Pervasive and Mobile Computing 30 (2016) 84–96

Contents lists available at ScienceDirect

Pervasive and Mobile Computing

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

Segmenting human activities based on HMMs using smartphone inertial sensors

Rubén San-Segundo *, Jaime Lorenzo-Trueba, Beatriz Martínez-González, José M. Pardo

Speech Technology Group, E.T.S.I. Telecomunicación, Universidad Politécnica de Madrid, Spain

HIGHLIGHTS

- Human Activity Recognition and Segmentation using Hidden Markov Models.
- Hidden Markov Models configuration analysis.
- Activity sequence modeling.

ARTICLE INFO

Article history:
Received 21 July 2015
Received in revised form 9 October 2015
Accepted 7 January 2016
Available online 18 January 2016

Keywords:
Human Activity Segmentation
Hidden Markov Models
Smartphone inertial sensors
Activity Sequence Model

ABSTRACT

This paper describes the development of a Human Activity Recognition and Segmentation (HARS) system based on Hidden Markov Models (HMMs). This system uses inertial signals from a smartphone to recognize and segment six different physical activities: walking, walking-upstairs, walking-downstairs, sitting, standing and lying down. All the experiments have been done using a publicly available dataset called UCI Human Activity Recognition Using Smartphones. The developed system improves the results obtained on this dataset in previous works. The main contribution of this paper is the incorporation of an Activity Sequence Model. The best results show an Activity Segmentation Error Rate of 2.1%.

1. Introduction

Using sensors (such as thermostats or photocells), computers can perceive environmental aspects: temperature or the lighting conditions of a room. Research into multisensor networks has increased significantly recently due to the reduction in the price of the sensor. These networks typically include cameras, indoor location systems (ILS), microphones, etc. Thanks to the information obtained from the sensors, computer-based systems can take more intelligent actions by adapting their behavior to the conditions of the context. In this respect, a possible application of sensor processing is the detection or recognition of different situations. When the number of situations is known, this application can be seen as a classification problem: some features are obtained from sensor signals and several models are generated for every different situation.

Thanks to the increase in sensor neural networks, the number of possible areas of research has also increased rapidly. One of these areas is Human Activity Recognition (HAR): the recognition of physical human actions. This area of research has attracted a lot of attention in the last 5 years due to the large number of promising applications and the increasing interest shown by government and commercial organizations. Based on this interest, several approaches have been proposed in the

* Correspondence to: E.T.S.I. Telecomunicación, Ciudad Universitaria SN, 28040 Madrid, Spain.
E-mail address: ruben.sansegundo@upm.es (R. San-Segundo).

http://dx.doi.org/10.1016/j.pmcj.2016.01.004
1574-1192/

literature for the recognition of human activities applied to different application domains such as healthcare [1,2], smart homes, ubiquitous computing, ambient-assisted living, surveillance, security [3–5], and manufacturing [6].

Smart Homes currently allow disabled and elderly patients to enjoy a continuous health and well-being supervision while they carry out Activities of Daily Living (ADL) at home. In general, these new homes incorporate new multimodal technologies including environmental sensors, user interfaces, computing devices and actuators. The main aspects to consider when developing these advanced homes are to guarantee an accurate supervision and a fast response in case of dangerous situations. These two aspects are especially relevant when monitoring people with frailty or chronic diseases such as Parkinson's disease (PD), Alzheimer patients [7] or visual impairments. For example, when a patient falls, the system must alert a nurse as soon as possible or, if the patient is doing an activity which is not permitted, alerting security staff [8].

Another interesting HAR application is the *ubiquitous identification of physical activity*. Obesity is a general human problem resulting from physical inactivity. This aspect is one of the main worries of the US Department of Health and Human Services. This Department has found a high correlation between increased physical activity and a lower risk of heart disease, stroke, high blood pressure, type II diabetes and even particular forms of cancer. These diseases can give rise to a significant financial loss: coronary heart disease and type II diabetes among Americans cost more than $250 billion [9]. In Europe, the total cost of coronary heart disease in the EU during 2003 was €44.7 billion ($56.5 billion) [10]. Thus, an interesting application comes about: monitoring physical activity, or the lack thereof.

This paper presents the development of a Human Activity Recognition and Segmentation (HARS) system using Hidden Markov Models (HMMs) to model inertial signals from a smartphone. This system incorporates an Activity Sequence Model (ASM) that allows the system performance to be improved. This paper is organized as follows. Section 2 describes the background. Section 3 summaries the main works using HMMs for HARS and highlights the differences and contributions of this paper. Section 4 describes the dataset and evaluation metrics used in this work. Section 5 presents an overview of the HMMs-based HARS system, describing the main modules. Section 6 includes the different analyses carried out for obtaining the best system configuration, and describes the incorporation of an Activity Sequence Model (ASM) into the system. The final results and discussions are presented in Section 7. Finally, Section 8 summarizes the main conclusions of this work.

2. Background

In the literature, there are several systems for HAR covering diverse application domains. These approaches can be categorized according to many different criteria: by sensor type, which is reliant on the signals measured (e.g. inertial, vision-based and physiological [11]); by sensor location, namely external sensing in which sensors are located in fixed positions in the environment, and wearable sensing when they are body-attached [12]; by a modeling principle, which can be data- or knowledge-driven depending on whether the HAR models are built given pre-existing datasets or from the exploitation of prior knowledge regarding a particular domain [13,14]; by a learning approach, which can be either supervised, semi-supervised or unsupervised [15–17]. This work focuses on developing a supervised HARS system.

Smartphone-based applications have advantages when compared with other well-known wearable HAR alternatives that use special-purpose devices or on-body sensor networks [18,19]. These advantages are the ease of device portability, the unobtrusive sensing provided by its embedded sensors and the processing power of new smartphones that allow online computation. Because of this aspect, in the last 5 years, some works focusing on HAR using smartphones have been developed: for instance in [20], the authors approach to using a smartphone for HAR considers its embedded triaxial accelerometers; additional results have also been presented in [15,21–24].

Human Activity Recognition and Segmentation can be seen as a pattern recognition problem, where a system extracts features from sensor signals, generates a model for each activity, and classifies the following activities based on these models. Machine Learning approaches that have already been applied to the recognition of activities include Naive Bayes [25], Markov Chains [18], Decision Trees [26], and Support Vector Machines (SVMs) [27]. Yang [28] uses the WEKA learning toolkit to compare the accuracy rates of several machine learning approaches: C4.5 Decision Trees, Naïve Bayes, k-Nearest Neighbor, and Support Vector Machines. The study found that vertical and horizontal features are more relevant for activity recognition than magnitude features alone. This feature set coupled with the C4.5 algorithm achieved 90.6% accuracy, using a ten-fold cross validation. In [29], the authors describe an approach for human activity detection using a smartphone accelerometer paired with a dedicated chest sensor. Some analyses was carried out to compare several pattern recognition algorithms: including C4.5, CART, SVM, Multi-Layer Perceptrons, and Naïve Bayes. In [15,22], data was collected from twenty-nine users using an Android phone while performing six different activities: Walking, Jogging, Stairs-Up, Stairs-Down, Sitting, and Standing. Three learning algorithms were evaluated: Logistic Regression, J48, and Multilayer Perceptron. According to their results, the overall accuracy is above 90%. For Stairs-Up vs. Stairs-Down the classification problem is harder. Another conclusion is that the neural network classification can detect Jogging and Stairs-Up better while J48 can effectively detect the other activities. Bayat et al. [30] expands these works by considering new human activities such as slow vs. fast walking or aerobic dancing.

In the literature, there are many works on human activity recognition but the segmentation problem is also very important [31]: to detect the initial and final times of one activity. There are some works on segmenting human activities [32] but not so many based on inertial signals (see the following section for more details). Detecting these times can provide advanced functionality to HAR systems: to know when users perform some actions, or how long a patient has been doing some specific activity.