Biomedical Signal Processing and Control 24 (2016) 114–119

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

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

Automatic Berg Balance Scale assessment system based on accelerometric signals

Pawel Badura*, Ewa Pietka

Faculty of Biomedical Engineering, Silesian University of Technology, Roosevelta 40, 41-800 Zabrze, Poland

ARTICLE INFO

Article history:
Received 29 June 2015
Received in revised form 2 September 2015
Accepted 14 October 2015
Available online 4 November 2015

Keywords:
Ambient assisted living
Balance assessment
Berg Balance Scale
Computer-aided diagnosis

ABSTRACT

This paper presents the automatic system for computer-aided balance assessment reflecting the Berg Balance Scale. The system employs inertial sensors for the data acquisition purposes. A set of features is extracted from multiple signal representations during the examination. A multilevel Fisher's linear discriminant is used to select most suitable features for each of the BBS tasks. The feature space dimensionality reduction and the multilayer perceptron classifier training both involve expert scoring on the observed examinations. The system is verified using data acquired during the BBS scoring of 64 elderly patients. Both assessment modes: the entire examination as well as separate BBS items, are evaluated and discussed using introduced assessment metrics.

1. Introduction

Clinical decision making in case of balance assessment is a challenging problem. Numerous factors might induce balance disorders or increase susceptibility to falls. Balance problems are often associated with diseases (*e.g.* multiple sclerosis, Parkinson's disease, neurological and musculoskeletal diseases [1,2]). The importance of this issue is enhanced by aging of contemporary societies. Thus, the clinical balance assessment has been deeply studied in the past decades [3]. The balance and gait analysis in terms of searching for certain measures or patterns, their diversity related to various impairments and disorders is often very profitable for clinical assessment and diagnosis purposes [4,5]. The gait speed or motion dimensions in triaxial coordinate system [6], time-frequency representations of acceleration or angular velocity data [4], acceleration derivatives [7] provide substantial numerical information for the assessment of various motion or postural issues.

All these issues are supported by the ambient assisted living (AAL) systems designed for the elderly telecare [8]. Such systems employ multiple data types, acquisition equipment and procedures for direct monitoring or computer-aided diagnosis and therapy planning [9] including video/audio maintenance, emergency call procedures, movement detectors, radiowave or ultrasound beacons, wearable devices with various sensors, etc. [8,10]. Apart from the immediate intervention applications, the AAL might offer more comprehensive functionalities in terms of long-term health state trends monitoring or a patient-specific model definition [11]. Such a perspective is clearly broader than a single, precise analysis and might be constructed by gathering available knowledge for the decision making process.

There are several functional examinations dedicated to the balance assessment [12]. The general idea is to select certain activities (changing positions, gait, standing or sitting, etc.) able to reflect balance abilities of the subject. The examinations differ in simplicity, time and equipment requirements, specific subject of assessment interest. The Tinetti Balance and Gait Examination [13] combines 24 balance and gait tasks for reliable fall prediction. The Activities-Specific Balance Confidence Scale (ABC) [14] evaluates different daily activities using a 16-item questionnaire. The Physiological Profile Approach (PPA) [15] involves a multiple tests, verifying vision, cutaneous sensation on the feet, leg muscle force, reaction time, and postural sway in stance. The Balance Evaluation Systems Test (BESTest) [16] consists of 36 items organized into 6 thematic issues, aggregating information from multiple sources, including examinations mentioned here, yet it takes ca. 30 min. Fast results are yielded by quick tests (*e.g.* "timed up and go" – TUG [17], functional reach [18]), yet yield the assessment might not be treated as comprehensive as in previously mentioned cases.

In our study the Berg Balance Scale (BBS) [19,20] has been found a reasonable examination, balancing the time, resources, and reliability factors. It consists of 14 different tasks, each rated in

* Corresponding author. Tel.: +48 322777466.
E-mail addresses: pawel.badura@polsl.pl (P. Badura), ewa.pietka@polsl.pl (E. Pietka).

http://dx.doi.org/10.1016/j.bspc.2015.10.005
1746-8094/

a 5-level scale (0 – 4): (1) sitting to standing, (2) standing unsupported, (3) sitting unsupported, (4) standing to sitting, (5) transfers, (6) standing with eyes closed, (7) standing with feet together, (8) reaching forward with outstretched arm, (9) retrieving an object from the floor, (10) turning to look behind, (11) turning 360°, (12) placing alternate foot on stool, (13) standing with one foot in front, (14) standing on one foot. The precise assessment specification and guidelines might be found in [19]. Based on the total score, the subject is assigned to one of three balance groups: wheelchair bound (0 – 20), walking with assistance (21 – 40), independent (40 – 56). The BBS is commonly used for balance assessment mainly due to its simplicity, universality, high (over 95 %) indicators of inter-rater reliability and specificity [12]. On the other hand, its fall prediction sensitivity has been questioned recently [21]. Also the possible uncertainty between two close scores remains an issue to be considered (an 8-point change is required to discover a significant condition change) [22]. An automated, more objective data analysis may improve the fall prediction sensitivity.

Our goal in this study is to design and evaluate an automatic balance assessment using BBS specification. To the best of our knowledge, there are no research reports on this issue. The computer-aided diagnosis assessment tool employs the AAL architecture based on triaxial inertial sensors [11,23]. Such a tool might be useful in remote telecare of the elderly in home environment, providing consistent numerical groundwork for balance monitoring. Preliminary research on this matter have been performed using 7 selected BBS activities and a group of 52 elderly patients [24] with the investigation on sensor location influence on assessment efficiency [25]. In this paper we propose the Automatic Berg Balance Scale Assessment System (ABBSAS) and involve the entire BBS examinations of 64 elderly patients into the training and testing procedures. The system uses a set of features extracted from signals. The evaluation and discussion employ several assessment reliability metrics.

The paper is organized as follows. The materials and ABBSAS is presented in Section 2 with all structure and methodology details. The experimental results are described in Section 3 and discussed in Section 4. The paper is concluded in Section 5.

2. Methods

2.1. Participants

The accelerometric data for the experiments has been acquired during full BBS examinations involving 64 patients (51 female and 13 male) with a mean age of 77.6 ± 6.6 (ranging between 61 and 91) with the mean BBS score reaching 43.2 ± 7.8 (ranging between 23 and 56) – Fig. 1a. They have been chosen from the group of patients under the care of the John Paul II Geriatric Hospital in Katowice, Poland. Some of them have been hospitalized for a longer period, some live independently and are supervised by the hospital. Thirty-nine patients have been generally assessed as “independent” and 25 as “walking with assistance” according to the BBS standard. Fig. 1b presents the scoring statistics for each BBS item. The study received approval from the Bioethics Committee of the Jerzy Kukuczka Academy of Physical Education in Katowice, Poland.

2.2. ABBSAS

The overall ABBSAS workflow (Fig. 2a) consists of a data acquisition/preprocessing unit and feature extraction as initial stages. Then, the large feature vector is passed to 14 classifiers of identical structure (Fig. 2b and c), yet designed for each BBS task separately, due to specific signal processing requirements. In a learning mode (Fig. 2b), the specific feature vector is selected for each task via a multilevel Fisher’s linear discriminant (FLD) analysis using expert assessments as training data. These features serve as input values for classifiers in the assessment mode (Fig. 2c).

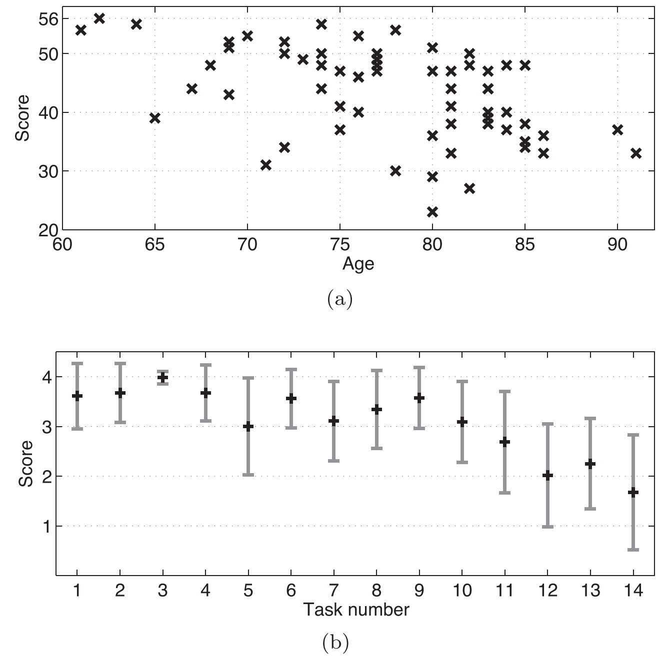

Fig. 1. BBS expert scoring distribution as a function of subject’s age (a) and scoring statistics throughout separate tasks (b). Error bars indicate mean scores along with standard deviations for each task.

2.2.1. Data acquisition and preprocessing

The input data is collected using the AAL architecture described in [11,26] under the physician and physiotherapist supervision. Each activity under consideration is monitored by 5 inertial body-fixed sensors (MPU6050 modules) located on both ankles, hips and on the back (at T6 vertebra). Each sensor produces two triaxial signals: acceleration $\mathbf{a}(t)$ normalized with respect to gravitational acceleration g and angular velocity $\boldsymbol{\omega}(t)$, both sampled at $f_s = 100$ Hz. The data is preprocessed in order to obtain the acceleration translated into the North-West-Up (NWU) coordinate system. To do so, the complementary filter is employed to estimate the rotation angles using $\mathbf{a}(t)$ and $\boldsymbol{\omega}(t)$ [27]. In order to prepare data for feature extraction stage, the jerk $\mathbf{j}(t)$ and jounce $\mathbf{s}(t)$ signals are computed as the first and second acceleration derivatives with respect to time.

2.2.2. Feature extraction

Due to diversity of activities under consideration, a feature vector **F** containing a large number of item has been proposed in order to provide discriminative data for automatic assessment [24]. The information is searched mainly in medium and high acceleration frequency channels.

The first group of features take into consideration time relations between the active and passive periods. The activity detection algorithm involves the short-time Fourier transform (STFT) calculated for each sensor and acceleration component with 0.5 Hz step and a 0.5 s non-overlapping Hamming window [24]. The total and normalized per second activity/inactivity time, as well as their ratio are included in **F**.

The STFT itself yields a large set of features, namely: the normalized energy in a medium frequency ([2, 8] Hz) range, the normalized energy and gradient-energy within selected frequency channels (*e.g.* 2, 5, 8 Hz). The binary STFT representation thresholded at a certain level θ provides the normalized energy and number of separate peaks throughout a binary profile within fixed frequency channel