic model adaptation and refinement.
- *Mobile real time AR application*: We demonstrate the effectiveness of our light-weight framework by deploying the activity recognition streaming application on a mobile platform for real time activity recognition.

To the best of our knowledge, no recognition/streaming system addresses all aforementioned contributions in a single framework. We termed this framework *STAR*, which stands for STream learning for mobile Activity Recognition. The rest of the paper is organised as follows. Section 2 provides a discussion of the research context. Fine treatment of the proposed framework and its details are presented in Sections 3 and 4. Section 5 reports the experimental results and analysis. Finally, Section 6 concludes the paper with a summary.

2. Related work

Activity recognition is a very wide research area that has been investigated from many perspectives. An immense research has been directed towards learning methods for recognising activities from sensory data. Most of these learning methods considered the deployment of supervised machine learning approaches. In supervised learning, labelled data is collected to train a classificatory model. Then, the built model is deployed for recognising activities from incoming unlabelled data. Various supervised learning techniques are commonly used for activity classification; these methods are reviewed in [22,21].

The vast of activity recognition research did not consider the adaptation of the classificatory model beyond the training phase [33]. They also assume the availability of a significant amount of labelled data in order to build an efficient classificatory model. These assumptions are non-realistic especially when dealing with streaming sensory data. The evolving data stream encounters various kinds of change. One of the main causes of changes concerns the personalisation of the recognition model. Different individuals might perform the same activity but in various ways. The most accurate recognition results can be obtained if we train the learning model with the annotated data for a specific user. Researchers investigated the impact of training the model on a personalised data and compared it with training the model on a general data collected from different users. The researchers demonstrated the improved accuracy when deployed subject specific data for training instead of the general model [16,29]. Retraining the model for user specific annotated data is not always applicable because of the scarcity of labelled data especially in the streaming environment. Moreover, model reconstruction is not realistic for real time recognition.

Recent research in [28] adjusted the learning model from person A with selected confident sample for another person B. The proposed algorithm is an integration of SVM classier and clustering approach for updating model automatically. However, the proposed system has not been evaluated in a streaming setting. The deployment of activity recognition system in streaming environment imposes more challenges as the change of data distribution when the stream evolves may cause the model to drift away from the actual data distribution.

Recently, few studies have considered the streaming nature of data for activity recognition. Krishnan and Cook [15] developed an efficient technique for handling streaming data based on windowing. This system is based on the fact that different activities can be characterised by various window lengths. The study evaluated different windowing techniques for analysing stream of activities. While the addition of this study to the field of activity recognition, research still requires addressing other research gaps. A limitation of the proposed approach is its inability to adapt the model post the deployment. The classifier is built with training data, with no flexibility to be adapted and personalised post the training phase.

MARS [9,10], stands for Mobile Activity Recognition System, is an incremental system for predicting activities in a data stream from a mobile device. The learning process in MARS is divided into two phases: training and recognition. In the training phase, user performs activities and annotates them interactively when data is collected from mobile sensors. The collected annotated data is saved for building the model offline. In the recognition phase, the incoming unlabelled data is then classified based on the offline built model. The study compared the results of both static decision tree and incremental Naive Bayes for evaluating the system performance. The proposed algorithms are light-weight thus can be deployed on mobile devices. Another recent research by Lockhart and Weiss [17] has presented the Actitracker system for mobile activity recognition in health care domain. Actitracker uses Random Forest model to build a general/universal classifier that could be replaced by a personalised model for a particular user. The system handles data stream with fixed time window and transmits data for backend server for processing.

Although, techniques presented in the aforementioned systems presented an efficient approach that combines activity recognition with stream mining in an ubiquitous environment, some challenges still to be addressed. These systems assume the availability of labelled data for each user; each individual has to collect and annotate data that represents the personalised activities for building the model. When new subject uses the system, the model has to be retrained with the data collected and annotated for this particular user. Training model in such way is impractical in streaming settings that require automated and incremental approach for 'adjusting' the model to fit a particular user. Moreover, the annotation process is time consuming, erroneous and not applicable for streaming environment.

Due to the scarcity of labelled data in streaming environment, selecting only the most profitable data with the minimum effect on performance is crucial for an effective recognition. According to Muslea et al. [20], the main goal of active learning algorithm is to find the most profitable and less costly data to label. Unlike incremental learning which does not require user input, active learning inquires user for true label. Many approaches have proposed for an efficient active learning in data streams, such as in [30,19,12]. Stikic et al. [27] employed a multi-sensor approach to choose important data to be labelled. Two approaches evaluated, selected data are these which classifier is least confident about or when two classifiers have a high degree of disagreement. Results showed improved performance when active learning is applied.

Our framework varies from other studies in terms of numerous aspects. State of the art activity recognition approaches rely on a static model that assumes no change occurring to the model beyond training. Few studies addressed the adaptation issue with