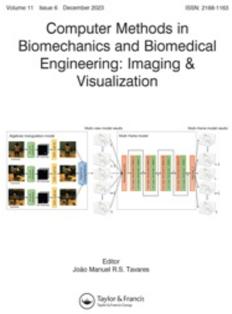
Computer Vision Versus Wearables Assessment of the Up-on-the-toes 30 Second Test



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Computer vision versus wearables assessment of the up-on-the-toes 30-second test

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ABSTRACT
The rising up-on-the-toes (UTT) 30-second test is used clinically to assess ankle muscle strength and endurance. Typically, the test is subjectively evaluated by counting how many UTT movements are completed. We have recently shown that the UTT test can be objectively assessed using signals from small inertial measurement units (IMUs). The current study investigates whether computer vision (CV) analysis of the UTT test gives comparable outcomes to IMU analysis. A CV-based system was applied to video recordings of 29 older adult participants (76.0 ± 4.3 years) performing the UTT test with IMUs attached to their feet. Angular velocity time series signals were generated using both IMU and video object detection of the right foot landmarks, enabling peak plantarflexion velocities during the ascent and descent phases to be extracted. Findings demonstrate that the CV-based approach produces closely aligned output metrics with IMU data, with coefficient of determination (R^2) values of ≥0.91.

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KEYWORDS
Up-on-the-toes (UTT); plantarflexion; Computer Vision (CV); Inertial Measurement Units (IMU)

1. Introduction

The era of precision diagnostics has paved the path to objectifying clinical assessment outcomes. Clinical approaches incorporating quantification techniques help alleviate the inherent subjectivity involved in clinical assessments. Lower limb strength is a strong determinant of functional independence among the elderly population (Foldvari et al. 2000). The ankle muscles play a crucial role in everyday tasks, such as standing from a chair, walking and negotiating stairs (Ishikawa et al. 2005; Reeves et al. 2009; Buckley et al. 2013; Cattagni et al. 2014, 2016; Tavakkoli Oskouei et al. 2021). The rising up-on-the-toes (UTT) 30-second test (UTT-30) is a commonly administered clinical assessment method for assessing ankle strength and endurance. Individuals rise onto their toes and descend back down repetitively as many times as they can within 30 s (Sman et al. 2014; Hébert-Losier et al. 2017). This test involves repetitive concentric–eccentric actions of the plantar-flexor muscles, with the number of raises completed used as a common performance measure (Hébert-Losier et al. 2009). Given the widespread implementation of the UTT test for clinical assessment and rehabilitation, standardising performance measures and protocols could yield a universally accepted approach to monitoring ankle function and recovery (Sman et al. 2014). In pursuit of objective measures for assessment outcomes, several assessment techniques have incorporated devices, such as motion capture systems (Halvorson et al. 2022; Das et al. 2023), inertial measurement units (IMUs) (Zahid et al. 2022) and, more recently, computer vision (CV) models (Boswell et al. 2023) to generate clinically acceptable test parameters associated with ankle strength and endurance. Marker-based motion capture systems are considered the gold standard for extracting three-dimensional kinematic data of joints (Mündermann et al. 2006; Ceseracciu et al. 2014; Colyer et al. 2018; Scataglini et al. 2024; Xu et al. 2024). That being said, the implementation of devices in clinical settings should prioritise low cost and ease of set-up (Hébert-Losier et al. 2009). A lack of standardisation regarding how UTT test is objectively monitored may have hindered the widespread adaptation of this simple clinical assessment (Lunsford and Perry 1995; Hébert-Losier et al. 2009). Moreover, even widely adopted evaluation metrics such as UTT repetition counts exhibit some intra-rater variability across existing studies (ICC = 0.79–0.84), suggesting that even straightforward measures can incur errors (André et al. 2016).

CV-based assessments leverage the use of readily available smartphones for video recordings, streamlining the analysis process by significantly reducing the setup cost and time (Fanton et al. 2022). Video recordings offer a broad and rich dataset by capturing holistic visual information, enabling CV systems to excel in making comprehensive analyses. Moreover, they offer the potential for end-to-end automation, handling the entire process from data capture and analysis to generating clinically meaningful metrics. Non-intrusive measurement methods eliminate the possibility of skin movement artefacts that affect marker-based motion analysis and encourage natural, unrestricted movement (Colyer et al. 2018). Furthermore, with the integration of cloud technology, data can be fed into existing CV frameworks for retrospective analysis, enabling continuous improvement and deeper insight. There is a compelling rationale to utilise such an accessible and cost-effective tool for the development of a clinically feasible assessment methodology capable of reliably tracking the UTT test and producing a clinically meaningful representation of movement performance. In light of this, we propose the application of a CV-based model on video recordings of the UTT-30.

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Comparative analysis was conducted to validate the CV-based approach wherein 29 older adults performed the UTT-30 with IMUs attached to their feet and simultaneously video recorded their movements; the recordings were subsequently processed by the CV model. More precisely, the plantarflexion angular velocity of the right foot was extracted from time series streams from both recording modalities to demonstrate the CV model's capability to generate results comparable to IMU analysis. By integrating plantarflexion peak velocity extraction techniques, we develop an autonomous system that synchronises computer and IMU generated time series signals in the time domain.

2. Methods

2.1. Participants

Twenty-nine healthy older adults living independently within the local community of the university volunteered to participate in the study (14 males, 15 females; mean ± SD, 76.0 ± 4.3 years, 1.7 ± 0.1 m and 70.2 ± 14.9 kg). All participants completed an in-house Health Questionnaire. The questionnaire asked details about current health status, including current medications taken, and about their physical abilities, with the information given used for screening. Inclusion criteria required participants to be over 70 years old, able to walk independently and continuously for 2–3 min without the use of any assistive devices (e.g. walking aids) or need to take a break and have an ability to rise from standing to up on the toes. Participants also needed to be free from neurological problems, injuries or clinical conditions that affected their balance or control of movement and not taking medications to address such problems. Exclusion criteria included any joint or muscle injury or significant pain, participation in any exercise beyond regular activity in the 48 hour prior to participation, excessive alcohol consumption within the previous 24 hours and any issues affecting their ability to flex and extend the ankle in either leg. Participants self-reported that they were mildly to vigorously active, as defined by the American College of Sports Medicine (ACSM) physical activity guidelines (Thompson et al. 2013). This screening ensured that the study population was representative of an active older adult population. The study was approved by the ethics committee of the University of Bradford, and all participants signed an informed consent form.

2.2. Protocol

Participants were asked to wear the corrective spectacles or lenses they would normally wear when walking. Participants were instructed to perform repetitive UTT movements (i.e. undertake a UTT-30 test; André et al. 2016) as high as comfortably possible and at a comfortable speed until indicated to stop (after 30 s). They were advised to ensure that their heel contacted the ground on each repetition. A chair was placed in front of the participant (oriented with the back of chair towards the participant) to use if they wished, with the instruction to lightly place their index fingers of each hand on the back of the chair if they felt they would lose their balance. To minimise the possibility of participants exerting force on the chair (when rising up on their toes), it was placed on a 26 cm high platform and approximately 0.4 m away from them – see Figure 6(a). These instructions ensured that the chair was used only as a safety precaution to prevent a potential momentary loss of balance resulting in a fall and was not used to provide functional support, which was in keeping with the inclusion criteria prohibiting assistive devices for mobility. All participants completed the UTT-30 on their first attempt, eliminating the potential of muscle or lower limb fatigue affecting performance.

2.3. Data collection

IMUs were attached to the dorsal surface of each foot and set to capture angular velocity data at 100 Hz (Zahid et al. 2022, 2023). A smartphone (Apple iPhone 13 Pro Max) with a 12 megapixel camera mounted on a tripod was set at a low height (~0.48 m), approximately 1 m from participants' right foot and perpendicularly to the sagittal plane. Video recordings (60 Hz) started 5 s prior to UTT-30 onset and ended 5 s after completion to ensure that the entire test was captured. Subsequent analysis focused on movements of the right foot using data from both recording modalities (i.e. CV and IMU).

3. Data processing

3.1. Object detection framework

MediaPipe is an open-source framework that was deployed to perform CV inference and landmark extraction for the obtained video recordings (Kim et al. 2023). Figure 1 depicts the 33 anatomical landmarks that can be extracted using the MediaPipe Pose Landmarker model. Pixel coordinates of four key landmarks: right hip, right heel, right foot index (toe) and the ground were used for the current analysis. The virtual reference point, termed 'ground', was derived using the *x*-coordinate of the right heel and the *y*-coordinate of the right foot index. The right heel, right foot index (toe) and the ground were the three reference points used to calculate the foot's inclination angle (Equation 1), enabling its angular velocity to be computed for UTT movements (Equation 2).

To mitigate against inaccurate tracking of the heel landmark, its vertical displacement across successive frames was computed based on the mean displacement observed in the *y*-coordinates of the hip and heel landmarks. The foot angular displacement (ϑ) and angular velocity (ω) were calculated using Equations 1 and 2, where X_{heel2} and X_{heel1} represent the *x*-coordinates of the heel in frame *n* and frame *n*–1, respectively. Similarly, Y_{index2} and Y_{index1} denote the *y*-coordinates of the foot index in frame *n* and frame *n*–1, respectively. $\theta_{plantarflexion\ Angle2}$ and $\theta_{plantarflexion\ Angle1}$ refer to the angle of the foot in frame *n* and frame *n*–1, respectively. The time between two consecutive frames, measured in seconds, is denoted by Δt.

$$\vartheta_{plantar\ flexion\ Angle} = \tan^{-1}\left(\frac{X_{heel2} - X_{heel1}}{Y_{index2} - Y_{index1}}\right) \qquad [1]$$

$$\omega_{deg/s} = \left(\frac{\vartheta_{plantar\ flexion\ Angle2} - \vartheta_{plantarflexion\ Angle1}}{\Delta t}\right) \times \left(\frac{180}{\pi}\right) \qquad [2]$$

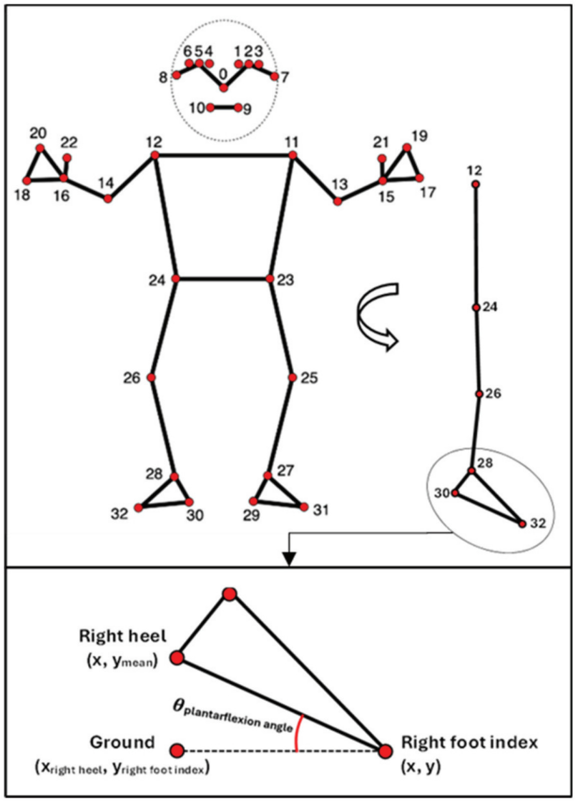

Figure 1. Schematic of the MediaPipe Pose Landmarker. Coordinate reference system: x = horizontal, y = vertical.

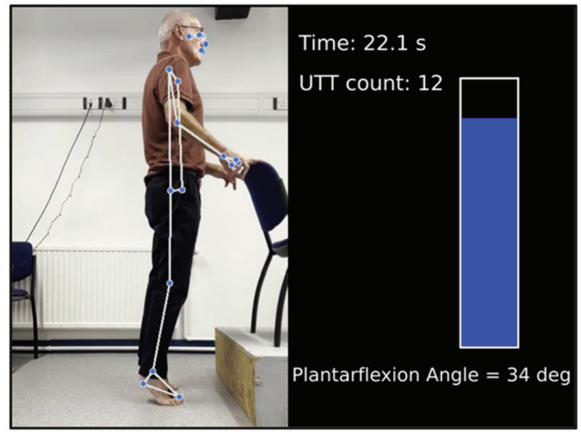

Figure 2. Computer vision model output window.

Python was used to deploy the MediaPipe model to the video recordings of the UTT-30. The OpenCV library was used to define the frame rate of incoming videos and establish a time stamp. Angular velocity time series signals were then generated for each participant. Figure 2 shows the output window of Python as the CV model generates the time series data on a frame-by-frame basis.

3.2. Time series signal analysis

Each UTT cycle is characterised by five distinct reference points (as shown in Figure 3): an initial positive peak in angular velocity, which reflects the rapid ascent onto the toes followed by a rapid decline to zero, which corresponds to the highest raising point. Then, the movement incurs a sharp negative peak in angular velocity, which marks the descent to a flat feet position. A full repetition is concluded by a second instance of zero angular velocity when a participant's heels come into contact with the ground. Finally, there is a short delay (zero velocity) before the next UTT movement is initiated.

3.3. Data extraction

The 'find peaks' function within the SciPy library in Python was used to customise the peak extraction process (details below). Positive and negative peaks were extracted from both the computer and IMU signals to facilitate three primary objectives used for comparative analysis between the CV and IMU systems:

(1) Synchronising CV and IMU signals.
(2) Computing ascent and descent foot angular velocities.
(3) Determining UTT count.

The IMU began recording data immediately after it was disconnected from the computer. Whereas, video recordings were started just before participants were instructed to begin the UTT-30 test. Consequently, there was an inherent time offset in the time-series signals from the two systems. Therefore, in each time-series, the first ascent onto the toes was used as a reference point to synchronise the two signals in the time

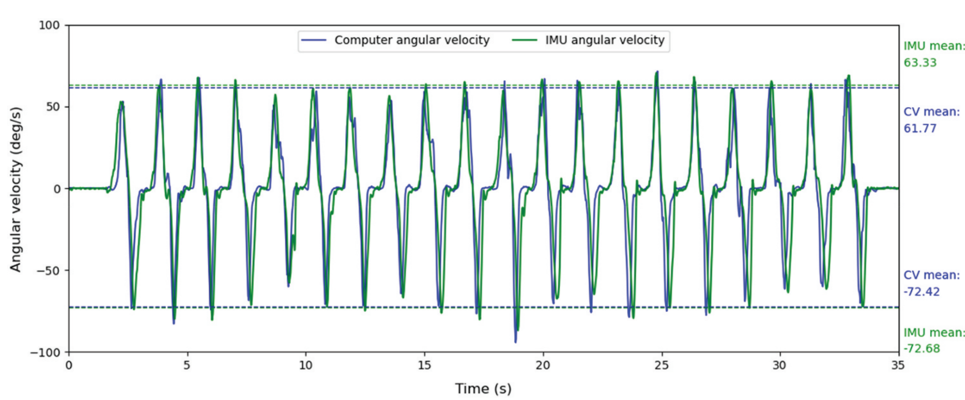

Figure 3. Synchronised CV and IMU angular velocity time series signals.

domain. This process was automated using Python and was achieved by identifying the time index of the first obvious/prominent plantarflexion (positive) angular velocity peak (t_1) in both the IMU and CV signals. The IMU and CV signals from 2.5 s prior to the t_1 time index up to 32.5 s after it (Figure 3) were the time series signals selected for analysis.

Computing the plantarflexion angular velocities of each of the repeated UTT movements was achieved by detecting the successive positive and negative peaks in the angular velocity time-series signal that were associated with each ascent and descent, respectively, of the repeated UTT movements (Zahid et al. 2022). This was accomplished using the following extraction parameters. 'Prominence' is a measure of how much a peak in a time-series signal stands out relative to its neighbouring peaks due to its height and location. A minimum peak height threshold of 50 deg/s was set, to define the minimum height a data point must exceed to be to be considered a peak. Additionally, a minimum *x*-axis distance of 0.5 s between two neighbouring peaks was set to define the minimum separation in time a data point must exceed to be considered a peak. These thresholds ensured accurate extraction of ascent and descent angular velocity peaks, minimising false positives and capturing only the distinct UTT movements.

These extraction parameters enabled signal peaks associated with the ascending and descending peak angular velocities to be discriminated in the two signals – an example of which is shown in Figure 4. Each consecutive UTT movement repetition was assigned a number that increased sequentially from 1 up to the total number of repetitions detected. Subsequently, angular velocity values were extracted for each of the numbered ascent and descent detected across the test for both CV and IMU data. Finally, the UTT count was determined as the number of positive peaks detected.

3.4. Statistical analysis

Two separate linear regression analyses were conducted on the CV and IMU data, one was used for peak ascent angular velocities (positive peaks) and another for peak descent angular velocities (negative peaks). The coefficient of each regression equation (R^2) was calculated to evaluate model fit and visualise the relationships within the scatter plots – see Figure 5. Table 1 highlights the difference between the CV and IMU determined mean ascent and mean descent angular velocities across the UTT repetitions for each participant. This analysis was implemented to ascertain whether a contactless CV approach has the capacity for achieving agreement with the assessment obtained from the recently validated IMU approach.

4. Results

All participants completed the UTT-30 successfully, as evidenced by the clear time series signals from each measurement method (i.e. CV and IMU). The UTT repetition count (group mean, 17.2 ± 6.2 repetitions) was exactly matched for all participants across both measurement methods (see Figure 3). The regression analysis highlights a high correlation between the CV and IMU methods, with high coefficient of determination (R^2) values of 0.94 and 0.91 for ascent and descent peak angular velocities, respectively. This analysis indicates a strong alignment between the two measurement methods, confirming the CV system's capability to accurately determine angular velocities during the UTT-30 similar to the IMU.

5. Discussion

The current study showcases the effectiveness of a CV-based methodology in evaluating the UTT-30. The results indicate that the mean plantarflexion velocities in both the ascent and descent phases align closely with those obtained using IMU analysis. It was demonstrated that the appropriate implementation of peak extraction techniques allows critical performance measures such as UTT repetition count to be extracted from time series signals of the test, with the CV system being an exact match with the IMU system across all participants. The

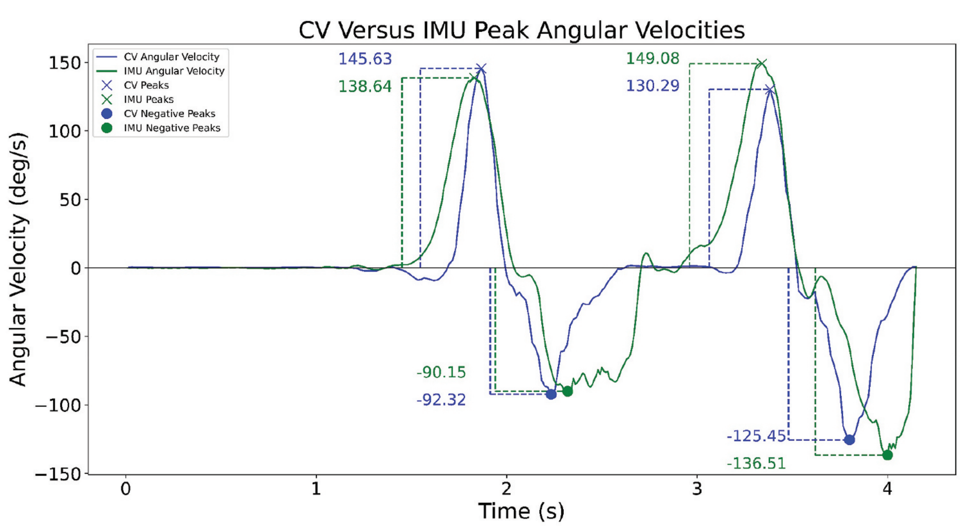

Figure 4. An example of peak extraction: CV versus IMU.

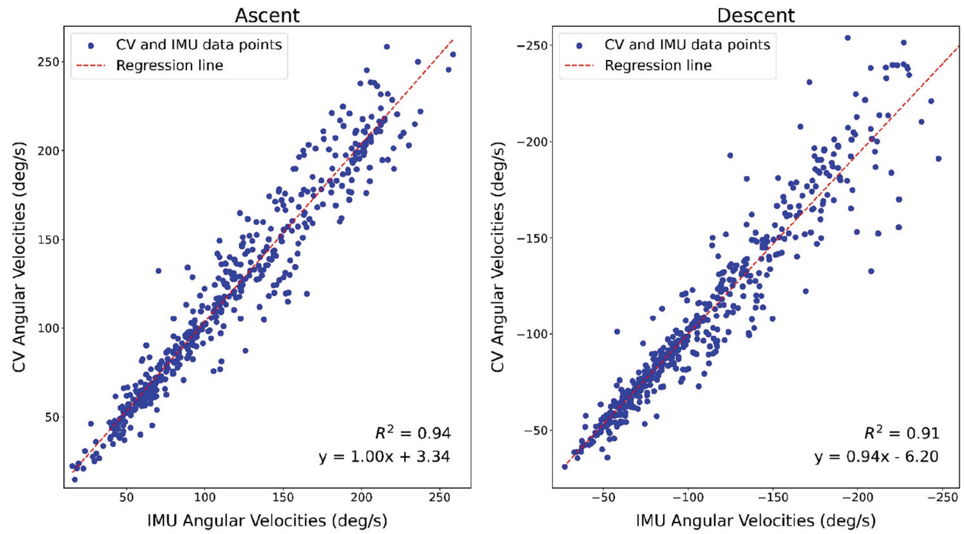

Figure 5. Regression analysis: peak angular velocities during the UTT-30 obtained using CV (*y*-axes) and IMU (*x*-axes).

UTT count derived from both methods also coincided with a manual count made from observing the videos.

In comparing the positive and negative angular velocity values extracted from the CV and IMU signals, it is apparent that the values determined from the CV signal consistently have a slightly smaller magnitude than those determined from the IMU signal (see Table 1). This is due to the different sampling frequencies used: CV at 60 Hz and IMU at 100 Hz. The use of a lower sampling rate will always have this limitation (Ciklacandir et al. 2022). However, such a limitation does not negate the contention made in the current study that a CV analysis approach of the UTT-30 test provides comparable test output data to that determined using IMUs. The high level of agreement between the CV methodology and the IMU data indicates that any increases or decreases in angular velocity across the UTT repetitions were detected equally as well by both the CV and IMU approaches (even though the absolute magnitude of the velocity values detected were consistently slightly smaller for the CV approach compared to IMU approach). Having said this, the scatter plots (Figure 5) indicate a very close fit to the regression line for the smaller magnitude velocity values (i.e. those <|150| deg/s), indicating a close match between CV and IMU derived data points. However, for the larger magnitude velocity values (those >|150| deg/s), the fit to the regression line is more variable. This is likely due to the lower sampling rate of the CV approach compared to the IMU approach, leading to a slight underestimation of velocity by the CV approach at higher-magnitude velocities. The use of a higher speed video camera would avoid this limitation. Alternatively, the angular displacement signal derived by the CV approach could be 'up'-sampled to 100 Hz prior to determining the angular velocity signal, which would also avoid this limitation.

It must be noted that angle-derived metrics arguably provide more accurate measurements than two-point measures (e.g. height the heel is raised) in the CV analysis of video recordings. This may be attributed to the fact that features that rely solely on two distinct points (e.g. like heel-ground distance) can be affected by camera-to-object distance during movement tracking. Angle measures mitigate this error by incorporating three reference points but can still be affected by parallax errors. This is one of the reasons why the foot plantarflexion angular velocity from the two measurement modalities was chosen instead of focusing on analysing vertical heel displacement over the repetitive UTT movements.

It is noteworthy that in using the highlighted CV-based approach to assess the UTT-30, participant anonymity can be easily achieved by excluding the image of participants from the processed videos and retaining only landmark data, as shown in Figure 6(b). Alternatively, the use of face detection algorithms to identify and then blur the faces in the video recordings could be automatically deployed. Such anonymous assessment methods mean that the CV approach could be readily adopted in clinical situations.

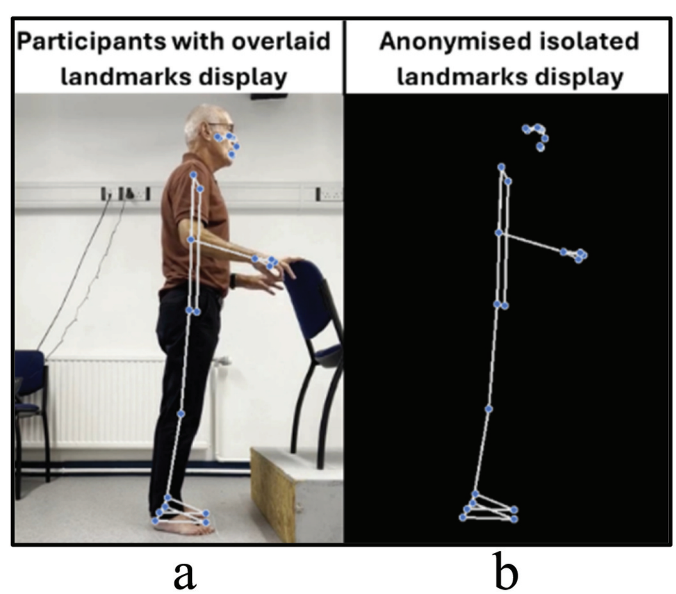

Figure 6. (a and b) CV anonymous output window.

Table 1. Comparison of mean plantarflexion angular velocities across UTT repetitions: IMU vs. CV for each participant. The difference (diff) indicates the difference in mean angular velocity between the IMU and CV systems, provided separately for ascent and descent.

	Ascent			Descent		
Subject	IMU	CV	diff	IMU	CV	diff
Mean plantarflexion angular velocity (deg/s)						
1	178.25	156.37	21.88	−155.95	−154.85	1.10
2	139.04	136.29	2.75	−93.22	−113.58	20.36
3	191.50	197.27	5.77	−163.14	−167.74	4.60
4	141.18	130.03	11.15	−118.16	−121.96	3.80
5	54.93	52.29	2.64	−41.84	−38.17	3.67
6	105.26	97.96	7.30	−67.29	−66.23	1.06
7	120.46	128.83	8.37	−101.90	−105.92	4.02
8	63.45	62.45	1.00	−58.49	−60.40	1.91
9	111.79	113.11	1.32	−103.06	−106.21	3.15
10	228.55	208.30	20.25	−212.93	−204.11	8.82
11	115.68	114.55	1.13	−73.90	−80.13	6.23
12	75.78	77.84	2.06	−63.91	−63.71	0.20
13	70.70	72.40	1.70	−110.36	−109.53	0.83
14	88.88	82.17	6.71	−71.91	−68.97	2.94
15	59.62	58.91	0.71	−71.46	−70.37	1.09
16	60.39	61.77	1.38	−97.92	−96.58	1.34
17	58.41	55.04	3.37	−84.92	−83.64	1.28
18	63.33	61.77	1.56	−72.68	−72.42	0.26
19	57.11	54.82	2.29	−58.28	−56.77	1.51
20	91.02	91.12	0.10	−91.53	−91.37	0.16
21	147.46	145.94	1.52	−143.14	−144.63	1.49
22	174.02	172.75	1.27	−186.19	−184.44	1.75
23	110.52	108.37	2.15	−99.46	−98.54	0.92
24	202.13	201.29	0.84	−174.53	−175.60	1.07
25	116.09	110.85	5.24	−79.06	−78.21	0.85
26	23.18	22.62	0.56	−53.12	−52.58	0.54
27	39.69	42.74	3.05	−68.45	−66.27	2.18
28	81.43	76.39	5.04	−90.48	−87.81	2.67
29	60.46	62.49	2.03	−95.24	−95.83	0.59
Mean	**104.49**	**101.96**	**4.32**	**−100.09**	**−100.57**	**2.77**

The CV-based method, as that presented in the current study, offers clear advantages over wearable technologies due to its low cost and ease of deployment, given that smartphones are ubiquitous. This is because wearable devices often require specialised software, professional setup and regular calibration to ensure accurate data collection, all of which increase the overall cost and complexity of their deployment. The process of collecting video data not only offers a contactless alternative to wearable technologies but also allows the UTT-30 test itself to be remotely monitored and assessed. CV analysis further facilitates a framework in which continuous improvements can be made, providing the flexibility to refine and adapt the data extraction process in ongoing assessments. As such, the CV method can be modified to capture new metrics from existing videos, expanding access to frequent assessments conducted in more natural and/or clinical settings. Additionally, the widespread availability of smartphones that are capable of recording videos at a frame rate of 60 FPS or higher broadens the potential use of the UTT-30 assessment, making remote monitoring and assessment of ankle strength and endurance more feasible.

6. Limitations and sources of error

6.1. Limitations

The UTT count and all output metrics were derived from the right foot time series signals. Consequently, the peak extraction method that distinguishes genuine full-range UTT-30 repetitions from incomplete attempts may not account for instances where individuals exhibit asymmetrical ankle function. Although the study did not include participants with lower limb injuries, adapting the camera setup to capture the movement of both limbs would carry obvious advantages for ongoing developments. This could be achieved by altering the recording perspective from a lateral to a posterior view or by simply recording both left and right perspectives of individuals simultaneously (e.g. by using two smartphones). Finally, footwear hindered the accurate tracking of foot movements, necessitating that the test was performed barefoot.

6.2. Sources of error

The automated measures embedded in the CV framework started by verifying that the number of angular velocity peaks in the CV and IMU time series signals were exactly matched: this was done prior to synchronising the signals in the time domain. This ensured there was a direct comparison of the peak angular velocity determined by each assessment approach for each of the UTT repetitions. The video camera was positioned at the height of each participant's lower limb, which minimised the potential of parallax error affecting the detection and extraction of landmark data. In addition, tracking of the hip landmark along with the heel landmark was used to compute an average vertical (*y*-coordinate) displacement of the 'heel', which reduced potential inaccuracies due to heel landmark tracking problems, e.g. due to movement of clothing occluding the heel from camera view during parts of the UTT movement. Finally, good lighting conditions were used during data collection to facilitate accurate automatic landmark detection. To mitigate potential errors in the IMU system, consistent placement of the IMUs on the dorsal surface of the foot was maintained across participants, ensuring that variations in angular velocity readings were not attributed to sensor positioning. Specifically, the IMUs were located along the midline of the foot 1 cm proximal to the metatarsophalangeal joint line. This ensured the sensors moved with the foot during plantarflexion – whilst the forefoot region (the toes) remained on the floor.

7. Conclusion

This study compares two measurement methods, CV and IMU, for determining the peak angular velocities of foot plantarflexion during the UTT-30 test. The results indicate a strong alignment between the two methods, with high coefficient of determination (R^2) values of 0.94 and 0.91 for ascent and descent peak angular velocities, respectively. Evaluation of standard video recordings of the UTT-30 using the highlighted CV-based approach offers a contactless alternative to wearable technologies for assessing ankle strength and endurance.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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Sarah Zahid is a final-year PhD candidate at the University of Bradford, where her research explores the use of wearable technology to assess ankle functionality in balance control and stair descent safety in older adults. She holds a Bachelor's degree in Forensic and Medical Sciences and a Postgraduate Diploma in Law, bringing extensive interdisciplinary experience in both forensic science and legal practice. She has presented her research findings at various conferences and has published 3 articles in peer-reviewed journals. She is also a member of the International Society of Gait and Posture Research and the International Society of Biomechanics.

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