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Sensor-based adaptive activity recognition with dynamically available sensors

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ABSTRACT

An activity recognition system essentially processes raw sensor data and maps them into latent activity classes. Most of the previous systems are built with supervised learning techniques and pre-defined data sources, and result in static models. However, in realistic and dynamic environments, original data sources may fail and new data sources become available, a robust activity recognition system should be able to perform evolution automatically with dynamic sensor availability in dynamic environments. In this paper, we propose methods that automatically incorporate dynamically available data sources to adapt and refine the recognition system at run-time. The system is built upon ensemble classifiers which can automatically choose the features with the most discriminative power. Extensive experimental results with publicly available datasets demonstrate the effectiveness of our methods.

1. Introduction

Sensor-based activity recognition has experienced its wide application in context-aware computing in the past decade, due to the important role it plays in everyday life. To name a few, recognizing human lifestyle can help to evaluate energy expenditure [1]; monitoring human activity in smart homes enables just-in-time activity guidance provisioning for elderly people and those suffering from cognitive deficiencies [4]; detecting walk and counting step can help to monitor elderly health [3].

State of the art activity recognition models usually rely on a static model, where only pre-defined data sources are considered while opportunistically available contexts which may potentially refine that the systems are ignored. Here we argue that dynamically discovered context is also significant for the adaptation and refinement of activity models. For example, in [33], the authors demonstrate that additional features such as vision features can help to improve the recognition accuracy for human activities, especially for static activities (e.g. sitting). Maekawa et al. [16] show in their work that, contextual information, such as the objects that the subjects interact with and the sound during the interaction, captured by camera and microphone can help to improve activity recognition performance. Extensive works prove that additional information such as location information [18], vital signs [12], readings from thermal sensor [7] and barometer [20] can also improve activity recognition accuracy.

Note that all the aforementioned extra data sources are specific to the post-deployment environment. Therefore, considering all the contextual information at the beginning of activity modelling is infeasible, due to the problem of data sparsity and the changes in the environment during post-deployment. Another motivation for our work is that sensors deployed for activity sensing are constantly broken and updated [15], so it is extremely important that the activity monitoring system can automatically evolve with the changing environment. Our work is inspired by [8], where the authors propose an autonomic context management system which is able to populate dynamically discovered contextual information sources for automatic context provisioning. We state here that several challenges need to be addressed in order to achieve an activity recognition system that is able to incorporate dynamically discovered context. First, incorporating new data sources would change the feature dimensionality, the pre-learned activity model should be flexible enough to allow for increment and decrement of the feature dimensionality. Second, the system should be able to automatically identify the context that have the discriminative power, while ignoring those with marginal discriminative power. Furthermore, as model refinement with dynamically available context usually requires the labels of the new examples to point out the direction of model adaptation, asking the user for the true labels is obtrusive. Therefore, selecting the most profitable and informative examples for adaptation is still challenging.

In this paper, we propose such an activity recognition system that addresses the aforementioned challenges. We practically

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analyse and choose a machine learning model that is flexible with the change of feature dimensionality and can automatically identify the most discriminative features. In order to retrain and adapt the activity model by incorporating the information provided by dynamically discovered data sources, we propose a method to choose the profitable examples without human intervention. Finally, we exploit temporal patterns of human behaviour and leverage graphical models to further improve the recognition performance. To conclude, this paper makes the following contributions.

1. We propose an activity recognition framework that can automatically incorporate dynamically discovered discriminative contexts, so as to improve activity recognition performance.

2. We propose a method that chooses the profitable and informative examples (incorporating discovered context) to retrain and adapt activity models without human intervention. We also propose a novel way of combining basic classifier (i.e., AdaBoost) with graphical models (i.e. Hidden Markov model and Conditional Random Field) in order to exploit the temporal information to improve the recognition accuracy.

3. We demonstrate our system with three publicly available datasets and analyse its effectiveness through comprehensive experimental and comparison studies. We also investigate the conditions under which the opportunistically discovered context is beneficial to recognition performance.

It should be noted that in this paper, we do not distinguish the concepts of new data sources, new features and new contexts. Since new data source and context can be seen as dynamically discovered information from the viewpoint of the whole system, while feature is from the viewpoint of the classifier. The remainder of this paper is organized as follows. In Section 2, we discuss related work. In Section 3, we briefly describe the system overview and architecture of our activity model, and detail each component in Section 4. Section 5 reports the experimental results and analysis, followed by Section 6 where we conclude this paper with a summary.

2. Related work

Activity recognition [29,28] is not a new topic, especially with the proliferation of smartphones where on-board sensors such as GPS, camera, microphone, accelerometers and gyroscope provide unprecedented opportunities for recognizing wide variety of human behaviours [11]. However, most of the state-of-the-art activity models are built upon static machine learning models, the reader is referred to [30] for more details.

Considering new context in dynamic environments to retrain and refine the activity model relates to model personalization and semi-supervised learning from the viewpoint of operation. Activity personalization adapts the general model to a specific user giving his/her data, while semi-supervised learning trains recognition models with labeled and unlabeled data. To name a few, Zhao et al. [34] propose a cross-people activity recognition algorithm for personalized activity-recognition model adaptation by integrating a decision tree and the k-means clustering algorithm. The predictions given by decision tree are re-organized by K-means, based on which the decisive thresholds in the tree are re-estimated. In [17], the authors train a classifier for each user. The ensemble classifiers are then weighted based on the error they make using the target user's data. While in the semi-supervised area, unlabelled examples classified with high confidence are added to the training dataset to retrain and refine the model. Examples are self-training, co-training [23] and label propagation [22]. The problem of aforementioned methods is that only high-confidence examples are considered, due to the fact that they can minimize the entropy [6]. However, high-confidence examples are less informative and make less contribution to the convergence of the model [23], especially for discriminative classifiers which perform classification based on the boundaries (i.e. hyperplanes in SVM), high-confident examples are normally far wary from the boundaries and are unhelpful for the boundaries adjustment. More importantly, those methods are built with statically defined input and are not suitable to cope with emerging context in dynamic environments.

Some other work leverage the knowledge-based method to deal with unseen data sources for activity recognition. For example, Tapia et al. [25] address the problem of *model incompleteness* by leveraging external knowledge base to measure the similarity between unseen features (object) and existing features, so that they are able to obtain the probability of an unseen object given the activity classes. While in [27], the authors perform activity recognition based on the object usage and human actions. With no label for the action data, they use common sense knowledge to build an activity model by jointly training Dynamic Bayesian Network and Virtual AdaBoost. They leverage common sense and Dynamic Bayesian Network (DBN) to derive most likely sequence for the accelerometer data. The sequence together with the accelerometer data is then fed to VirtualBoost to learn the action model, which in turn is combined with DBN to recognize activity. Those methods, however, rely heavily on existing knowledge to activity recognition. In this light, they are not applicable in the situation that we have no prior knowledge about dynamically discovered data sources.

Other research even performs activity recognition with dynamic sensor selection or information fusion. For example, in [9], the authors generate multiple processing plans for the context to be monitored. The system dynamically updates the processing plans when sensors are newly registered or de-registered. The logical processing plans represent a set of processing modules (i.e. feature extraction, classification modules) to derive the context while physical processing plans associate logical processing plans with different sensors and computing sources. Specifically, their system tries to achieve a desired classification accuracy while prolonging the system lifetime by minimizing the number of activated sensors. In another work, Zappi et al. [32] introduce a scheme to dynamically select the sensor set for activity recognition in order to achieve the trade-off between accuracy and power. Since those work mainly focus on the aspect of energy-efficiency, they simply train each activity with all the available sensors, so that when the sensors are registered at runtime, the system already has the knowledge of how to post-process the sensor data, hence this limits the scalability of the system. Gjoreski et al. [5] propose a novel context-based approach (CoReAmI) to address the problem of combining multiple sources of information extracted from sensor data. However, instead of addressing existing problems, the proposed methods in this paper target a completely different problem of incorporating dynamically available sensor modalities.

Our system varies from other research in numerous aspects. Existing activity recognition system relies on a static model that makes the assumption of definitive input from the data sources, while we also consider dynamically available contextual information for activity model refinement and adaptation. Previous activity models usually intake high-confident examples for model adaptation, while we propose a method to identify the most profitable examples without human intervention. Finally, instead of viewing activity examples as independent individuals, we exploit the temporal characteristic of human behaviours in different stages of our system to improve recognition accuracy.

3. Framework

In this section, we will introduce our framework. The workflow of our system can be divided into three phases: *modelling*, *learning*