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Classification and suitability of sensing technologies for activity recognition

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ABSTRACT

Wider availability of sensors and sensing systems has pushed research in the direction of automatic activity recognition (AR) either for medical or other personal benefits e.g. wellness or fitness monitoring. Researchers apply different AR techniques/algorithms and use a wide range of sensors to discover home activities. However, it seems that the AR algorithms are purely technology-driven rather than informing studies on the type and quality of input required. There is an expectation to over-instrument the environment or the subjects and then develop AR algorithms, where instead the problem should be approached from a different angle i.e. what sensors (type, quality and quantity) a given algorithm requires to infer particular activities with a certain confidence? This paper introduces the concept of activity recognition, its taxonomy and familiarises the reader with sub-classes of sensor-based AR. Furthermore, it presents an overview of existing health services Telecare and Telehealth solutions, and introduces the hierarchical taxonomy of human behaviour analysis tasks. This work is a result of a systematic literature review and it presents the reader with a comprehensive set of home-based activities of daily living (ADL) and sensors proven to recognise these activities. Apart from reviewing usefulness of various sensing technologies for home-based AR algorithms, it highlights the problem of technology-driven cycle of development in this area.

1. Introduction

In the last two decades sensors have become cheaper, smaller and widely available, residing at the edge of the Internet. Some such examples are wearable personal activity (PA) trackers (e.g. Fitbit, Nike+ FuelBand, etc.). However, the available commercial off-the-shelf (COTS) sensors are only capable of ‘sensing’ a small subset of user activities—mostly outdoor sport activities (type of activity, distance covered, time taken, etc.) and estimation of additional information such as energy expenditure (either kcal or self-crafted metrics e.g. Nike’s fuel-points). However, a large part of our lives, and increasingly so in the advanced age, is spent in the home, yet very little is known about our activities and behaviour in there.

We are surrounded by a multitude of sensing devices and Mark Weiser’s vision of ubiquitous computing [120] is starting to materialise in the advances made in embedded networked systems currently addressed as the Internet of Things (IoT). The significant increase in devices streaming low-level information over the Web presents many new challenges. Whilst many researchers present this as a big data challenge, we believe that many of the environments and applications will require to justify the value and process relatively small data, making this a two-faceted problem requiring to consider the highly distributed, non-interoperable, small and relatively “lonely” data. Efficient and accurate activity recognition (AR) algorithms are needed in order to make sense of this data and provide useful/actionable information and services in the human activity monitoring context. However, the task of AR is not trivial and the reality is that not all user activities are recognisable using all available sensors and algorithms. Often we simply do not know what activities people do on daily basis. Self-reporting techniques i.e. asking people to log their own activities, do not always work and there is an increasing need for automation. If sensorised systems were capable of reporting on all user activities this would enable researchers to undertake a very broad range of clinical and longitudinal studies. An analysis of a single activity (e.g. walking) in isolation is often insufficient to judge on one person’s physical condition or to judge on the success of an intervention. Instead, researchers and doctors are in need to gain a complete picture/profile of a person to observe changes and relationships that arise over time.

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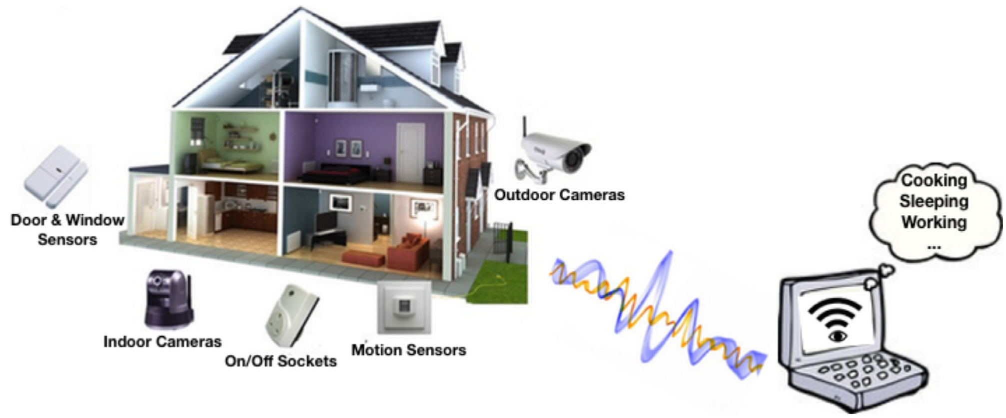

Fig. 1. From real-world to activity recognition via sensors.

This paper was motivated by the need to answer the question as to what are best sensor data and technologies in terms of their capability to support accurate recognition of a large set of activities of daily living (ADLs), and it is a result of a systematic literature review focused on works reporting using such technologies. It mainly focuses on *sensor-based* and not on the *vision-based* AR, however examples are also given from this field. Section 2 gives motivation for automatic activity recognition, describes the taxonomy of AR present in the literature, introduces health services, taking the example of the UK National Health Service (NHS) Telecare and Telehealth solutions, and provides an insight into subclasses of *sensor-based* AR. Section 3 introduces the hierarchical taxonomy of human behaviour analysis tasks and explains the origin of the dictionary of ADLs used in the analysis. Tasks and sub-tasks of ADLs are organised hierarchically and each category is analysed separately. The paper concludes with a discussion (Section 4) which summarises findings and highlights the problem of technology-driven AR algorithms development.

2. Background

According to the World Health Organization (WHO), between 2015 and 2050 the proportion of the world's population over 60 years will nearly double from 12% to 22% [122]. Only in the UK, in 2010 "10 million people were over 65 years old. The latest projections are for 5.5 million more elderly people in 20 years' time and the number will have nearly doubled to around 19 million by 2050" [28]. An ageing population and the increase in chronic illnesses such as diabetes, obesity, cardiovascular and neurological conditions have influenced research directing it towards sensor-based solutions. One of the medical conditions which affects a large proportion of each country's population is stroke—affecting 15 million people worldwide each year [124]. With so many elderly citizens and an ageing society, healthcare systems all over the world are at financial risk. New models of healthcare are needed, in which technology can be utilised not only to reduce the cost of care but also to assist elderly citizens' well-being and in living an independent life. NHS in England has brought to life 15 Academic Health Sciences Networks (AHSN) to mainly "deliver measurable gains in health and wellbeing" [112]. The NHS currently faces the problems of: reduced public funding, rising costs and increased demand; and sees the solution in inverting the current healthcare system towards personalised and decentralised healthcare [109]. Sensor technology is the main medium through which this patient-centric healthcare model can be accomplished.

Adaptation of sensor technology in order to satisfy healthcare requirements raises many challenges, ranging from the selection of suitable sensors and their (user) acceptance to finding efficient and reliable AR algorithms. How to select the suitable technology? How would a clinician or a researcher know which sensor is fit for a given purpose, bearing in mind some pre-determined constraints (e.g. cost, privacy constraints)?

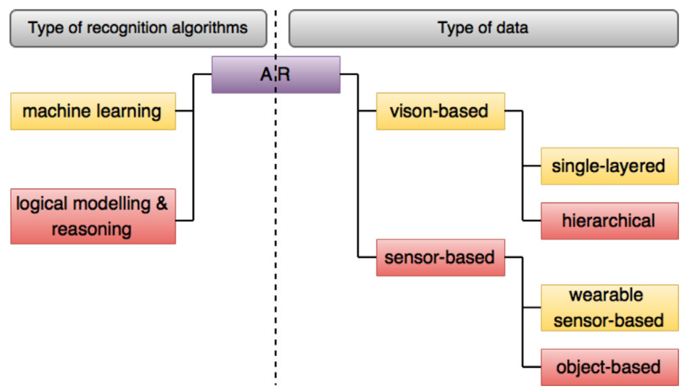

Fig. 2. Activity recognition taxonomies.

A sensor measures a single real-world parameter/variable and turns it into an analogue or digital signal. A single measurement may be useful for simple applications (e.g. temperature monitoring in the office) and may be sufficient to discover very simple events (e.g. fire in the office), but it is often insufficient for an automated system that can infer all the activities taking place in an area of interest. Therefore, a fusion of multiple sensor readings is often needed for an activity recognition system to reconstruct what has been captured—as visualised in Fig. 1. There are multiple ways of approaching AR, described in the reminder of this section. The strength of the IoT lies in the foundations of the Internet i.e. distribution of resources, support for common naming schema/ontologies, common access strategies, and availability of computational resource to mention a few. The challenge is to locate and fuse the right pieces of (sensor) information together in order to infer activities of interest at the best quality of information possible.

2.1. Activity recognition and taxonomy

Activity recognition is "the process whereby an actor's behaviour and his/her situated environment are monitored and analysed to infer the undergoing activities. It comprises many different tasks, namely activity modelling, behaviour and environment monitoring, data processing and pattern recognition" [24]. There are many approaches for delivering AR which have been classified by various taxonomies—as illustrated by Fig. 2. One classification is based on the data type the AR system processes and thus there are two main classes: *vision-based AR* and *sensor-based AR* [24,99].