ELSEVIER

Pattern Recognition Letters
journal homepage: www.elsevier.com

A new paradigm for autonomous human motion description and evaluation: application to the Get Up & Go test use case

Juan Pedro Bandera[a], Rebeca Marfil[a,**], Adrián Romero-Garcés[a], Dimitri Voilmy[b]

[a]*Grupo de Ingeniería de Sistemas Integrados, ETSI Telecomunicación, Universidad de Málaga, Campus Teatinos s/n, Málaga, 29071, Spain*
[b]*ICD/Living Lab ActivAgeing (UMR CNRS 6281), Troyes University of Technology, 12 Rue Marie Curie, 10004 Troyes, France*

ABSTRACT

Human Motion Analysis is receiving a growing attention in the field of assistive technologies. Portable systems, able to be carried home or mounted on socially assistive robots, can help in monitoring and evaluating the autonomy level of elderly people in the upcoming silver society. This paper presents a new paradigm to describe and evaluate human motion that can be used in these scenarios. The proposal is based on parametric segmentation and evaluation of action primitives. These actions can be combined in different sequences or even evaluated in parallel, providing a modular solution that can easily adapt to the analysis of new behaviours or motion tests. The particular use case of the Get Up & Go test has been used to study the validity of the proposal. Autonomous evaluation of the gaits of different performers have been achieved using data captured by a Kinect 2.0 device mounted on a social robot. Experiments have also involved gait data captured with a precise Vicon Nexus system based on markers, to compare with previous results and characterize capture errors of the Kinect device. Results show that the proposed system is adequate to be used in these scenarios.

1. Introduction

In the last twenty years, the applications and research interest in the Human Motion Analysis (HMA) field have grown significantly. It has become a focus topic for researchers in virtual modelling, rehabilitation processes, ergonomics, gait analysis, robotics or surveillance applications, amongst others (Moeslund et al., 2006; Chen et al., 2013; Wang et al., 2015a). These applications are usually classified depending on the required level of precision, this level being inversely proportional to the degree of invasiveness and imposed environmental constraints.

However, new application fields - that are growingly demanding - are arising for HMA. Among them, a particularly interesting one, due to the current evolution of the world population. According to the estimations of the United Nations, by 2050, one out of every five people in the world will be over 60 years old (DG-ECFIN and AWG, 2014). For this *silver society*, it is necessary to design and implement models that help elderly people age healthily and maintain their autonomy and well-being. These models imply multidisciplinary approaches, in which social, medical or engineering dimensions have to be considered. Thus, the Active Ageing approach requires the development of autonomous systems to monitor the status and activities of a person, without interfering with them. Motion evaluation becomes an important feature for these systems: falls (or risk of falling), manipulation issues or motion impairments are among the key causes of autonomy loss among the elderly population. Consequently, motion tests are a key part of Comprehensive Geriatric Assessment (CGA) procedures, designed to capture data on the medical, psychosocial and functional capabilities and limitations of elderly people (Matthews, 1984).

Autonomous tools - that evaluate human motion, both in their daily life activities and performing motion clinical tests - will have to be precise, but yet, will avoid imposing any constraints on the patient. E.g., no special environments, markers or garments should be used. Ideally the point of view from which motion sequences are captured should not be imposed. This is to allow the performing of these evaluations, from any monitoring camera, in the person's environment (e.g. her house). In practice, however, the problem has to become achievable. Portable devices appear as an interesting solution to facilitate

**Corresponding author: Tel.: +34952132845;
e-mail: `rebeca@uma.es` (Rebeca Marfil)

home rehabilitation, as the person can locate them in a proper spot to capture her motion (Lahnera et al., 2015). On the other hand, socially assistive robots (Feil-Seifer and Mataric, 2005), among other important characteristics, are also able to carry sensors, and identify where the person is, and capture her motion from a certain perspective. They can also be equipped with the processors required to execute HMA algorithms, that are often computationally expensive (Moeslund et al., 2006).

This paper proposes a new paradigm for autonomous human motion description and evaluation, which has been designed as a general system, able to adapt to different data inputs and scenarios. The proposed HMA system detects a set of different actions in a certain motion, and combines the evaluation of these actions to provide an integrated score for the complete motion. Expert knowledge is used to perform the motion segmentation and evaluation processes. Actions are stored in a library, allowing the medical specialist to (i) use them as components to create new motion exercises; or (ii) autonomously search for particular actions in a perceived motion. It has been developed within the framework of the CLARC EU project[1].

The rest of the paper is organized as follows: Section 2 describes recent research works, in the field of HMA, related to the proposed paradigm. This paradigm is described in Section 3. In order to provide a practical evaluation framework for the proposal, it has been used to evaluate human gait in the Get Up & Go test, commonly employed in CGA processes. Section 4 introduces the test, and details as regards the splitting and evaluation criteria for the actions that compose it. Section 5 describes the experiments performed to test the validity of the approach, using two different Motion Capture (MoCap) systems: a Vicon Nexus 1.8.5 MoCap system, and a Kinect 2.0 device mounted on CLARC, a socially assistive robot for CGA processes developed in the CLARC project. Section 6 discusses the obtained results and concludes the paper.

2. State of the art

The HMA proposed in this paper is intended to be integrated in portable devices or socially assistive robots, that capture human motion in daily life environments. Traditionally, MoCap systems that meet these requirements are vision-based systems, that employ data provided by a single camera or a pair of stereo cameras. The survey of Moeslund et al. (2006) describes these systems, that can be basically divided into model-free approaches, that directly map visual perception to pose space, and model-based approaches, that use a model to help in the tracking and pose estimation processes (Moeslund et al., 2006). Despite the variety of approaches and algorithms used, the effectiveness in capturing human motion was limited. At best, this is due mainly to the sensitivity of monocular cameras and stereo systems to lighting variations, noise, partial occlusions or pose ambiguities (Bandera, 2010; Moeslund et al., 2006).

The apparition of the PrimeSense sensor, employed in devices such as Kinect or Asus Xtion, became a key event in the research on non-invasive, portable motion analysis. These devices are cheap, small and offer quite accurate 3D estimations for perceived points (D. and Pinto, 2015). Along with them, new algorithms appeared. They allow the detecting and tracking of human motion based on the depth images they provide. The most extended solution is the proposal of Shotton et al. (2013), employed in the Kinect for Windows SDK. This model-free approach infer human poses using a decision forest to classify features extracted from the depth images. The decision forest is trained using hundreds of thousands of virtual poses. Wang et al. (2015a) offers a complete analysis of the accuracy of this algorithm to estimate human pose, for both generations of Kinect devices (Kinect 1 and Kinect 2.0).

These cheap RGB-D sensors, and the algorithms they employ to capture human pose, have become the reference in the state-of-the-art in the field of non-invasive and portable HMA (Chen et al., 2013; Wang et al., 2015a). However, they have a limited precision, sample rate and field of view (Wang et al., 2015a). These constraints prevent them from being widely used in rehabilitation scenarios, or motion evaluation applications (Lahnera et al., 2015), although the number of contributions in these fields have been increasing these last years. Thus, Kargar et al. (2014) use an RGB-D Kinect sensor to capture three gait parameters (number of steps, duration of each step, turning time) and three anatomical parameters (distance between elbows, angle between legs and knee flexion angles). These six features are used in a Classification Support Vector Machine Type 1 (C-SVM) classifier to automatically classify gaits in the Get Up & Go test into two categories: high risk of falling or low risk of falling. The obtained classification accuracy is 67.40%, on tests conducted over 12 elderly people. Cippitelli et al. (2015) detect skeleton joints from lateral motion. They use raw depth data and anthropometric relationships to infer the joint positions on a frame-by-frame temporal basis, without the need for learning phases nor modeling support. Extracted joints are intended to be used in the evaluation of the Get Up & Go test.

In the field of action segmentation and recognition, the Kinect device also appears frequently in the literature. Ghorbel et al. (2015) employ it to obtain a fast descriptor for action recognition. They use cubic splines to interpolate human trajectories from relevant points, and linear SVM for the training and classification steps. Wang et al. (2015b) propose an unsupervised temporal repetition segmentation algorithm, that relies on frequency analysis of kinematic parameters, zero-velocity crossing detection and adaptive k-means clustering to segment a motion into a sequence of actions. However, these studies do not evaluate perceived actions, and do not consider overlapping motions.

3. Proposed Human Motion Analysis system

The proposed HMA approach divides a complete motion, G, into a set of discrete actions, a_i, to be evaluated. Known actions are stored in an action library, called *ActionsLib*. Therefore, a complete motion, G, can be defined as an ordered combination of actions stored in this library $C(\{a_i\})$. Figure 1 shows an example of a motion divided into actions. As depicted, different

[1] http://www.clarc-echord.eu/

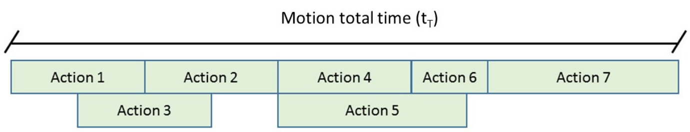

Fig. 1. An example of a sequence of actions.

actions can be executed sequentially, but they can also overlap (e.g. the action 'wave hand to say hello' may be simultaneous to the action 'walking straight'). In the current implementation of the HMA system, two overlapping actions are simply defined as actions that are simultaneously searched for in the motion.

Each action stored in the *ActionsLib* is a primitive component defined by a *starting* condition, an *ending* condition and an *evaluation* function, and they are independent from each other. Besides, they do not require any prior or post condition in the motion to be detected and evaluated. These specifications allow actions to be employed as motion primitives. They can be detected individually in a certain motion, used in competitive approaches for action recognition, or arranged in any order to create new motion sequences. Starting and ending conditions include kinematics, dynamics, and even external factors to infer precisely when an action starts and ends. In the proposed HMA approach, these conditions are searched for in a motion G in order to segment it into actions, following the defined sequence $C(\{a_i\})$ (in which, as mentioned above, certain actions may be simultaneous to other actions).

To evaluate a motion G defined by a set of N discrete actions, the evaluation function of each action and the action execution time (the difference between ending and starting times) are used. The evaluation functions take into account time-related issues, kinematics and dynamic relations, and additional factors to provide a score s_i about the motion of each action a_i. Therefore, each action a_i is characterized by two values: the action score s_i, and the action execution time t_i, defined as the action finish time t_i^f minus the action starting time t_i^s, i.e. $t_i = t_i^f - t_i^s$.

The motion total score s_T can be obtained as a weighted sum of the action values s_i. To compute the motion total time t_T, a subset of actions A_s is firstly defined in which only $M \leq N$ actions are included. Then, motion total time is computed as the difference between the maximum finish time and the minimum starting time for all the actions included in A_s. Eq. 1 and Eq. 2 show how s_T and t_T values are computed, respectively. $w_i \in [0, 1]$ are real values. These values, and the set of actions included in A_s, are set *a priori*, usually via the empirical assessment of human experts.

$$s_T = \frac{\sum_{i=1}^{N}(w_i \cdot s_i)}{\sum_{i=1}^{N} w_i} \quad \forall a_i \in A_s \tag{1}$$

$$t_T = \max_i t_i^f - \min_i t_i^s \quad \forall a_i \in A_s \tag{2}$$

Eq. 1 shows that certain actions may not have any influence on the evaluation of the motion, although they are a part of it. Besides (Eq. 2), there can be actions whose execution time is not added to the total execution time. This is a requisite to allow overlapping actions (e.g. in Fig. 1, t_3 and t_5 should not be added to t_T). There are also motion sequences in which certain actions do not form part of the gait to be analyzed (see in example the *Seated* action in the Get Up and Go test, Fig. 2).

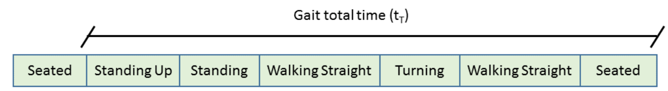

Fig. 2. Sequence of actions for the Get Up And Go test.

4. The Get Up And Go test: use case

Gait/balance disorders are the second cause of falls in elderly adults (Rubenstein, 2006), and is a major public health issue. The Get Up And Go test (Mathias et al., 1986) is designed to detect these disorders. In this test, the patient is asked to stand up from a chair, walk in a straight line for around three meters, turn back, return to the chair and sit down. The goal is to measure balance, detecting deviations from a confident, normal performance. Different factors influence this measure, including symmetry, bending or time used to execute certain movements. Results are provided on a five-point scale: 1 = normal; 2 = very slightly abnormal; 3 = mildly abnormal; 4 = moderately abnormal; 5 = severely abnormal. A person with a score of 3+ is at risk for falling. The proposed HMA system has been employed in this test to autonomously evaluate human walking.

The Timed Up And Go test (Podsiadlo and Richardson, 1991) is a variant of the Get Up And Go test. It measures the total execution time to infer the risk of falling. A normal performance should take less than 12 seconds, and execution times over 20 seconds are associated to relevant risk for falling. It is interesting to notice that computing execution time for each action (Section 3) makes the proposed system automatically able to evaluate patients' actions in this test.

4.1. Action splitting criteria

The Get Up and Go test can be divided into a set of sequential actions (Figure 2). All of these actions have been included in the *ActionsLib* library. In the first experiments presented in this paper, the total score for the test is computed by making an average of each score for the different individual actions (i.e. all w_i are similar). As Section 5 details, this criterion changed for the last experiments, in which the *Seated* action was detected, but not used in the score computation (i.e. $w_1 = 0$ and $w_i = 1/6$ $\forall i \in [2..7]$). Regarding test's time, the first action (Seated) is never included in the computation: in the test definition, the person may remain seated as long as required without impacting the result. Hence, the *Seated* action is the only one left out of A_s for the Get Up and Go time computation.

A description of these actions, and their *starting* and *ending* conditions, employed to evaluate the gait, is provided below. Figure 3 shows the most relevant axis and planes defined in human anatomy, to help the understanding of these descriptions.

4.1.1. Seated

The person remains seated.

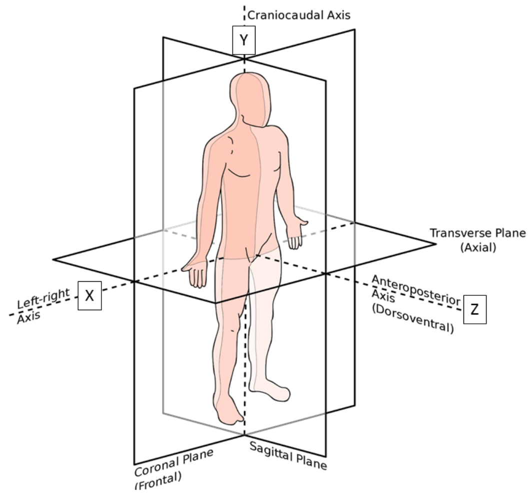

Fig. 3. Axis and planes of the human body.

- *Starting Condition*: Hips and Knees at the same height (difference in the vertical axis < 20 cm). Knees advanced more than 20 cm with respect to the Hip in the Anteroposterior axis. Head-Hip vector aligned with the Craniocaudal (vertical) axis (angle < 0.2 radians).

- *Ending Condition*: The person begins bending to stand up. As discussed further (Section 5), this condition involves detecting the beginning of the peak in the torso bending angle (Craniocaudal axis), that occurs when the person stands up (Schenkman et al., 1990).

4.1.2. Standing Up

The person stands up from a chair.

- *Starting Condition*: Hips and Knees at the same height (difference in the vertical axis < 15 cm). Knees advanced more than 20 cm with respect to the Hip in the Anteroposterior axis.

- *Ending Condition*: Hips higher than Knees (difference in the vertical axis > 25 cm (Schenkman et al., 1990)).

4.1.3. Standing

The person stands still.

- *Starting Condition*: Hips at least 20 cm higher than Knees (Schenkman et al., 1990). Projections of hips and knees in the Transverse (Axial) plane very close (distance < 20 cm). Head-Hip vector aligned with the Craniocaudal (vertical) axis (angle < 0.2 radians).

- *Ending Condition*: Hip displacement in the Transverse (Axial) plane > 30 cm.

4.1.4. Walking Straight

In this action the person walks, more or less in a straight line.

- *Starting Condition*: Hips begin to move in the Transverse (Axial) plane. More precisely, the starting frame is marked as the one in which the hip has moved more than 20 cm with respect to the initial position.

- *Ending Condition*: The person deviates too much from a straight line (shoulder axis rotates more than 0.4 radians with respect to the initial orientation), or stops (hip moves at less than 10 cm/sg, a value far under the average walking speed (Bohannon, 1997)).

4.1.5. Turning

The person changes direction, turning approximately 180 degrees.

- *Starting Condition*: The Shoulder axis (vector that goes from left shoulder to right shoulder) rotates in the Transverse plane more than 0.20 radians with respect to the initial shoulder axis.

- *Ending Condition*: Hips move more than 10 cm/sg in a direction that is approximately opposed to the initial direction (the absolute value of the angle between the current walking direction and the starting walking direction is over 2.5 radians), meaning that the person has turned completely.

4.1.6. Sitting

The person starts the action standing near a chair, and ends it when she sits.

- *Starting Condition*: Hips at least 20 cm higher than Knees (Schenkman et al., 1990). Projections of hips and knees in the Transverse (Axial) plane very close (distance < 20 cm).

- *Ending Condition*: Hips and Knees at the same height (difference in the vertical axis less than 15 cm). Knees advanced 30 cm or more with respect to the Hips (person seated) in the Anteroposterior axis.

4.2. Gait evaluation

The previous actions are evaluated considering only the motion of the person, without the presence of objects or other environmental conditions. For all the actions in the Get Up And Go gait, a set of k scores sc_i^{action} is computed, and the action score is obtained as $sc^{action} = \frac{\sum_1^k sc_i^{action}}{k}$.

4.2.1. Seated

While seated, the person should remain stable. Torso bending is used as an indication of instability. Being α the angle between the spine and the vertical axis registered during the Seated action, two scores, sc_1^{seated} and sc_2^{seated}, are computed as follows[2]:

[2] All magnitudes use the International System of Units

$$sc_1^{seated} = \begin{cases} 10 & \text{for } |\max(\alpha)| < 0.26 \\ \frac{10\cdot(0.79-|\max(\alpha)|)}{0.53} & \text{for } 0.26 < |\max(\alpha)| < 0.79 \\ 0 & \text{for } |\max(\alpha)| > 0.79 \end{cases}$$
$$sc_2^{seated} = \begin{cases} 10 & \text{for } |\bar{\alpha}| < 0.26 \\ \frac{10\cdot(0.52-|\bar{\alpha}|)}{0.26} & \text{for } 0.26 < |\bar{\alpha}| < 0.52 \\ 0 & \text{for } |\bar{\alpha}| > 0.52 \end{cases} \tag{3}$$

4.2.2. Standing Up

The Standing Up action is evaluated using two parameters: Lateral torso bending angle in the Coronal (XY) plane (β) and time to stand up (t_{su}). Thresholds for t_{su} have been selected according to Schenkman et al. (1990), although in their studies only the gaits of 9 women (ages ranged from 26 to 36 years) were evaluated. The two related scores, sc_1^{stup} and sc_2^{stup}, are computed as follows:

$$sc_1^{stup} = \begin{cases} 10 & \text{for } |\max(\beta)| < 0.1 \\ \frac{10\cdot(0.2-|\max(\beta)|)}{0.1} & \text{for } 0.1 < |\max(\beta)| < 0.2 \\ 0 & \text{for } |\max(\beta)| > 0.2 \end{cases}$$
$$sc_2^{stup} = \begin{cases} 10 & \text{for } t_{su} < 2 \\ \frac{10\cdot(6-t_{su})}{4} & \text{for } 2 < t_{su} < 6 \\ 0 & \text{for } t_{su} > 6 \end{cases} \tag{4}$$

4.2.3. Standing

Three parameters are going to be evaluated for this action. The first score (sc_1^{st}) considers the torso bending angle. This angle (α) is computed as in the Seated action. A high bending angle is a sign of instability. The second score (sc_2^{st}) measures the hip motion in the Transverse (XZ) plane, being $\max(h_d)$ the maximum displacement of the hip in this plane. The third score (sc_3^{st}) measures the time the person remains standing. Although this factor should not be *a priori* a sign of instability, in the Get Up And Go test, physicians consider the patients' hesitation when the latter starts to walk.

$$sc_1^{st} = \begin{cases} 10 & \text{for } |\max(\alpha)| < 0.1 \\ \frac{10\cdot(0.2-|\max(\alpha)|)}{0.1} & \text{for } 0.1 < |\max(\alpha)| < 0.2 \\ 0 & \text{for } |\max(\alpha)| > 0.2 \end{cases}$$
$$sc_2^{st} = \begin{cases} 10 & \text{for } |\max(h_d)| < 0.2 \\ \frac{10\cdot(0.4-|\max(h_d)|)}{0.2} & \text{for } 0.2 < |\max(h_d)| < 0.4 \\ 0 & \text{for } |\max(h_d)| > 0.4 \end{cases} \tag{5}$$
$$sc_3^{st} = \begin{cases} 10 & \text{for } t_{su} < 5 \\ 5 & \text{for } 5 < t_{su} < 10 \\ 0 & \text{for } t_{su} > 10 \end{cases}$$

4.2.4. Walking Straight

If no perspective or environmental constraints are imposed, gait evaluation usually focuses on the feet motion to obtain HMA results. However, as explained above, the proposed HMA system should be able to use motion, as perceived by a socially assistive robot in daily life environments. The sensors mounted on these robots are usually not able to capture feet motion precisely (Wang et al., 2015a). Thus, other trajectories are used to infer the different stability parameters in this action. The final score in the Walking Straight action depends on five different remarkable items (Öberg et al., 1994; Paróczai et al., 2006; Rubenstein, 2006).

The first score (sc_1^{walk}) measures the average step length $\overline{steplength}$, computed by measuring the total hip displacement in the Transversal (XZ) plane, and dividing it by the number of steps. The number of steps is computed by counting how many times the distance of the projections of the left and right knees in the Anteroposterior axis crosses zero.

The second score (sc_2^{walk}) measures the maximum torso bending angle during walking, This angle (α) is computed as in the Seated action, but higher thresholds are employed as the torso moves more during walking. A high bending angle is a sign of instability.

The third score (sc_3^{walk}) measures the variation in the vertical position of the Hip (h_{hip}). A high value is a sign of an odd gait, stumbles or slips.

The fourth score (sc_4^{walk}) measures the maximum aperture of the legs in the Frontal plane. The aperture is measured as the angle (γ) between the projection of the Knee - Hip vector in the Frontal plane, and the vector, in the Frontal plane, perpendicular to the vector going from the Hip to the base of the Spine.

The fifth score (sc_5^{walk}) evaluates the ability of the person to walk straight. It measures the lateral displacement of the hip (d_{hip}) during the walking process.

$$sc_1^{walk} = \begin{cases} 10 & \text{for } |\overline{steplength}| > 0.4 \\ 5 & \text{for } 0.2 < |\overline{steplength}| < 0.4 \\ 0 & \text{for } |\overline{steplength}| < 0.2 \end{cases}$$
$$sc_2^{walk} = \begin{cases} 10 & \text{for } |\max(\alpha)| < 0.2 \\ \frac{10\cdot(0.4-|\max(\alpha)|)}{0.2} & \text{for } 0.2 < |\max(\alpha)| < 0.4 \\ 0 & \text{for } |\max(\alpha)| > 0.4 \end{cases}$$
$$sc_3^{walk} = \begin{cases} 10 & \text{for } |h_{hip}| < 0.1 \\ 5 & \text{for } 0.1 < |h_{hip}| < 0.2 \\ 0 & \text{for } |h_{hip}| > 0.2 \end{cases} \tag{6}$$
$$sc_4^{walk} = \begin{cases} 10 & \text{for } |\gamma| < 0.3 \\ 5 & \text{for } 0.3 < |\gamma| < 0.7 \\ 0 & \text{for } |\gamma| > 0.7 \end{cases}$$
$$sc_5^{walk} = \begin{cases} 10 & \text{for } |d_{hip}| < 0.5 \\ 5 & \text{for } 0.5 < |d_{hip}| < 1.5 \\ 0 & \text{for } |d_{hip}| > 1.5 \end{cases}$$

4.2.5. Turning

A markerless HMA system mounted on a socially assistive robot is able to capture human motion from only one perspective. Considering this constraint, the turning action implies a high degree of self-occlusion for the joint trajectories of the person. While trajectories can be inferred or extrapolated in these circumstances, these results are too noisy, and not useful for evaluation purposes (e.g. the algorithms employed by the

Kinect SDK will provide a usable Skeleton only at the beginning and at the end of the turning action).

Due to these limitations, the evaluation of the turning action is based only on the time used by the patient to turn, t_{turn}:

$$sc_1^{turn} = \begin{cases} 10 & \text{for } t_{turn} < 2 \\ 5 & \text{for } 2 < t_{turn} < 5 \\ 0 & \text{for } t_{turn} > 5 \end{cases} \tag{7}$$

4.2.6. Sitting

The evaluation of this action faces the same issues as the evaluation of the Turning action. So the evaluation is again based only on measuring time $t_{seating}$.

$$sc_1^{sitting} = \begin{cases} 10 & \text{for } t_{sitting} < 2 \\ 5 & \text{for } 2 < t_{sitting} < 5 \\ 0 & \text{for } t_{sitting} > 5 \end{cases} \tag{8}$$

5. Experiments

The proposed HMA system has been analyzed through three sets of experiments, in which the gait of different people performing the Get Up & Go test is processed using the proposed HMA system. The dataset of all the experiments presented in the paper is available at the web page of the CLARC EU Project[3].

In all experiments human motion has been captured using a Kinect 2.0 device mounted on a socially assistive robot. The robot and the person were located as shown in Fig. 4. The robot remains in a fixed position during all the gait evaluation process. Human motion is extracted from Kinect RGB-D images using the Microsoft Kinect SDK[4]. This software is adequate for extracting human motion in the range between one meter and four meters employed in these tests. The height of the Kinect device mounted in the social robot (1.5 meters), together with is Field of View of 70.6 x 60 degrees, allows perceiving the whole body of the person for the complete test.

The first set of experiments involves capturing human motion using also a second MoCap system: a Vicon Nexus precise MoCap system with 8 infrared cameras and passive markers. The experiments' insights aim at using precise motion sequences, recorded by the Vicon system, as input for the proposed HMA system. The results offer a good analysis of the different possibilities for the method when precise enough data is used. These results can be compared with those obtained when the same performance is captured using the sensor mounted on the social robot. Using Vicon data as ground-truth, this experiment is useful to characterize the capture errors of the Kinect sensor, when this sensor and its associated software (i.e. the Microsoft Kinect SDK) is employed to capture human motion.

The second set of experiments is conducted in a daily life scenario, where motion is captured using only the Kinect 2.0 sensor mounted on the social robot (Fig. 4). These experiments analyze the adequacy of the proposed HMA system to autonomously evaluate human motion, using only sensors mounted on a mobile social robot.

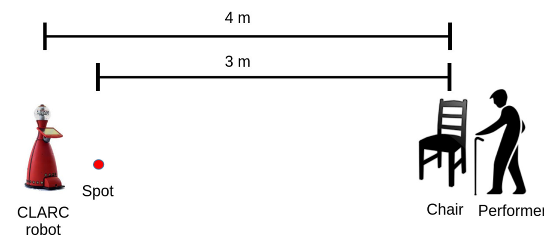

Fig. 4. Experimental setup.

In the third set of experiments, patients of the rehabilitation units at Hospital Civil de Málaga performed the Get Up and Go test while the robot captured their motion. Again, the robot and the performer were located as Fig. 4 shows, and the robot used the proposed algorithm to autonomously evaluate the test. Results provided by the robot were compared against the evaluations provided by a physiotherapist. These experiments aim at demonstrating the usefulness of the proposed method as an autonomous tool to evaluate the Get Up and Go and Timed Up and Go tests, within the framework of the CLARC EU project.

5.1. Experimental Setup 1

The first set of experiments was conducted in the facilities of the ActivAgeing Living Lab[5]. These experiments focus on the gait capture and analysis processes. They involve capturing human gait using two MoCap systems: a Vicon Nexus 1.8.5[6] system based on infrared markers, and the Kinect 2.0 device mounted on CLARC robot.

Four people, with no *a priori* stability issues, performed the Get Up & Go test several times, in this first experiment. Table 2 shows relevant data about these performers.

5.2. Error characterization for the Kinect 2.0

The first experiment allows the computing of the capture errors for the joints provided by the Kinect 2.0 device mounted on the CLARC robot. These errors are obtained using the Vicon Nexus 1.8.5 marker positions as ground-truth, given the high precision of this MoCap system (<0.5 mm).

The capture errors have been obtained following these steps:
a) *Obtain joint positions for the Vicon system* that can be compared with the ones provided by the Kinect sensor. Vicon joint positions are obtained from Vicon markers, usually in a direct one-to-one correspondence, although for some of them (e.g. Head joint) the position is computed by averaging positions of nearby markers.
b) *Align Vicon and Kinect gaits in time*. A synchronization frame allows the alignment of both time frames. Performers

[3]http://www.clarc-echord.eu/resources.html
[4]available for download at https://www.microsoft.com/en-us/download/details.aspx?id=44561
[5]http://www.activageing.fr/
[6]https://www.vicon.com/downloads/documentation/nexus-185-product-guide

were required to wave their right hand while seated, before performing the Get Up & Go test. The vertical peaks of the hand motion are searched for manually in both sequences to obtain the time offset between them.

c) *Interpolate Vicon trajectories to Kinect sampling instants*. Interpolant functions are obtained using third order spline interpolation, adequate for human gaits (Bandera, 2010; Ghorbel et al., 2015). Interpolant functions are then evaluated in the Kinect sampling instants.

d) *Transform Vicon trajectories from Vicon to Kinect coordinates*. A least squares estimation of the transformation is obtained using an implementation of Horn's quaternion based algorithm (Horn, 1987). The trajectories of the SpineShoulder joint are used to obtain the transformation matrix. Only the first part of the gait, when the person is facing the robot, is employed to compute this transformation. As detailed below, Kinect 2.0 data are more precise for this part of the gait.

e) *Obtain mean errors and standard deviations for each joint*, using Vicon data as ground-truth.

The main source of error for the Kinect 2.0 data, processed by the Microsoft Kinect SDK, is related to its perspective constraints. This MoCap system is designed to capture the gait of people that are *facing* the Kinect device. Skeleton is obtained from disparity silhouettes using a model-free approach based on decision trees (Shotton et al., 2013). These trees are obtained from a training phase in which only frontal silhouettes were used, so the MoCap system looks for the best frontal matching silhouette, regardless of the person's orientation. Thus, left and right joints are mirrored when the person is not facing the Kinect mounted on the robot, but returning to the chair (see Fig. 4). Besides, the Kinect algorithm locates joints on the surface of the tracked body, as the distance is computed from the disparity values provided by the RGB-D device. A person not facing the Kinect would have joint positions not only mirrored in the lateral coordinate, but also in the frontal coordinate (i.e. joints will be incorrectly located on her back).

Due to these limitations, capture errors were characterized for two cases. In the first one, complete Get Up & Go gaits were used. In the second case, only the part of the gait in which the person faces the robot is employed to compute errors.

Figures 5 and 6 show the obtained errors for each joint in the two described cases. As expected, for the complete gaits (blue bars) the mirror effect produces important errors in the lateral (X) coordinate. These errors grow as the distance from the joint to the vertical axis of the body grows. Errors in the frontal (Z) coordinate are affected by the erroneous depth estimation described above. Errors in the vertical (Y) coordinate, on the other hand, remain nearly unchanged for both complete and partial gaits.

The errors when only frontal gaits are considered (red bars) avoid previous effects, and are consequently smaller. Table 1 details the values of these errors for each joint. These values are coherent with the ones provided by Wang et al. (2015a). The worst errors are associated to the ankle and foot joints, that are nearly out of the field of view of the system. The rest of the joints have mean errors below 15 cm (the average value for all these errors is 11.7 cm). These errors, obtained for the Get

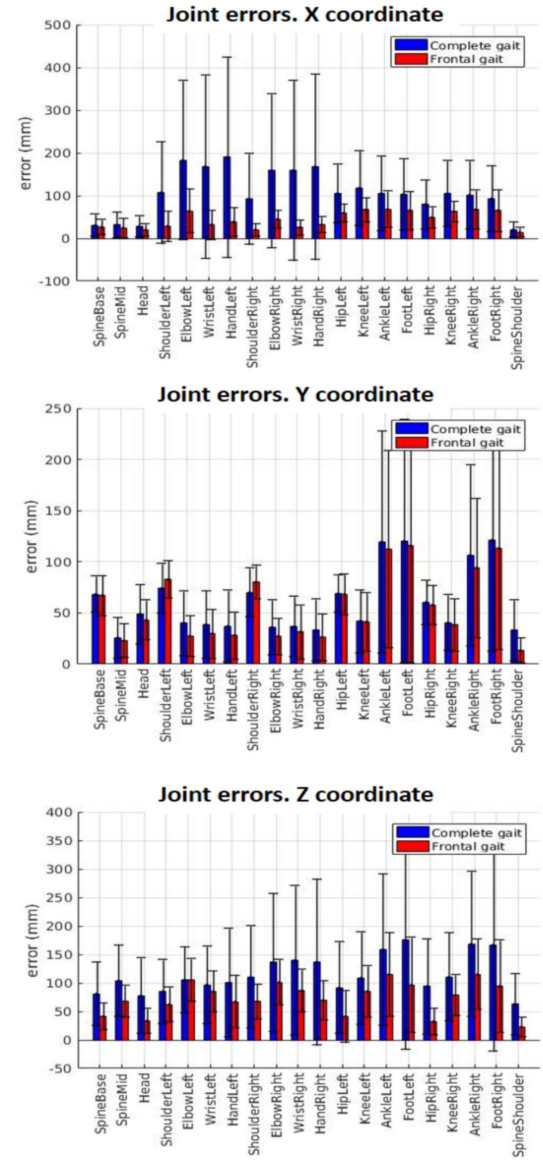

Fig. 5. XYZ joint errors in complete gaits vs XYZ joint errors considering only frontal gaits.

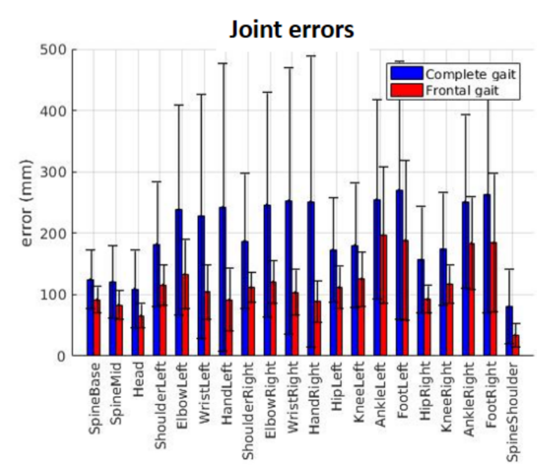

Fig. 6. Joint errors in complete gaits vs Joint errors considering only frontal gaits.

Table 1. Mean error and standard deviation for the joint positions captured with the Kinect 2.0, considering only frontal gaits.

	Mean Error (mm)	Std dev (mm)
Spine Base	91.83	21.18
Spine Mid	83.32	23.54
Head	65.75	19.64
ShoulderLeft	115.70	33.44
ElbowLeft	133.12	56.24
WristLeft	104.41	44.58
HandLeft	91.58	51.57
ShoulderRight	111.84	24.99
ElbowRight	120.82	35.22
WristRight	103.58	37.34
HandRight	88.75	34.06
HipLeft	111.84	34.14
KneeLeft	125.70	44.32
AnkleLeft	196.82	111.41
FootLeft	188.07	130.66
HipRight	92.58	22.37
KneeRight	117.35	30.56
AnkleRight	183.76	75.29
FootRight	184.30	112.99
SpineShoulder	34.10	19.28
AVERAGE	**117.26**	**48.14**

Table 2. First experiment: Results of the gait analysis for the Get Up And Go test.

Person parameters		Test results					
	Gender	Vicon Nexus 1.8.5			Kinect 2.0		
ID	Gender Age Weight Height	Time (secs)	Score (0-10)	Score (5-1)	Time (secs)	Score (0-10)	Score (5-1)
1	Female	13.19	7.57	2	12.1	8.79	1
	80 years	14.86	8.04	1	14.6	8.58	1
	68.4 Kg	15.9	8.04	1	15.9	8.04	1
	164 cm	12.72	7.89	2	13.9	9.13	1
2	Female	7.37	7.46	2	7.1	9.44	1
	71 years	6.67	7.26	2	6.4	7.36	2
	56.2 Kg	6.99	6.84	2	6.6	7.44	2
	164 cm	8.1	7.53	2	7.3	7.24	2
3	Male	15.52	8.33	1	15.5	8.82	1
	69 years	14.55	8.02	1	13.9	8.62	1
	78.3 Kg	8.91	7.11	2	8.4	7.92	2
	180 cm	9.66	8.14	1	9.3	8.84	1
		x	x	x	8.7	9.41	1
4	Female	x	x	x	8.7	7.50	2
	23 years	7.77	7.00	2	7.8	7.62	2
	57.5 Kg	11.11	7.52	2	11.1	8.49	1
	162 cm	11.91	8.19	1	12.1	8.94	1

Up & Go test, can be extrapolated to other motion sequences (Wang et al., 2015a). They prevent using the Kinect 2.0 device as a precise motion analysis tool. However, this sensor is accurate enough as to provide a certain estimation of the motion of a person facing the device. Regarding HMA applications, the device could be useful if only parameters that are invariant to lateral and frontal mirroring are employed. As Section 4 describes, the actions employed in the analysis of the Get Up & Go test meet this criterion.

5.2.1. Experiment 1 results. Vicon vs Kinect

Captured gaits were processed by the proposed HMA system. Table 2 shows obtained results, using two scales: real values between 0 and 10 (the scale employed by the system for its inner computation, where 10 is the best score), and integer values from 5 to 1 (the scale defined for the Get Up & Go test, where 1 is the best score). As commented above, none of the patients suffered stability issues. Obtained scores match this condition. All results are in the range 6-8 (”Very slightly abnormal”) and 8-10 (”Normal”). The Timed Get Up And Go results are mostly under the 12 seconds threshold that is employed to differentiate between normal and below normal performance. All of them are under the 20 seconds threshold that is considered acceptable to discard any risk of falling.

Scores obtained using both data sets are very similar, although the Vicon system tends to produce slightly worse scores. The main difference is that the HMA system was unable to process two of the Vicon gaits. These issues are due to a lost marker (P6, first test), and a late initialization of the Vicon capture (P3, fourth test), that avoids detecting the beginning of the gait.

5.3. Experimental Setup 2

The scenario where the second set of experiments was conducted is the apartment's living room of the ActivAgeing Living Lab. Tests were similar to the ones executed in the first scenario, but here no constraints were imposed on the users. No markers were attached to the people, and experiments were performed in a daily life environment. Motion was captured using only the Kinect 2.0 sensor mounted on the CLARC robot.

21 adult people took part in this second set of experiments. None of them had *a priori* issues regarding balance and stability. Seven performers were researchers of the CLARC project (5 men and 2 women aged between 30 and 45). The rest of the performers were not familiar with the system (2 health professionals and 14 seniors). Among the seniors, there were 10 women and 4 men. They were aged between 62 and 93 years old, divided as such : 60-70 years: 5 participants, 70-80 years: 4, 80-90 years: 3 participants. Each of them executed the test only once, after listening to the instructions.

The system failed in initializing the motion for two of the performers. Another performer was lost by the tracker when turning, so the gait was not valid. Another gait was not correctly divided into actions due to the Seated action being not correctly segmented. The remaining 17 gaits could be captured and fully processed.

5.3.1. Experiment 2 results. Daily life scenario

Table 3 shows the scores obtained for these 17 gaits. It also includes the total time employed by each performer (i.e. the Timed Up And Go result). As described above (Fig. 2), this value does not include the time of the Seated action, as the Time Up And Go test starts when the performer begins to move from the seated position.

Again, results match the ones expected for people with no stability issues. All results are in the range 6-8 (”Very slightly abnormal”) and 8-10 (”Normal”). The Timed Up And Go results are also coherent. The 11th performance shows a case in which one of the actions (Standing) has not been detected. While the gait has been processed, the system generates an alert as this gait should be reviewed by a clinician to determine what was wrong. In this case, the performer began walking while she was standing up, so starting and ending condition for the Standing action were met in the same sample, making the action be marked as not performed.

Figure 7 shows the trajectories of the base of the spine for an example gait. It can be seen that the Z coordinate of the tra-

Table 3. Second experiment (Kinect 2.0 mounted on CLARC): Results of the Get Up & Go test for healthy people. Scores are provided in the five-level scale of the test. System's scores are also provided in a 0-10 range for the complete gait and each action. Minimum action scores are highlighted.

Id	Time (secs)	Total Score	Action scores (0-10)								
			TOTAL	TOTAL (No Seated)	Seated	StndUp	Standing	Walk. St.	Turning	Walk. St.	Seating
1	8.6	1	**9.72**	**9.67**	10	9.74	**9.07**	9.89	10	9.35	10
2	15.7	2	**7.53**	**7.73**	6.29	6.31	7.41	8.84	10	8.82	**5**
3	10.1	1	**8.51**	**8.26**	10	10	7.06	9.80	10	7.73	**5**
4	9.5	1	**8.18**	**8.22**	7.91	**5.65**	7.41	9.69	10	6.61	10
5	11.4	1	**8.76**	**8.55**	10	10	8.77	9.79	10	7.76	**5**
6	14.9	1	**9.04**	**8.87**	10	10	**5.60**	8.80	10	8.87	10
7	9.3	1/2	**8.18**	**7.87**	10	**5**	8.88	9.70	10	8.68	5
8	9.8	1	**9.18**	**9.04**	10	10	**6.67**	8.75	10	8.84	10
9	5.6	1	**9.76**	**9.71**	10	9.96	**8.67**	9.90	10	9.78	10
10	14.3	1	**8.80**	**8.59**	10	10	8.68	8.78	10	**4.13**	10
11	6.2	1/2	**8.07**	**7.91**	10	8.99	**-**	8.89	10	9.63	10
12	12.2	1	**8.78**	**8.65**	9.57	10	9.39	7.67	10	**4.86**	10
13	9.2	2	**7.49**	**7.07**	10	5.60	7.40	8.37	10	6.09	**5**
14	18.1	2	**7.42**	**6.91**	10	10	7.92	7.83	10	6.16	**0**
15	10.7	2	**7.90**	**7.62**	9.54	10	7.18	8.85	10	**4.73**	5
16	14.6	2	**6.78**	**6.24**	10	10	7.33	7.46	5	7.67	**0**
17	14.1	1	**8.56**	**8.32**	10	10	9.43	5.85	10	9.66	**5**

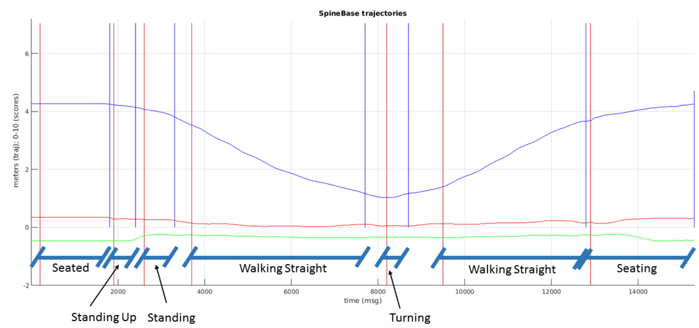

Fig. 7. Trajectory of the SpineBase joint (red=X; green=Y; blue=Z).

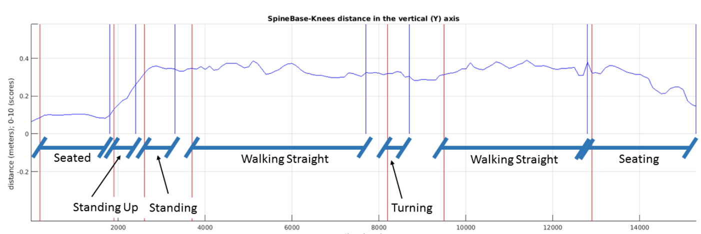

Fig. 8. Distance in the vertical axis between the knees and the base of the spine.

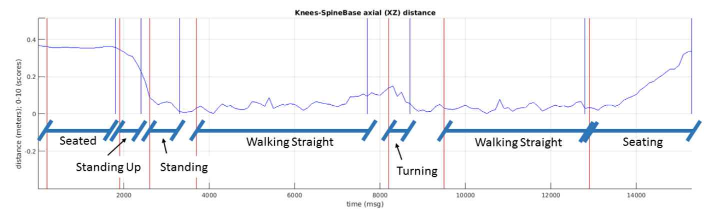

Fig. 9. Distance in the Transverse plane between the knees and the base of the spine.

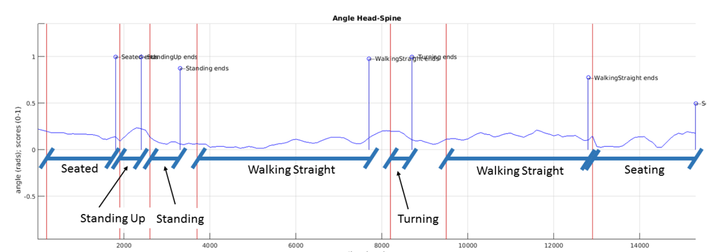

Fig. 10. Head-SpineBase axis angle with respect to the vertical (Y) axis.

jectory provides a good measure of the distance walked in the test, around 3 meters in this example (Fig. 4). The minimum value of this trajectory is located in the turning action, but it is not useful to obtain starting or ending points for it. On the other hand, the height of the SpineBase joint (Y coordinate) reveals detecting the Standing and Seating actions as a meaningful parameter. However, the distances between the average position of the knees and the base of the spine (Figures 8 and 9), offer the same discriminative potential and, being relative measures, are invariant against offset errors and different performers.

The angle between the axis that goes from the head to the base of the spine, with respect to the vertical (Y) axis, is used in the stability evaluation for nearly all the actions. It is also a key feature to separate the Seated and Standing Up actions. Figure 10 shows that this angle has a peak just before the torso begins to move up from seated to standing position. This peak appears in all collected gaits, and is related to the *Flexion Momentum* phase. According to Schenkman et al. (1990) this phase marks the beginning of the standing up action. The proposed approach uses the moment in which this flexion motion starts to separate Seated and Standing Up actions.

After a review of the results and a discussion with medical experts, it seemed that the initial importance given to the *Seated* action may not be adequate: all experiments show a high score for this action except for two cases, but in these cases the *Seated* action score is strongly correlated with the *Standing Up* action score. While human experts may get some clues about stability while the patient is seated *before* performing the test, and that is the reason why the *Seated* action was included, the influence of these factors may not be compared in equal terms against the scores obtained by the rest of the actions, performed *while* the person is doing the test. Hence, using the *Seated* score in an autonomous evaluation of the Get Up and Go test may be wrongly increasing the final result, to the point that in this experiment, the 11th performance gets the highest score ("Normal") even after one action was lost. Due to these reasons, a new evaluation in which the *Seated* action is not computed ($w_1 = 0$ and $w_i = 1/6 \ \forall i \in [2..7]$) was executed. The results are shown in Table 3. As expected, they do not significantly change with respect to previous ones but, in average, scores are slightly lower.

5.4. Experimental Setup 3

The third set of experiments was conducted in the rehabilitation units of Hospital Civil de Málaga. There, patients with physical and/or neurological issues performed the Get Up and Go test while the CLARC robot autonomously evaluated their gait. The *Seated* action was detected and segmented, but it did not contribute to the total time of the test, nor to the total score. The robot and the patient were located as Fig. 4 shows. The patients had never met the robot before, but they were instructed *a priori* about how to perform the test. A physiotherapist also evaluated the performances, and his evaluations were compared against the ones provided by the CLARC robot.

Nineteen volunteers took part in the experiments. The system was not able to correctly segment the complete gait for performers #5, #10, #13 and #16. Performers #14 and #18 were unable to finish the test.

5.4.1. Experiment 3 results. Patients

Table 4 shows the scores obtained in this experiment for both the Get Up & Go and the Timed Up & Go tests. For the later, the table depicts the time measured by the robot. The human expert agreed with all these values so his evaluation has not been explicitly included in the table. For the Get Up and Go test, results provided by the robot match exactly the ones provided by the physiotherapist for most performances (61.53%). The robot is more restrictive than the human expert for three patients (23.01%). In one case (patient #7) the robot provides a better score for the Get Up & Go test (3 instead of 4). However, it correctly detects the risk of falling, both in the Get Up & Go and, specially, in the Timed Up & Go autonomous evaluations. Finally, results for performer #1 show a different situation: here, the robot marks the gait as 2 = very slightly abnormal, while it should have detected a certain risk of falling (the physiotherapist provided a score of 3 = mildly abnormal).

6. Conclusions

Results show that the proposed HMA system is able to correctly evaluate human motion. The system requires the complete gait to be perceived before evaluating it, but once the gait is captured the analytic nature of the algorithm allows producing fast responses. The algorithm is autonomous and it does not impose any constraints on the performer nor the environment. Experiments have involved successful autonomous evaluation of human gait in the Get Up & Go test. These results have been validated against the ones obtained using precise input data. No significant differences have been detected in the final scores for the Get Up & Go test in these two cases. The splitting approach seems correct to evaluate human motion. The use of modular actions to represent a complete motion facilitates generalization and adaptability for different scenarios. Encoding these actions requires expert knowledge to manually tune their conditions and evaluation functions. While this is a drawback if this knowledge is difficult to encode, it also offers a high degree of control over the evaluation criteria. On the other hand, the system has been tested using mainly motion composed by sequential actions. Further work will extend it to consider more complex action relations (e.g. actions that can start only after another one has started).

As experiments show, the proposed HMA system is robust against noisy motion perception. However, it is also affected by partial perception or occlusions that are common in daily life environments. The proposal, based on sequential detection, is not robust against errors that affect one of the actions: if an action is not correctly detected, the chances of this issue invalidating the complete gait analysis are high.

The paper also allows studying the adequacy of the Kinect 2.0 sensor to evaluate human motion, at least for use cases like the Get Up & Go test. While the results obtained are satisfactory, there are several drawbacks that should be taken into account. First of all, the Microsoft Kinect SDK has a strong constraint: it only captures the motion of people facing it. This does not render this MoCap software unusable for more general scenarios, as the current paper shows, but imposes a careful design that ensures that these constraints are not affecting the results.

Kinect 2.0 also offers too noisy data for the ankles and foot motion. According to Wang et al. (2015a), these errors are possibly due to Time of Flight (ToF) artifacts. Fusing Kinect data with information provided by other sensors could help reducing these perception issues. For example, most social robots use devices, such as LIDAR, to navigate. It would be possible to infer feet positions from these data.

Regarding the evaluation system, further expert assessment may impose different evaluation criteria for different motions. For example, for the Get Up & Go test evaluated in this paper, the total score for the gait is obtained by averaging action scores. But a very low value in a particular action may indicate a high risk of falling, even if the rest of the gait scores are good. Table 3 marks the minimum action score of each gait, showing that some of them are far below the averaged, total score. A non-averaged evaluation, based on different weights or even discriminant thresholds, will most probably better suit this test. More evaluations of gaits of frail elderly people, assessed by clinicians, will be conducted in the CLARC project, to determine which actions should trigger an alert of falling risk, regardless of the rest of the gait.

Experiments involving patients have revealed so far that the proposed HMA system is able to provide robust, coherent and accurate results for the Timed Up & Go test. However, the current ability of the system to evaluate the Get Up & Go test can be described as a limited success. While results are promising and mostly coherent with the ones provided by a human expert, it seems clear that any gait classified as 'abnormal' should be reviewed by a physiotherapist. On the other hand, all performances classified by the system as 'normal' (i.e. the ones achieving the highest score) can reliably be associated to a person with no particular risk of falling.

Table 4. Third experiment (Kinect 2.0 mounted on CLARC): Autonomous evaluation of the Get Up & Go test for patients in the rehabilitation units of Hospital Civil (Málaga). Both a physiotherapist and the proposed system have provided scores for each patient in the five-level scale. System's scores are also provided in a 0-10 range for the complete gait and each action. Minimum action scores are highlighted.

			Physiot.	**System**	**Time**	**Action scores (0-10)**							
Id	**Age**	**Gender**	**Score**	**Score**	**(secs)**	TOTAL	StndUp	Standing	Walk. St.	Turning	Walk. St.	Seating	Diagnosis
1	61	Male	3	2	12.1	**7.28**	10	6.84	9.83	10	7.06	**0**	Knee lesion, Stroke
2	64	Female	2	2	13.1	**6.93**	7.74	8.85	7.63	**5**	7.36	**5**	Stroke
3	47	Male	2	2	13.2	**7.85**	7.38	8.35	7.90	10	8.51	**5**	Cervical myelopathy
4	68	Female	1	1	9.3	**9.21**	10	10	**7.51**	10	7.74	10	Disc herniation
6	72	Male	1	2	13.8	**7.16**	7.74	8.19	9.59	**5**	7.41	**5**	Cauda equina
7	82	Female	4	3	27.9	**5.62**	10	6.6	9.63	**0**	7.5	**0**	Elbow fracture
8	47	Female	1	2	9.8	**7.42**	**4.75**	7.39	9.73	10	7.67	**5**	-
9	67	Female	1	1	7.1	**9.33**	10	8.35	9.87	10	7.76	10	Left arm issues
11	37	Male	1	2	11.4	**7.62**	9.91	7.44	9.59	**5**	8.83	**5**	Meniscus lesion
12	62	Female	2	2	13.9	**7.87**	10	8.25	9.33	**5**	9.67	**5**	Osteoporosis
15	75	Female	2	2	13.5	**6.89**	**2.75**	-	9.91	10	8.7	10	Fibromyalgia
17	62	Male	1	1	7.4	**8.36**	9.99	7.85	9.91	10	7.42	**5**	Osteoporosis
19	85	Male	1	1	11	**8.39**	10	7.82	9.81	10	7.71	**5**	-

Further deep tests, assessed by medical experts, and involving people affected by different issues, will be intensively addressed in the next two years. Evaluation criteria, inter-action relations and parameter adjustment will be reviewed over a wider population in order to increase the robustness and accuracy of the proposal, and the validity of the obtained results. But the current implementation of the system can already be considered an interesting tool for screening and monitoring. It may not be precise enough so as to autonomously provide a definitive score for a medical test, but it can provide a rough diagnostic. In the Get Up & Go test, it allows discarding some performers as having a risk of falling, or alert an expert supervisor if any issue is detected in the gait.

Acknowledgments

This work has been partially funded by the European Union ECHORD++ project (FP7-ICT-601116) and the TIN2015-65686-C5-4-R Spanish Ministerio de Economía y Competitividad project and FEDER funds. The authors warmly thank the members of the "Amis du Living Lab" community, and the patients and medical staff at Hospital Civil de Málaga, for their participation in this research, as well as the interns Marion Olivier and Daniel Saadeddine.

References

Bandera, J.P., 2010. Vision-based gesture recognition in a robot learning by imitation framework. PhD dissertation. University of Málaga.

Bohannon, R.W., 1997. Comfortable and maximum walking speed of adults aged 20-79 years: reference values and determinants. Age and Ageing 26, 15–19.

Chen, L., Wei, H., Ferryman, J., 2013. A survey of human motion analysis using depth imagery. Pattern Recognition Letters 34, 1995–2006.

Cippitelli, E., Gasparrini, S., Spinsante, S., Gambi, E., 2015. Kinect as a tool for gait analysis: Validation of a real-time joint extraction algorithm working in side view. Sensors 15, 1417–1434.

D., P., Pinto, L., 2015. Calibration of kinect for xbox one and comparison between the two generations of microsoft sensors. Sensors 15, 27569–27589.

DG-ECFIN, AWG, 2014. The 2015 Ageing Report: Underlying Assumptions and Projection Methodologies. Technical Report. European Commission Directorate-General for Economic and Financial Affairs Unit Communication and interinstitutional relations.

Feil-Seifer, D., Mataric, M.J., 2005. Defining socially assistive robotics, in: Proc. of the 2005 IEEE C9th Int. Conf. on Rehabilitation Robotics, pp. 465–48.

Ghorbel, E., Boutteau, R., Boonaert, J., Savatier, X., Lecoeuche, S., 2015. 3d real-time human action recognition using a spline interpolation approach, in: Proc. of the 2015 International Conference on Image Processing Theory, Tools and Applications, pp. 61–66.

Horn, B.K.P., 1987. Closed-form solution of absolute orientation using unit quaternions. J. Opt. Soc. Am. A. 4, 629–642.

Kargar, A.H., Mollahosseini, A., Struemph, T., Pace, W., Nielsen, R.D., Mahoor, M.H., 2014. Automatic measurement of physical mobility in get-up-and-go test using kinect sensor, in: Proc. of Annual Int. Conf. of the IEEE Eng. in Medicine and Biology Society, 201, pp. 3492–3495.

Lahnera, M., Musshoffa, D., Pellengahra, C.v.S., Willburgera, R., Hagenb, M., Ficklschererc, A., Engelhardtd, L.V., Ackermanne, O., N., L., G., V., 2015. Is the kinect system suitablefor evaluation of the hip joint range of motion and as a screening tool for femoroacetabular impingement (fai)? Technology and Health Care 23, 73–82.

Mathias, S., Nayak, U.S.L., Isaacs, B., 1986. Balance in elderly patients: the get-up and go test. Arch. Phys. Med. Rehabil. 67, 387–389.

Matthews, D.A., 1984. Dr. marjory warren and the origin of the british geriatrics. J. Am. Geriatr. Soc. 34, 253–258.

Moeslund, T.B., Hilton, A., Krüger, V., 2006. A survey of advances in vision-based human motion capture and analysis. Computer Vision and Image Understanding 104, 90–126.

Öberg, T., Karsznia, A., Öberg, K., 1994. Cjoint angle parameters in gait: Reference data for normal subjects, 10-79 years of age. Journal of Rehabilitation Research and Development 31, 199–213.

Paróczai, R., Bejek, Z., Illyés, A., Kocsis, L., Kiss, R.M., 2006. Gait parameters of healthy, elderly people. Physical Education and Sport 4, 49–58.

Podsiadlo, D., Richardson, S., 1991. The timed up & go: A test of basic functional mobility for frail elderly persons. Journal of the American Geriatrics Society 39, 142–148.

Rubenstein, L.Z., 2006. Falls in older people: epidemiology, risk factors and strategies for prevention. Age and Ageing 35, 37–41.

Schenkman, M., Berger, R., Riley, P., Mann, R., Hodge, W.A., 1990. Whole-body movements during rising to standing from sitting. Physical Therapy 70, 638–651.

Shotton, J., Sharp, T., Kipman, A., Fitzgibbon, A., Finocchio, M., Blake, A., Cook, M., Moore, R., 2013. Real-time human pose recognition in parts from single depth images. ACM Commun. 56, 116–124.

Wang, Q., Kurillo, G., Ofli, F., Bajcsy, R., 2015a. Evaluation of pose tracking accuracy in the first and second generations of microsoft kinect, in: Proc. of the IEEE International Conference on Healthcare Informatics 2015 (ICHI 2015), pp. 380–389.

Wang, Q., Kurillo, G., Ofli, F., Bajcsy, R., 2015b. Unsupervised temporal segmentation of repetitive human actions based on kinematic modeling and frequency analysis, in: Proc. of the International Conference on 3D Vision 2015, pp. 4321–4329.