ARTICLE IN PRESS

Neurocomputing ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Neurocomputing

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

Multiple density maps information fusion for effectively assessing intensity pattern of lifelogging physical activity

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ARTICLE INFO

Article history:
Received 1 March 2016
Received in revised form
8 June 2016
Accepted 28 June 2016

Keywords:
Physical activity
Lifelogging
Mobile device
Intensity pattern
Dempster-Shafer theory
Information fusion

ABSTRACT

Physical activity (PA) measurement is a crucial task in healthcare technology aimed at monitoring the progression and treatment of many chronic diseases. Traditional lifelogging PA measures require relatively high cost and can only be conducted in controlled or semi-controlled environments, though they exhibit remarkable precision of PA monitoring outcomes. Recent advancement of commercial wearable devices and smartphones for recording one's lifelogging PA has popularized data capture in uncontrolled environments. However, due to diverse life patterns and heterogeneity of connected devices as well as the PA recognition accuracy, lifelogging PA data measured by wearable devices and mobile phones contains much uncertainty thereby limiting their adoption for healthcare studies. To improve the feasibility of PA tracking datasets from commercial wearable/mobile devices, this paper proposes a lifelogging PA intensity pattern decision making approach for lifelong PA measures. The method is to firstly remove some irregular uncertainties (IU) via an Ellipse fitting model, and then construct a series of monthly based hour-day density map images for representing PA intensity patterns with regular uncertainties (RU) on each month. Finally it explores Dempster-Shafer theory of evidence fusing information from these density map images for generating a decision making model of a final personal lifelogging PA intensity pattern. The approach has significantly reduced the uncertainties and incompleteness of datasets from third party devices. Two case studies on a mobile personalized healthcare platform MHA [1] connecting the mobile app *Moves* are carried out. The results indicate that the proposed approach can improve effectiveness of PA tracking devices or apps for various types of people who frequently use them as a healthcare indicator.

1. Introduction

Physical inactivity is a well-known severe health risk leading to a variety of chronic and obesity related diseases [2,3] in modern society. As an intuitive reflection of their underlying pathophysiology, continuous physical activity (PA) measurement in daily life is increasingly crucial to these patients for designing specific rehabilitation programs to promote an active lifestyle. Thus, the accuracy and stability of access to PA related information is of significant interest to the research community.

Traditionally, PA measurement recognizes the type, duration, and intensity of a broad range of activities and quantifies energy expenditure. For the purpose of assuring accuracy in accessing PA associated energy expenditure, typical PA measurement solutions require subjects to wear special devices in lab or clinical environments to acquire sensory signals, and then analyse them with advanced machine learning algorithms for recognizing different types of PA [4–6]. While these solutions deliver relatively high accuracy of PA measurement they are less feasible for long-term measurement in free-living conditions, often termed as 'life-logging' PA measures. The reason is because analysis of raw sensor data consumes too much energy on the portable/wearable device. Battery and storage capacity are key limiting factors when assessing one's PA pattern in a free-living environment [7,8].

As PA measurement devices are becoming more affordable, lightweight and portable, the prevalence of commercial wearable devices and mobile apps with processed outcomes in smart healthcare fields [9–13] make monitoring and tracking lifelogging PA associated information possible (such as walking, running, intensity, duration, etc.) to objectively ensure consecutive care for users. Particularly, the intensity of lifelogging PA data observed by such inertial sensors is often categorized into five levels: sedentary, light, moderate, vigorous and high intensity based on the metabolic equivalents (METs) cut-offs [3], which has been broadly adopted as a standard of PA levels for achieving healthcare life

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http://dx.doi.org/10.1016/j.neucom.2016.06.073
0925-2312/

Please cite this article as: J. Qi, et al., Multiple density maps information fusion for effectively assessing intensity pattern of lifelogging physical activity, Neurocomputing (2016), http://dx.doi.org/10.1016/j.neucom.2016.06.073

styles. However, the classification simply offers a generally instantaneous measure that exhibits deficiency of accumulated evaluation and assessment for lifelogging personal PA intensity patterns thereby restricting its usefulness.

Research as to how we can better take advantage of these scattered and heterogeneous data has become a critical issue when used in long-term observation for healthcare prevention and research purposes. The difficulty is that a certain amount of indicative PA data collected from existing inertial sensor-based wearable devices and mobile phones contains a variety of uncertainties. For instance, PA intensity observed by the app *Moves* [10] indicates that it often turns itself off to conserve energy for mobile devices. The wrist band *Withings* [11] produces erroneous PA recognition results occasionally since PA related human life patterns in free-living conditions are dynamic, diverse and noise-sensitive. Such results have a negative impact on the energy expenditure and PA intensity evaluations. The uncertainties are quite common but can prove challenging to eliminate. Nonetheless, based on existing works, to our best knowledge, almost none contributes such wrapped and scattered datasets from commercial devices to lifelogging PA intensity analysis for healthcare support. This work is the first attempt to address these uncertainties and, one step further, to improve the efficiency of low-cost wearable and mobile devices for one's PA intensity pattern in a long range effort.

The remainder of this paper is structured as follows. Section 2 presents the literature review of related work. Section 3 describes the proposed PA intensity pattern decision making approach. Section 4 reports two case studies for evaluating the proposed method in the MHA platform [1,14]. Finally, the conclusions and future work are presented in Section 5.

2. Related work

Lifelogging, refers to the process of capturing one's entire life using digital devices for health and wellness, e.g. medical intervention or physical activity recommendation. In early attempts, lifelogging PA monitoring was preliminarily surveilled by image capturing via an external camera [15–17]. However, this approach could be deemed an invasion of privacy for the general public other than the subject and this has made it a less popular mechanism. Modern technology extends the definition of lifelogging into broader ranges. Wearable devices nowadays have been widely utilized to continuously track one's PA such as wearable camera, wristwatch and mobile phone [18]. The SenseCam wearable camera, a form of visual lifelogger, worn over one's neck, has been explored as an everyday activity data recorder in [19–21] by the means of analysis of a series of captured photos. Compared with traditional indoor/outdoor cameras, personal privacy of this wearable camera has a higher level of protection. Although there is general consensus that the device is appropriate for healthcare purpose, in most of cases, its cost is somewhat prohibitive for patients or researchers in a controlled lab environments. Recording and storage of a high volume of lifelogging pictures is also a big challenge for SenseCam.

In recent years, low-cost costumer wearable PA trackers with embedded inertial sensors are generating increasing public attention. Popular products, such as *Fitbit Flex* [22], *Nike+Fuelband* [23], *Endomondo* [24] etc., are wristband devices that record PA information (e.g. steps, distance, and calories burnt) and other physiological information (e.g. heartbeat rate). Some third party Application Programming Interfaces (or APIs) of wearable devices have provided the functions to assess the intensity of PA walking speed. For instance, Fitbit [22] classifies the intensity of daily activities into very active, moderately active, lightly active and sedentary. Mobile apps, such as *Moves* [25] is based on smartphone 3D accelerometer data and GPS information which allows tracking the user's movements including location, distance and speed. *Moves* records a series of walking segments containing duration, distance and speed.

Evidently, customer PA monitors have addressed some practical issues such as storage, battery life and cost, especially mobile apps which are often free. Nevertheless, PA recognition results offered by mobile devices are widely divergent as a result of different places being carried by different users such as pocket or handbags [26,27]. Furthermore, the diverse life pattern of an individual person may cause huge indeterminateness, as they perform PA in varying ways owning to age, gender, weight, etc. Hence, a specific PA tracking model that fits one group of user may not fit another one [28]. In addition to that, some applications often automatically switch off themselves for energy efficiency which has contributed to missing data. In general, the uncertainties of lifelogging PA from customer devices here is divided into two types as our previous work investigated [29]:

Irregular uncertainty (IU): randomly and accidently occurs in lifelogging PA data. The causes of these uncertainties include device malfunctions or faults, breakdown of a third party server, misuse of devices or sudden change of personal circumstance. The occurrence of IU will appreciably impact the efficiency and accuracy of assessing personal health.

Regular uncertainty (RU): frequently and persistently occurs in lifelogging PA data. The causes resulting in these uncertainties are mainly from some regular influencing issues, like intrinsic sensors' errors, differentiation of personal physical fitness and changes of environment. The occurrence of regular uncertainty in physical activity data is inevitable so that it is impossible to completely eliminate these uncertainties.

Accordingly, these uncontrolled conditions are the key issues that cause relatively low accuracy of wearable device or mobile phone data logger compared with traditional non-naturalistic experiments. The encapsulated datasets, consequently, tend to be scattered, erroneous and unserviceable for long range healthcare studies.

To address the aforementioned challenge, our work attempts to take on these uncertainties for lifelogging PA intensity observation. To enhance device performance, we first use an ellipse fitting model for reducing IU of life-logging PA measures in an Internet of Things (IoT) environment. Secondly, hour-day density map images are constructed to represent the RU pattern on each month. We then propose Dempster-Shafer theory of an evidence based lattice model applying to these density map images fusion for determining a robust lifelogging PA intensity pattern. Unlike the five categories based on MET, in this work, only two basic standards of intensity (active and sedentary) are considered for long term observation. We believe that our work will help bring attention to the opportunities available for using datasets from commercial wearable devices and mobile phones for the purpose of healthcare studies and will stimulate additional work in this area.

The Ellipse fitting algorithm is represented as a circular form via projection to an image plane, which is often used to remove scattered or noisy data samples through setting points to the best fit or geometric fit [30,31]. In comparison with a curve fitting function such as Gaussian fitting [32] or smoothing fitting [33], the Ellipse fitting method is more suitable for the aggregative samples that belong to elliptical conic and excluding non-elliptical data [34]. Furthermore, the method has low computation cost and is easy to implement.

The density map is a visualization technique that uses different colours for presenting different activity levels in the image. In the work [35], an activity density map based visualization method is proposed for analyzing passive infrared motion sensor data for