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Brief Communication

Activity Recognition Using Multiple Inertial Measurement Units

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Abstract

Objectives: This paper addresses the design of an ambulatory monitoring system based on a set of wearable, wireless inertial measurement units able to perform activity recognition for healthy individuals and Parkinson's disease patients, as well as analyze and assess the severity of levodopa induced dyskinesia.

Material and methods: The monitoring system is composed of six Shimmer3 modules placed at different positions of the individual's body. Both healthy individuals and one patient performed a protocol of simple daily life activities while wearing the Shimmer3 modules. As an initial step, validity of the monitoring system in identifying healthy individuals' activities is assessed. Data corresponding to the activities was separated and features in both time and frequency domains were extracted. Multiple factor analysis was used to evaluate and infer the relationships between the different module positions. A method of feature selection was implemented to determine the most important features, positions and sensors included in the different modules. The classification of activities was done using a KNN classifier.

Results: Promising results were obtained in classifying the activities of healthy individuals, with a global accuracy of 77.6%. However, certain adaptation is required for the application on Parkinson's disease patients.

Conclusion: While activity recognition for healthy individuals using this system was successful, further evaluation of the contribution of each module needs to be done in order to determine optimal module positions. To validate the obtained results on Parkinson's disease patients, a larger study based on more patient acquisitions is envisioned.

Keywords: Bioinformatics; Biomedical sensors; Signal Processing

1. Introduction

In the past few decades, activity recognition through wearable sensing devices has become a widely researched area finding applications in various domains such as medicine, security and entertainment. In particular, several medical applications have been concerned with utilizing these non-invasive, wearable devices for detecting motor symptoms of patients.

Parkinson's disease is the second most common neurodegenerative disorder, following Alzheimer's. This disease is characterized by several motor symptoms such as hypokinesia, bradykinesia, freezing of gate, and tremor as well as motor complications of treatment methods such as dyskinesia. The assessment of the motor symptoms today is based on clinician rated scales and patient diaries. Although some of these scales, such as the Unified Parkinson's Disease Rating Scale (UPDRS), have proven to have reliable test-retest performance, they remain to be subjective, short-based assessments that lack the ability to quantify the disease's motor complications [1]. Therefore, research has been aimed towards finding a more objective,

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long-term automated method for the detection and quantification of Parkinson's disease motor symptoms [2].

Recent studies have been conducted that aim to detect certain motor symptoms such as tremor, bradykinesia and hypokinesia using kinematic sensors. However, these studies are usually concerned with the assessment of one or two motor symptoms and are based on short time recordings of patients in somewhat restricted environments (see [3] for review). The enhancement of therapeutic measures lies in understanding the complexity and evolution of motor complications that manifest both due to disease progression as well as the implementation of the therapeutic plan itself. In order to do that, there is a need for a long-term and reliable monitoring device that is able to assess the patient's general motor state, detect and quantify motor symptoms, providing an objective means for determining disease progression [4]. Because of that need, there exists a link between the field of ambulatory monitoring of Parkinson's disease motor symptoms and the field of activity recognition.

Although there have been many advances in the field of activity recognition, several issues still remain urging further exploration of the currently available technologies in enhancing the accuracy of classifying daily activities [5]. Some of the most commonly used types of sensors in activity recognition today are inertial sensors such as accelerometers and gyroscopes, magnetic sensors, and physiological signal measurement devices. Studies have reported varying results based on these different types of sensors, mostly due to differences in the types of activities to be recognized and depending on the application at hand. The objective of this paper is to propose the design of a new ambulatory monitoring system based on a set of wearable, wireless inertial measurement units able to perform daily life activity recognition for healthy individuals and Parkinson's disease patients.

Section 2 introduces the system of data acquisition, along with the placement of modules, the incorporated sensors and the activity protocol performed. Following that, the signal processing method is explained and the extracted features are described, including a brief summary of multiple factor analysis, the feature selection method and K Nearest Neighbor (KNN) classification. Section 3 presents the obtained results for both multiple factor analysis and KNN classification, while Section 4 shows the results of the primary application of the developed algorithm on a Parkinson's disease patient. In Section 5, a brief conclusion is presented.

2. Materials and methods

2.1. Data acquisition

The entire system of acquisition is composed of six Shimmer3 modules [6] placed at different segments of the subject's body (Fig. 1). The modules were attached using elastic straps and did not affect the subject's free movement. Each of the sensing modules contains the five following sensors: triaxial low noise accelerometer, triaxial wide range accelerometer, triaxial gyroscope, triaxial magnetometer, temperature sensor, and altimeter. The sensors all operated under the same sampling rate

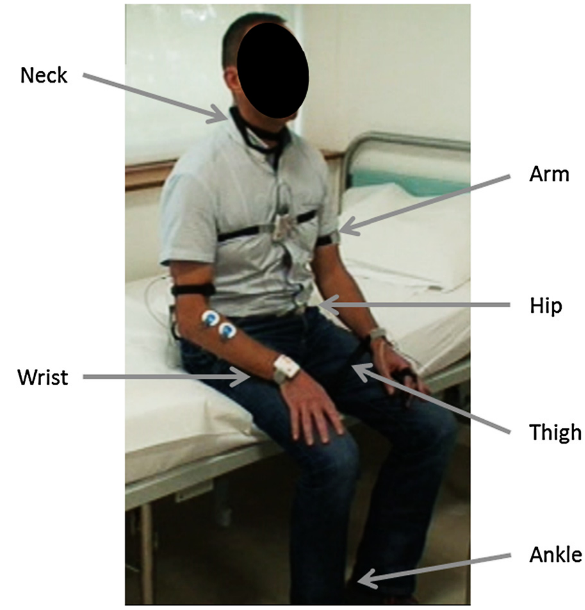

Fig. 1. Shimmer3 module positions.

Table 1
Description of the protocol including six module positions, six sensors (two not used) and seven activities.

6 Positions	6 Sensors	7 Activities
Neck	Triaxial LN Acc	Walking
Wrist	Triaxial WR ACC	Standing
Arm	Triaxial Gyroscope	Lying
		Sitting
Hip	Triaxial Magnetometer	Writing
Thigh	Temp (not used)	Reading
Ankle	Altimeter (not used)	Eating

of 512 Hz and data was collected on each module's internal memory card. For the analysis of movement, only the signals collected from the accelerometers, gyroscope and magnetometer were considered. Twelve different signals were therefore collected from each shimmer module, and a total of seventy-two signals were analyzed for all module positions.

Nine healthy subjects (3 males and 6 females) participated in the data acquisition protocol which consisted of a series of $N = 7$ simple daily life activities (see Table 1). The activities were performed during the session without interruption and data acquisition was done continuously. Each subject performed the same protocol twice, on two different days. During the acquisition sessions, subjects were instructed to act freely and perform each activity at their own pace. The period of each activity was timed for an average of two minutes and subjects were then instructed to move on to the next activity. The sessions were video-taped, and the exact start and end times of each activity were annotated based on the collected video recordings.

Fig. 2 shows examples of collected signals from sensors of a single module (Ankle) during two different activities (walking and lying down).