Expert Systems with Applications 41 (2014) 6138–6146

Contents lists available at ScienceDirect

Expert Systems with Applications

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

Discrete techniques applied to low-energy mobile human activity recognition. A new approach

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ARTICLE INFO

Keywords:
Pattern recognition
Discretization method
Qualitative systems
Smart-energy computing
Energy saving

ABSTRACT

Human activity recognition systems are currently implemented by hundreds of applications and, in recent years, several technology manufacturers have introduced new wearable devices for this purpose. Battery consumption constitutes a critical point in these systems since most are provided with a rechargeable battery. In this paper, by using discrete techniques based on the Ameva algorithm, an innovative approach for human activity recognition systems on mobile devices is presented. Furthermore, unlike other systems in current use, this proposal enables recognition of high granularity activities by using accelerometer sensors. Hence, the accuracy of activity recognition systems can be increased without sacrificing efficiency. A comparative is carried out between the proposed approach and an approach based on the well-known neural networks.

1. Introduction

In recent years, thanks largely to the growing interest in monitoring certain sectors of the population, such as elderly people with dementia and people in rehabilitation, activity recognition systems have experienced an increase in both number and quality of results. However, most of these results incur high computational costs, and hence cannot be applied on a general-purpose mobile device due to their excessive energy consumption.

Although, the calculation of the physical activity of a user, based on data obtained from an accelerometer, remains a current research topic, numerous limitations have been identified that make these systems uncomfortable for users in general.

The first difference observed between the many systems developed is the type of sensor used. There are systems using specific hardware (Ravi, Dandekar, Mysore, & Littman, 2005), while others use general-purpose hardware (Hong, Kim, Ahn, & Kim, 2008). Obviously, the use of generic hardware constitutes a benefit for users, since their availability, low cost, and versatility are points greatly in their favour; not to mention the reduction in the risk of loss, since these devices have already been integrated into everyday objects, such as users' smartphones. However, general purpose devices are used for other purposes, such as making phone calls, surfing the Internet, and listening to music. For this reason, the physical activity recognition system must be executed in background mode and cause the least impact on the system as possible, in terms of complexity and energy consumption.

Another difference found between the proposals surveyed is the number and position of the sensors. In Brezmes, Gorricho, and Cotrina (2009), it can be observed that the accelerometer sensor is placed in a glove and a multitude of activities are recognized depending on the movement of the hand. In contrast, other studies use either various sensors placed on many parts of the body (Bicocchi, Mamei, & Zambonelli, 2010; Lepri, Mana, Cappelletti, Pianesi, & Zancanaro, 2010) or a wearable wireless sensor node with a static wireless non-intrusive sensory infrastructure (Paoli, Fernández-Luque, & Zapata, 2011) to recognize these activities. According to certain comparative studies and previous research based on multiple sensors, these last two types of sensors provide greater accuracy.

However, in studies, such as Hong et al. (2008), a sensor is kept in a user's pocket or worn on the hip, which is more wearable on the monitored person, and requires much lower infrastructure.

Once the most comfortable alternative for users is determined, some device sensors could be chosen to perform the activity monitoring. Some research uses data not only from accelerometers and a gyroscope (Dernbach, Das, Krishnan, Thomas, & Cook, 2012), but also from other sources, such as microphones, light sensors and voice recognition to determine the context of the user (Kwapisz, Weiss, & Moore, 2011) and ECG sensors (Li et al., 2010; Pawar, Chaudhuri, & Duttagupta, 2007; Ward, Lukowicz, Troster, & Starner, 2006) for this purpose.

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http://dx.doi.org/10.1016/j.eswa.2014.04.018
0957-4174/

The first example, which incorporates microphone and bluetooth devices, helps to obtain contextual information about the user environments and would be appropriate to perform a more in-depth analysis of the activity, for instance, whether the user is walking in a disco or at home, or whether s/he is alone or with someone. However, high-level activity recognition (walking, playing, running or standing up) is carried out using other sensors. On the other hand, ECG can help determine high-level activities by means of heart-rate processing. In this sense, certain activities (walking or running) could be discerned based on the effort exerted. However, the problem here is that ECG sensors are both expensive and uncomfortable for the user.

Thus, the present work is focused on the recognition of physical activities carried out by users by means of their mobile devices, and hence special attention must be paid to energy consumption and the computational cost of the methods used.

There are related studies where data for activity recognition is obtained through mobile devices where this data is sent to a server to process the information (Altun, Barshan, & Tunçel, 2010). In these cases, computational cost is no limitation and hence methods of a more complex nature can be used. In contrast, efficiency is a crucial issue when processing is carried out within the mobile device itself (Fuentes, Gonzalez-Abril, Angulo, & Ortega, 2012; Reddy et al., 2010).

Taking previous works into account, physical activity monitoring through smartphones presents the following challenges:

- To decrease, as far as possible, the risk of forgetting the processing device so that continuous monitoring can be performed anywhere and any time.
- To reduce the drain of energy on the smartphone, by developing an accurate and efficient system.
- To integrate learning and monitoring on the device itself, in realtime and without sharing server information.

In order to reduce the cost associated to accelerometer and gyroscope signal analysis, this paper opts for an innovative approach based on a discretization method that uses only accelerometer sensors since with these good results can be achieved and a lot energy can be saved (the more sensors used, the greater the consumption). Furthermore, the data is processed in the mobile itself, and therefore the efficiency is better than if data were sent to a server, and the result is obtained in real time. Thanks to this discretization process, the classification cost is much lower than it would be with continuous variables, and therefore the life of the battery is longer. It is therefore possible not only to eliminate the correlation between variables during the recognition process, but also to minimize the energy consumption of the process.

The remainder of the paper is organized as follows: Section 2 describes the method of data capture through the mobile device using an accelerometer sensor, and outlines all the physical activities that can be recognized by the system described. In Section 3, a new process, that discretizes continuous variables and provides classification, is presented. Section 4 shows a comparison between the new method and other methods used previously in the literature. Finally, in Section 5, a discussion is given on the various advantages of the proposed algorithm as well as on certain challenges and tasks that are currently being developed for the described recognition system.

2. Activity recognition

2.1. Embedded sensors and battery impact

Throughout this work, a KR3DM triaxial accelerometer integrated into a Google Nexus S is used. This sensor has a range of sampling frequencies between 25 Hz and 1500 Hz. Specific frequency is defined by each piece of software by using Android primitives. At these sampling rates, the device used for the testing process is configured to operate at 50 Hz in order to prevent excessive use of data and to reduce the computational cost. Therefore, based on the Nyquist–Shannon theorem, it can be ensured that signals with significant energy components below 25 Hz are liaison free. Depending on where the user takes the device, vibrations and any other kind of noise could be present with frequency components over 25 Hz, but these are of no interest in this work. However, the human-activity frequency range is much lower than the sampling band chosen. By using accelerometers taped to the body while running, Bhattacharya, McCutcheon, Shvartz, and Greenleaf (1980) found the main frequency components between 1–18 Hz at the ankle. As will be seen later, our work proposes placing the device at the hip, where acceleration forces are lower than at the ankle, and hence frequencies at this position are also lower.

On the other hand, a lower frequency allows the computation cost to be reduced thanks to the fact that each feature is obtained from accelerometry data. Furthermore, by reducing this processing time, the system becomes faster, more efficient and consumes less energy. Indeed, for contextual systems, with their intensive use of sensors, the high-energy consumption required must be taken into account not only in obtaining the data but also in its processing. A typical smartphone from the latest generation has a multitude of sensors that are commonly used, such as GPS (Morillo, Ramirez, Garcia, & Gonzalez-Abril, 2012), NFC, and a microphone. This means that, as result of high energy consumption, the useful time between device charges remains very low.

By applying Moore's law, it can be observed that manufacturers increase their processing power at least twice each year, in contrast to battery development, which has failed to double over the last five years. Battery life is not a secondary consideration, since, according to a survey performed by North American Technologies (Forrester, 2011), it stands as the second most important purchase decision factor for buyers of smartphones. Users acceptance, in the context of aware applications in general and of activity recognition systems in particular, is therefore critical. For this reason, in this work, not only has an accurate and fast system been developed, but a low energy consumption model is also presented from the viewpoint of discrete techniques.

There are various solutions using specific hardware (Choudhury et al., 2008) that have a high degree of autonomy. However, the problems faced by these elements are, as outlined earlier, the risk of losing and/or forgetting the device and the discomfort for users. Furthermore, these solutions are usually very expensive. In recent years, a large number of personal devices able to monitor the activity level have been developed by large companies, such as Adidas (Fig. 1), and Nike (Fig. 2). However, the aims of this work, even though related, are quite different. Both of these commercial devices allow the physical activity level to the detected. This is interesting from the point of view of calories burned. The limit imposed on the number of activities constitutes the main disadvantage of these systems, since they can only detect certain parameters, such as the number of sprints or total distance covered. Although these features are significant, for many users the number of these activities may be insufficient, for example, for users involved in a physical rehabilitation process which must be monitored by doctors. In these cases, activity recognition should have greater granularity to detect activities. The activities our system is able to discern will be discussed in the following section.

In short, although our proposal has been tested with smartphone embedded sensors, no limitation whatsoever is envisaged. In this paper, a new independent-sensor technique for activity recognition is presented, which uses and continues the work in Soria Morillo, Ortega Ramirez, and Gonzalez-Abril (2012). Thus, this