ARTICLE IN PRESS

Pervasive and Mobile Computing ▮ (▮▮▮▮) ▮▮▮–▮▮▮

Contents lists available at ScienceDirect

Pervasive and Mobile Computing

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

Fast track article

Information gain-based metric for recognizing transitions in human activities

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ARTICLE INFO

Article history:
Received 20 April 2016
Received in revised form 23 November 2016
Accepted 4 January 2017
Available online xxxx

Keywords:
Human activity recognition
Temporal segmentation
Information gain
Routine discovery

ABSTRACT

This paper aims to observe and recognize transition times, when human activities change. No generic method has been proposed for extracting transition times at different levels of activity granularity. Existing work in human behavior analysis and activity recognition has mainly used predefined sliding windows or fixed segments, either at low-level, such as standing or walking, or high-level, such as dining or commuting to work. We present an Information Gain-based Temporal Segmentation method (IGTS), an unsupervised segmentation technique, to find the transition times in human activities and daily routines, from heterogeneous sensor data. The proposed IGTS method is applicable for low-level activities, where each segment captures a single activity, such as walking, that is going to be recognized or predicted, and also for high-level activities. The heterogeneity of sensor data is dealt with a data transformation stage. The generic method has been thoroughly evaluated on a variety of labeled and unlabeled activity recognition and routine datasets from smartphones and device-free infrastructures. The experiment results demonstrate the robustness of the method, as all segments of low- and high-level activities can be captured from different datasets with minimum error and high computational efficiency.

1. Introduction

Understanding human behavior plays a key role in many context-aware applications such as targeted advertising and location-based services. Developing the science to analyze human activities and to describe how people move during their daily life promises to address a wide range of challenges. The work described in this paper is concerned with finding transition times when one changes his/her activity during a specific period of time. The activity could be a fine-grained activity (e.g., sitting, standing or running) or a coarse-grained activity, which is an aggregate of low-level activities and has a more complex semantic (e.g., shopping, working at the office or commuting). In this paper, we define fine-grained activities as low-level activities, and coarse-grained activities as high-level activities. A consequent key challenge is that these activities may be recorded in a variety of different data sources, e.g. sensor data, connectivity data, device-free data, and mobility data. To handle this, we present an information gain-based temporal segmentation method applicable to a wide range of pervasive data. Temporal segmentation approaches split time series into several homogeneous and non-overlapping intervals (segments). The output of applying temporal segmentation to the human activity data is a set of transition times (See Fig. 1).

Studying the transition times of human daily activities is important not only for understanding the mobility patterns but also for providing context-aware services in pervasive systems [1]. For example, a user may want to get the news

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http://dx.doi.org/10.1016/j.pmcj.2017.01.003
1574-1192/

Please cite this article in press as: A. Sadri, et al., Information gain-based metric for recognizing transitions in human activities, Pervasive and Mobile Computing (2017), http://dx.doi.org/10.1016/j.pmcj.2017.01.003

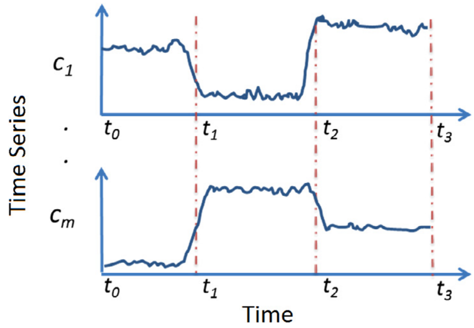

Fig. 1. Temporal Segmentation with m time series $[c_1 \dots c_m]$ and 3 segments. t_1 and t_2 are the transition times and $[t_0 - t_1]$, $[t_1 - t_2]$ and $[t_2 - t_3]$ are the segments.

whenever he arrives home or before commuting to work. Furthermore, extracting transition times from daily activities is very useful in urban computing because it shows when people usually change their locations during a day. City planners use this information to improve transportation, urban planning, and environment [2].

Temporal segmentation is the key to processing low-level and high-level human activities. Regarding low-level activities, many techniques have been applied for activity recognition using various kinds of sensor data [3–6]. However, there is a need to segment the data prior to recognition or prediction tasks as the transition times between the activities are unknown. Regarding high-level activities (e.g. office work or dining), temporal segmentation helps us to understand humans' mobility patterns across the whole day. For example, assume one leaves home at 7 am, works at the office from 9 am to 5 pm, and goes outdoor until 12 am every day. With this interpretation, his daily routine can be expressed as home (7 am) → commuting (9 am) → office (5 pm) → outdoor (12 am) → home. [12 am–7 am], [7 am–9 am], [9 am–5 pm] and [5 pm–12 am] are the temporal segments in this example that convey semantic meaning about the routine. The temporal segmentation method proposed in this paper extracts transition times not only in low-level activities but also in high-level activities, namely at the routine level.

To deal with human behavior data, a generic and fast temporal segmentation method that is applicable to heterogeneous data is proposed in this paper. As the input data is not just a single time series, a multivariate method is required. Furthermore, the time series may come from heterogeneous channels with different ranges and different types (i.g., accelerometer, gyroscope, and thermometer). Our method is generic because it can handle multiple time series regardless of their heterogeneity and the varying correlation between multiple sensor channels (e.g. whether the data are positively or negatively correlated). A segmentation method ideally needs to be unsupervised opposed to supervised learning which requires data to be labeled. The computational cost of the algorithm should also be taken into account [7]. Methods analyzing high-level activity have been usually applied to small data including only a few tens of users [8,9]. However, in many real-world applications, data comes from large sources like smartphones in a city that requires fast approaches. Our approach is enough fast to process data from hundreds of users in few hours.

To introduce our approach, Information Gain-based Temporal Segmentation (IGTS), let us consider smartphone connectivity data. Connectivity data specifies that the smartphone is connected to which access point or cell tower at each time. In this case, the results illustrate when users usually change their locations during a day. We treat the mean values of the time series (i.e. connectivity to the Cell Tower IDs) in each segment as a random variable and thus each segment has an entropy. Based on information theory, entropy reflects uncertainty. Correspondingly, in our case, entropy refers to the predictability of user locations. The IGTS algorithm finds low-entropy segments that means the users' locations are 'predictable'. As information gain gives the expected reduction in entropy after the segmentation, it is used as an effective cost function for finding coherent segments. As a result, the best segmentation is the one with highest information gain value.

To find the best segmentation with the highest information gain, an optimization method should be deployed. We propose two approaches for optimization: TopDown and Dynamic Programming (DP). TopDown optimization is faster while it cannot guarantee to provide the global optima. On the other hand, DP optimization results in the global optima. In order to apply DP to our approach, the cost function is modified otherwise DP and the cost function are not compatible. Both TopDown and dynamic programming approaches are useful for specific applications due to the trade-off between the accuracy and running time.

The main contributions of this paper are as follows:

- We introduce information gain as the cost function for temporal segmentation problem. We argue that information gain, which gives the expected reduction in entropy after the segmentation, is an effective cost function to find coherent segments.
- A data transformation stage has been introduced to handle the data heterogeneity challenge for all information gain-based temporal segmentation problems in both low- and high-level activities.