Journal of Biomechanics xxx (2018) xxx–xxx

Contents lists available at ScienceDirect

Journal of Biomechanics

journal homepage: www.elsevier.com/locate/jbiomech
www.JBiomech.com

An instrumental approach for monitoring physical exercises in a visual markerless scenario: A proof of concept

Marianna Capecci [a], Maria Gabriella Ceravolo [a], Francesco Ferracuti [b], Martina Grugnetti [a], Sabrina Iarlori [b], Sauro Longhi [b], Luca Romeo [b,*], Federica Verdini [b]

[a] Neurorehabilitation Clinic, Department of Experimental and Clinical Medicine, Polytechnic University of Marche, 60126 Ancona, Italy
[b] Department of Information Engineering, Polytechnic University of Marche, 60131 Ancona, Italy

ARTICLE INFO

Article history:
Accepted 8 January 2018
Available online xxxx

Keywords:
Telerehabilitation
Motion analysis
Markerless
Microsoft Kinect

ABSTRACT

This work proposes a real-time monitoring tool aimed to support clinicians for remote assessing exercise performances during home-based rehabilitation. The study relies on clinician indications to define kinematic features, that describe five motor tasks (i.e., the lateral tilt of the trunk, lifting of the arms, trunk rotation, pelvis rotation, squatting) usually adopted in the rehabilitation program for axial disorders. These features are extracted by the Kinect v2 skeleton tracking system and elaborated to return disaggregated scores, representing a measure of subjects performance. A bell-shaped function is used to rank the patient performances and to provide the scores. The proposed rehabilitation tool has been tested on 28 healthy subjects and on 29 patients suffering from different neurological and orthopedic diseases. The reliability of the study has been performed through a cross-sectional controlled design methodology, comparing algorithm scores with respect to blinded judgment provided by clinicians through filling a specific questionnaire. The use of task-specific features and the comparison between the clinical evaluation and the score provided by the instrumental approach constitute the novelty of the study. The proposed methodology is reliable for measuring subject's performance and able to discriminate between the pathological and healthy condition.

1. Introduction

Telerehabilitation may offer an opportunity for an individualized rehabilitation program and is based on regular monitoring of the patient's progresses respect to the treatment aim and subject's expectation (Hailey et al., 2011; Steel et al., 2011).

The most of the available telerehabilitation tools failed to provide a functional monitoring of the motion during exercise execution, such as a physiotherapist does during the ambulatory training. Differently from the wearable-based sensors, markerless-based technologies provide attractive solutions for the users who are free from wearing active markers, attached to the body (Saini et al., 2012). Human motion assessment approaches are generally supported by statistical machine learning methods that compare a motion sequence, correctly performed and a priori recorded, with the observation sequence (*template* based methodologies).

However, the use of *template* based approaches does not always allow to:

- target specific clinical features of subjects with motor and cognitive disabilities;
- provide a motion assessment with specific and clear functional feedback (e.g., "Is the primary goal of the exercise satisfied?").

In this paper, clinicians identify some motion key descriptors (i.e., kinematic features) which represent a set of rules (e.g. relative angles and distance, position, velocity), that describes a specific task usually employed in a rehabilitation program. Such set defines the "motion sample" in terms of motor-functional targets and postural constraints. These features are extracted by the Kinect v2 skeleton tracking system and processed by a set of bell-shaped functions properly designed during the training stage in order to provide disaggregated scores. The reliability assessment has been performed through a cross-sectional controlled design study, comparing algorithm scores with respect to blinded judgment provided by clinicians.

* Corresponding author.
E-mail addresses: m.capecci@univpm.it (M. Capecci), m.g.ceravolo@univpm.it (M.G. Ceravolo), f.ferracuti@univpm.it (F. Ferracuti), grugnetti.martina@gmail.com (M. Grugnetti), s.iarlori@univpm.it (S. Iarlori), sauro.longhi@univpm.it (S. Longhi), l.romeo@univpm.it (L. Romeo), f.verdini@univpm.it (F. Verdini).

https://doi.org/10.1016/j.jbiomech.2018.01.008
0021-9290/

2. Related works

In the last years, many research projects focused on developing affordable, acceptable and reliable telerehabilitation applications, wearable and vision sensors based (Daponte et al., 2014; Arpaia et al., 2014; van Diest et al., 2013, 2014; Kutlu et al., 2016; Metcalf et al., 2013; Palacios-Navarro et al., 2015; Chang et al., 2013; Su et al., 2014; González-Ortega et al., 2014; Zhou and Hu, 2008; Kizony et al., 2017; Lange et al., 2012). In this scenario, Microsoft Kinect, based on Red-Green-Blue Depth (RGB-D) camera, is used at home as unobtrusive, markerless and low-cost assistive technology for human action recognition (Wang et al., 2014; Chaaraoui et al., 2014; Lee et al., 2015), fall detection (Stone and Skubic, 2015), gait measurement (Erik and Marjorie, 2013) and for supporting patients and physiotherapists in the rehabilitation program (van Diest et al., 2013, 2014; Morrison et al., 2016). It has been integrated into a telerehabilitation system to provide physiotherapy program for upper (Kutlu et al., 2016; Metcalf et al., 2013) and lower limbs (Palacios-Navarro et al., 2015; Seamon et al., 2016) in subjects with neurological or orthopedics disorders (Chang et al., 2013; Su et al., 2014) and for cognitive training (González-Ortega et al., 2014). The accuracy of Microsoft Kinect was analyzed with respect to movement artefacts (Gonzalez-Jorge et al., 2015) or to gold standard systems during different motor tasks such as gait analysis (Xu et al., 2015; Dolatabadi et al., 2016; Mentiplay et al., 2015; Clark et al., 2013), static (Xu and McGorry, 2015; Galna et al., 2014; Schmitz et al., 2014) and dynamic postures (Capecci et al., 2016b; Reither et al., 2018; Mobini et al., 2014; van Diest et al., 2014; de Albuquerque et al., 2012; Macpherson et al., 2016).

The motion analysis in a telerehabilitation system, generally, is based on automated segmentation (Lin and Kulic, 2014), identification (Fernandez de Dios et al., 2014) and assessment of movements employing statistical machine learning or action similarity algorithms. In this context, *template* based methods are usually employed to assess the correspondence among trajectories of a reference exemplar (e.g. physiotherapists) and patients (Zhao et al., 2014). These reference trajectories can be used to train a statistical machine learning model (Yang et al., 2012; Capecci et al., 2016a; Karg et al., 2015; Ozturk et al., 2016; Leightley et al., 2017) or computing a time warping distance (Hu et al., 2015; Zhang et al., 2016; Su et al., 2014).

Machine learning algorithms, such as neural networks (Yang et al., 2012), hidden markov model (Karg et al., 2015; Capecci et al., 2016a) and principal component analysis (Ozturk et al., 2016) have been used to discriminate between healthy and pathological subjects during different motor tasks, while dynamic time warping was employed (Su et al., 2014; Zhang et al., 2016) to produce an index of mobility with respect to an exemplar of the target movement.

3. Experimental protocol

3.1. Population

Subjects enrolled in the study were 57: 28 healthy subjects composed the *Control* group (14 female, range: 22–76, mean $\pm$ std: 36.4 ± 16.9) while 29 subjects composed the *Experimental* group (15 female, 17–76, 58.6 ± 13.8). The subjects belonging to *Experimental* group suffered from chronic disabilities due to neurological (i.e., Parkinson's Disease: 8 female, 51–76, 63.8 ± 8.7 and Cerebral Stroke: 4 female, 17–72, 56.4 ± 17.2) and musculoskeletal disorders (i.e., Backpain: 3 female, 30–72, 49.8 ± 16.7) as diagnosed by the physicians of the Neurorehabilitation Clinic of the University Hospital of Ancona (Italy) for disease management. Since the *Control* group served for defining criteria to accurately describe exercises, their age range was selected in order to match with the larger part of adulthood and not with respect to the age range of the *Experimental* group. None of the subjects enrolled in the study reported recent traumas, dementia or practiced sports at a competitive level. The study was conformed to the Helsinki protocol for clinical trials and was approved by the local ethics committee. All subjects signed the informed consent form.

3.2. Motor tasks description

Clinicians selected five exercises widely used for physiotherapy of axial disorders (Kisner and Colby, 2012). Exercises #1–#4 involve upper body movements: lateral tilt of the trunk with the arms in extension (Fig. 1a), lifting of the arms with trunk extension (Fig. 1b), trunk rotation on the transverse plane with arms in elevation (Fig. 1c), pelvic rotations on the transverse plane (Fig. 1d). The Exercise #5 actively involves the lower body with a squatting movement (Fig. 1e). Subjects were asked to perform the exercises, except the Exercise #4, holding a bar with both hands. Each exercise was repeated five times consecutively in order to mimic a real training and obtain an average motor behavior, useful for a reliable statistical assessment. The starting posture was characterized by the subject in the upright position with his/her legs slightly apart, at a distance of about 3 meters in front of the Kinect sensor. The exercise selection followed clinical and technical reasons. Firstly, the described exercises are basic motor tasks aimed at improving axial function acting on proximal joints range of motion and trunk flexibility. They are part of any motor training in the warm-up phase and can be performed even by elderly subjects with mild to moderate disability (Kisner and Colby, 2012; Hutson and Ward, 2015). The technical reason lies in the choice of exercises useful to test the assessment tool during gestures involving body segments (i.e., the arms in Exercises #1, #2, #3, the trunk in Exercise #4 and the legs in Exercise #5) moving in the frontal, sagittal and transverse planes.

4. Methods

An overview of the proposed approach is depicted in Fig. 2. The tool encapsulates three different stages: the collaborative design, the feature extraction, and the movement assessment stage. In the collaborative design stage, a set of kinematic features and functional rules are identified based on exercise characteristics and clinician indications. Afterwards, the same features are extracted from the virtual joints recorded by Kinect v2 (feature extraction stage). The evaluation of the physical movement is carried out through a comparison between features related to patients and those derived from the Control subjects. Hence, a function assigns a score based on the subject performance (movement assessment stage).

4.1. Collaborative design stage

For each exercise, clinicians followed the description of motor tasks indicated by the literature (Kisner and Colby, 2012; Kopper et al., 2012; Graci et al., 2012; Lander et al., 1986; Robert-Lachaine et al., 2015) explaining how to perform the exercise properly. Accordingly, they identified the biomechanics of movements and postures in order to define features useful for the assessment of the exercise. The collaborative design procedure aims to identify the kinematic features which describe the movement in term of motor-functional targets, postural and temporal constraints. Hence, they are labelled respectively into primary outcomes (POs), control factors (CFs) and frequency variability (FV). POs are