Preliminary Study on the Design of a Low-cost Movement Analysis System
Reliability Measurement of Timed Up and Go Test

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Abstract: In this paper, we present experiments on the design of a novel movement analysis system for real-time balance assessment in the frail elderly. Using the Microsoft Kinect sensors, we capture TUG (Timed Up and Go) tests and mainly analyze the transfer from sitting-to-standing and back-to-sitting which represent two of the most commonly executed human movements. Nine spatio-temporal parameters were extracted from recorded joint positions by 3D skeletal sequence processing. In order to validate and evaluate the developed system, practical test experiences have been performed on ten healthy young subjects, who were asked to realize the TUG in three different conditions: normal, cognitive and motor. Obtained results showed good measurement reliability and reproducibility with important precision. In addition, we observed that even for young healthy subjects, there is a significant difference of movement parameter between normal condition and cognitive condition, which represents a stimulating result in the dual task paradigm field. This preliminary study opens a new research and development way for geriatric health which implies multiple aspects: user-friendly, hygiene, low-cost, home-based environment, and automatic autonomy assessment.

1 INTRODUCTION

Geriatric rehabilitation has become a major public health issue. The balance assessment in the frail elderly consists to assess functional capacity and fall risk, and help determine the underlying reasons for balance disorders. Also, it can allow to objectify progress or deterioration and measuring the patient's autonomy. Thus, many strategies of balance assessment are developed. Most of these strategies involve complex operations to perform in clinical environment and require the presence of a health professional to determine the score for each person.

Clinical balance assessment can be classified into three broad categories: system assessments, quantitative assessments and functional assessments. The system assessments are helpful to determine the underlying causes of the balance deficit. However, all balance rating scales are relatively course measures of complex motor behaviour and all subjective assessments can easily suffer from tester bias (Mancini and Horak, 2010). Regarding quantitative assessments, several systems are being exposed to the market, but they are not scientifically validated before being offered to therapists, except some systems such as the static or dynamic posturography platforms. In general, functional balance tests assess performance on a set of motor tasks on a 3 to 5 point scale or use a stop as watching to time how long the subject can keep up balance in a specific posture. Several clinical tests exist such as Tinetti and TUG. This functional approach is usually used to detect balance problem existence. However, clinical balance assessments give subjective results that are usually not responsive enough to rate low progress or deterioration in a subject's ability to balance (Mancini and Horak, 2010). Indeed, clinical human evaluation is limited in terms of the parameters evaluated.

In elderly autonomy and independence maintaining context, it is very interesting to realize functional balance assessments automatically in home-based environment using artificial vision technology. If an innovative device associated with video processing is capable to assess the motor abilities of the frail elderly, health professionals could be alerted in case of deterioration. The earlier balance problem detection and the precocity of rehabilitation could allow, through a primary or secondary prevention, prolong-

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ing autonomy and independence of elderly. In addition, we can increase the number of studied parameters with fairly accurate measurement, by balance assessment automation.

This paper is organized as follows: in section 2 some related works of human motion analysis for rehabilitation by computer vision are cited. Section 3 presents the proposed real-time system from data acquisition to feature parameter extraction after a brief description of the TUG test. Section 4 illustrates experiment tests and obtained analysis results with ten healthy young subjects. Finally, we discuss and conclude this preliminary study in section 5.

2 RELATED WORK

Several methods have been developed for human motion analysis and applied to rehabilitation research. For example, marker-based systems (MBS) usually use infrared cameras to detect markers placed on the patients' bodies. These systems are accurate and yield highly robust measurements of a person's motion. However, MBS involve frequently the use of expensive specialized equipment and are impractical to move. Furthermore, passive or active markers must be correctly placed on the body before each capture session which makes such systems obtrusive and inappropriate for home-based rehabilitation.

In (Hagler et al., 2010), the authors propose a system for continuous and unobtrusive in-home assessment of gait velocity which is based on estimating walking speed from noisy time and location data collected by a "sensor line" of restricted view passive infrared motion detectors. Indeed, sensor suites provide information upon the daily activity levels of monitored subjects, and arrays of such sensors allow obtaining velocity measurements on a continuous basis in home settings. However, such systems do not yield measurements of the detail necessary for assessment of fall risk, particularly, spatial and temporal gait parameters (other than walking speed), TUG duration and sit-to-stand time.

Recent pervasive/ubiquitous healthcare and wireless sensor networks incorporate multimodal sensing and computer vision. The pervasive and ubiquitous computing aim to integrate information and computing into the everyday physical world, so that this technology is available to everyone in any context. Wireless sensor network nodes increasingly include inertial sensors such as accelerometers and gyroscopes which have been used for activity detection and gestural recognition.

Several studies identify the Kinect's potential for use in rehabilitation. Indeed, Kinect is an inexpensive and portable sensor that includes a RGB camera, a depth sensor and a multi-array microphone. It provides full-body 3D motion capture, facial and gesture recognition. Although the accuracy of Kinect is limited, it still provides a good tradeoff between cost and portability and could be used at home for rehabilitation exercises (Bonnechère et al., 2012). Recently, Kinect has been shown to be able to create a 3D human model with similar accuracy to expensive and complex 3D body scanning systems (Weiss et al., 2011). Moreover, it allows to evaluate gait velocity (Stone and Skubic, 2011), hand and elbow movements and anatomical landmark displacement and trunk angle during commonly performed clinical tests of postural control that represent favorable results when compared to some existing 3D motion analysis systems. In (Gabel et al., 2012), a method for full body gait analysis using Kinect is presented. It consists in applying a supervised learning approach to automatically and accurately extract a set of gait parameters, using the 3D virtual skeleton as the input to the learned model. Likewise, Kinect is able to obtain some kinematic and anatomical mapping data with a similar degree of accuracy to more expensive 3D motion analysis and scanning systems (Clark et al., 2012).

In this paper, we propose a low-cost, robust and home-based system for real-time balance assessment in the frail elderly. Our system can accurately measure several parameters that have been shown relevant for balance assessment using the Kinect sensor and Software Development Kit. It automatically and accurately extracts shoulder kinematics and TUG duration by the use of the 3D skeleton, with robustness to environmental changes and variations in the placement of the Kinect sensor. We demonstrate how a rich set of parameters can be extracted. Furthermore, we suggest that the proposed method is not cumbersome since in a typical use-case a Kinect sensor can be placed in a fixed position at home. In addition, our system requires no human intervention and no markers or wearable sensors will be attached to the body.

3 FUNCTIONAL BALANCE ASSESSMENT SYSTEM DESIGN PRESENTATION

3.1 Timed Up and Go Test Description

The Timed Up and Go test is a clinical measure of balance and mobility in the elderly and in neurological populations. The TUG is relatively simple, requires no special equipment or training and is easily included as part of the routine medical examination. It consists of a sequence of sit-to-stand (STS), walking a distance of 3 m, turning and back-to-sit (BTS). The total time taken to complete the TUG test allows predicting the risk of falling. A score of 12 s is considered as the upper limit of normal mobility. Abnormal mobility was defined as having a TUG score of $>=$ 20 s. The TUG has been modified to add a secondary task that could be cognitive or motor. In the TUG-cognitive, subjects were asked to complete the test while naming some names that begin with a certain letter and the TUG-motor consists of completing the TUG while carrying a cup of water. A score of 15 s on the TUG-cognitive and 14,5 s on the TUG-motor is associated with increased risk of falls (Mancini and Horak, 2010).

In general, the TUG rests upon one time measure to evaluate the overall performance of a sequence of tasks. However, it can provide specific information on components of each task that could disclose more specific mobility problems. The TUG includes two actions that are commonly executed throughout the different stages of the human lifetime: STS and BTS. For both STS and BTS, the shoulder was the first to move and the last to stop, and it moved in the sagittal plane with a forward-upward (STS) and downward-backward (BTS) displacement. These movements allow estimating some parameters that were identified in the literature as relevant for balance assessment (Manckoundia et al., 2006). These parameters are the following: a) movement duration, b) shoulder path curvature, c) trunk angle, and d) ratio which matches the vertical phase duration divided by the horizontal phase duration.

3.2 Experimental Setup and Data Acquisition

We use image processing technology with Kinect to detect patients' TUG movements. The proposed system automatically produces virtual skeleton corresponding to the patient's joint position, and this skeleton information allows determining in real-time spatio−temporal parameters which are relevant for the balance assessment.

To extract parameters for balance assessment, we captured Kinect skeleton recordings of the TUG movement realized by the subject with time synchronized (see Figure 1). Therefore, we used the data acquired to compute the parameters set. The Kinect sensor was placed to capture the image of the subject at an approximate distance of 2−2,5 m to the chair, at a height of 50−60 cm above the floor. The subject directly faced the Kinect sensor. The Kinect sensor and its SDK produce a 3D virtual skeleton to establish the positions of 20 skeleton joints on a human form. For example, skeleton tracking determines where a user's head, hands, knees, and center of mass are. For each of these skeleton joints, X, Y, and Z values are reported. Kinect provides approximately 30 skeleton frames per second.

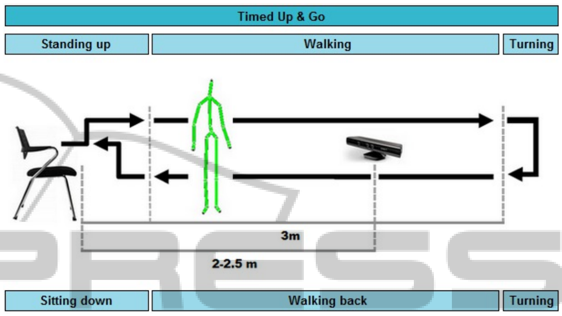


Figure 1: Overview of the proposed system with Kinect sensor.

3.3 Kinematic Parameter Extraction Process

To begin the calculation of parameters, it is first necessary to determine whether the subject is sitting or not. The posture and position of a subject's body joints define a pose; more specifically, it is the relationship of each joint to another. A pose is detectable by either intersection or position of joints or the angle between joints, using one or more plane. The distance between two points for 2D and 3D points is respectively given by:

$$d_2 = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{1}$$

and:

$$d_3 = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2} \tag{2}$$

Regarding the joint angles, we can draw a triangle using any two joint points. The third point of the triangle is derived from the other two points. The Law of Cosines formula defined as:

$$c^2 = a^2 + b^2 - 2ab\cos C \tag{3}$$

where C is the angle opposite side c, gives us the value of any desired angle. Transforming the formulas to solve for the unknown angle C yields:

$$C = \arccos(\frac{a^2 + b^2 - c^2}{2ab}) \tag{4}$$

Extracted features correspond to the kinematics of shoulder displacement during STS and BTS and the TUG duration. STS is composed of two main phases: the first phase is the forward flexion and the second, the extension phase, started on lift-off of the buttocks from the seat and ended when maximum hip, trunk and knee extension and maximum head flexion velocity were reached. BTS is characterized by a movement in the opposite direction than STS: downward and backward.

Shoulder Path Curvature. Shoulder paths during forward and backward displacements were similar and almost straight, therefore the curvature of path for upward and downward displacements were only calculeted (Manckoundia et al., 2006). Curvature is defined as:

$$cur = \frac{D_{max}}{L} \tag{5}$$

where L corresponds to a straight line passing between the initial and the final position of shoulder displacement and D_{max} means the maximal perpendicular distance measured from the actual path to the straight line.

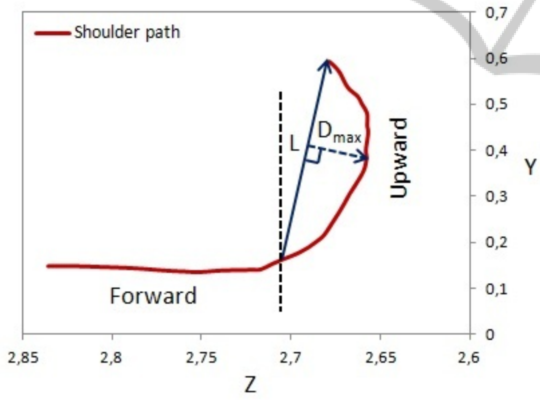


Figure 2: Shoulder path during STS transfer. Curvature of paths is given by the ratio Dmax/L.

Ratio. The ratio is computed using the following relationship:

$$ratio = \frac{D_{vph}}{D_{hph}} \tag{6}$$

where D_{vph} and D_{hph} they represent, respectively, the vertical and the horizontal movement duration.

Trunk Angle. It refers to the angle θ between the trunk and the vertical plane passing through the center of mass of the body (see Figure 3).

Movement Duration. The total movement duration of shoulder motion, during STS, corresponds to the time interval between the moment when the shoulder depth component exceeded $8,5\%$ of its initial position, and the moment when the head vertical component reaches or exceeds 94% of the size of the person which was calculated. The thresholds are experimentally determined. In BTS, it is defined as the time interval between the moment when the shoulder vertical component dropped its peak value, and the moment when the vertical components of the hips reach their minimum values and the trunk angle reaches its limit.

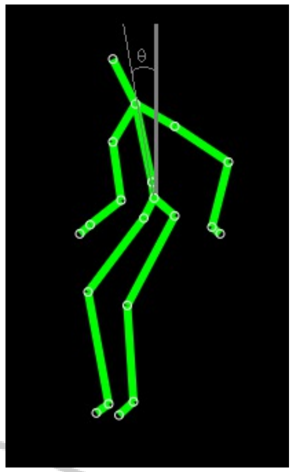


Figure 3: Trunk angle calculation.

TUG Duration. TUG duration, measured in seconds, means the total time taken to perform all TUG tasks. It corresponded to the time interval between the moment when the forward phase starts and the moment when the backward phase ends.

4 EXPERIMENT RESULTS

4.1 Experimental Protocol

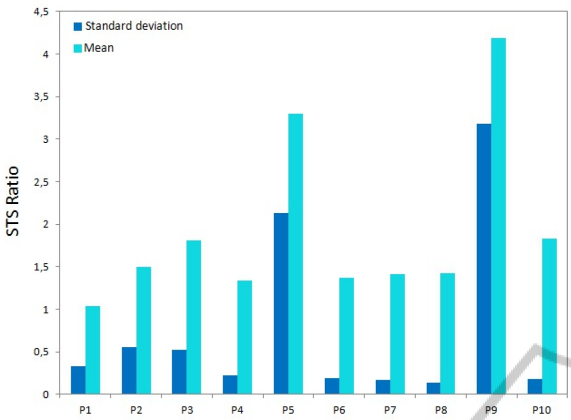
Ten healthy young subjects participated in the present study. Subjects were asked to complete three trials for each of three TUG conditions: the TUG alone (TUG−normal), the TUG−cognitive and the TUG−motor. Subjects were given verbal instructions to rise from a chair, walk 3 m, cross a mark on the floor, turn around, walk back, and sit down again.

4.2 Result Analysis

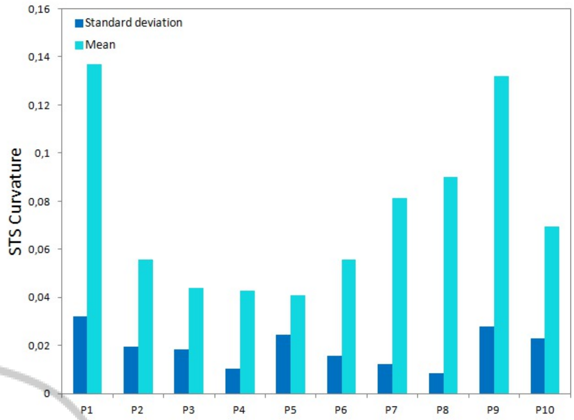
Figure 4 shows STS parameter histograms for TUG−normal. In this section, the confidence interval (CI) is defined as:

$$I_c = [\bar{x} - 1,96\frac{s}{\sqrt{n}}; \bar{x} + 1,96\frac{s}{\sqrt{n}}] \tag{7}$$

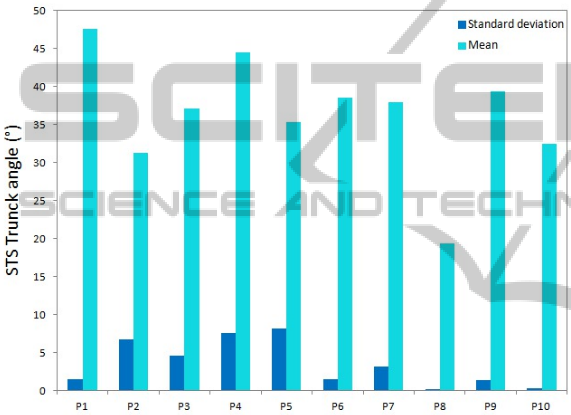
where $\bar{x}$, s and n represent, respectively, the mean, the standard deviation and the size of the sample. The



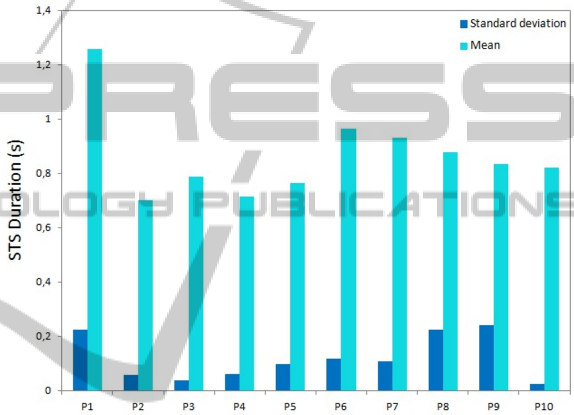
(a) Histogram of STS ratio parameter.



(b) Histogram of STS curvature parameter.



(c) Histogram of STS trunck angle parameter.



(d) Histogram of STS duration parameter.

Figure 4: Histogram of STS ratio, curvature, trunck angle and duration parameters of 10 young healthy subjects (P1-P10).

CI of the ratio, the curvature, the trunck angle and the duration during STS for the TUG-normal are, respectively, [1,038; 2,798], [0,051; 0,098], [31,162; 41,548], and [0,744; 0,987]. For the ten subjects, 70% of the mean values of ratio, trunck angle and duration are contained in their CI. This indicates that the variability of parameter measurement is reduced between the different subjects for these three parameters and we suggest that our system processes good measurement reliability. Regarding the curvature, only 50% of the mean values are in the CI. Indeed, the calculation is based on the outbreak of the vertical phase which takes into account the size differences between subjects. Therefore, the variability of curvature values between subjects is not related to a miscalculation of our system, but rather to inter-individual differences.

In figure 5, duration of STS was shorter than duration of BTS which was proved in the work of Mourey (Manckoundia et al., 2006).

Concerning dual TUG task, in TUG-Normal, mean values of the TUG duration are between 8,21

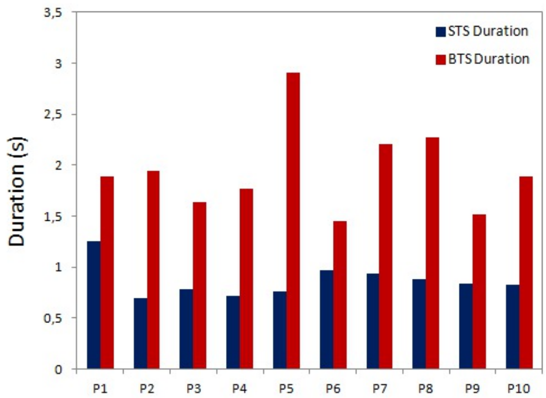


Figure 5: Comparison between STS duration and BTS duration.

s and 11,89 s, in TUG-motor, they are between 8,18 s and 12,65 s and in TUG-cognitive, they are between 8,21 s. and 14,84 s. These values refer to healthy subjects as the limit score of each test is not exceeded (see Section 3.1). These results are compatible with previous studies. During STS, mean value of trunck angle is between $18,30°$ and $49,62°$, and in BTS, it is between $-3,53°$ and $54,68°$.

The only parameter showing a main effect of the factor ”condition” is the ratio in BTS transfer. For this parameter, Kolmogorov-smirnov and Shapiro-Wilk tests showed that the distribution follows a NORMAL law (see Figure 6). Results from the one-way analysis of variance (one-way ANOVA), whose factor is condition, showed that there was a high variability in the BTS ratio between normal condition and cognitive condition (F(2, 27)= 4,2954, p= ,02401). A post hoc within condition analysis was performed and showed that there is a significant difference between normal condition and cognitive condition, this last result is very stimulating regarding the literature about dual task paradigm field. In aging, the automatic motricity seems less efficient and some functional activities, as the TUG, need a cognitive involvement (Teasdale and Simoneau, 2001). Some authors proposed that the BTS motion could be an interesting tool to assess posturo-motor abilities (Manckoundia et al., 2006) in aged adults. Here we showed that a simple BTS analysis can reveal an impairment involved by the dual task condition even in a population of young adults.

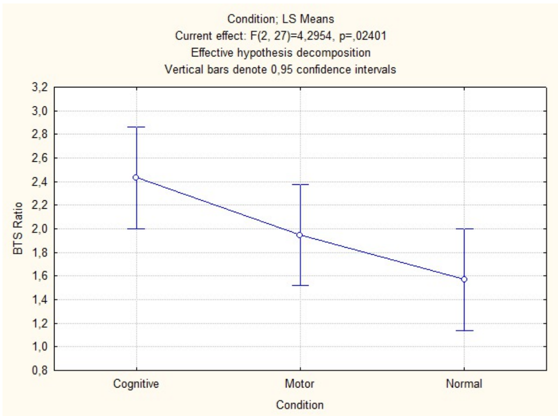


Figure 6: Result of one-way ANOVA analysis.

5 CONCLUSIONS

In this work, we have presented a novel movement analysis system for real-time balance assessment in the frail elderly. It captured and recorded the TUG test movement using a Kinect sensor and nine spatio-temporal parameters were automatically extracted for sit-to-stand and back-to-sit transfers by 3D real-time video processing. Obtained experiment results with ten healthy young subjects showed good measurement reliability and reproducibility with important precision. In addition, we showed that even in young healthy subjects, some modifications of motor patterns can be seen in dual task condition. Moreover, our system allows detecting some very fine changes in posturo-motors abilities.

Our future works consist to perform TUG test for real-time balance assessment in the frail elderly to validate the proposed system in real world condition. This study will open a new research and development way for geriatric health which implies multiple aspects: user-friendly, hygiene, low-cost, home-based environment, and automatic autonomy assessment.

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