Multisensor Data Fusion for Activity Recognition Based on Reservoir Computing

Filippo Palumbo[1,2], Paolo Barsocchi[1], Claudio Gallicchio[2], Stefano Chessa[1,2], and Alessio Micheli[2]

[1] ISTI Institute of CNR, Pisa Research Area, via Moruzzi 1, I-56124, Pisa, Italy
{filippo.palumbo,paolo.barsocchi,stefano.chessa}@isti.cnr.it
[2] Computer Science Department, University of Pisa, Pisa, Italy
{palumbo,gallicch,ste,micheli}@di.unipi.it

Abstract. Ambient Assisted Living facilities provide assistance and care for the elderly, where it is useful to infer their daily activity for ensuring their safety and successful ageing. In this work, we present an Activity Recognition system that classifies a set of common daily activities exploiting both the data sampled by accelerometer sensors carried out by the user and the reciprocal Received Signal Strength (RSS) values coming from worn wireless sensor devices and from sensors deployed in the environment. To this end, we model the accelerometer and the RSS stream, obtained from a Wireless Sensor Network (WSN), using Recurrent Neural Networks implemented as efficient Echo State Networks (ESNs), within the Reservoir Computing paradigm. Our results show that, with an appropriate configuration of the ESN, the system reaches a good accuracy with a low deployment cost.

Keywords: AAL, Activity Recognition, Neural Networks, Sensor Data Fusion, WSN.

1 Introduction

Activity Recognition (AR) is an emerging field of research, that takes its motivations from established research fields such as ubiquitous computing, context-aware computing and multimedia. Recognizing everyday life activities is a challenging application in pervasive computing, with a lot of interesting developments in the health care domain, the human behavior modeling domain and the human-machine interaction domain [1]. From the point of view of the deployment of the activity recognition solutions, we recognize two main approaches depending on whether the solution adopts wearable devices or not. The solutions that make use of wearable devices are the more established and studied. In these solutions the wearable devices are generally sensors (for example embedding accelerometers, or transducers for physiological measures) that make direct measures about the user activities. For example, a sensor placed on the user ankle may detect the number of steps based on the response of an embedded accelerometer that is shaked with a specific pattern every time the user makes

J.A. Botía et al. (Eds.): EvAAL 2013, CCIS 386, pp. 24–35, 2013.

a step. On the other hand, the disadvantage of this approach is that wearable devices can be intrusive on the user, even if, with recent advances in technologies of embedded systems, sensors tend to be smaller and smaller. Solutions that avoid the use of wearable devices instead, are motivated by the need for a less intrusive activity recognition systems. Among these solutions, those based on cameras are probably the most common [2]. However, even though this approach is physically less intrusive for the user, it suffers from several issues: low image resolution, target occlusion and time-consuming processing, which is still a challenge for real-time activity recognition systems. Furthermore, user privacy is also an important issue, especially if cameras are used to continuously monitor the user itself. More recently, a new generation of non wearable solution is emerging. These solution exploits the implicit alteration of the wireless channel due to the movements of the user, which is measured by devices placed in the environment and that measure the Received Signal Strength (RSS) of the beacon packets they exchange among themselves [3]. In our activity recognition system we use a mix of the two approaches. Specifically we use both wearable and environmental sensors and we base the recognition of the user activity both on accelerometers embedded on the wearable sensors and on the RSS of the beacon packets exchanged between all the sensors (both wearable and environmental). A second important achievement of our system is the use of a distributed machine learning approach, in which the sensors themselves perform activity classification by using embedded learning modules. Specifically, in the class of Recurrent Neural Network, we take into consideration the efficient Reservoir Computing (RC) [4] paradigm in general, and the Echo State Network (ESN) [5, 6] model in particular. In order to support distributed neural computation on the sensors we use a Learning Layer: a software component developed within the framework of the Rubicon project [7] that implements a distributed ESN embedded in the sensors and in more powerful devices such as PCs or gateways. We base our approach on some recent works [8–10] that classify activities based on accelerometer (in fact, accelerometers have been widely accepted due to their compact size, their low-power requirement, low cost, non-intrusiveness and capacity to provide data directly related to the motion of people) and on some of our recent works in which we used RSS and neural networks to make predictions on user movements [11–16]. To the best of our knowledge, this is the first work that investigates the use of common wireless sensor devices deployed in the environment in combination with wearable sensors embedding accelerometers, in order to increase the performance of the activity recognition system. The rest of the paper is organized as follows. Section 2 presents a reference scenario, Section 3 describes the overall architecture of the activity recognition system, and Section 4 anticipates some experimental results about the performance of our system. Finally, Section 5 draws the conclusions.

2 Scenario

The main objective of the proposed system is to implement an activity recognition system (ARS) that recognizes the following activities: Walking, standing