# Skeleton Timed Up and Go

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***Abstract*— This paper presents a novel approach to fully automate the Timed Up and Go Assessment Test (TUG) in professional environments. The approach, called Skeleton Timed Up and Go (sTUG), is based on the usage of two Kinect for Xbox 360 sensors. sTUG supports the execution and documentation of the traditional TUG assessment test and furthermore calculates nine events, which demarcate the five main components during a run. On two days we conducted an experiment with five elderly aged 70-84 and four males aged 29-31 in the activity laboratory of the OFFIS Institute, Oldenburg to proof the reliability and feasibility of the system. Results demonstrate that sTUG can precisely measure the total duration of traditional TUG and is capable of detecting accurately nine motion events which demarcate the components during a run.**

***Keywords*-Assessment; Timed Up and Go (TUG); sTUG; Sensor Fusion; Mobility**

## I. Medical Motivation

The demographic shift, termed "double aging of the society", results in more elderly people needing health services and less younger people who can finance and supply these services. Geriatrics is the medical sub-specialty that focuses on the health care of multi-morbid and elderly patients. It estimates the functional status of a patient with a so called geriatric assessment which is a "multidimensional process designed to assess an elderly persons functional ability, physical health, cognitive and mental health, and socio-environmental situation" [1]. To estimate the functional abilities in the mobility domain, one of the most used is TUG Test. Despite its common use in the daily clinical practice some problems have been identified e.g. results depend on the subjective execution of the caregiver and execution is often documented by hand, which makes it time and personnel consuming. These problems show an indisputable need for making the execution of the TUG Test more efficient and comparable.

## II. Related Work

In this section we explain and describe the usage of the assessment test and its limitations. Then the state of the art systems that support the TUG Test technical are presented.

In 1991 D. Podsiadlo and S. Richardson [2] introduced the Timed Up and Go Assessment Test as a simplified clinical test for evaluating the general mobility and balance of particular elderly patients. The test consists of five components which have to be executed by the patient: he has to get up from a chair, walk 3m forward, turn around, walk back and sit down again. After completing the test the patient is placed in a result group based on its performance. This result groups provide hints for needful actions to a caregiver. By measuring only the complete execution, the aim was to objectify the predecessor of the test, in which the ability of the patient were rated on a more subjective 5-point scale [3].

Patients with problems performing activities of daily living (according to the Barthel Index [4]) and handicapped mobility need more than 30 seconds to complete the test. In contrast to subjects without balance deficits, which completed the test in under 10 seconds [4]. The TUG test also reveals balance deficits [5] and shows good test-retest reliability [6]. The test can also be utilized to predict the risk of elderly to fall [7].

But other detectable moving weaknesses and the timing of the single components are ignored. Frenken [9] identified some general problems e.g. place of execution, test awareness of patients, subjective execution by caregivers, and required effort for executing and documenting assessment tests.

For all we know, only three original systems have been described to support TUG technically. Higashi [10] has developed a system which detects the single components of the TUG Test by using two gyroscopes and accelerometers. The system shows a good correlation (r = 0.998) between the calculated time for the components by the system and measured time by therapist through video analysis. Salarin and Zampieri [11] developed an instrumented version of TUG called iTUG. They use seven inertial sensors attached to forearms, shanks, thighs and the sternum to measure four major components. Frenken [12] integrated different ambient sensors into a chair to perform the TUG Test, which he calls ambient TUG (aTUG). He uses a light barrier, 4 force sensors and a laser range scanner to detect the components. In comparison to the video analysis the different components are detected with a simular precision. To our knowledge no marker-less vision based system to technical support the full TUG Test exist today.

It has been shown that body worn sensors can reliable measure the TUG assessment test during every day clinical practice. However, the need to attach sensors to a patient increase the total execution time and increase the test awareness. The uses ambient sensors which reduces the test awareness, but depends on expensive equipment e.g. laser range scanner and on special chair.

## III. Approach

Our new approach to technically support the TUG Test is based on the use of the skeleton detection capabilities of the Kinect for Xbox 360 system. We call this approach

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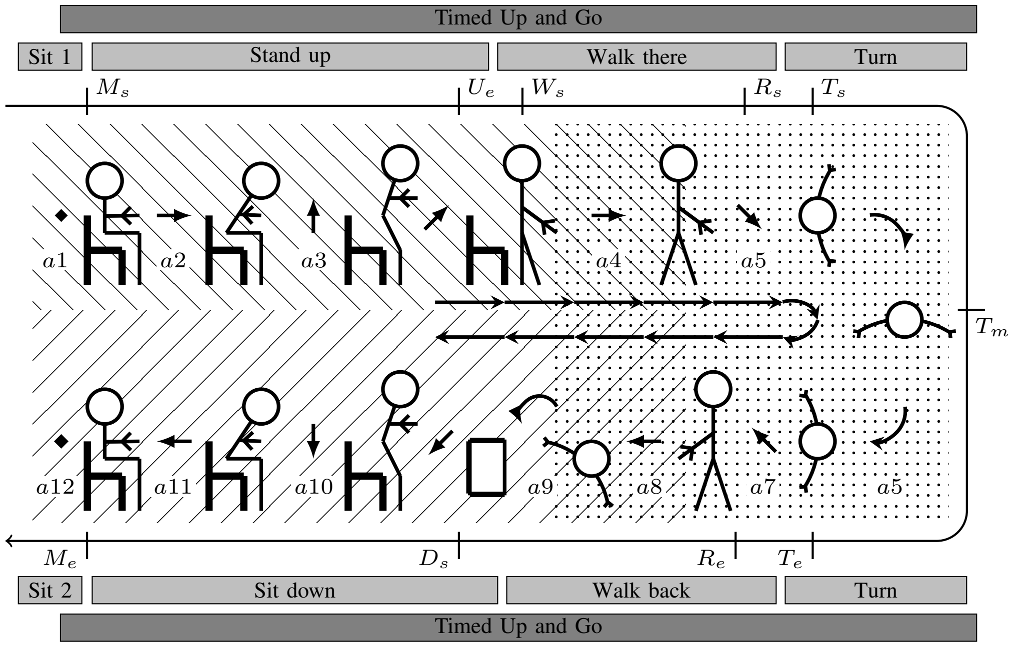



Fig. 1: sTUG concept: components, events, actions and view and detection area of the sensors [12, Fig.1]. *Dark gray box*: TUG assessment test, *light gray boxes*: components, *dashed* and *dotted area*: view and detection area of sensor one and sensor two. $M_s$-$M_e$: detected events. $a1$-$a12$: actions during assessment.

Skeleton Timed Up and Go (sTUG). First we will describe the system setup and the preprocessing steps to generate a useful track (Section III-A). Afterwards we describe how the system objectively detects nine motion events which demarcate the components during a run. (Section III-B).

### A. Aperture Setup

Because a single sensor can not cover the whole action area of the test, we use two Kinect sensors to record a run. They are directed towards the chair and are placed on opposite sides to prevent inferences. Sensor one records the front of the action area (dashed area in Figure 1 and dashed rectangle in Figure 2). Sensor two records the back part of the action area (dotted area in Figure 1 and dotted rectangle in Figure 2).

To determine the orientation of the sensors a checkerboard is used [16]. It is placed in the overlapping viewing area of the sensors (Figure 2), parallel to the seat, with the point of origin (B) on the ideal walking path. This assures that the main movement directions are along the axis and simple to interpret orientation exists.

To combine the detections of the two sensors into a single track first all detections are transformed into world coordinates. Second all skeletons are removed, which are outside the optimal detection range or are outside the action area. Finally, to combine the two sensor sensors the detections of sensor one are preferred during the action walking 1 and the detections of sensor two are preferred during the action walking 2. This results in a distinct state for each frame, which gives a track of the patient for each joint position over the time during the test.

### B. Event detection

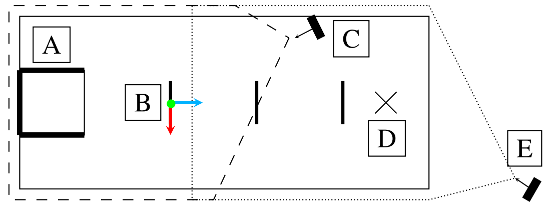
An event is defined as a set of joint positions at a specific time with a corresponding value $E = \{S_t, v\}$. To detect the nine events we defined two generic functions which find the moment which corresponds to a local extreme and two functions which find the moment when the joint value drops or rises below or above a threshold.

After the patient received the start signal, he should get up from the stationary sitting position, in an upright position which enables him to walk towards the turning point. To get up the patient has to move the upper body forward to move his center of gravity over his feet, to be able to lift his body up. While erecting his body or when erected, the person can start to walk forward. During this process the events *start moving* ($M_s$) and *start walking* ($W_s$) can be detected by observing the acceleration of the shoulder center point in z-direction and *end uprising* ($U_e$) can be detected by observing the shoulder center point in y-direction.

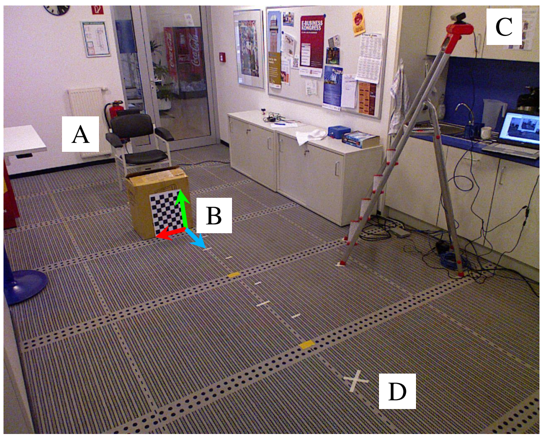
*1) start moving:* The first maximum in z-direction is caused by leaning forward (blue line in Figure 3a). The event is detected, by searching for $M_s = tmax(sc'_z, L_1, S_s, thresh(L_1))$ backwards from the first local maximum $L_1 = lmax(sc'_z, S_s, S_e, l_1)$.

*2) end uprising:* The first maximum in y-direction is caused by the up lifting (green line in Figure 3a). The event is detected, by searching for $D_s = tmin(sc'_y, L_2, S_e, thresh(L_2))$ forward from the local maximum $L_2 = lmax(sc'_y, M_s, S_e, l_1)$.

*3) start walking:* The minimum, after the maximum from forward leaning belongs to the start walking (blue line in Figure 3a). The event is detected, by searching for the local




(a) Schematic system setup. *Solid line*: action area, *dashed line*: view and detection area of sensor one, *dotted line*: view and detection area of sensor two, *cross*: optimal turning point, *thick small line*: 1 m marks.




(b) System setup up from day 2 as seen by sensor two (E).

Fig. 2: Schematic system setup (a) and experiment setup as viewed by sensor two (b). *A*: aTUG apperatus, *B*: sensor one, *C*: sensor two, *D*: optimal turning point, *E*: point of origin, *red*: x-axis, *blue*: y-axis, *green* : z-axis.

minimum $W_s = lmin(sc'_z, L_1, S_e, l_1)$.

After getting up and walking forward, the aim is to to change from walking away from the chair to walk towards the chair. To walk in the opposite direction the patient has to turn his body in the direction of the chair and he has to change the walking direction. During this process, the events *start turning* ($T_s$) and *end turning* ($T_e$) are detected. These events can be detected by observing the distance and acceleration between the right and left shoulder in x-direction. The events *start accelerating* ($A_s$) and *end accelerating* ($A_e$) can be detected by observing the speed of the shoulder center point in z-direction (blue line in Figure 4b). The event *max turn* ($T_m$) is located between these actions, it corresponds to the farthest position of the patient from the chair.

*4) max turn:* The minimum in x-direction of the shoulder distance corresponds with this event (red line in Figure 4a). The event is detected, by searching for the local minimum $T_m = lmin(sd_x, W_s, S_e, l_2)$.

*5) start rotating:* The maximum left from $T_m$ is caused by turning of the shoulder line from being orthogonal to the ideal walking path to being parallel (green line Figure 4a). The event is detected, by searching for $R_s = tmin(sd'_x, L_3, S_s, thresh(L_3))$ backwards from the local maximum $L_3 = lmax(sd'_x, T_m, S_s, l_3)$.

*6) end rotating:* The minimum right from *max turn* is caused by the turning the shoulder line back to being orthogonal to the ideal walking path. The event is detected, by searching for $R_e = tmin(sd'_x, L_4, S_e, thresh(L_4))$ forward from the local minimum $L_4 = lmax(sd'_x, T_m, S_e, l_3)$.

*7) start accelerating:* The event is detected, by searching for $A_s = tmax(sc_z, T_m, S_s, m)$ (blue line in Figure 4b).

$m$ is the mean walking speed of the patient $m = mean(sc'_z, W_s, T_m)$.

*8) end accelerating:* The event is detected, by searching for $A_s = tmin(sc_z, T_m, S_s, m)$ (blue line in Figure 4b).

After turning around and walking towards the chair the aim is to sit down and rest. Here the events *start lowering* ($D_s$) and *end moving* ($M_e$) can be detected, these events can be detected similar to *start moving* and *end uprising*.

*9) end moving:* the last minimum is caused by leaning backward (blue line in Figure 3b). The event is detected, by searching for $M_e = lmin(sc'_z, L_5, S_e, thresh(L_5))$ forward from the local minimum $L_5 = lmax(sc'_z, S_e, S_s, l_1)$.

*10) start lowering:* The last minimum in y-direction is caused by lowering (green line in Figure 3b). The event is detected, by searching for $D_s = tmax(sc'_y, L_2, S_e, thresh(L_5))$ backwards from the first local minimum $L_6 = lmin(sc'_y, M_e, S_s, l_1)$.

## IV. Experiment

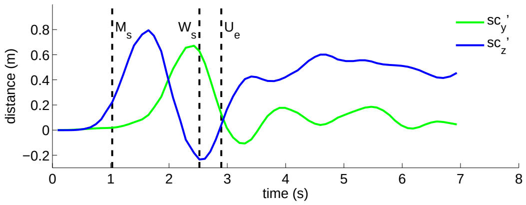
In order to prove the general feasibility of sTUG to automate TUG assessment test, we conducted an experiment with two main goals. First to compare the precision of skeleton-based measurements with respect to aTUG and the traditional stopwatch measurement (Tab. I). Second to evaluate whether the sTUG apparatus and algorithms for a reliable detection and compute the defined events. A correct and precise detection is considered according to hand labeled events in the video sequences.

The experiment was conducted on two days with two different age-groups in the activity lab of the OFFIS institute. On the first day the experiment was held with a group of five elderly patients, two males and three females, with age ranging from 70 to 84 years. All patients suffered from age related medical conditions, which were documented. On the second day (two weeks later) the experiment was repeated with four of the five elderly (one female could not attend a second time) and with a second group consisting of four healthy males with age ranging from 29 to 31 years, none suffering from any medical condition.

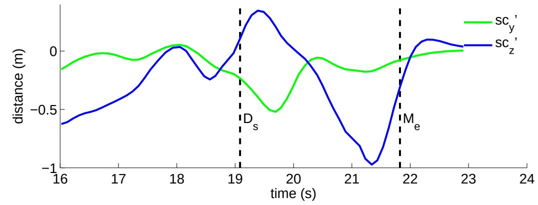
The two Kinect sensors were set up and transformation was determined as described in Section III-A. Figure 2b shows the setup from day 2 as seen by sensor two.

### A. Execution

On the first day only the elderly took part in the experiment, all of whom had previously participated in a TUG Test. One by one the patients were asked into the experiment area and performed twice the TUG Test that was record with the aTUG apperatus and our system.

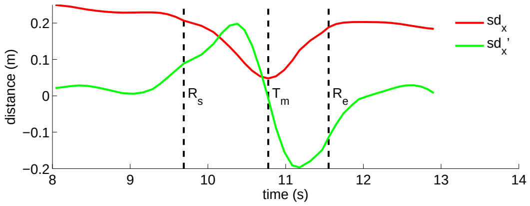



(a) *Green line*: acceleration of shoulder center joint in y-direction, *blue line*: acceleration of shoulder center joint in z-direction, $M_s$: *start moving*, $W_s$: *start walking*, $U_e$: *end uprising*.

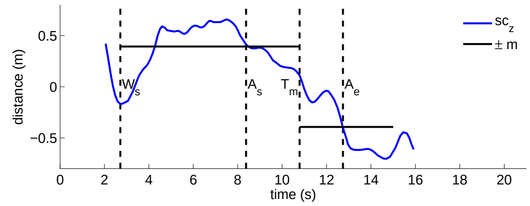



(b) *Green line*: acceleration of shoulder center joint in y-direction, *blue line*: acceleration of shoulder center joint in z-direction, $D_s$: *start lowering*, $M_e$: *end moving*.

Fig. 3: Analysis of events related to stand up and walk there (a) and walk back and sit down (b) (Day 1, run A1).




(a) *Red line*: distance between left and right shoulder in x-direction, *green line*: first derivative of distance, $T_m$: *max turn*, $R_s$: *start rotating*, $R_e$: *end rotating*.




(b) *Blue line*: velocity of shoulder center point in z-direction, *black line*: mean walking speed, $T_m$: *max turn*, $A_s$: *start accelerating*, $A_e$: *end accelerating*.

Fig. 4: Analysis of events related to turn (Day 1, run A1).

We followed the same procedure on the second day, except that the patients were asked to wear white cuffs to achieve better reflection and thus improve the measurement results of the laser range scanner for the aTUG apperatus. After conducting the experiment with the elderly again, the second group participated in the experiment.

## V. Results

Five people completed the experiment on day one and eight people completed it on day two (column 1 Table I&II: person, day and run). The test was recorded with the stopwatch, the aTUG apperatus and the sTUG. From the videos five events where extracted by manual video analysis. Results of the video analysis are assumed to be most precise.

*1) Video analysis:* In all videos, the following five events were labelled: *start moving* ($M_s^v$) last frame before first visual movement away from the lean in the upper body. *Start walking* ($W_s^v$), *start turning* ($T_s^v$), *end turning* ($T_e^v$) and *end moving* ($M_e^v$).

Table I shows the results for the first part of the experiment, minimum, maximum, mean and standard deviation, over all runs. Durations for different measurement techniques (column 2-5), the difference to the video analysis (column 6-8), the difference between the two technical systems (column 9) and the difference between the detected start and stop events of the technical systems (column 10-11). Mean difference for stopwatch and sTUG are highly precise ($0.1s$). Standard deviation for sTUG is the lowest for all methods ($0.15s$). The standard deviation for the stopwatch was significantly higher with $0.68s$, this may be due the fact, that humans cannot measure more objectively than sensors. The mean difference between aTUG and the video and sTUG is much higher with $1.4s$ and $1.5s$. Because of that we examined the detected start and stop events (column 10-11). The mean difference for start and stop are both high with a low standard deviation. This indicates a systematically error. In contrast to sTUG, which detects the first movement of the upper body, the aTUG apperatus uses total weight change to detect the start and stop event. The problem is that the patient to lift himself up, he has to lean his upper body forward, which seems not to cause enough total weight change, to be detected immediately.

The aim of the second part of the experiment was to proof the feasibility of the event detection. For that we compare the events detected by the system with the labelled events and did a visual confirmation. As can be seen in Table II the detection of the events *start moving* and *end moving* (column 2 and 10) are highly precise with a mean difference of $0.07s$ and $0.01s$, which corresponds to approximately one frame and both have a very low standard deviation. *Start walking* shows a good precision with a mean of $-0.12s$. For the start and end of the component turning we detect two events each ($R_s$, $A_s$ and $A_e$, $R_e$). The start and end events $T_s^v$ and $T_e^v$ of the video analysis for the component turning equal the combination of the two events of the system. Hence we could only compare tow detected events to the same hand labelled event of the video analysis. The average difference for the detected events (column 5-8) is low. The video analysis event results in a slightly higher standard deviation. The events *end uprising* and *start lowering* (column 3 and 10) could we not label manually, therefore did we compare them to the next closes event and check them manually. Both events do not show any significant abnormalities.

TABLE I: Comparison of measuring techniques for the traditional TUG. Column 2-5: measured duration for $D^v$: video analysis, $D^w$: stopwatch, $D^s$: sTUG, $D^a$: aTUG apperatus. Column 6-8: difference of measuring technique to video analysis. Column 9: difference between the two technical systems. Column 10-11: difference between measured start $M_s$ and stop event $M_e$ of the two technical systems.

| | $D^v$ | $D^w$ | $D^s$ | $D^a$ | $D^v - D^w$ | $D^v - D^s$ | $D^v - D^a$ | $D^a - D^s$ | $M_s^a - M_s^s$ | $M_e^a - M_e^s$ |
|---|---|---|---|---|---|---|---|---|---|---|
| min | 7.29 | 6.55 | 7.16 | 5.85 | -1.39 | -0.40 | 0.57 | 0.65 | 0.45 | -1.24 |
| max | 30.64 | 31.72 | 26.47 | 29.00 | 1.16 | 0.13 | 1.95 | 2.35 | 0.96 | -0.67 |
| mean | 13.00 | 13.10 | 11.93 | 11.64 | -0.10 | -0.12 | 1.36 | 1.50 | 0.64 | -0.92 |
| std | 6.08 | 6.44 | 5.44 | 6.06 | 0.68 | 0.15 | 0.35 | 0.37 | 0.16 | 0.14 |

TABLE II: Comparison of detected events (Section III-B) with events of the video analysis (Section V-1).

| | $M_s - M_s^v$ | $W_s - W_s^v$ | $U_e - W_s^v$ | $R_s - T_s^v$ | $A_s - T_s^v$ | $A_e - T_e^v$ | $R_e - T_e^v$ | $D_s - M_e^v$ | $M_e - M_e^v$ |
|---|---|---|---|---|---|---|---|---|---|
| min | -0.28 | -0.75 | -0.09 | -0.33 | -1.24 | -0.46 | -1.08 | -2.87 | -0.30 |
| max | 0.00 | 0.11 | 1.34 | 1.76 | 0.80 | 1.47 | 0.66 | -1.54 | 0.28 |
| mean | -0.07 | -0.12 | 0.42 | 0.10 | -0.02 | 0.06 | -0.17 | -2.05 | 0.01 |
| std | 0.08 | 0.19 | 0.44 | 0.43 | 0.33 | 0.37 | 0.43 | 0.37 | 0.13 |

## VI. Conclusion

Within this paper we showed how the Timed Up and Go Assessment Test can be fully automated and conducted with two low cost and ambient Kinect for Xbox 360 sensors.

We explained how to place the sensors and transform the coordinates, preprocess and combine the transformed joint positions and how to calculate nine events, that demarcate the components. We performed an experiment with multi-morbid elderly and health adults to evaluate the feasibility and reliability of the system. Results showed that the system can calculate the duration of the TUG Test with high accuracy and detect nine events accurately and with high precision, which demarcate the five components.

Through the use of the next version of the Kinect SDK we expect a reduction of failed detections, because it does not longer state that it is not usable for sitting situations [17]. We plan to inspect the scenarios in case of support through a second person during the test and the influence of walking aids. Also, we plan to calculate more gait and balance parameters during the different components. We hope to compare the detected events from the two technical systems more closely and improve the accuracy in general. Finally, we want to validate the precision of the system to a marker based tracker.

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