Evaluating Parameters of the TUG Test Based on Data from IMU and UWB Sensors

Adamantios Ntanis*‡, Nicholas Kostikis*§, Ilias Tsimperis*¶, Kostas Tsiouris†**, George Rigas*‖, Dimitrios Fotiadis†††

**PD Neurotechnology Ltd.*, Ioannina, Greece
{‡a.ntanis, §n.kostikis, ¶i.tsimperis, ‖g.rigas}@pdneurotechnology.com

†*Unit of Medical Technology and Intelligent Information Systems, University of Ioannina and Biomedical Research Institute, Foundation for Research & Technology – Hellas*, Ioannina, Greece
**tsiourisk@gmail.com, ††fotiadis@cc.uoi.gr

***Abstract*—The Timed Up and Go (TUG) test is a well-established, standardized test used to assess various aspects of a patient's mobility. Although its reliability is proven, instrumentation is necessary for acquiring accurate information. This work evaluated the instrumentation of the TUG test using devices based on inertial measurement unit (IMU) and UWB radar sensors, and subsequently assessed test-related motion parameters, extracted from their data. To that end, five healthy individuals participated in three sessions of a TUG test, performed in slow, normal and fast speeds, while an IMU-based wearable device, the PDMonitor®, and an ultra-wideband (UWB) radar, the Aria Sensing® LT102, monitored their motion. The sessions were also timed, recorded on video, and annotated as a post-processing step. Results showed that both approaches performed very well in estimating walking duration ($R^2 = 0.96$ for IMU and $R^2 = 0.98$ for UWB) and turning duration ($R^2 = 0.74$ for IMU and $R^2 = 0.66$ for UWB). Moreover, for the IMU sensors, the test duration had excellent correlation with annotations ($R^2 = 0.98$) and results showed that gait kinematic features could be used as predictors ($AUC = 0.9955$) of detecting a high TUG score ($T^{\text{TUG}} > 13.5\,\text{s}$), identifying increased fall risk. On the other hand, gait speed estimated using UWB data had excellent correlation ($R^2 = 0.95$) with speed calculated using annotations. The different characteristics of the two approaches, and their good performance in the TUG test's segmentation and assessment of gait parameters, indicate that they could be fused to augment the resulting information.**

***Index Terms*—IMU sensors, UWB radars, TUG test, Motion analysis, Kinematic analysis.**

I. Introduction

FOR patients and senior individuals, physical mobility, along with gait, balance, as well as the ability to go out alone and walk safely is of paramount importance. One well established, standardized test, used in clinical practice, is the Timed Up and Go (TUG) [1], which is based on the Get Up and Go (GUG) test [2], and it is commonly used to assess gait, balance, fall risk and general mobility [3]–[7]. During the TUG test, the patient is instructed to rise from an armchair, walk 3 meters, turn 180°, walk back to the armchair and sit down, while being observed and timed. As a result, the test can be segmented into the following subtasks, or else segments: 1) sit-to-stand, 2) walking-out, 3) turning, 4) walking-in, 5) turning around, and 6) stand-to-sit [8]. The setup of a classic TUG test can be seen in Figure 1.

Since its inception, the TUG test was proven to be reliable, with low inter-rater and intra-rater variability [9]–[11]; correlate well with balance scores [12], gait speed and ADL indices (Activities of Daily Living); and predict the patient's ability to walk outside alone safely (fall risk) [13]. These characteristics showed that the test is a promising tool to quantify mobility and monitor changes longitudinally [1], [2]. Technically, the TUG test can be easily taught to healthcare professionals, can be executed rather quickly and requires very basic instrumentation, namely an armchair, a stopwatch and a marker for the 3 meters' distance. The score extracted from the TUG test is the time one takes to complete it. Subjects with time greater than $13.5 - 14$ s have a higher probability of experiencing falls [1].

IMU sensors can be used to achieve higher accuracy in timing the TUG segments (sit, stand, walk, turn, walk, turn around, stand and sit) and the respective transitions, as well as to analyze individual spatial and temporal components. Instrumenting the TUG test (iTUG) with IMU sensors has been shown to result in better fall risk assessment than the original TUG test, regarding patients with Parkinson's disease (PD), disability or cognitive impairment [14]. The iTUG, with IMU sensors, has also been found sufficient to accurately quantify the TUG test's phases for clinical applications [15].

The use of radars is another approach for instrumenting the TUG test given their suitability for assessing mobility. In [16] the researchers managed to correctly identify the stand-to-sit phase of the TUG test using a Doppler radar, while in [17], UWB radars, complemented by insoles with force sensors, have been found sufficient for contactless TUG testing.

In this work, the instrumentation of the TUG test is evaluated, using both, a set of IMU sensors and a UWB radar.

This research was funded by the European Regional Development Fund of the European Union and Greek national funds through the Operational Program Competitiveness, Entrepreneurship, and Innovation, under the call RESEARCH–CREATE–INNOVATE (project name: HealthSonar, project code: T1EDK-03990).

978-1-6654-6975-3/22/$31.00 ©2022 IEEE

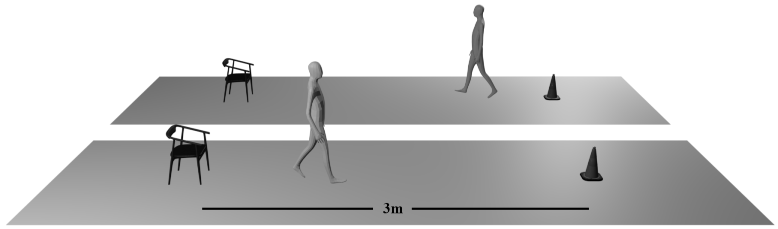

Fig. 1: The setup of a classic TUG test. In the foreground appears the walking-out phase, while in the background appears the walking-in phase. The distance between the chair and the cone is $3\,\mathrm{m}$.

Moreover, TUG test motion parameters are extracted from the data of both sources and are subsequently assessed. A comparison of the two methods, including the strengths and weaknesses of each one, as well as the first steps towards fusing them, are discussed for the first time, to the best of our knowledge. The importance of this work lies in the novel approach of instrumenting the TUG test with devices based on both IMU and UWB sensors simultaneously, and subsequently evaluating the extracted gait parameters from the data of those sources, and comparing them to one another. This is significant for a number of reasons.

First, a combination of the two sensors (IMUs and UWB) can lead to the extraction of enhanced information regarding the mobility of the participants of the TUG test, superior to both the classic TUG test, and to its single-sensor instrumented variations (when only IMU or only UWB sensors are used). More specifically, the classic test provides to the physicians only the time each subject takes to finish it, leaving off the table valuable mobility information. On the other hand, the single-sensor instrumentation approaches (with only IMUs or only UWB sensors), while providing a wealth of information regarding the performance of the test subjects, they can still only capture a specific set of mobility parameters due to the fact that IMU sensors and UWB radars excel at different tasks. IMUs offer accurate timing and gait kinematic features, while UWB radars offer accurate distance and gait speed estimation. Thus, a combination of both aforementioned sensors can lead to a holistic instrumentation approach of the TUG test, enhancing the resulting test information by providing diverse data that are, either impossible to be acquired with only one of them, or at least very difficult. Moreover, information resulting from a combined approach (using both IMUs and UWB) in instrumenting the TUG test can facilitate accurate test segmentation into its different parts (i.e. sit-to-stand, walking-out, turning, walking-in, turning around and stand-to-sit) which can be crucial to healthcare professionals [8].

Second, IMU sensors are ubiquitous and a core component of many medical and consumer devices (for example fitness trackers). The same can not be said for the UWB radars at the moment, but this is rapidly changing, as more and more applications use them. As a reference, in the healthcare and fitness market, that is related to this work, UWB radars are currently most commonly used for remote health monitoring [18], assisted living of elders and patients [19] and monitoring of sleep [20], [21]. Such applications use UWB radars because they excel at extracting vital signals, such as respiration and heart rate [18], as well as at recognizing the presence of people and identifying falls, which is of special interest when monitoring elders. With the already ubiquitous nature of IMU sensors and the incoming widespread adoption of UWB radars, research about them is rising, and is poised to have a substantial impact in the future, especially for medical devices. More specifically, an increased research interest, can lead to breakthroughs that can further propel the development of new medical devices based on both UWB and IMU sensors, with extended capabilities, applicable to various branches of medicine. An example is the application presented within these pages, as well as any possible future directions that it might take (e.g. instrumentation of other standardized tests). To be more specific, the demonstrated applicability of a combined approach of UWB and IMU technology to new tasks pertaining to gait assessment, such as the TUG test, can help extend the capabilities of medical devices targeted to remote mobility monitoring of both healthy and patient populations in clinical and home environments. Physicians and especially movement disorder experts could be enabled to perform evaluations of the mobility of their patients remotely and extract accurate and diverse analytics about their motion in real time.

II. Materials and Methods

The subjects that participated in the TUG tests were 5 healthy volunteers (4 men and 1 woman). Each one performed the test 6 times with 3 different speeds, switching between slow, normal and high speed every 2 test repetitions (resulting in a total of 30 TUG tests). For the instrumentation of the tests two devices were simultaneously used. The first one, utilizing IMU sensing technology, was the PDMonitor® system and the second was the Aria Sensing® LT102 UWB radar. The sessions were also timed, by a researcher that was part of team that designed the experiment, and recorded on video.

For the TUG test, a set of motion parameters were extracted using data from both sensors, while others were device-specific. The parameters evaluated with both sensors were the walking duration (time from the first to the last step) and the turning duration (duration of the turn at the $3\,\mathrm{m}$ mark). Moreover, IMU sensors enabled the estimation of the test duration (TUG test score), i.e. the walking duration plus the duration of the sit-to-stand and stand-to-sit phases, as well as the "normalized stride length". The latter is shown in this work to be a predictor of one's TUG test performance. As a side note, for the estimation of the "normalized stride length", the range of movement was also estimated using data from the IMU sensors. On the other hand, the UBW radar provided gait speed estimation of the participants, while the total test duration was out of scope of this work due to the more complex, and less accurate, nature of identifying the sit-to-stand and stand-to-sit phases using the UWB sensor. The differences in the extracted measures using the two sensors stems from the fact that each one excels in different tasks. IMUs can easily provide accurate timing and gait kinematic features, while UWB radars can accurately estimate distance and speed. There is a variety of spatio-temporal gait parameters that have been used in the evaluation of the TUG test [22]. The best set of parameters for a test such as the TUG can only be defined based on the use case, as there are plenty of gait characteristics that could be targeted for extraction from a rich dataset of IMU and UWB sensor data. In this work, the parameters to be estimated were chosen in such a way so, first to extract the temporal information of the test (the test duration, the walking duration and the turning duration) and second to showcase the advantages of each sensor in a meaningful, regarding the test results, way. The IMUs targeted gait parameters (range of movement, "normalized stride length" etc.), while the UWB radar targeted distance and gait speed parameters.

A. Instrumentation based on IMU sensors

PDMonitor® is a Class IIa medical device intended to be used by patients diagnosed with Parkinson's disease for diagnostic and clinical purposes, whereas in this work it is used for data recording. The PDMonitor® [23] includes 5 wearable sensing devices (2 devices worn on the shanks, 2 on the wrist and 1 on the torso) for movement data logging, each one equipped with the LSTM9DS1, a 9-axis IMU (accelerometer, gyroscope and magnetometer) module with a sampling frequency of 59.5 Hz. For the estimation of the TUG test's parameters, data from the two shank sensors, as well as the torso sensor, were collected and used.

Data from the shank sensors were utilized towards the identification of the basic gait cycle events, which led to the estimation of the walking duration, the range of movement and, as a result, the "normalized stride length". The events identified include the maximum swing (MS), toe off (TO) and initial contact (IC). Their respective timestamps, used in the formulae listed below, were defined as T^{MS}, T^{TO} and T^{IC}. More specifically, the gait cycle events were identified through peak detection in the readings of the Z axis of one shank gyroscope, $g_z^S(t)$, for every walking step i, as depicted in Figure 2. The implementation is similar to the one presented in [24]. It should be noted that, IMU sensors in both shanks are needed in order to be able to identify the exact timing of the first and the last step. Other measures, like the range of movement, for healthy individuals, can be estimated using only one shank sensor, as it is expected to be similar for both legs. However, in case of subjects with impaired gait, there will

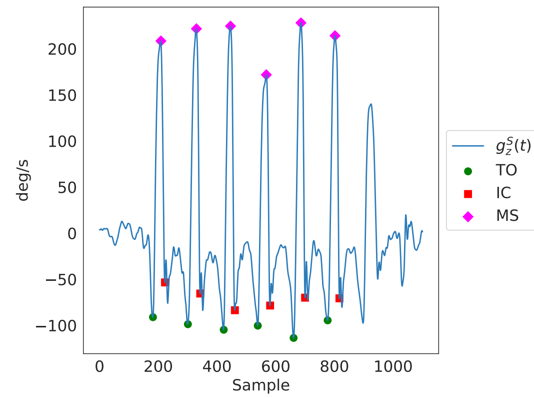

Fig. 2: Detection of basic gait cycle events. The signal is the Z axis' readings of the shank gyroscope.

be significant difference in these measures between the two legs, therefore data from both shanks should be considered. In addition to the data from the shank sensors, data from the torso sensor were utilized towards building a linear regression model, for the estimation of the turning duration, as well as, a threshold function, for the estimation of the total test duration (TUG test score). The torso sensor was chosen because it had fewer degrees of freedom (DOF).

Walking duration. The duration between the first and the last step was considered as the walking duration of the participants. The first and the last step were identified based on the first and last maximum swing (MS) event respectively.

Turning duration. The turning duration (T^{TR}) was estimated using a linear regression model based on the readings of the X axis of the gyroscope placed on the torso. The X axis is the main rotation axis for the specific experiment configuration. The model used for the estimation of the turning duration was the following:

$$T^{\mathrm{TR}} = 0.32 + 3.15 \cdot (T^{70} - T^{40}) \tag{1}$$

In the previous relationship, T^{40} and T^{70}, represent the time points when the total gyroscope's angle $\theta(t)$ exceeded $-40°$ and $-70°$ respectively. The total angle was calculated using:

$$\theta(t) = \int_{\tau}^{t} g_x(t)dt \tag{2}$$

where τ is the time of the first step. Note, this is an approximation of the turning duration and may have significant error for impaired patients (i.e. due to Parkinson's disease).

Total test duration. The energy of the torso gyroscope sensor was used to estimate the time duration of the subjects performing the test based on the following binary variable:

$$M(t) = \begin{cases} 1, & \sqrt{\left(g_x^T(t)^2 + g_y^T(t)^2 + g_z^T(t)^2\right)^2} \geq 25 \\ 0, & \sqrt{\left(g_x^T(t)^2 + g_y^T(t)^2 + g_z^T(t)^2\right)^2} < 25 \end{cases} \tag{3}$$

where $g_x^T(t)$, $g_y^T(t)$ $g_z^T(t)$ are the readings of the X, Y and Z axes of the torso gyroscope, respectively. A median filter was applied in order to remove small movements before and after the test. The beginning and the end of each test were determined by the first and last point, respectively, where $M(t)$ was equal to 1. Note that this method assumes that the TUG test data were well-separated from data resulting from other activities before and after the test. To ensure that, subjects were instructed to stay still before and after the test.

Range of movement. The shanks' range of movement (R) was estimated by calculating the area of the total gyroscope's energy, from one shank gyroscope's readings, $g_x^S(t)$, $g_y^S(t)$ $g_z^S(t)$, between the zero crossings of the maximum swing peaks (Z_i^0 and Z_i^1), using the trapezoidal rule:

$$R(i) = \int_{t=Z_i^0}^{t=Z_i^1} \sqrt{\left(g_x^S(t)^2 + g_y^S(t)^2 + g_z^S(t)^2\right)^2}\, dt \tag{4}$$

Normalized stride length. Based on a previous internal pilot study, an estimation of the "normalized stride length" ($\hat{S}$) was calculated using the range of movement (R) and gait cycle events (T^{IC}, T^{TO}):

$$\hat{S}(i) = 20 + 2.6 \cdot R(i) \cdot \left(1 - \frac{T_i^{\mathrm{IC}} - T_i^{\mathrm{TO}}}{T_i^{\mathrm{IC}} - T_{i-1}^{\mathrm{IC}}}\right) \tag{5}$$

B. Instrumentation based on a UWB radar

For the TUG tests, 4 of the 5 participants (3 men and 1 woman) had their motion tracked by the Aria Sensing® LT102 UWB radar sensor. The LT102 radar was placed opposite to the chair used for the test in such a way that the participants were pacing at all times back and forth the same virtual line between the radar and the chair. The radar itself was enclosed in an in-house designed and 3D printed case and mounted on top of a tripod.

MTI data frames. Each data frame represents the echoes returned to the radar once reflected from the objects present in the environment and processed using a Moving Target Indicator (MTI) algorithm. The algorithm is built into the LT102 as a mode of operation and was used for better motion tracking. The radar was configured to return 20 frames of data per second, and detect motion in a range between 0.5 and 6m. As a result, each frame was consisting of 857 data points.

Frame processing. The distance of the moving target was indicated by the position of the maximum element after it was mapped to a linearly spaced set of distances over the detection interval (in our case $0.5 - 6\,\mathrm{m}$). Then, the amplitude envelope of the signal was extracted by calculating the magnitude of the analytic signal we produce using the Hilbert transform. After the processing of all frames, a set of values was acquired (considered as a distance signal), denoting the distance of the target at the time indicated by the respective timestamp (logged at the time of every frame acquisition).

Distance processing. First the generated distance signal was processed. More specifically, a median filter was applied to the signal for outlier removal, and then a moving average filter for smoothing it. For the purposes of this work, 3 distinct regions were identified in the distance signal of the TUG test. Those corresponded to the periods before, during and after the walking assessment. In order to extract the second region, the point at which each participant reached the $3\,\mathrm{m}$ mark was used as a reference in search of the first and the last step (that is the $0\,\mathrm{m}$ mark). For this purpose, two indexes were identified, the "left" and the "right". Using them, the signal was trimmed and the period of the walking phase of the test was extracted.

Walking duration. The walking duration of each participant was computed through the timestamps of the distance values corresponding to the "left" and "right" indexes found in the previous step.

Turning duration. The turning duration was estimated through the number of frames acquired while each subject remained at a specific distance from the $3\,\mathrm{m}$ mark (i.e. within a $0.45\,\mathrm{m}$ radius). The number of frames was then converted into a duration using the radar's sampling rate. To this end, the $3\,\mathrm{m}$ mark in the distance signal was, again, used as a reference.

Average gait speed. The average gait speed of each participant was evaluated by calculating the differences between the elements of the distance signal (displacements), summing up their magnitudes (total distance) and dividing them by the duration of the walking period.

III. Results

Data from IMU sensors and from a UWB radar, led to the extraction of common parameters of the TUG test (i.e. walking time, turning time), but each sensor on its own, also resulted in enhanced information regarding the performance of the participants by providing unique, to that sensor, test parameters (i.e. total turning time, range of movement, "normalized stride length", gait speed).

A. Common Parameters

The estimated walking duration from UWB and IMU sensor data, versus annotations, is presented in Figures 3a and 3d, respectively. The estimated turning duration from UWB and IMU sensor data, versus annotations, is presented in Figures 3b and 3e respectively. The estimated walking duration, for both sensors, had an excellent correlation ($R^2 = 0.96$ for IMU and $R^2 = 0.98$ for UWB) with the one extracted from the videos. The estimated turning duration, for both sensors, was also highly correlated with annotations ($R^2 = 0.74$ for IMU and $R^2 = 0.66$ for UWB), however turning, especially in normal and high speed, is quite hard to accurately annotate with an accuracy greater than 2 seconds (≤ 2 sec) and identify in sensor data. In any case, the performance of the two solutions, regarding the aforementioned common measures, is comparable, with the IMUs being slightly more accurate.

B. Device-Specific Parameters

The estimated test duration, calculated only for the case of the IMU sensors, had excellent correlation with the video data ($R^2 = 0.98$). The "normalized stride length" of Equation 5 was calculated and associated with the participant's test performance (TUG test score). More specifically, three groups of TUG test durations were considered: $1)$ less than $12\,\mathrm{s}$,

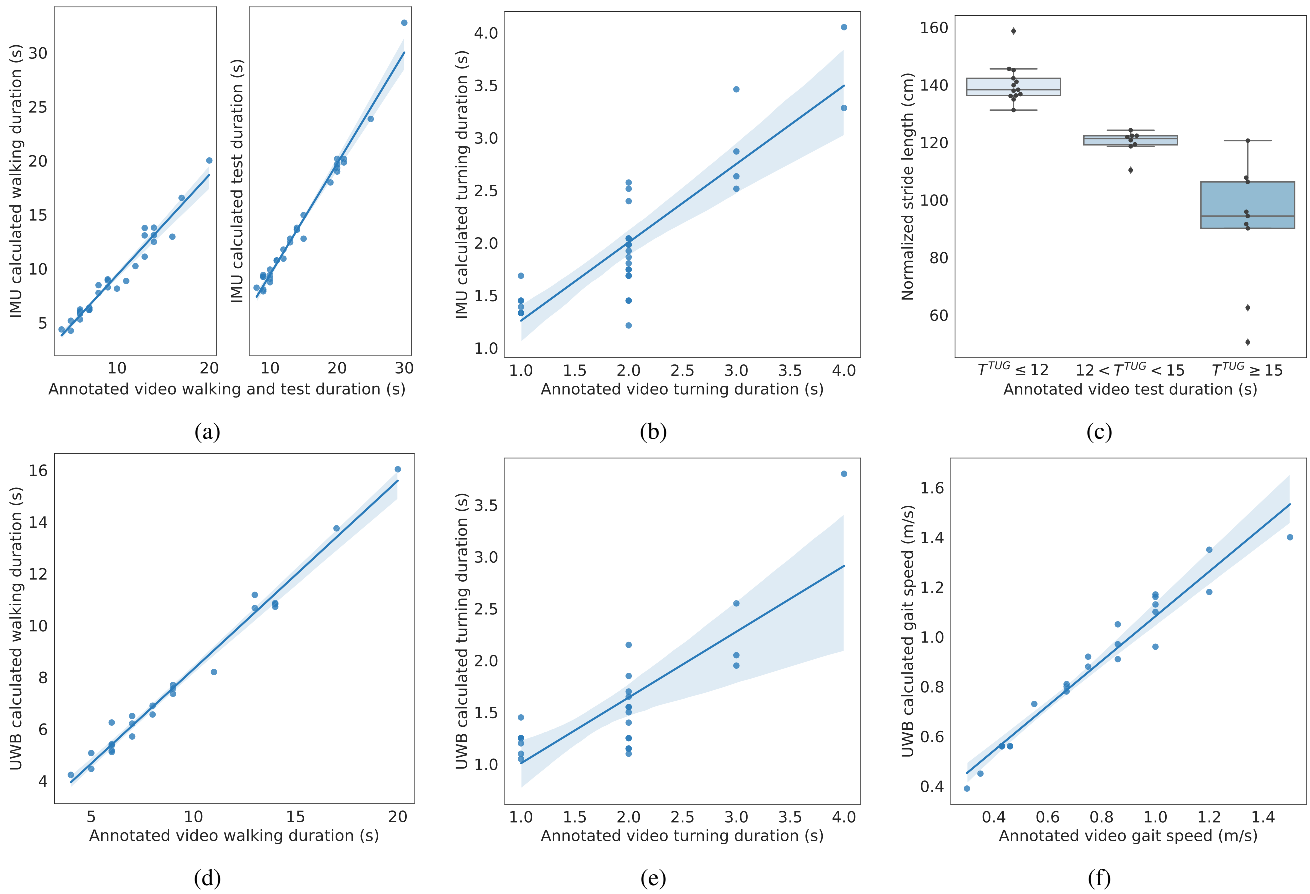

Fig. 3: Results for the estimation of parameters of the TUG test with the UWB radar and the IMU sensors. All figures represent correlation results between IMU/UWB sensor data and annotated video data, except for the box plot of Figure (3c). Specifically: (3a) Total and walking duration (IMU). (3b) Turning duration (IMU), (3c) "normalized stride length" versus TUG test duration categories (IMU), (3d) Walking duration (UWB), (3e) Turning duration (UWB), (3f) Gait speed (UWB).

2) more than $12\,\mathrm{s}$ and less than $15\,\mathrm{s}$, and 3) more than $15\,\mathrm{s}$. A box plot with the TUG test score of each participant, versus their "normalized stride length" is presented in Figure 3c. Moreover, using IMU data, the "normalized stride length" was evaluated as a predictor of each subject's TUG test performance through a Receiver Operating Characteristic (ROC) analysis. All groups have statistically important differences ($p < 0.001$). The performed ROC analysis resulted in $AUC = 0.9955$ of detecting a high TUG score ($T^{\mathrm{TUG}} > 13.5\,\mathrm{s}$). Finally, for the UWB radar, the gait speed of each subject was estimated, resulting in excellent correlation with the video data ($R^2 = 0.95$). This was expected since UWB sensors are well-suited to measure distance and speed (Figure 3f).

IV. Discussion

Using IMU sensors, temporal parameters of the TUG test, i.e. the test's total, walking and turning duration were evaluated with high accuracy. Moreover, gait kinematic measures extracted from IMU data were shown to be a predictor of one's TUG score and could be used to detect subjects with an increased fall risk. Using the UWB radar, the TUG test's walking and turning duration, and the participants' gait speed, were estimated with high accuracy. Extracting temporal information from the sit-to-stand and stand-to-sit phases from the UWB radar data, was not in the scope of this work due to the increased complexity and inaccuracy. As a result, the total duration of the TUG test was not calculated for that case. It is important to note that, for the purposes of this work, only healthy individuals took part in the testing scenarios, thus the results need to be further validated in patient populations as well. Summarizing, the advantages and disadvantages of IMU and UWB sensors in instrumenting the TUG test, compared to the stopwatch, that is commonly used in the classic version of the test, are presented in Table I.

IMU sensors are able to continuously monitor subjects in their daily lives and parameters, such as the "normalized stride length", allow for continuous home monitoring of gait and also for balance assessment for specific groups (such as, elders, patients with Parkinson's disease or multiple sclerosis). On the other hand, UWB radar technology is better at estimating distance and speed. Also, a UWB radar can monitor individuals in a contactless manner, albeit usually only from the position that it is mounted to. In a future work we are going to evaluate the fusion of the two technologies (fusing data from both IMU

TABLE I: Comparison between different technologies for the instrumentation of the TUG test.

Technology	Advantages	Disadvantages
Stopwatch	Easy to find. No additional equipment necessary for the base TUG test.	Prone to error. No additional measures are extracted through this approach.
UWB radars	Unobtrusive monitoring. Accurate distance and speed estimation.	Gait kinematic measures are not easily provided without further processing.
IMU sensors	Accurate timing. Gait kinematic features. Free activity monitoring.	Difficult to mount the sensors. Speed and distance estimation is not easily provided.

and UWB sensors) in order to better assess the TUG test's parameters and estimate measures such as the stride length, and other gait kinematic features. Moreover, we will evaluate the time-to-raise and time-to-sit using the UWB radar.

V. Conclusions

This work evaluated the instrumentation of the TUG test with IMU and UWB sensors, and assessed the gait kinematic parameters that were extracted from their data for the case of healthy individuals. Some parameters were common between the two sensors (walking duration, turning duration), while others were unique to each one (total test duration, gait kinematic measures, distance and speed). The approach used was, to the best of our knowledge, never tried before, and thus it paves the way for accurate, ubiquitous, multi-sensor instrumentation of the TUG test, and generally for remote mobility monitoring of both healthy and patient subjects (after validating our results with them). This is of special interest given the proliferation of IMU sensor-based devices and the increased popularity of UWB radars in medical applications. Although both technologies have advantages and disadvantages, fusion of the two could be used to extract additional measures with high accuracy (i.e. stride length, gait speed).

References

[1] D. Podsiadlo and S. Richardson, "The timed "up & go": a test of basic functional mobility for frail elderly persons," *Journal of the American geriatrics Society*, vol. 39, no. 2, pp. 142–148, 1991.

[2] S. Mathias, U. Nayak, and B. Isaacs, "Balance in elderly patients: the" get-up and go" test." *Archives of physical medicine and rehabilitation*, vol. 67, no. 6, pp. 387–389, 1986.

[3] A. Salarian, F. B. Horak, C. Zampieri, P. Carlson-Kuhta, J. G. Nutt, and K. Aminian, "itug, a sensitive and reliable measure of mobility," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 18, no. 3, pp. 303–310, 2010.

[4] R. C. Van Lummel, S. Walgaard, M. A. Hobert, W. Maetzler, J. H. Van Dieën, F. Galindo-Garre, and C. B. Terwee, "Intra-rater, inter-rater and test-retest reliability of an instrumented timed up and go (itug) test in patients with parkinson's disease," *PloS one*, vol. 11, no. 3, p. e0151881, 2016.

[5] A. F. R. Kleiner, I. Pacifici, A. Vagnini, F. Camerota, C. Celletti, F. Stocchi, M. F. De Pandis, and M. Galli, "Timed up and go evaluation with wearable devices: validation in parkinson's disease," *Journal of bodywork and movement therapies*, vol. 22, no. 2, pp. 390–395, 2018.

[6] K. Jackson, R. Sample, and K. Bigelow, "Use of an instrumented timed up and go (itug) for fall risk classification," *Physical & Occupational Therapy In Geriatrics*, vol. 36, no. 4, pp. 354–365, 2018.

[7] R. Bergquist, C. Nerz, K. Taraldsen, S. Mellone, E. A. Ihlen, B. Vereijken, J. L. Helbostad, C. Becker, and A. S. Mikolaizak, "Predicting advanced balance ability and mobility with an instrumented timed up and go test," *Sensors*, vol. 20, no. 17, p. 4987, 2020.

[8] C.-Y. Hsieh, H.-Y. Huang, K.-C. Liu, K.-H. Chen, S. J.-P. Hsu, and C.-T. Chan, "Subtask segmentation of timed up and go test for mobility assessment of perioperative total knee arthroplasty," *Sensors*, vol. 20, no. 21, p. 6302, 2020.

[9] T. Herman, N. Giladi, and J. M. Hausdorff, "Properties of the 'timed up and go'test: more than meets the eye," *Gerontology*, vol. 57, no. 3, pp. 203–210, 2011.

[10] J. J. Bedoya-Belmonte, M. d. M. Rodríguez-González, M. González-Sánchez, J. M. B. Pitarch, A. Galán-Mercant, and A. I. Cuesta-Vargas, "İnter-rater and intra-rater reliability of the extended tug test in elderly participants," *BMC geriatrics*, vol. 20, no. 1, pp. 1–5, 2020.

[11] T. M. Steffen, T. A. Hacker, and L. Mollinger, "Age-and gender-related test performance in community-dwelling elderly people: Six-minute walk test, berg balance scale, timed up & go test, and gait speeds," *Physical therapy*, vol. 82, no. 2, pp. 128–137, 2002.

[12] C. J. Nightingale, S. N. Mitchell, and S. A. Butterfield, "Validation of the timed up and go test for assessing balance variables in adults aged 65 and older," *Journal of Aging and Physical Activity*, vol. 27, no. 2, pp. 230–233, 2019.

[13] J. R. Nocera, E. L. Stegemöller, I. A. Malaty, M. S. Okun, M. Marsiske, C. J. Hass, N. P. F. Q. I. I. Investigators *et al.*, "Using the timed up & go test in a clinical setting to predict falling in parkinson's disease," *Archives of physical medicine and rehabilitation*, vol. 94, no. 7, pp. 1300–1305, 2013.

[14] G. Sprint, D. J. Cook, and D. L. Weeks, "Toward automating clinical assessments: a survey of the timed up and go," *IEEE reviews in biomedical engineering*, vol. 8, pp. 64–77, 2015.

[15] J. Beyea, C. A. McGibbon, A. Sexton, J. Noble, and C. O'Connell, "Convergent validity of a wearable sensor system for measuring subtask performance during the timed up-and-go test," *Sensors*, vol. 17, no. 4, p. 934, 2017.

[16] Y. Adla, R. Soubra, M. Kasab, M. Diab, and A. Chkeir, "Automatic classification of the stand-to-sit phase in the tug test using machine learning," *International Journal of Computer and Information Engineering*, vol. 15, no. 11, pp. 586–590, 2021.

[17] J. C. Ayena, L. Chioukh, M. J.-D. Otis, and D. Deslandes, "Risk of falling in a timed up and go test using an uwb radar and an instrumented insole," *Sensors*, vol. 21, no. 3, p. 722, 2021.

[18] F. Khan, A. Ghaffar, N. Khan, and S. H. Cho, "An overview of signal processing techniques for remote health monitoring using impulse radio uwb transceiver," *Sensors*, vol. 20, no. 9, p. 2479, 2020.

[19] W. Khawaja, F. Koohifar, and I. Guvenc, "Uwb radar based beyond wall sensing and tracking for ambient assisted living," in *2017 14th IEEE Annual Consumer Communications & Networking Conference (CCNC)*. IEEE, 2017, pp. 142–147.

[20] H. B. Kwon, D. Son, D. Lee, H. Yoon, M. H. Lee, Y. J. Lee, S. H. Choi, and K. S. Park, "Hybrid cnn-lstm network for real-time apnea-hypopnea event detection based on ir-uwb radar," *IEEE Access*, vol. 10, pp. 17 556–17 564, 2021.

[21] Y. Zhou, D. Shu, H. Xu, Y. Qiu, P. Zhou, W. Ruan, G. Qin, J. Jin, H. Zhu, K. Ying *et al.*, "Validation of novel automatic ultra-wideband radar for sleep apnea detection," *Journal of thoracic disease*, vol. 12, no. 4, p. 1286, 2020.

[22] R. Buraschi, J. Pollet, J. H. Villafañe, B. Piovanelli, and S. Negrini, "Temporal and kinematic analyses of timed up and go test in chronic low back pain patients," *Gait & Posture*, vol. 96, pp. 137–142, 2022.

[23] N. Kostikis, G. Rigas, S. Konitsiotis, and D. I. Fotiadis, "Configurable offline sensor placement identification for a medical device monitoring parkinson's disease," *Sensors*, vol. 21, no. 23, p. 7801, 2021.

[24] B. R. Greene, D. McGrath, R. O'Neill, K. J. O'Donovan, A. Burns, and B. Caulfield, "An adaptive gyroscope-based algorithm for temporal gait analysis," *Medical & biological engineering & computing*, vol. 48, no. 12, pp. 1251–1260, 2010.