Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 96 (2016) 672 – 681

Procedia Computer Science

20th International Conference on Knowledge Based and Intelligent Information and Engineering Systems

Activity detection in smart home environment

Pavle Skocir*, Petar Krivic, Matea Tomeljak, Mario Kusek, Gordan Jezic

University of Zagreb, Faculty of Electrical Engineering and Computing, Internet of Things Laboratory, Unska 3, HR-10000 Zagreb, Croatia

Abstract

Detection of human activities is a set of techniques that can be used in wide range of applications, including smart homes and healthcare. In this paper we focus on activity detection in a smart home environment, more specifically on detecting entrances to a room and exits from a room in a home or office space. This information can be used in applications that control HVAC (heating, ventilation, and air conditioning) and lighting systems, or in Ambient Assisted Living (AAL) applications which monitor the people's wellbeing. In our approach we use data from two simple sensors, passive infrared sensor (PIR) which monitors presence and hall effect sensor which monitors whether the door is opened or closed. This installation is non-intrusive and quite simple because the sensor node to which sensors are connected is battery powered, and no additional work to ensure power supply needs to be performed. Two approaches for activity detection are proposed, first based on a sliding window, and the other based on artificial neural network (ANN). The algorithms are tested on a dataset collected in our laboratory environment.

Peer-review under responsibility of KES International

Keywords: event recognition; activity detection; data filtering; Internet of Things

1. Introduction

Rapidly increasing number of physical devices that are connected to the Internet enables accelerated development of Internet of Things (IoT) applications that can improve our quality of lives[1]. By the end of 2020 it is expected that 20 billion connected devices will be deployed, while in 2016 the number of connected devices in use is 6.4 billion[2]. Applications that use connected devices can be grouped into three main domains[3]: industrial domain, smart cities domain, and health & well-being domain.

Smart homes as a part of smart cities domain are often mentioned in the surveys that focus on IoT[1,3,4]. By connecting devices as thermostats to the Internet, home automation systems enable remote control of HVAC (heating, ventilation, and air conditioning) systems via web or mobile applications. Additionally, within smart grid devices can suggest optimizations of energy consumption by creating a schedule by which home appliances are turned on at the time of more favorable tariffs. Certain applications enable even more advanced capabilities, such as controlling home appliances according to user location. For instance, turning on the heating when user is on her/his way home,

* Pavle Skocir, MSc. Tel.: +385-1-6129-838; fax: +385-1-6129-832.
E-mail address: pavle.skocir@fer.hr

Peer-review under responsibility of KES International
doi:10.1016/j.procs.2016.08.249

or turning on the lights and multimedia system when a user enters the room. Advancements in sensing technologies, embedded processors and communication systems also enhanced integration of independent living services from the health domain within a smart home setting[5]. These services are often referred to as Ambient Assisted Living (AAL) and their main goal is to determine the wellness of elderly people, people with disabilities, or people with acute or chronic pathologies living independently in their home[6].

Wellness of people can be inferred by monitoring activities of daily living (ADL). These activities can be detected by capturing and analyzing time series sensor data originating from various smart sensors of AAL, e.g. motion detectors, heart rate monitors or similar. Activities that could be detected include sleeping, eating, toileting, relaxing, watching TV[5,7], or entering and exiting a home[8]. Detected activities can further be analyzed to detect patterns in behavior by applying machine learning techniques. During regular operation, algorithms detect changes in pattern behaviour which might be an indication of a problem and a trigger for alerting emergency services.

This work focuses on one particular activity within a smart home that can be used for AAL purposes, detection of entrances and exits to and from a room in a home or an office space. By having this information, HVAC or lighting systems can be controlled, or wellness of users can be monitored (e.g. if user stays for too long in a bed in her/his bedroom might imply a problem with user's health). We want to detect these activities by using two simple sensors, passive infrared sensor (PIR) which monitors presence and hall effect sensor which monitors whether the door is opened or closed. The sensors are connected to a battery-powered sensor node, that can be referred to as M2M device[9]. This installation is non-intrusive, it allows residents to stay in their home or office without any intrusion. Furthermore, the installation of the M2M device with sensors is quite simple because the M2M device is battery powered, and no additional work to ensure power supply needs to be performed. This is convenient especially for implementation in homes of elderly people who reluctantly accept even minor construction works in their homes. However, the fact that devices do not have access to unlimited power supply requires taking energy efficiency into account. This particular topic has been in focus of our previous work[9,10,11].

Section 2 describes related work in connection with activity detection. Section 3 presents our two approaches for detecting a particular type of activities, entrances and exits to and from a room. First approach is based on a sliding window, and the other on artificial neural network (ANN). Section 4 evaluates the effectiveness of the proposed approaches, while Section 5 presents concluding remarks.

2. Related work

Activity detection techniques have been widely researched and some of the findings focusing on smart home domain will be presented in this section. Before finding algorithms that could recognize activities in real time, research activities were focused on offline mechanisms which use static data sets, in which all the data is firstly stored and then analyzed. Hong and Nugent[12] focus on segmenting sensor data to extract each segment of consecutive sensor events associated with a complete activity. They detect using the toilet, taking a shower, leaving the house, going to bed and preparing meals. By taking into account correlations of locations, objects and sensors with activities being monitored, they propose three approaches to sensor stream segmentation: location-based approach, model-based approach and dominant centered model-based approach. All three algorithms showed similarly good performances for segmentation and activity classification. However, they point out that the increased prevalence of pervasive technologies such as mobile phones, tablet computers and wireless sensor networks could have an impact on these algorithms since they are all based on mappings between objects and activities, and between locations and activities.

Tao Gu et al.[13] present a way to avoid usual supervised learning phase in the machine learning process for activity recognition. They base their algorithm on object-use fingerprints and test it on various everyday activities such as: making coffee, making phone calls, washing clothes, taking pills, reading books, just to mention a few. The main idea is to retrieve objects used in a specified activity from the Web and identify the relevance weight for each retrieved object. Since activities may share common objects, it is also necessary to mine a set of contrast patterns from object terms and their relevance weights for each activity class. Segmenting data is done using the sliding window combined with "MaxGap" and "MaxGain" segmentation heuristic algorithms to determine the beginning and ending of activity. The result shows that this recognition algorithm achieves precision of 91.4%, which is almost as good as hidden Markov model algorithm which includes a learning phase (93.5%).