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

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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.

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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

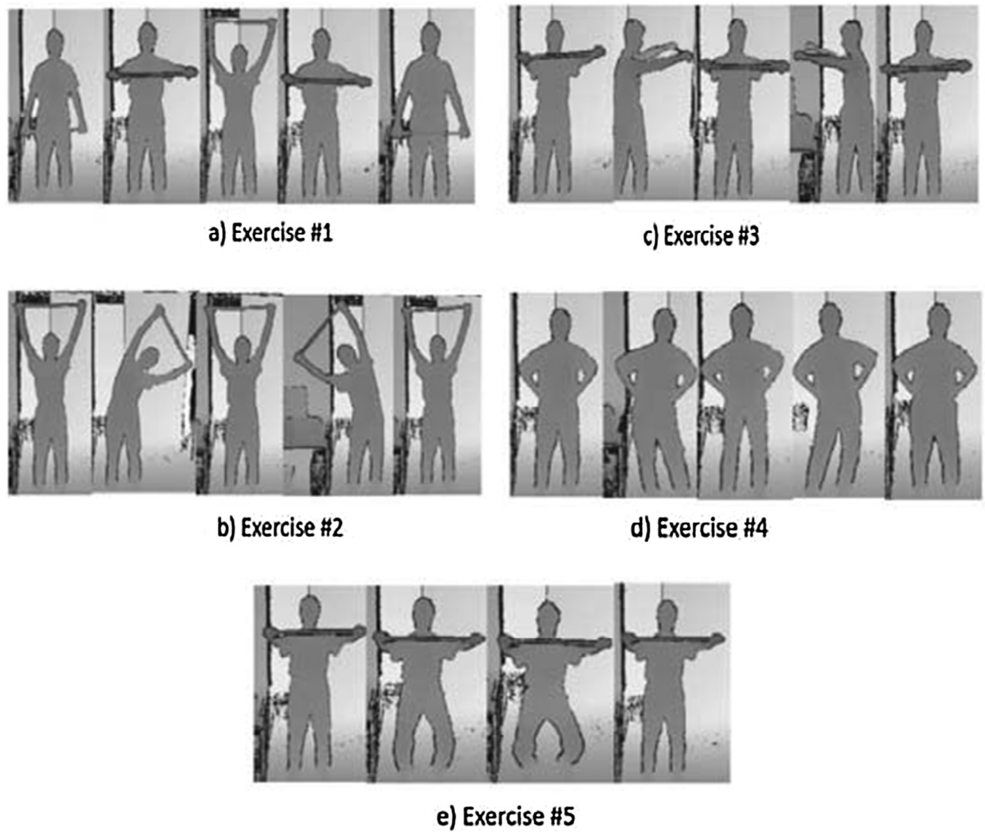

Fig. 1. Description of the five exercises, part of any motor training in the warm-up phase, selected for the study: Ex. #1, #2 and #3 are related to upper body, in particular arm movement on the three spatial axial planes, Ex. #4 stresses the trunk, while Ex. #5 concerns the lower body, namely the legs.

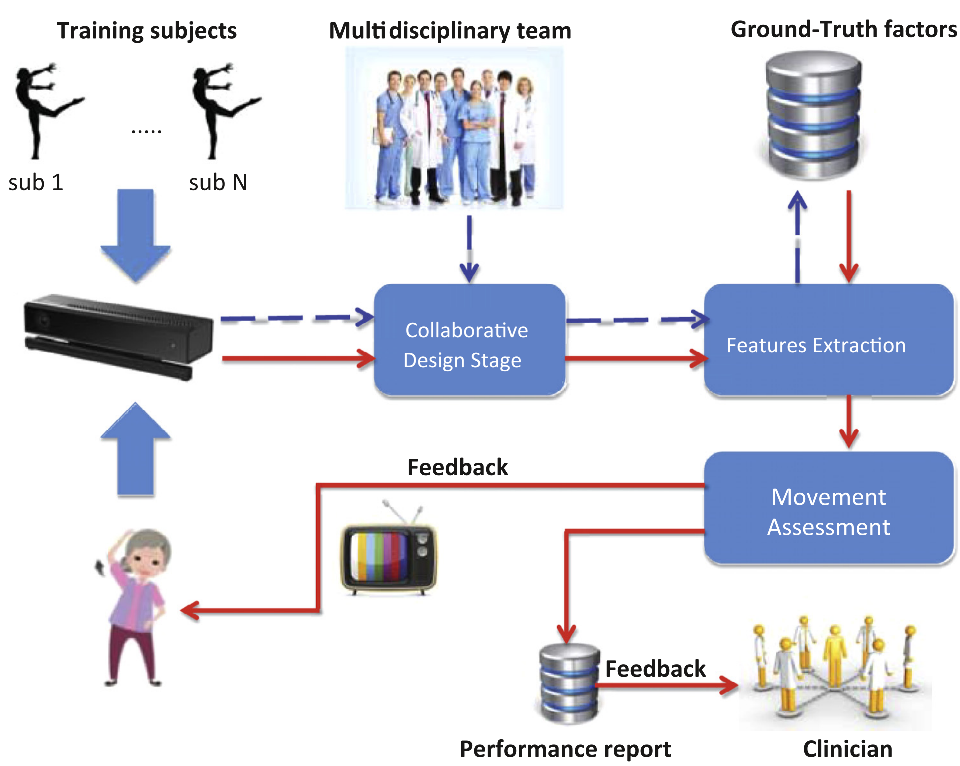

Fig. 2. The system overview shows how the main phases of the projects (i.e., Collaborative design stage, Feature extraction and Movement assessment) are connected: the blue dotted lines highlight the steps in which the clinicians are involved while the red continuous lines connect the outputs the methodology provides. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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the targets that subjects have to reach while CFs are the postures that must be satisfied during the exercise execution. Since the exercises are composed by different repetitions, the frequency is a relevant factor: subjects are expected to follow a constant speed, whereas aged and disabled people can show high-frequency variability (Studenski, 2011). All POs and CFs are represented in terms of relative distances, angles, and anatomical surfaces, while FV is a temporal distance.

Table 1 illustrates respectively the extracted PO for each exercise and the extracted CF for Exercise #1. POs are extracted in terms of Local Minima (LMin) and Local Maxima (LMax) of the related kinematic features shown in Fig. 3a–e. The hip normalization is performed for the PO of Exercise #4 ($x_{min,max}, z_{min,max}$). Since all the remaining features corresponding to POs and CFs of Exercise #1, #2, #3, #5 and CF of Exercise #4 are extracted in terms of relative angles, distances and anatomical surfaces, the normalization is not needed.

CFs are partitioned in Absolute (ACF) and Relative (RCF) Control Factor. The former describes an achievement of a global constraint, mandatory for all subjects (inter-subjects), (e.g. subjects have to maintain the elbow extended to 180°), while the latter describes an achievement feature that must be maintained during each repetition by the subjects (intra-subject), (e.g. subjects have not to move the hands).

4.2. Feature extraction stage

The feature extraction stage aims to extract the POs, CFs and FV from the motion pattern acquired by Kinect v2. We verified the accuracy of the Microsoft Kinect with respect to the stereophotogrammetric system (gold standard) in recognizing and evaluating these features during Exercise #1, #2, and #5 in the published paper (Capecci et al., 2016b).

The extracted spatial features are filtered with a 3rd order, zero-phase, low-pass Butterworth filter in order to reduce the effects of the measurement noise (Mehran, 2012). Due to its maximum flat passband nature this type of filter is also often used to remove high frequencies from digitalized kinematic data acquired by Kinect Skeletal tracking (see (Capecci et al., 2016b; Scano et al., 2014; Rocha et al., 2015)). The cut-off frequency f_c is fixed at 1 Hz selected as the optimal value according to the residual analysis introduced in (Winter, 2009). Frequency variability is computed considering the time difference between two consecutive PO peaks (i.e. local maxima).

Fig. 4a shows the POs extracted from one Control subjects (subA) during Exercise #1. Zero Velocity Crossings (ZVC) (Pomplun, 2000) is applied to compute the PO of each exercise. Among these stationary points, only local minima/maxima under specific amplitude and temporal threshold are selected respectively in order to avoid spurious peaks checking the spatial and temporal resolution. The amplitude threshold is empirically set as the mean value of the considered feature, while the temporal threshold t_{th} is selected using the recorded samples m and the number of repetitions performed by the subjects (i.e., $n = 5$) as $t_{th} = \frac{m}{2n}$.

The CFs are extracted for each recorded frame. An example of two CFs, extracted from control subject A, during Exercise #1 is shown in Fig. 4b and c. The subject satisfies the ACF when reaches or overcomes the objective threshold (see Fig. 4b). Instead, RCFs are analyzed considering the parameter variation respect to the mean value obtained by the subject during the whole trial (see Fig. 4c).

Table 1
PO description related to each exercise considered in this study.

PO (see Fig. 3a–e)		
Exercises	Tag	Description
1	$\alpha_{L,R_{min,max}}$ (Fig. 3a)	LMin and LMax of underarm angle in the sagittal plane
2	$\beta_{L,R_{min,max}}$ (Fig. 3b)	LMin and LMax of the lateral shoulder flexion in the frontal plane respect to hip
3	$d_{x_{min}}$ (Fig. 3c)	LMin of the horizontal distance between elbows
4	$x_{min,max}, z_{min,max}$ (Fig. 3d)	LMin and LMax of the spine base oscillation in the transverse plane
5	$\theta_{L,R_{min,max}}$ (Fig. 3e)	LMin and Lmax of the knee angles in the sagittal plane
CF (see Fig. 3f)		
Exercise 1	Tag	Description
ACF	$\gamma_{L,R}$	Elbow extension angles
ACF	$\phi_{L,R}$	Knee extension angles
RCF	$\psi_{L,R}$	Hip angles
RCF	A_t	Torso Area
RCF	d_h	Hands Distance
RCF	d_a	Ankle Distance

4.3. Score function

A bell-shaped function is used to rank the patient performance and to provide the scores. The generalized bell function depends on three parameters obj, b, and Δ as given by:

$$y = \frac{1}{1 + \left|\frac{input - obj}{\Delta}\right|^{2b}} \tag{1}$$

where obj is the target value, Δ is the admitted tolerance and $input$ refers to the considered PO, CF or FV features. Together with the tolerance, b controls the slope at the crossover points. The target and tolerance values are assigned statistically based on the training stage described in the next Section. The parameter b is set empirically to 2, according to the clinicians, in order to provide a less restricted evaluation. The score ranges from 0 to 100. On the basis of exercise scope, each subject can achieve the objective if he/she remains in the tolerance of the target value, overcomes the target value or remains under this threshold. Therefore three score functions (see Eqs. (2)–(4)) are designed depending on how the exercise medical goal must be achieved:

$$score1 = y \tag{2}$$

$$score2 = \begin{cases} y, & \text{if } input \leqslant obj \\ 100 & \text{if } input > obj \end{cases} \tag{3}$$

$$score3 = \begin{cases} y, & \text{if } input \geqslant obj \\ 100 & \text{if } input < obj \end{cases} \tag{4}$$

The score related to PO is the average respectively for each local minima $\left(PO^{min}_{score_i}\right)$ and/or maxima $\left(PO^{max}_{score_i}\right)$ during the five repetitions ($n = 5$):

$$PO^{min}_{score} = mean\left(PO^{min}_{score_{i=1...n}}\right) \tag{5}$$

$$PO^{max}_{score} = mean\left(PO^{max}_{score_{i=1...n}}\right) \tag{6}$$

The total PO score $\left(PO^{tot}_{score}\right)$ is computed as the mean of the PO^{min}_{score} and PO^{max}_{score}. CF score is figured out for each recorded frame (number of samples, t) of the specific k constraint ($CF^{k=1...l}$). The total CF score $\left(CF^{tot}_{score}\right)$ is computed by:

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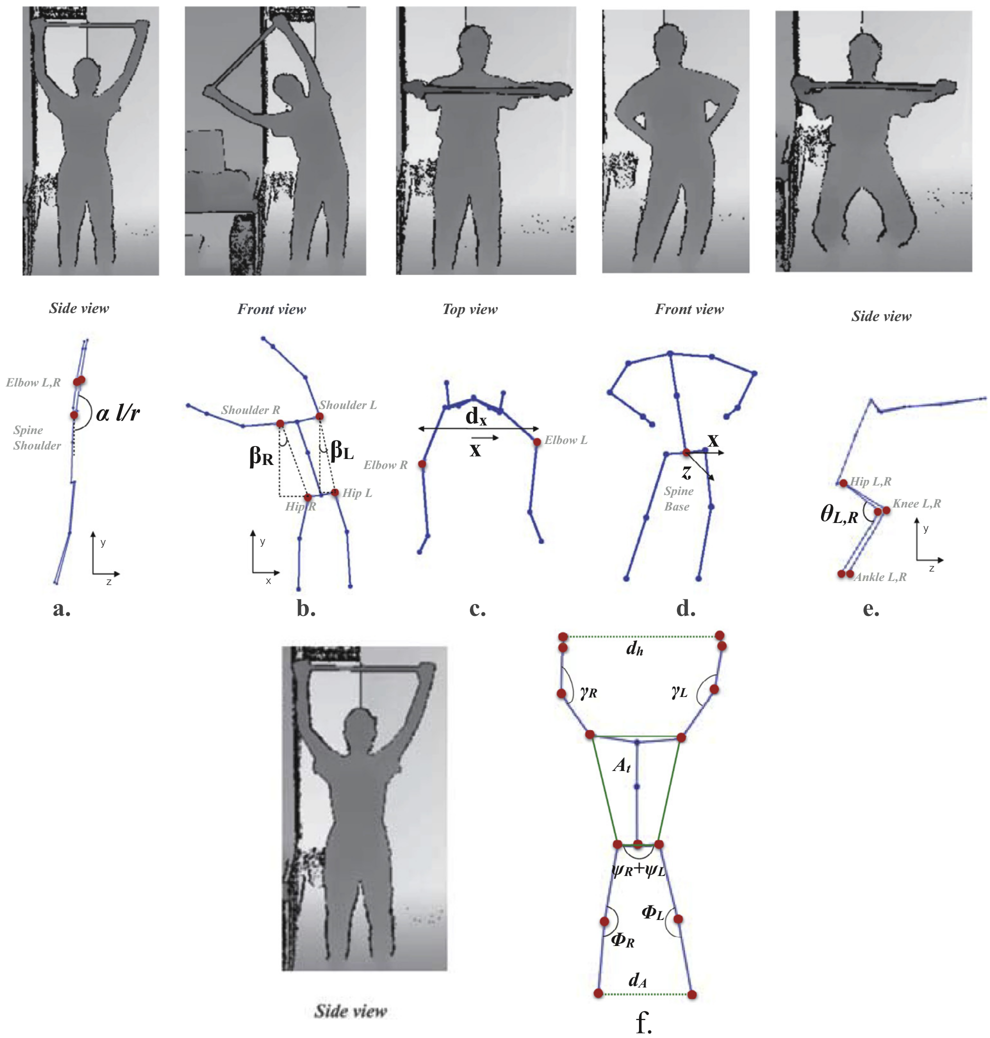

Fig. 3. Kinematic features: PO (a–e) and CF (f) extraction.

$$CF^{k}_{score} = mean\left(CF^{k}_{score_{i=1\dots t}}\right) \tag{7}$$

$$CF^{tot}_{score} = mean\left(CF^{k=1\dots l}_{score}\right) \tag{8}$$

The FV score is computed for each time difference between two consecutive peaks of PO (i.e. local maxima). Then the total FV score is given by:

$$FV^{tot}_{score} = mean(FV_{score_{i=1\dots n-1}}) \tag{9}$$

The Total Score (TS) is the mean of the $PO^{tot}_{score}, CF^{tot}_{score}, FV^{tot}_{score}$.

4.4. Training stage

During the training stage the objective (*obj*) and tolerance (Δ) values are computed for each feature respectively as mean and standard deviation of POs, CFs and FV extracted from the *Control* group ($s = 1\dots28$). The PO target (PO_{obj}) is computed respectively as the mean, while the tolerance value (PO_{Δ}) is set as the standard deviation (std).

$$PO_{obj} = mean(PO_{s=1\dots28}) \tag{10}$$

$$PO_{\Delta} = std(PO_{s=1\dots28}) \tag{11}$$

Also, the ACF target (ACF_{obj}) and tolerance (ACF_{Δ}) are computed considering respectively the mean and std for all the recorded frame.

$$ACF_{obj} = mean(ACF_{s=1\dots28}) \tag{12}$$

$$ACF_{\Delta} = std(ACF_{s=1\dots28}) \tag{13}$$

Instead, for RCF the target value changes among subjects and it is computed as the respective mean value, while the tolerance (RCF_{Δ}) is the std of each signal normalized to zero mean (RCF^{norm}_{s}).

$$RCF_{\Delta} = std\left(RCF^{norm}_{s=1\dots28}\right) \tag{14}$$

Since each subject can perform the exercise at different speeds, also the FV_{Δ} is the std of each feature normalized to zero mean (FV^{norm}_{s}).

$$FV_{\Delta} = std\left(FV^{norm}_{s=1\dots28}\right) \tag{15}$$

4.5. Data analysis

The reliability of the instrumental approach is assessed taking into account three different aspects:

1. measuring the correlation between the algorithm scores and the averaged judgment of two expert clinicians (M.C. and M.G.) who scrutinized the recorded videos and responded to the questionnaire employed in Capecci et al. (2016a) and detailed in Appendix A about the gesture correctness, amplitude, variability, and posture;

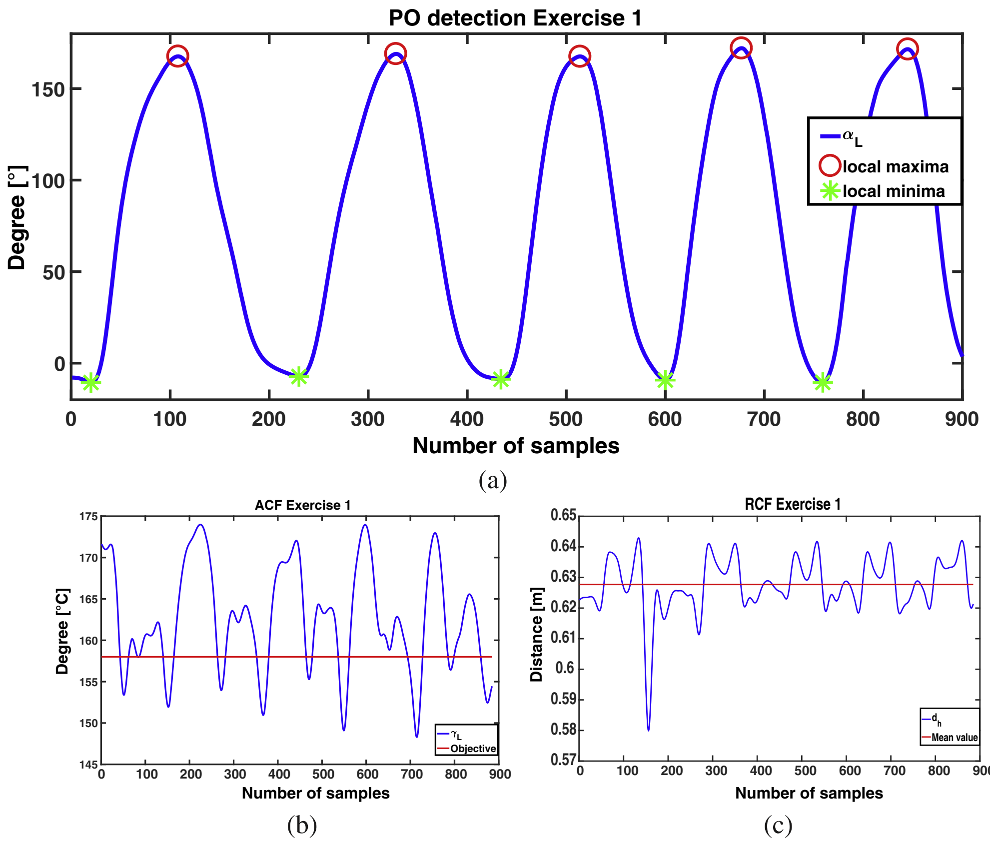

Fig. 4. PO($\alpha_{L_{max,min}}$) (a), ACF (γ_L) (b) and RCF (d_h) (c) computed from subA during Exercise #1.

2. studying the ability to discriminate healthy subjects (i.e. *Control* group) with respect to disabled people (i.e., *Experimental* group);
3. analyzing how the single features and the related scores contribute to the final outcome and identifying which feature is able to discriminate between group.

Clinicians observed videos and fulfilled a 10-item Likert questionnaire in order to quantify the clinical judgment about the exercise execution (see Appendix A). The first three questions investigated the functional goal, whereas the last seven items controlled the posture maintained during the exercise. Three outcome measures are then calculated: the clinical Total Score (cTS) as the sum of the scores of all ten questions, the clinical Primary Outcome score (cPO) as the sum of the scores of the first three questions and the clinical Control Factors (cCF) as the sum of the last seven items. To the best of authors knowledge, in literature, no other assessment questionnaires are presented in order to record clinicians' judgment about subjects exercise performance. Therefore, authors choose to propose this scale (Capecci et al., 2016a) and checked for inter-rater reliability applying Cohens Kappa test that resulted high ($K > 0.8$) assessing measures taken from both controls as well as patients. Since the Kolmogorov Smirnov test rejected the null hypothesis that the score data comes from a standard normal distribution, the non-parametric Mann-Whitney U test is used to perform the between-group comparison.

5. Results

The correlation analysis with the cPO is performed averaging the PO and FV scores. The analysis of relationship between machine and clinicians based assessment shows a medium ($\rho > .4$) and significant ($p < .02$) correlation for TS and PO score in all the exercises with the exception of Exercise #5 (see Table 2). This significant correlation was recognized on the *whole* sample (*Control* and *Experimental* group) and on the *Experimental* group.

Fig. 5a and b shows respectively the box plot of the scores computed by the algorithm and clinicians for both groups separately (i.e. *Experimental* and *Control* subjects).

The between-group comparison performed by the Mann–Whitney U test discloses that the Total Score, provided by the rule-based approach, is able to detect significant differences among subjects without pathological history (i.e. *Control* group) with respect to subjects suffering from pathologies, that induce motor disability or pain (i.e. *Experimental* group) (see Table 3). The Primary Outcome score is able to distinguish between groups except for the case of Exercise #2. The Control Factor score unveils significant differences between Control and Experimental people in the case of Exercise #2 and #4, whereas the Frequency Variability score is significantly different between healthy (*Control*) and disabled (*Experimental*) subjects in the case of Exercise #1, #4 and #5. All acquired clinical measures are able to discriminate between *Control* and *Experimental* subjects (see Table 3).

5.1. Features analysis

The canonical correlation analysis was performed for Exercise #1 between the feature scores provided by the algorithm with respect to cPO and cCF (see Fig. 6). The correlation increases respectively for PO scores ($\rho = 0.649$ for *Experimental* Group, and $\rho = 0.549$ for the Whole Sample) and CF scores ($\rho = 0.777$ for *Experimental* Group, and $\rho = 0.637$ for the Whole Sample).

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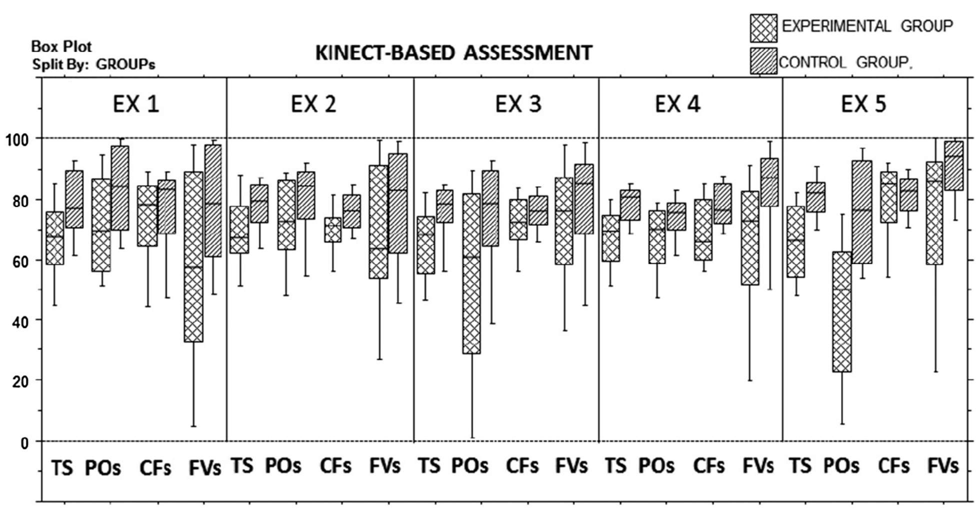
Table 2
Spearman rank correlation test: ρ values (Z value; p value).

Ex.	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 5
TS					
Whole sample	.54 (3.6;.0003)	.45 (3.0;.002)	.46 (3.1;.002)	.64 (4.3; <.0001)	.3 (2.1;.03)
Experimental group	.44 (2.3;.02)	.41 (2.3;.02)	.46 (2.6;.001)	.62 (3.5; <.0005)	.2 (n.s.)
PO					
Whole sample	.48 (3.3;.001)	.45 (3.0;.002)	.51 (3.4;.001)	.6 (4.0; <.0001)	.51 (3.4;.001)
Experimental group	.57 (3.1;.002)	.55 (3.1;.02)	.50 (2.8;.005)	.66 (3.7; <.0002)	.41 (2.3;.02)
CF					
Whole sample	.2 (n.s.)	.52 (3.5;.0005)	.42 (2.8;.005)	.41 (2.7;.007)	.1 (n.s.)
Experimental group	.2 (n.s.)	.41 (2.3;.02)	.47 (2.7;.008)	.3 (n.s.)	.3 (n.s.)



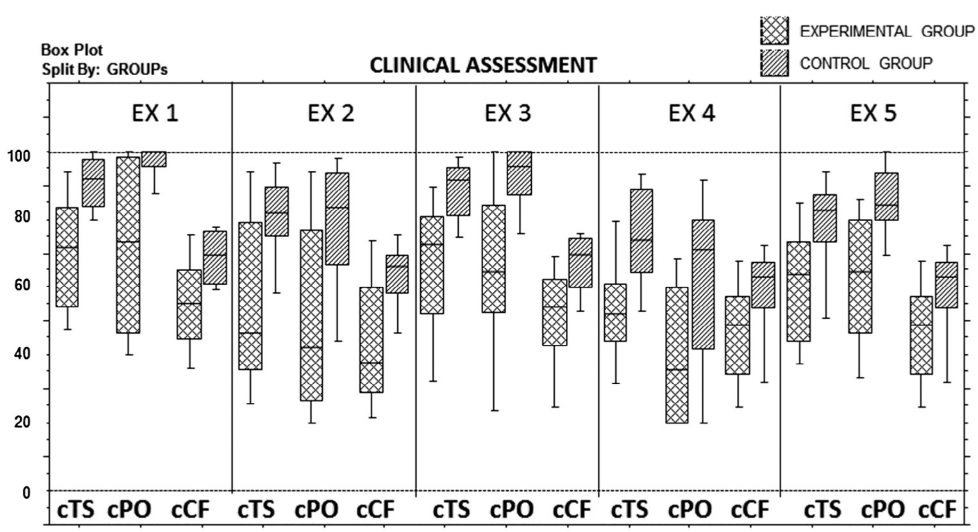


Fig. 5. Box plot rule-based assessment scores (a) and clinical scores (b) split by *Experimental* and *Control* group.

The computed weights of each feature are reported in Fig. 7. The most relevant PO for Exercise #1 is the $\alpha_{L/R_{max}}$ (i.e., the maximum angle of the underarm angle). While the most salient CF is the extension of the elbow angles (i.e.,$\gamma_{L/R}$).

The Mann-Whitney U test was performed for each PO and CF in order to recognize which feature was more discriminative to identify groups. Results point out that none features are statistically significant for discrimination. Anyway the $\alpha_{L/R_{max}}$

Table 3
Results of comparative statistics (Z value; p value by Mann Whithney U test) of rule-based assessment scores and clinical scores: *Experimental* subjects versus *Control* subjects.

Ex.	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 5
Rule-based scores					
TS	−2.9;.003	−2.4;.01	−3.2;.001	−3.6;.0003	−4.1; <.0001
PO	−2.3;.02	n.s.	−2.6;.01	−2.1;.03	−4.2; <.0001
CF	n.s.	−2.5;.01	n.s.	−2.4;.01	n.s.
FV	-2.1;.03	n.s.	n.s.	−2.9;.003	−2.4;.02
Clinical scores					
cTS	−4.4; <.0001	−3.6;.0003	−4.5; <.0001	−4.5; <.0001	−3.6;.0003
cPO	−3.8;.0002	−3.3;.001	−4.0; <.0001	−3.2;.001	−4.5; <.0001
cCF	−4.1; <.0001	−3.7;.0002	−3.9; <.0001	−4.6; <.0001	−2.8;.005

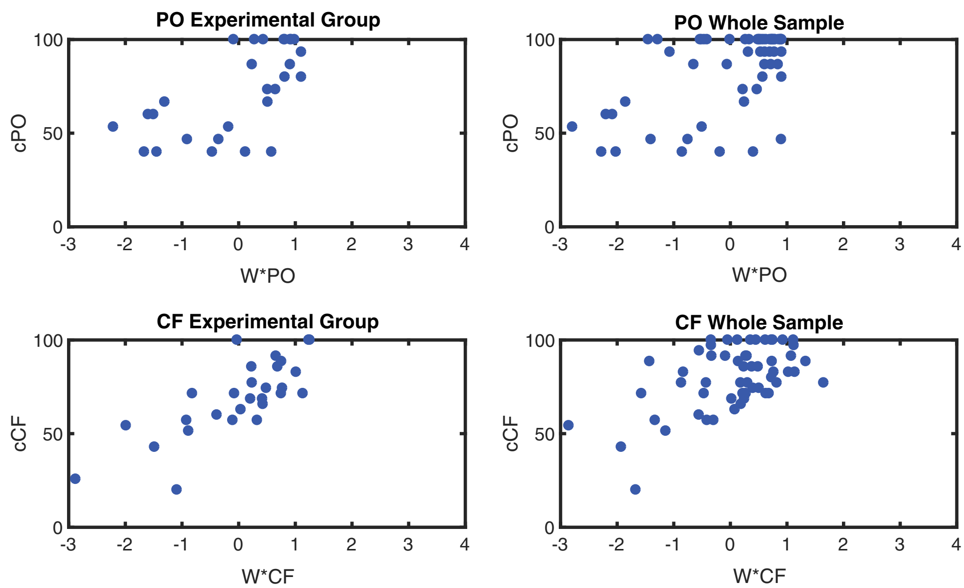


Fig. 6. Canonical correlation between the univariate outcome scores computed by the instrumental approach and the clinical primary and control factor outcome (i.e., cPO and cCF). The x-axis shows the PO and CF scores multiplied for their related weight while y-axis reports cPo and cCF.

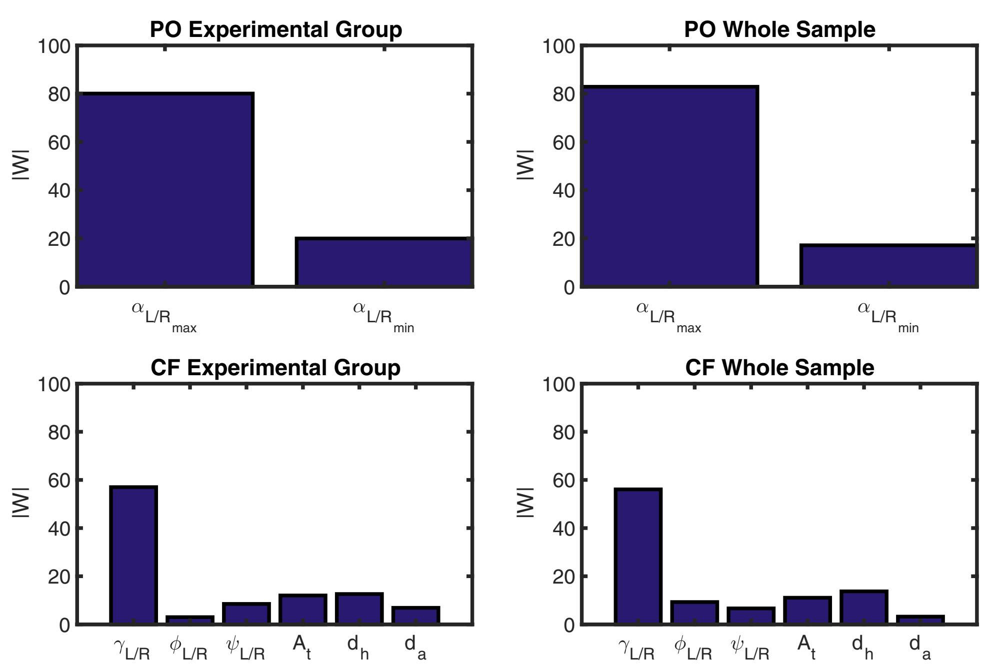


Fig. 7. Weights of each PO and CF Exercise #1 (the sum of the weights was normalized to 100), related to Experimental Group and Whole Sample.

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($Z = 1.7, p = .092$), $\gamma_{L/R}$ ($Z = 1.6, p = .105$) and d_h ($Z = 1.4, p = .153$) are close to the boundary of significance.

6. Discussions

Telerehabilitation offers some benefits and advantages for people suffering from neurological and orthopedic diseases (Hailey et al., 2011; Steel et al., 2011; Bendixen et al., 2009; Brennan et al., 2009; Constantinescu et al., 2010; Johansson and Wild, 2011). Complex and intrusive technologies like electromyography (Russell et al., 2011), optoelectronic motion analysis or wearable inertial systems cannot be routinely adopted in a physiotherapy ambulatory or at home, because of their costs and low acceptability and usability, as defined by the Unified Theory of Acceptance and Use of Technology criteria (UTAUT (Venkatesh et al., 2003)). On the other hand, more than one wearable sensor (i.e. accelerometer) is required to accurately describe motion and posture (Winters et al., 2003; Iosa et al., 2016), disagreeing with the UTAUT (Venkatesh et al., 2003). Therefore, vision-based systems are preferable for monitoring the whole body motion during the execution of a functional movement in a delimited environment. Although there is a growing interest towards telerehabilitation, most of the available systems failed to provide a direct accurate monitoring of the motion during exercise.

In this paper, a Kinect based system is proposed for assessing motor performance during rehabilitation. With respect to similar systems yet presented in the literature (Zhao et al., 2014; Metcalf et al., 2013; Palacios-Navarro et al., 2015; Chang et al., 2013; González-Ortega et al., 2014; Su et al., 2014), three main innovations, apart from using Microsoft Kinect v2 as the sensor, are introduced:

1. the machine-based movement assessment is realized with rules derived from the exercise kinematic, whereas most of the studies used probabilistic model (Ciabattoni et al., 2016; Karg et al., 2015) or action similarity algorithm (Su et al., 2014; Hu et al., 2015; Zhang et al., 2016);
2. the reliability of the assessing system has been performed comparing algorithm results with respect to blinded clinicians judgments;
3. the algorithm is able to recognize separately both the correct posture of different body segments (named postural Control Factors) and, contextually, the correct kinematic outcomes (named Primary Outcomes) during the exercise.

The rule-based approach allows to overcome the preliminary construction of a large sample database of controls stratified by gender, age and anthropometric measures, as required, for instance, by *template* based approaches (Ciabattoni et al., 2016; Karg et al., 2015; Su et al., 2014; Hu et al., 2015). Anyway, healthy subjects may wrongly perform some exercises: as found in this study, the maximum value of clinical postural score (cCF) is around the 75%.

The algorithm provides a disaggregated quantitative score for each PO, CF, which are the main information for supporting patients directly and clinicians remotely (Kairy et al., 2009; Hailey et al., 2011). To the best of authors' knowledge, no available systems have showed these markerless and low-cost features.

The system reliability has been tested on five exercises widely used to treat neurological and musculoskeletal diseases (Hutson and Ward, 2015; Kairy et al., 2009; Kisner and Colby, 2012). The method followed in this study can be usefully applied for many other exercises (e.g., K3Da dataset (Leightley et al., 2015)) adopted in the rehabilitation context: the procedure used to design the algorithm and to identify the outcome measures is the key rule to generalize the approach.

In order to generalize the experiment and its results, the enrolled groups are heterogeneous for age range and pathologies. The correlation, respect to clinicians' judgments, highlights a significant reliability of TS and PO scores, while the CF scores result less accurate for assessing postural features. In particular, dynamic movements may include different postures adverse to the vision sensor characterized by joint occlusion (Capecci et al., 2016b). On the other hand also the clinical assessment can be affected by bias and errors due to the discrete clinical scale grading (e.g. rarely vs sometimes vs often) and to the visual evaluation of a 3D human movement performed through 2D video images. These elements and the sample heterogeneity can be the responsible for the wide variability of clinical measures, as shown in Fig. 5b. The between-group comparative statistic shows that TS and PO scores discriminate between healthy and disabled subjects while CF and FV scores are less effective to do it in the case of Exercise #1, #3 and #5. The TS is a comprehensive measure, able to give a reference value, useful for both patients and clinicians, while PO score is able to depict the reaching of the primary outcome of the exercise. Accordingly, CF score remains the awkward measure due to its implicit complexity while the FV values show a subject- and pathology-dependency (Serrao et al., 2017).

The canonical analysis was able to identify those features that most influence the PO and CF scores. However, neither of the feature alone was completely reliable at discriminating between group, possibly due to highly variable movement patterns provided by subjects with motor impairments. Hence, we recommend combining the assessment of different features to increase the discriminative power and the generalization of this approach.

7. Conclusions

Monitoring the accuracy of subjects posture and movements during rehabilitation stage is performed continuously by the physiotherapist in order to guarantee the best outcome and avoid side effect as pain or falls (Kisner and Colby, 2012; Kopper et al., 2012; Graci et al., 2012; Lander et al., 1986; Robert-Lachaine et al., 2015). However, when exercise is performed in the home environment, the issue of gesture monitoring is critical. We proposed a tool able to provide an instrumental monitoring of motor performance during motor training for axial disorders, that may be adopted in a telerehabilitation scenario. It resulted reliable when compared to clinical judgment and efficacious at discriminating between patients and healthy subjects. The tool provides different outcome measures: a synthetic score (TS) that was the most consistent measure, a score describing movement features (PO) that was the most reliable with respect to clinicians decision and a score describing postural features (CF) that was the most variable measure during both instrumental and clinical assessment, reflecting the limits of Kinect camera as well as of the clinical judgment. As future works authors aim to validate the reusability of the proposed methodology with respect to other dataset proposed in literature such as the K3Da dataset (Leightley et al., 2015). Furthermore, authors aim to integrate this tool in a telerehabilitation system allowing subjects to carry out tailored exercises at home, exploiting continuous feedback of their performances.

Conflict of interest

The authors declare that there is no conflict of interest.

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Appendix A

Exercise accuracy assessment

Please, observing the entire exercise (all repetitions), answer the questions signing one of the following chance:

1=Never	2=Rarely	3=Sometimes	4=Often	5=Always

1. Is the primary goal of the exercise reached (i.e., the extension of the upper limbs, trunk rotation with upper limbs elevated to 90°, squatting, etc.)?
2. Is the exercise repeatable?
3. Is the amplitude of the movement complete?
4. Is the posture of the head correct?
5. Is the posture of the right arm correct?
6. Is the posture of the left arm correct?
7. Is the posture of the trunk correct?
8. Is the posture of the pelvis correct?
9. Is the posture of the right leg correct?
10. Is the posture of the left leg correct?

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