Expert Systems with Applications 42 (2015) 6423–6432

Contents lists available at ScienceDirect

Expert Systems with Applications

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

Activity recognition with weighted frequent patterns mining in smart environments

Jiahui Wen [a,b,*], Mingyang Zhong [a], Zhiying Wang [b]

[a] School of Information Technology and Electrical Engineering, The University of Queensland, QLD 4072, Australia
[b] School of Computer, National University of Defense Technology, Changsha, China

ARTICLE INFO

Article history:
Available online 30 April 2015

Keywords:
Data mining
Association rule
Activity recognition
Global and local weight
Smart environments

ABSTRACT

In the past decades, activity recognition has aroused a great interest for the research groups majoring in context-awareness computing and human behaviours monitoring. However, the correlations between the activities and their frequent patterns have never been directly addressed by traditional activity recognition techniques. As a result, activities that trigger the same set of sensors are difficult to differentiate, even though they present different patterns such as different frequencies of the sensor events. In this paper, we propose an efficient association rule mining technique to find the association rules between the activities and their frequent patterns, and build an activity classifier based on these association rules. We also address the classification of overlapped activities by incorporating the global and local weight of the patterns. The experiment results using publicly available dataset demonstrate that our method is able to achieve better performance than traditional recognition methods such as Decision Tree, Naive Bayesian and HMM. Comparison studies show that the proposed association rule mining method is efficient, and we can further improve the activity recognition accuracy by considering global and local weight of frequent patterns of activities.

1. Introduction

Activity recognition (de la Concepción, Morillo, Gonzalez-Abril, & Ramírez, 2014; Fernández-Caballero, Castillo, & Rodríguez-Sánchez, 2012) has aroused a great interest in the past decade and has been addressed by many research groups using different kinds of physical devices and reasoning techniques. The great interest in activity recognition can be explained in many ways. On one hand, because of the unprecedented growing speed of the ageing population around the world (Chernbumroong, Cang, Atkins, & Yu, 2013), one can imagine that elderly health-care will cost increasingly large amount of government budget in the future. However, monitoring Activities of Daily Living (ADL) (Reisberg et al., 2001) such as sleeping, cooking and eating can help the aged to live independently at home, and detecting the abnormal situation as soon as possible can reduce the danger to the minimum extent. On the other hand, as the increasing computational capability and memory storage enable the intelligent computing units to be deployed invisibly around the environments, there is a growing interest in the area of context-awareness computing. Environment-embedded sensors make it possible to gather various context information to guide the applications to be intelligent and behave adaptively toward the benefits of the residents. Human activity is one of the most important context, and activity recognition bridges the gap between various context-aware applications and intelligent ambient sensors.

Activity recognition is related to expert and intelligent systems from two aspects. Firstly, activity recognition can be viewed as a middleware between low-level sensors and high-level context-aware applications. The high-level context-aware applications are expert systems which make decisions towards the benefits of the users by reasoning the current observations against the pre-defined domain knowledge. For example, one application may turn the smartphone into *silence* mode if the on-going activity is *meeting*. In this example, the pre-defined rule to change smartphone's mode and the activity recognition component can be regarded as *knowledge base* and *inference engine* respectively, which are the two most important sub-systems in expert systems. On the other hand, activity recognition system itself can be viewed as an expert and intelligent system. It learns knowledge from the labelled data and performs inference to reason activities based on current sensor readings. Activity recognition can explicitly specify the knowledge base such as the decision rules in Decision Tree.

* Corresponding author at: School of Information Technology and Electrical Engineering, The University of Queensland, QLD 4072, Australia.

E-mail addresses: j.wen@uq.edu.au (J. Wen), m.zhong1@uq.edu.au (M. Zhong), zywang@nudt.edu.cn (Z. Wang).

http://dx.doi.org/10.1016/j.eswa.2015.04.020
0957-4174/

The learned knowledge can also be implicitly specified, such as the transition probability in Hidden Markov model (HMM), the support vectors in Support Vector Machine (SVM), the weights of potential functions in Conditional Random field (CRF). The inference process depends on the machine learning techniques used for activity recognition, and it includes dynamic programming in HMM and CRF, inner product between test vector and support vectors in SVM.

Based on the activities to be recognised, there are mainly two ways of recognition using different types of sensors. One is to attach sensors to human body to capture the physical activity signals such as acceleration and angular velocity (Banos, Damas, Pomares, Prieto, & Rojas, 2012; Kwon, Kang, & Bae, 2014), and then machine learning models are trained with the labelled data and used to classify the test data. The other one is to recognise high-level activities through the interactions between the people and the environments (Azkune, Almeida, López-de Ipiña, & Chen, 2015; Chernbumroong et al., 2013; Ordóñez, Iglesias, De Toledo, Ledezma, & Sanchis, 2013; Wen & Zhong, 2015). The argument for the second method is that high-level activities usually share common sets of physical actions, and are difficult to differentiate based solely on physical signals. However, these kinds of high-level activities can be characterised by the objects used by people, people's location and the time they perform the activities, and these objects can be obtained from sensors such as electrical ID tags deployed in the environments (Gu, Chen, Tao, & Lu, 2010; Palmes, Pung, Gu, Xue, & Chen, 2010).

Even though there are numerous ways for human activities recognition, with each addressing a certain aspect of the problems during the recognition model construction, some issues are still needed to be addressed. First of all, most of the activity recognition systems disregard the discriminative power of the features they choose. Even if some works (Banos et al., 2012; Könönen, Mäntyjärvi, Similä, Pärkkä, & Ermes, 2010) use greedy algorithm to select the best group of features that are able to yield high accuracy, all the features are applied for classification if they are selected in the previous step, ignoring the fact that some features may not be informative in discriminating an activity from another. For example, the irrelevant features in the feature vector may contribute to the error when calculating the distance in instance-based classifiers. Furthermore, human activities, characterised by the sensor events in smart environments, may show some degree of overlap and are difficult to distinguish using traditional methods (Rashidi, Cook, Holder, & Schmitter-Edgecombe, 2011). Note that the *overlap* is termed as the phenomenon that different activity classes share the same set of sensor events and are difficult to differentiate solely based on the types of sensor events they triggered. However, the frequencies of sensor events may be different for the activity classes and can be used to discriminate them. For example, activity a_1 triggers sensor events $\{s_1, s_3, s_3, s_3\}$ and activity a_2 triggers sensor events $\{s_1, s_1, s_1, s_3\}$. The two activities trigger the same set of sensor events $\{s_1, s_3\}$ and are impossible to differentiate based solely on the types of triggered sensor events. However, the activities have different frequencies in these two sensor events, and these knowledge can be mined to recognise overlapped activities.

In this paper, we apply association rule mining techniques to find frequent patterns of human behaviours from annotated daily life logs and use the frequent patterns to classify the human activities based on the sensor readings. In this way, the frequent patterns of each activity are characterised by the sensors triggered more frequent by the activity than by the others. This is reasonable, since people tend to perform certain activities in the same place and use the same objects, thus trigger almost the same sensors every time they perform the activities. For example, people are always cooking in the kitchen and interacting with the kitchenware. In other words, human behaviours can be characterised by the surrounding sensor readings, and in turn, the sensor readings can be regarded as the patterns of human behaviours, thus it can be used to recognise human activities if they are frequent enough. The contributions of this paper can be concluded as follows:

1. We propose an efficient association rule mining algorithm to find the relationships between the activities and their frequent patterns in smart environments.
2. We use the association rules to build a classifier that is able to achieve a higher performance than traditional classifiers commonly used for activity recognition in smart environments.
3. We also incorporate the global and local weights of sensor events in different activities to differentiate overlapped activities.

The reminder of this paper is organised as follows: Section 2 describes the related work. Section 3 details how to use the association rules to build a classifier, while Section 4 describes the mining process of the association rules and the experiment results are presented in Section 5. Finally, we conclude our work in Section 6.

2. Related work

2.1. Association rule and associative classifier

Traditionally, association rules mining (Rodríguez-González, Martínez-Trinidad, Carrasco-Ochoa, & Ruiz-Shulcloper, 2013) is used to find the frequent itemsets among the historical transactions and discover unknown relationships so as to provide information for decision making or prediction (Rajasethupathy, Scime, Rajasethupathy, & Murray, 2009).

An association rule is presented as $X \Rightarrow Y$ where X and Y are disjoint set of items and are called the antecedent and consequent of the association rule respectively. Two conventional criteria that are used to evaluate an association rule are *support* and *confidence*. The support of a rule is the ratio of the transactions that contain both of its antecedent X and consequent Y, while the confidence of a rule is the ratio of transactions that contain its antecedent also contain its consequent. Only the associations rules that meet the user-specified minimum support and minimum confidence are of interest. Apriori algorithm (Agrawal et al., 1994) is the most simple and efficient association rule mining algorithm that iterates the steps of candidate generation and pruning to find the frequent itemsets, while FP-growth algorithm (Han, Pei, & Yin, 2000) transforms all the transactions into a compact representation of a tree, avoiding the candidate generation.

Associative classification is another research topic which means to extract association rules from the training dataset and select some of them to construct the classification models, and is demonstrated in CBA, CMAR and CPAR (Chien & Chen, 2010) to achieve a better performance than traditional classifiers such as Decision Tree. Recently, many research works (Pach, Gyenesei, & Abonyi, 2008) also extend the associative classification to deal with numerical data by introducing the concept of fuzzy sets. Some others (Yan, Zhang, & Zhang, 2009; Qodmanan, Nasiri, & Minaei-Bidgoli, 2011) even use the genetic algorithm to learn the membership function of fuzzy logic or to mine the association rules without user-specified minimum support.

The difference between the aforementioned methods and our association rules mining methods is that, we leverage the special characteristics of the activity data in smart environments and propose an efficient rules mining method for activity recognition. This is crucial because sensor readings of the datasets from smart