Expert Systems with Applications 39 (2012) 8013–8021

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

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

Daily living activity recognition based on statistical feature quality group selection

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ARTICLE INFO

Keywords:
Activity recognition
Ambulatory monitoring
E-health
E-monitoring
Feature selection
Knowledge extraction

ABSTRACT

The benefits arising from proactive conduct and subject-specialized healthcare have driven e-health and e-monitoring into the forefront of research, in which the recognition of motion, postures and physical exercise is one of the main subjects. We propose here a multidisciplinary method for the recognition of physical activity with the emphasis on feature extraction and selection processes, which are considered to be the most critical stages in identifying the main unknown activity discriminant elements. Efficient feature selection processes are particularly necessary when dealing with huge training datasets in a multidimensional space, where conventional feature selection procedures based on wrapper methods or 'branch and bound' are highly expensive in computational terms. We propose an alternative filter method using a feature quality group ranking via a couple of two statistical criteria. Satisfactory results are achieved in both laboratory and semi-naturalistic activity living datasets for real problems using several classification models, thus proving that any body sensor location can be suitable to define a simple one-feature-based recognition system, with particularly remarkable accuracy and applicability in the case of the wrist.

1. Introduction

The percentage of EU citizens aged 65 years or over is projected to increase from 17.1% in 2008 to 30.0% in 2060. In particular, the number of 65 years old is projected to rise from 84.6 million to 151.5 million, while the number of people aged 80 or over is projected to almost triple from 21.8 million to 61.4 million (*EUROSTAT: New European Population projections* 2008–2060). It has been calculated that the purely demographic effect of an ageing population will push up health-care spending by between 1% and 2% of the gross domestic product (GDP) of most member states. At first sight this may not appear to be very much when extended over several decades, but on average it would in fact amount to approximately a 25% increase in spending on health care, as a share of GDP, in the next 50 years (European Economy Commission, 2006). The effective incorporation of technology into health-care systems could therefore be decisive in helping to decrease overall public spending on health. One of these emerging health-care systems is daily living physical activity recognition.

Daily living physical activity recognition is currently being applied in chronic disease management (Amft & Tröster, 2008; Zwartjes, Heida, van Vugt, Geelen, & Veltink, 2010), rehabilitation systems (Sazonov, Fulk, Sazonova, & Schuckers, 2009) and disease prevention (Sazonov, Fulk, Hill, Schutz, & Browning, 2011; Warren et al., 2010), as well as being a personal indicator to health status (Arcelus et al., 2009). One of the principal subjects of the health-related applications being mooted is the monitoring of the elderly. For example, falls represent one of the major risks and obstacles to old people's independence (Najafi, Aminian, Loew, Blanc, & Robert, 2002; Yu, 2008). This risk is increased when some kind of degenerative disease affects them. Most Alzheimer's patients, for example, spend a long time every day either sitting or lying down since they would otherwise need continuous vigilance and attention to avoid a fall.

The registration of daily events, an important task in anticipating and/or detecting anomalous behavior patterns and a primary step towards carrying out proactive management and personalized treatment, is normally poorly accomplished by patients' families, healthcare units or auxiliary assistants because of limitations in time and resources. Automatic activity-recognition systems could allow us to conduct a completely detailed monitoring and assessment of the individual, thus significantly reducing current human supervision requirements.

The primary difficulty in activity recognition lies in designing a system the reliability of which is independent of the person carrying out the exercise or the particular style of execution of the activity in question. Complexity is further increased by distortion elements related to system monitoring and processing, along with the random character of the execution. Most studies to date have been based on laboratory data (i.e., involving direct

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doi:10.1016/j.eswa.2012.01.164

supervision by the researcher) and have achieved successful recognition of the most prevalent everyday activities (lying, sitting, standing and walking: Aminian et al., 1999; Karantonis, Narayanan, Mathie, Lovell, & Celler, 2006; Maurer, Smailagic, Siewiorek, & Deisher, 2006; Ravi, Dandekar, Mysore, & Littman, 2005). Nonetheless, the apparently good recognition results obtained during supervised experiences cannot be extrapolated to habitual real-life conditions (Könönen, Mäntyjärvi, Similä, Pärkkä, & Ermes, 2010).

The ideal scenario would be a naturalistic monitoring context consisting of a scenario with no intervention on the researcher's part and without the subject's cognitive knowledge about the exercise conducted, but unfortunately this is currently unfeasible. Some studies have applied a so-called semi-naturalistic approach (Bao & Intille, 2004; Ermes, Parkka, Mantyjarvi, & Korhonen, 2008; Foerster, Smeja, & Fahrenberg, 1999; Pirttikangas, Fujinami, & Nakajima, 2006; Uiterwaal, Glerum, Busser, & van Lummel, 1998), an intermediate between laboratory and naturalistic monitoring based on the inference of the hidden activity through the proposal of a related exercise, thus minimizing the subject's awareness of the true nature of the data being collected. This approximation is somewhat more realistic than laboratory experimental setups.

The classic method for activity identification is based on three main stages: feature extraction (e.g., statistical features (Baek, Lee, Park, & Yun, 2004; Maurer et al., 2006; Ravi et al., 2005), wavelet coefficients (Nyan, Tay, Seah, & Sitoh, 2006; Preece, Goulermas, Kenney, & Howard, 2009; Preece et al., 2009) or other custom-defined coefficients (He, Liu, Jin, Zhen, & Huang, 2008; Mathie, Coster, Lovell, & Celler, 2003)), feature selection (e.g., principal or independent component analysis (Mantyjarvi, Himberg, & Seppanen, 2001), forward–backward selection (Pirttikangas et al., 2006), correlation (Maurer et al., 2006), etc.) and classification (primarily supervised learning approaches such as artificial neural networks (Engin et al., 2007; Parkka et al., 2006; Zhang et al., 2005), support vector machines (Begg & Kamruzzaman, 2005; Parera, Angulo, Rodríguez-Molinero, & Cabestany, 2009; Sazonov et al., 2009), Bayesian classifiers (Bao & Intille, 2004; Wu, Osuntogun, Choudhury, Philipose, & Rehg, 2007) and hidden Markov models (Minnen, Starner, Essa, & Isbell, 2006; Sazonov et al., 2011), among others). For a detailed review of classification techniques used in activity recognition the reader is referred to Preece, Goulermas, Kenney, and Howard (2009) and Preece et al. (2009).

Evidently, all these stages are important, but in this work we want to emphasize the importance of selecting the most interesting features to improve the efficiency of the subsequent pattern recognition systems, especially bearing in mind the rather discouraging results obtained with semi-naturalistic data. It is well known that a large number of features are directly translated into numerous classifier parameters, so keeping the number of features as small as possible is in line with our desire to design classifiers with good generalization capabilities, the best scenario being a knowledge inference system defined by just a few features. Consequently, we propose here an automatic method to extract a subset of the most important features to be used in activity recognition, which is especially suitable for looking for optimum single-feature classifiers with multiclass absolute discrimination capability.

The rest of the paper is organized as follows: Section 2 contains a description of the experimental setup, preprocessing process, features extracted from the data and the proposed rank-based feature selection method. Section 3 presents the results obtained, including a comparison of the performance of several different approaches. These results are subsequently discussed in Section 4 and our final conclusions are summarized in Section 5.

2. Methods

2.1. Experimental setup

Our experimental setup starts from a set of signals corresponding to acceleration values measured by a group of sensors (accelerometers) attached to different strategic parts of the body (hip, wrist, arm, ankle and thigh) for several daily activities[1] following both laboratory and semi-naturalistic monitoring schemes (Bao & Intille, 2004). Our study is focused on the four most common physical activities that are of particular relevance to health-care applications: *walking*, *sitting and relaxing*, *standing still* and *running* (Fig. 1). Although other daily living activities may be chosen, we have specifically considered these four for the pairwise similarities between walking/running and sitting/standing, both with respect to the way they are performed and the energy they entail, although this assumption may be distorted under natural circumstances.

2.2. Signal processing

The initial information provided by the sensors has some artifacts and noise associated to the data acquisition process. Bearing in mind that a 20 Hz sampling is sufficient to assess habitual daily physical activity (Bouten, Koekkoek, Verduin, Kodde, & Janssen, 1997; Mathie, Coster, Lovell, & Celler, 2004), a low-pass elliptic filter with 20 Hz cutoff frequency, followed by a 0.5 Hz cutoff frequency high-pass elliptic filter are applied to respectively remove the high frequency noise and the gravitational acceleration component from the signal (Fahrenberg, Foerster, Smeja, & Müller, 1997). Other proposals such as mean/median or wavelet-based filtering (Najafi et al., 2002) could be assessed for signal enhancement, but we will consider them in the next feature extraction phase.

2.3. Feature extraction

It is common in works concerning activity recognition to use a reduced feature set to characterize the monitored signals, mainly composed of statistical, time-frequency and heuristic features. The validity of this approach has been demonstrated in laboratory-context experiments, but due to the difficulty of precise knowledge inference concerning semi-naturalistic monitoring, a wider analysis is needed to reveal any unidentified powerful discriminant features, even those lacking obvious physical interpretability.

Thus we generated a parameter set comprising 861 features corresponding to a combination of statistical functions such as median, kurtosis, mode, range and so on, and magnitudes or functions obtained from a domain transformation of the original data such as energy spectral density, spectral coherence and wavelet coefficients ("*a*1 to *a*5" and "*d*1 to *d*5" Daubechies levels of decomposition) among others, for both signal axes. "Fisher asymmetry coefficient of the *X* axis signal histogram", "*Y* axis signal energy spectral density maximum" or "*X* axis–*Y* axis cross correlation harmonic mean" are possible examples of features obtained from the complete set defined (Table 1). Several of these features have been tested in previous works primarily on time and frequency domain (for example, amplitude peak (Laerhoven & Gellersen, 2004), arithmetic mean (Lee & Mase, 2002; Wang, Yang, Chen, Chen, & Qinfeng Zhang, 2005), variance or standard deviation (Heinz et al., 2003; Kern, Schiele, & Schmidt, 2003), energy and correlation between axes (Bao & Intille, 2004; Ravi et al., 2005), etc.), but many of them are unprecedented in this context. Features are extracted from the

[1] Database facilitated in Bao and Intille (2004) by Prof. Stephen Intille (Massachusetts Institute of Technology).