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Analyzing human gait and posture by combining feature selection and kernel methods

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ABSTRACT

This paper evaluates a set of computational algorithms for the automatic estimation of human postures and gait properties from signals provided by an inertial body sensor. The use of a single sensor device imposes limitations for the automatic estimation of relevant properties, like step length and gait velocity, as well as for the detection of standard postures like sitting or standing. Moreover, the exact location and orientation of the sensor are also a common restriction that is relaxed in this study.

Based on accelerations provided by a sensor, known as the '9×2', three approaches are presented extracting kinematic information from the user motion and posture. First, a two-phases procedure implementing feature extraction and support vector machine based classification for daily living activity monitoring is presented. Second, support vector regression is applied on heuristically extracted features for the automatic computation of spatiotemporal properties during gait. Finally, sensor information is interpreted as an observation of a particular trajectory of the human gait dynamical system, from which a reconstruction space is obtained, and then transformed using standard principal components analysis, finally support vector regression is used for prediction.

Daily living activities are detected and spatiotemporal parameters of human gait are estimated using methods sharing a common structure based on feature extraction and kernel methods. The approaches presented are susceptible to be used for medical purposes.

1. Introduction

One of the consequences of chronic diseases and strokes is the limitation of the motion capacity and a straightforward lack of physical activity, having a direct impact on quality of life of the patient. By extracting spatiotemporal parameters from human gait and posture, medical treatments would count with valuable additional information, allowing a better diagnose and treatment assessment for diseases like Parkinson's [1], diabetes [2], and for the early detection of other conditions like risk of falling, avoiding possible hip break episodes and its consequences in elderly people [3].

Usual instruments to supervise patient's mobility are based on the subjective perceptions of an observer or the use of large and expensive measurement equipment like posturometers or walkway systems [4]. Moreover, during the last decade several advances have been developed on wearable systems based on accelerometry for the automatic extraction of spatiotemporal gait parameters [27] and daily activity monitoring [28]. Compactness and objectiveness of inertial based devices allow the development of truly ambulatory systems predicting and detecting gait anomalies in real-time, overcoming the need of questionnaires [5] and clinical trials, where users may act differently from real life conditioned by the environment (e.g., being observed) and other uncontrolled variables like lack of memory of the patients.

The use of inertial sensors to extract this information has been successfully applied in diverse studies, e.g., [6]. Nevertheless, available systems for the reliable ambulatory extraction of spatiotemporal gait parameters usually require the use of several devices [7] and often carrying a bunch of wires along the body communicating devices [8,9]. Moreover, recently developed wireless ambulatory systems [9,10] still need more than one device in order to extract features like step size, stride length, and step velocity from human gait using gyroscopes tied at legs. Wearing these devices on the legs during daily life activity seems a drawback, leaving the application scope of this method to clinical environments. In the case of accelerometers, they are usually positioned at the dorsal side of the trunk, near the region of the L3 vertebra of the subject, since it is the center of mass (CoM) location. In this position, 3D CoM acceleration, velocity and displacement can be estimated [10,11].

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However, our studies on usability indicated that this position is not practical when sitting or performing some daily physical activities. To the best of our knowledge, there is no any user-friendly wearable device/location that patients may use outside the hospital.

A measurement system composed by a single device would cover the need of an ambulatory solution easy to be worn during daily life. This system imposes a challenge for the extraction of reliable information from the limited signals obtained. This paper study the use of one of such simple systems, motivated by the high impact that it will have on the end-users acceptability. Other approaches using just one device [11] are sensitive to the precise location and adjustment of the sensor on the patient: lumbar zone, chest or lateral hip. Some of them inclusive requires a non-intuitive location (foot, knee, ankle), forcing the user to modify natural motions during sitting, standing and laying postures and transitions. Besides, works on ambulatory activity monitoring using a single sensor rely on the off line processing of logged data. The purpose of our research is to analyze human gait and posture using features extracted from signals provided on-line by a small-sized wearable sensor module located in the patient's waist. Therefore, this system can be used everywhere during daily life avoiding the need of special infrastructure. The measurement system employed in this study is briefly described in Section 2 where a comparison with other devices is also presented.

This work is based on two results, the first one is oriented to demonstrate that the system can be used to detect diverse human postures, thus, using kernel based algorithms, the system offers detection properties similar to those of already commercially available systems. Second, kernel methods are used to extract gait spatiotemporal properties from accelerometry data.

The posture detection and gait properties estimation approaches may be discriminated as follows: (i) a two-phases procedure implementing feature extraction from raw acceleration signals and support vector machine (SVM) based classification; (ii) the use of support vector regression (SVR) on heuristically extracted features from acceleration signals for step length and velocity estimation and (iii) an approach based on the assumption that sensor information encapsules information of an unknown dynamical system resulted during the human gait, standard principal component analysis and SVR completes this spatiotemporal properties estimation.

The remaining of the paper is organized as follows. Section 2 reviews other accelerometry systems used to analyze human motion, it also presents a comparison with the accelerometry system used in this study. Section 3 presents the approach to identify among five common motion activities. Section 4 describes a regression approach to estimate step length and velocity from acceleration signals collected from the subject's waist. Section 5 tackles the same problem but using an approach based on intrinsic properties of a hidden dynamical system. Finally, Section 6 concludes the paper with some remarks and comments about future research.

2. System overview

First a review of the features of some accelerometry based systems is presented, then the system used for this study is described and compared with other devices.

2.1. Accelerometry based systems for human motion systems

Later, detection and classification of human daily living activity have received wide attention from the research community. Besides the sensor used in this study, so-called '9×2', there are already several commercial physical activity monitors that manage to detect several activities: Shimmer [29] is a small wireless wearable sensor that can also record and wirelessly transmit physiological and kinematic data in real-time. Its small size, however, constraints battery duration to 3–4 h when using a 50 Hz sampling rate. Xsense MTi [31] is a system containing gyroscopes, accelerometers and magnetometers. The internal low-power digital signal processor runs a real-time sensor fusion algorithm providing drift-free 3D orientation data. Xsense MTw [31] sends data using RF communication technology, however, battery duration is reduced from 18.5 to 3.5 h. The mcroberts DynaPort MiniMod [32] supports applications where a subject wears the sensor at the lower back for a longer period of time under free-living conditions and it is able to analyze the patient's quantity of movement.

Other specialized platforms exist, having battery life as main feature, like activPAL [33]. It identifies and classifies individual's free-living activity like sitting, standing and walking. Data can be collected during 10 days using a very low sampling rate, and no on-line process can be implemented. Physilog, developed at EPFL, [8] has no wireless data transmission. MicroStrain 3DM-GX1 [35] considers nine axes of measurement, but it presents the same restrictions that Xsens MTi. Finally, Activity Monitor [33] is an IMU, worn in the wrist, developed to measure physical activity. It is endowed with RF for wireless communication.

Special attention should be presented to the commercial platform MiniSun IDEEA (Intelligent Device for Energy Expenditure and Activity) [34] specifically designed to measure movement, it may compute duration, frequency and intensity of diverse types of human physical activity (PA). The working principle of IDEEA is the constantly monitoring of the body and limb motions through five sensors attached to the chest, thighs, and feet. Data are then downloaded to a computer for off-line analysis at the end of each test. For the calibration of IDEEA, the subject was asked to sit in an upright position with feet and thighs parallel to the floor and the upper body in a vertical position. Calibration takes 5 s, this process ensures a maximal deviation of 15 degrees in each direction. Although it detects locomotion well (such as walking or running), activities involving mainly arm motion, such as rowing, swinging a ball or bat, operating a vacuum cleaner, etc. would not be correctly identified.

These examples demonstrate that despite that human activity is already successfully identified using commercially available devices, it is either employing several sensors on the patient's body or extracting data to be processed of-line, preventing the use of its outputs in real-time applications like tele-care, automatic infusion of drugs or ambient intelligence integration. Restricting the number of devices in the system and demanding on-line detection and extraction imposes challenges for the technical and algorithmic approaches.

2.2. '9×2' System description

The inertial system is a single unit device. All the electronic components plus a Li-on battery (1000 mA h) are encapsuled in a $78\times37\times10$ mm black case. It weights 125 g (battery included). The prototype also includes a wall battery charger. Fig. 1 shows the prototype and its corresponding μSD card.

Internally, the system includes the classical elements of an Inertial Measurement Unit (IMU) as well as a system dedicated to the battery control and energy consumption optimization. The status of both, the battery level and the main application process, is shown to the user using a very simple user interface comprised of three LEDs (light emission diodes). A switch allows the user to interact with the device at any time. Fig. 1 shows the device.

Table 1 shows a technical comparison of the analyzed commercial platforms. Presented information for each platform is its sampling rate, battery life, dimensions, processing capacity, datalog function, wireless communication, and sensors included (accelerometers, gyroscopes and magnetometers).