Pervasive and Mobile Computing 10 (2014) 138–154

Contents lists available at ScienceDirect

Pervasive and Mobile Computing

journal homepage: www.elsevier.com/locate/pmc

Activity recognition on streaming sensor data

Narayanan C. Krishnan *, Diane J. Cook

School of Electrical Engineering and Computer Science, Washington State University, Pullman, WA 99164-2752, USA

ARTICLE INFO

Article history:
Received 12 April 2012
Received in revised form 3 July 2012
Accepted 3 July 2012
Available online 15 July 2012

Keywords:
Streaming
Online
Real-time
Activity recognition
Mutual information

ABSTRACT

Many real-world applications that focus on addressing needs of a human, require information about the activities being performed by the human in real-time. While advances in pervasive computing have led to the development of wireless and non-intrusive sensors that can capture the necessary activity information, current activity recognition approaches have so far experimented on either a scripted or pre-segmented sequence of sensor events related to activities. In this paper we propose and evaluate a sliding window based approach to perform activity recognition in an on line or streaming fashion; recognizing activities as and when new sensor events are recorded. To account for the fact that different activities can be best characterized by different window lengths of sensor events, we incorporate the time decay and mutual information based weighting of sensor events within a window. Additional contextual information in the form of the previous activity and the activity of the previous window is also appended to the feature describing a sensor window. The experiments conducted to evaluate these techniques on real-world smart home datasets suggests that combining mutual information based weighting of sensor events and adding past contextual information to the feature leads to best performance for streaming activity recognition.

1. Introduction

Advances in pervasive computing have resulted in the development of unobtrusive, wireless and inexpensive sensors for gathering activity information, which when coupled with state of the art machine learning algorithms are critical to the development of a wide variety of applications. One such application area is that of smart environments where activity information is used to monitor and track the functional status of residents. A good number of on-going projects in smart environment and activity recognition such as the CASAS project [1], MavHome [2], PlaceLab [3], CARE [4] and the Aware Home [5] stand testimony to the importance of this research area. The need for the development of such technologies is underscored by the aging population [6], the cost of health care [7] and the importance that individuals place on remaining independent in their own homes [8]. Individuals need to be able to complete Activities of Daily Living (ADLs) such as eating, grooming, cooking, drinking and taking medicine, to lead a functionally independent life. Thus automating the recognition and tracking of these ADLs is an important step toward monitoring the functional health of a smart home resident, which has also been recognized by family and caregivers of Alzheimer's patients. This is the primary motivation behind much of the activity recognition research in smart environments.

Activity recognition (AR) is a challenging and well researched problem. The different approaches proposed in the literature differ primarily in terms of the underlying sensing technology, the machine learning models and the realism of the environment in which activity information was gathered. Irrespective of the sensing technology and machine learning model, the literature is abundant with AR techniques that work extremely well on scripted or pre-segmented sequences of

* Corresponding author. Tel.: +1 5093354287.
E-mail addresses: ckn@eecs.wsu.edu (N.C. Krishnan), cook@eecs.wsu.edu (D.J. Cook).

1574-1192/$ – see front matter © 2012 Elsevier B.V. All rights reserved.
doi:10.1016/j.pmcj.2012.07.003

activity. While this is a first step toward developing AR, real-world deployment of these systems requires AR techniques to work on streaming/online data among other scenarios such as concurrent and interleaved activity execution. This is also important in the context of developing assistive technologies for the elderly that can help them in completing ADLs (such as prompting systems [9,10]). There is a need for online activity recognition techniques that can classify data as it is being collected which is the basis for tracking the progress of the activity. This is a challenging problem as data that completely describe an activity is not generally available in such situations and the algorithm has to rely on the partially observed data along with other contextual information to make a decision on the activity being performed.

The work presented in this paper attempts online AR on discrete binary motion sensor data obtained from real-world smart homes. The approach classifies every sensor event based on the information encoded in a sliding window of preceding sensor events. It explores both fixed static window size and dynamic varying window size, along with investigating modifications to the sliding window protocol that takes into account the temporal and spatial relationships between the different sensors. It also encodes the context of the window in terms of the classification probabilities of activities in the preceding window and the previously recognized known activity. This methodology is evaluated on data collected from three smart apartments over a period of six months. These datasets represent the activities performed by a single resident of the smart home. One of the facets of the work presented in this paper that sets it apart from other related work is the dataset that is used to evaluate the algorithms. Our dataset reflects the complexities of unconstrained real-world data that cannot be observed in other datasets. We present the first application of the sliding window method for dealing with discrete motion sensor events. Another factor that distinguishes our work from the rest is the inclusion of sensor events that do not belong to any of the known activity labels for performance evaluation. This is a common problem that one faces when scaling the AR approaches to real-world settings. It makes the first attempt at trying to understand how the state of the art techniques perform in complex real-world settings, where the subject is living in their natural habitat and conducting their daily routine with no instructions whatsoever from the researchers. The focus on the evaluation is to study the effectiveness of the activity models, trained and tested on data collected from the same smart home. We are not trying to study how well the activity models generalize across different apartment layouts and different residents.

The rest of the paper is organized as follows. Section 2 discusses briefly the related work on AR. A discussion on the different methodologies for processing streaming data is presented in Section 3. The sliding window methodology adopted in this paper along with the accompanying modifications are described in Section 4. Section 5 presents the experimental setup for evaluating the proposed methodology along with a description of the smart apartment dataset. The results are presented and discussed in Section 6. Section 7 summarizes the work presented in the paper along with providing directions for future work.

2. Related work

The goal of activity recognition is to recognize human physical activities from data collected through different sensors. It is a well researched area and hence there exists a number of approaches for activity recognition [11]. These approaches vary depending on the underlying sensor technologies that are used for gathering the activity data, the different machine learning algorithms used to model the activities and the realism of the environment in which the activity data is collected and AR is performed.

2.1. Sensors for AR

Advances in pervasive computing have seen the development of a wide variety of sensors that are useful for gathering information about human activities. Wearable sensors such as accelerometers are commonly used for recognizing activities that are primarily defined by ambulatory movements (such as walking, running, sitting, standing, lying down and falling) as demonstrated by earlier efforts [12,13]. More recently researchers are exploring smart phones equipped with accelerometers and gyroscopes to recognize ambulatory movements and gesture patterns [14,15]. Most of these approaches have been able to recognize activities primarily characterized by movements in real time [16] through a sliding window protocol. Since the movement information related to activities is typically well represented within a window of the data from accelerometers with a high sampling rate, a sliding window based approach is appropriate for recognizing these activities in real-time.

Environment sensors such as infrared-based motion detectors or reed switch based door sensors have also been used for gathering information about a more general set of ADLs such as cook, leave home, sleep, eat, etc.; as explored by others [17–20]. These sensors are adept in performing location based activity recognition in indoor environments just as GPS is used for outdoor environments [21]. Some actives such as wash dishes, take medicine, use phone, etc. are characterized by unique objects of interaction. Researchers have explored the usage of RFID tags and shimmer sensors for tagging these objects of interaction and thus be able to perform AR. For instance, Philipose et al. [22] use the count of objects of interaction obtained through the activation of RFID tags to decipher the activities being performed in the environment and Palmes et al. [23] mine the web to determine which objects are essential for recognizing a particular activity and use this information to build activity models.

Researchers have also used data from video cameras monitoring and recognizing different activities [24,25]. The use of video cameras for AR is very prevalent in security related applications. However, their usability in the context of smart