Towards the Combination of Statistical and Symbolic Techniques for Activity Recognition

Extended Abstract

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I. Introduction

Techniques for activity recognition are fundamental components of any context-aware system. Indeed, precise knowledge of the user's current activity is necessary in order to thoroughly tailor services to the user's context.

To this aim, in the last years many research efforts have been devoted to devise statistical techniques for recognizing basic physical activities based on data retrieved from body-worn sensors (e.g., [1], [2], [3]). An intriguing research issue is how to integrate those statistical techniques with symbolic ones in order to *i)* refine statistical predictions, and *ii)* derive more complex activities. The intuition behind this research direction is that the current user's context (e.g., artifacts and persons in the user's surrounding environment) may give useful hints about the possible activities performed by the user herself. Given an ontology that models the addressed scenario, those hints can be automatically derived through ontological reasoning and used to refine the prediction of the statistical classifier. Moreover, ontological reasoning can be performed to derive complex activities described in terms of simpler activities and symbolic constraints about the user's context (like, e.g., in [4]). For instance, one possible condition to recognize the activity *giving a class* is the case in which the user is a teacher, the user's current location is a classroom, some students are in the classroom, and the user is writing on a blackboard.

At the EveryWare Lab[1] of the University of Milano we are working on a comprehensive framework to address these research issues by means of a systematic combination of ontological reasoning and statistical activity recognition techniques. After having highlighted research issues and reviewed related works, Marc Weiser's *Sal* scenario[2] will be used throughout the talk as a running example to illustrate our proposed solution. Then, preliminary experimental results will be presented, and open issues, as well as future research directions, will be discussed.

[1]http://everywarelab.dico.unimi.it/
[2]http://nano.xerox.com/hypertext/weiser/SciAmDraft3.html

II. A framework for combining ontological reasoning and statistical activity recognition

The proposed activity recognition framework is graphically depicted in Figure 1. The lower layer (SENSORS) includes body-worn sensors (providing data such as accelerometer readings and physiological parameters) and sensors spread in the environment.

Data provided by environmental and body-worn sensors are communicated through a wireless connection to the USER MOBILE DEVICE, and merged with sensor data retrieved by the device itself (e.g., data provided by an embedded accelerometer) to build a *feature vector* that will be used by a statistical classifier to predict the current user's activity. The device also continuously keeps track of the current physical location provided by a GPS receiver. When the GPS reading is not available or not sufficiently accurate (e.g., indoor), localization is performed by an external LOCATION SERVER (e.g., a GSM triangulation system provided by the network operator, or an RFID system). The GIS module is in charge of mapping the physical location reading to the most specific symbolic location that correspond to that physical location. This information will be used by the COMBINED ONTOLOGICAL/STATISTICAL ACTIVITY RECOGNITION (COSAR) module to refine the statistical predictions, since location can give useful hints about which activities a user can or cannot perform. Note that the framework can be easily extended to consider other context data than location. The COSAR module

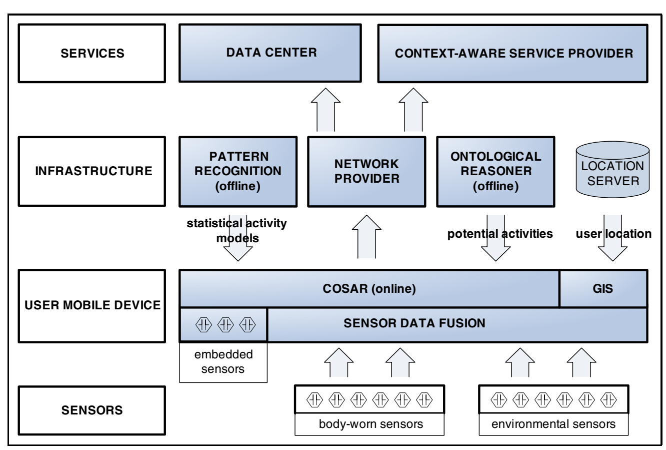

Fig. 1. The proposed activity recognition framework

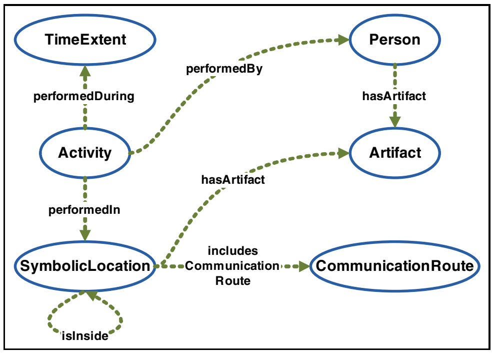

Fig. 2. The core of the defined ontology

takes advantage of a novel OWL-DL [5] ontology to represent and reason with activities, symbolic locations, communication routes, artifacts, persons and time granularities, as well as relations and constraints among them. The main classes and properties of the defined ontology are graphically depicted in Figure 2. For instance, the ontological definition of the activity BRUSHINGTEETH is:

$$\text{BRUSHINGTEETH} \sqsubseteq \text{PERSONALACTIVITY} \sqcap \forall\, \text{PERFORMEDIN}.\,(\,\exists\, \text{HASARTIFACT.SINK}\,) \sqcap \ldots$$

According to the above definition, BRUSHINGTEETH is a subclass of PERSONALACTIVITY that can be performed only in locations that contain a SINK (that is defined as a subclass of WATERFIXTURE); other restrictions may follow, but they are not considered here for simplicity. Hence, by performing ontological reasoning the COSAR module can determine that BRUSHINGTEETH is not a possible activity if a user is, e.g., inside a room that does not include water fixtures; on the contrary, it is a possible activity if the user is inside a rest room.

Ontological reasoning is performed offline by the INFRASTRUCTURE layer, which also includes a PATTERN RECOGNITION module that is in charge of deriving a statistical model of the considered activities. The results of ontological reasoning and pattern recognition are communicated offline to the COSAR module. In addition, the infrastructure layer includes a network provider offering the connectivity necessary to exchange data between modules at different layers, and, in particular, to communicate activity information to remote data centers and context-aware service providers.

III. Preliminary Results

At the time of writing, a prototype of the proposed framework has been implemented. In this preliminary implementation, accelerometer data are retrieved using *Small Programmable Object Technology (SPOT)* by Sun® Microsystems. SPOTs are shown in Figure 3 together with the used GPS receiver. Since SPOTs lack a Bluetooth interface it is not possible to directly connect them with a mobile device. Hence, sensor readings are stored on the sensors themselves, and communicated offline to the COSAR algorithm to perform classification. The COSAR algorithm is implemented in Java. In order to perform statistical pattern recognition, it

Fig. 3. Sensors used in the preliminary implementation

takes advantage of *Weka*[3], a Java-based toolkit that provides APIs for implementing several machine learning algorithms. Ontological reasoning is performed by means of the *RacerPro*[4] Java libraries.

Preliminary experiments have been conducted, concerning the recognition of 10 different activities performed both indoor and outdoor by 6 volunteers wearing one sensor on their left pocket and one sensor on their right wrist to collect accelerometer data, plus a GPS receiver to track their current physical location. This setup reproduces the situation in which data are acquired from an accelerometer embedded in a fitness watch, and from an accelerometer and a GPS receiver embedded in a mobile phone. Since in the current implementation of this framework the GIS module is only simulated, physical locations were manually mapped to symbolic locations. Preliminary results show that the COSAR technique significantly outperforms solely statistical techniques in terms of activity recognition rates without introducing significant computational overhead at run time.

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[3] http://www.cs.waikato.ac.nz/ml/weka/
[4] http://www.racer-systems.com/