Microprocessors and Microsystems 52 (2017) 381–390

Contents lists available at ScienceDirect

Microprocessors and Microsystems

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

Optimizing the configuration of an heterogeneous architecture of sensors for activity recognition, using the extended belief rule-based inference methodology

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ARTICLE INFO

Article history:
Received 6 February 2016
Revised 4 September 2016
Accepted 30 October 2016
Available online 5 November 2016

Keywords:
Heterogeneous architecture of sensors
Optimization
Efficient power-aware
Activity recognition
Ambient intelligence
Feature selection
Data-driven

ABSTRACT

Smart environments are heterogeneous architectures with a broad range of heterogeneous electronic devices that are with high in processing capabilities for computing, considering low power consumption. They have the ability to record information about the behavior of the people by means of their interactions with the objects within an environment. This kind of environments are providing solutions to address some of the problems associated with the growing size and ageing of the population by means of the recognition of activities that can offer monitoring activities of daily living and adapting the environment. In order to deploy low-cost smart environments and reduce the computational complexity for activity recognition, it is a key issue to know the subset of sensors which are relevant for activity recognition. By using feature selection methods to optimize the subset of initial sensors in a smart environment, this paper proposes the adaption of the extended belief rule-based inference methodology (RIMER+) to handle data binary sensors and its use as the suitable classifier for activity recognition that keeps the accuracy of results even in situations where an essential sensor fails. A case study is presented in which a smart environment dataset for activity recognition with 14 sensors is set. Two optimizations with 7 and 10 sensors are obtained with two feature selection methods in which the adaptation of RIMER+ for smart environment provides an encouraged performance against the most popular classifiers in terms of robustness.

1. Introduction

The number of elderly will reach 2 billion by the year 2050 and a key issue for this people is to stay as long as possible in their own homes in order to have a healthy ageing and wellbeing [44,45]. One of the most common diseases in this group is related to cognitive processes such as dementia. These illnesses are currently incurable; hence efforts are focused towards delaying their progression. In the early stages of dementia, it is useful to provide support in the form of prompting through the completion of activities of daily living (ADL) in addition to offering a series of reminders for tasks such as medication management, eating or grooming [12,19,25].

Smart environments are built heterogeneous architectures with a broad range of multiples and different electronic devices that are with high in processing capabilities for computing, considering low power consumption. These environments have the ability to record information about the behavior of the person by means of his/her interaction with the objects within an environment [8]. So, smart environments are residences with a heterogeneous architecture of sensor in which sensors are connected to a range of objects or locations and networked and used to identify people in the environment and their actions [5]. This kind of environments are adapted to perceive the user contexts in order to help people in their ADL providing a smart solutions to address some of the problems associated with the growing size of the population.

The sensor-based activity recognition [1,5,31,35,48] is at the core of smart environments. So, the process of activity recognition aims to recognize the actions and goals of one or more person within the environment based on a series of observations of actions and environmental conditions. It can, therefore, be deemed as a complex process that involves the following steps: (i) to choose and deploy the appropriate sensors to objects within the smart

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http://dx.doi.org/10.1016/j.micpro.2016.10.007
0141-9331/

environment; (ii) to collect, store and process information and, finally, (iii) to classify activities from sensor data through the use of computational activity models.

Traditionally, approaches used for sensor-based activity recognition have been divided into two main categories: Data-Driven (DDA) and Knowledge-Driven (KDA) Approaches [5].

The former, DDA, are based on machine learning techniques in which a pre existent dataset of user behaviors is required. A training process is carried out, usually, to build an activity model which is followed by testing processes to evaluate the generalization of the model in classifying unseen activities [21,41]. The advantages of the DDA are the capabilities of handling uncertainty and temporal information. However, these approaches require large datasets for training and learning, and suffer from the data scarcity or the cold start problem [5].

Regarding KDA, an activity model is built through the incorporation of rich prior knowledge gleaned from the application domain, using knowledge engineering and knowledge management techniques [5,7]. KDA has the advantages of being semantically clear, logically elegant, and easy to get started. Nonetheless, they are weak to deal with uncertainty and temporal information as well as the activity models can be considered as static and incomplete.

In order to the take advantage of the main benefits provided by DDAs and KDAs and to avoid some of their common disadvantages, some hybrid approaches have been developed such as the extended belief rule-based inference methodology (RIMER+) that was proposed in [34]. Knowledge Base of RIMER+ is based on Extended Belief Rule-Bases (E-BRB), which are able to capture (i) sample data and expert knowledge in a homogeneous way; (ii) nonlinear and causal relationships; and (iii) several types of uncertainty related to expert knowledge and data.

In the literature, we can find multiple smart environments with different heterogeneous architectures that are equipped with a large set of multiple and different sensors in order to carry out an activity recognition process. For example in the smart environment presented in [9] are involved 39 sensors and in the smart environment shown in [47] are involved 52 sensors. Although there has been significant progress in sensor-based activity recognition with promising results, which offer improvements with the problems associated with the growing size of the population, it still remains expensive to deploy a full set of sensors within a smart environment [36,50].

Therefore, the selection of an appropriate set of the sensors in the heterogeneous architecture, which are placed in objects within the environment, is an important issue in order to effectively monitor and capture the user's behavior along with the state change of the environment. This selection has a direct influence on the sensor data that will be used in the activity classification process. So, the current challenge is to know what configuration of initial sensors is the essential for activity recognition, i.e., the optimization of sensors in the heterogeneous architecture on a smart environment. This optimization process should imply the selection of a subset of the original sensors without loss of accuracy for activity recognition, even if one of the essential sensors fails because there are any technical failure or any sensor are deactivated, subsequently returning wrong values.

Feature selection methods [13] provide a way to select a subset of relevant features to generate a classifier or a model from a dataset obtained from a real process. Thus, these methods can identify which of the features are relevant or if there are interdependency relations between them. The use of feature selection methods in smart environments has been conducted in some studies [17,18,20]. However, none of them has shed light on the classifier which should be used in conjunction with feature selection methods in order to keep the accuracy, providing robustness.

In this paper, we focus on the use of feature selection methods to optimize the subset of initial sensors for activity recognition in a smart environment with binary sensor in order to reduce costs from a technology perspective, maintaining accuracy for activity recognition as well as reducing the computational complexity. Furthermore, this paper suggests the adaptation of RIMER+[34] like an approach for activity recognition, which is called R+DRAH. This new adaptation is focused on handle binary sensor data due to the fact the traditional RIMER+ works with values between 0 and 1. So, this new version offers accuracy in a smart environment for activity recognition with binary sensor optimization, being also robust in situations in which a relevant sensor fails. A case study for activity recognition, in which two optimizations of sensors are obtained using feature selection, is carried out. An evaluation of R+DRAH against the most popular DDA classifiers is performed, considering the situation when a sensor failure in order to provide robustness.

The remainder of the paper is structured as follows: Section 2 presents related works in the activity recognition area. Section 3 reviews RIMER+ that will be used in our proposal. Section 4 discusses how RIMER+ is adapted in R+DRAH to focus specifically on works in smart environments. Section 5 discusses the feature selection methods in order to optimize the set of sensors within a smart environment. Section 6 presents an empirical study which analyzes two feature selection methods for the purpose of sensors optimization for activity recognition with R+DRAH, considering the situation when a sensor failure in order to evaluate and analyze the robustness.

2. Background

In this section, the basic notions to understand our proposal are reviewed.

2.1. Sensor-based activity recognition

Advances in sensors technology developments have encouraged research on the problem of activity recognition based on processing data obtained by sensors [5]. In order to interpret the sensor data to infer activities, it is necessary to build activity models. In this section, we review the approaches to build activity models.

Activity models can be built by means of DDA or KDA. Both approaches are reviewed in the following subsections:

2.1.1. Data-driven approaches

The DDA learn activity models from preexistent large-scale datasets of users' behaviors using data mining and machine learning techniques. These approaches imply the generation of probabilistic or statistical activity models by means of training and learning processes. So, the activity inference is based on a probabilistic or statistical classification.

Some of the most popular classifiers based on DDA approaches are briefly reviewed below:

- Naive Bayes classifier (NB) [16]. The basic idea in NB classifier is to use the joint probabilities of sensors and activities to estimate the category probabilities given a new activity. This method is based on the assumption of sensor independence, i.e. the conditional probability of a sensor given an activity is assumed to be independent of the conditional probabilities of other sensors given that activity.
- Nearest Neighbor (NN) [11]. This classifier is based on the concept of similarity [7] and the fact that patterns which are similar, usually, have the same class label. An unlabeled sample is classified with the activity label corresponding to the most frequent label among the k nearest training samples.