Gait & Posture 121 (2025) 64–69

Contents lists available at ScienceDirect

Gait & Posture

journal homepage: www.elsevier.com/locate/gaitpost

Validation of a video-based pose estimation algorithm for the assessment of balance error scoring system in single limb stance test

Yu Yuan Lee *, Lena Fennen, Rosemary Dubbeldam

University of Münster, Institute of Sport and Exercise Sciences, Department of Movement Science, Germany

ARTICLE INFO

Keywords:
Balance error scoring system
Single Limb Stance Test
Video-based motion analysis
Digital balance assessment
Pose estimation algorithm

ABSTRACT

Background: Single Limb Stance Test (SLST) is a reliable and validated test to estimate balance performance. However, assessment of the SLST performance, e.g. by using the Balance Error Scoring System (BESS), can be time-consuming and subjective. To deliver effective balance interventions, a reliable and accessible balance assessment method is imperative.

Research question: Can video-based pose estimation be effectively utilized to validate the BESS assessment for SLST, as compared to both human observation and marker-based assessment methods?

Methods: 60-second eyes-closed SLST trials were recorded using an iPad camera and a marker-based motion capture system. Mediapipe was applied to estimate the whole-body kinematics from the video recordings. The kinematic data were processed by threshold-based error detection algorithms to calculate the corresponding BESS total and sub-scores. To validate the video-based BESS assessment, the results were compared to human and marker-based motion capture system BESS assessments using repeated measures ANOVA and correlation coefficients (CC).

Results: There was no significant difference in the BESS total score between the assessment methods and the correlation between assessment methods was good with CC's ranging from 0.69 to 0.77. However, a significant difference in BESS forefoot and heel lifting sub-scores between the video-based and the human or marker-based assessments was found because Mediapipe failed to capture the detail of the foot motion.

Significance: Video-based pose estimation is a reliable and accessible method to assess SLST performance. It can be used to examine and speed up SLST assessment using the BESS total score. However, future research and development in capturing foot motion is needed.

1. Introduction

Balance capacities are among the most critical and pertinent indicators related to structural or functional decline [6], postural stability [10] and health-fitness levels [16]. The deterioration of balance can be attributed to various factors, among which, aging [1,2] or physical injuries such as ankle sprains [4,5]. Furthermore, balance capacities can significantly impact fall rates [9] which affects a substantial portion of the older population. To deliver personalized and effective balance interventions, a reliable and validated assessment is imperative.

Currently, questionnaires like the Occupational Balance Questionnaire [19] or The Activities of Balance Confidence [11] are commonly employed for clinical assessment. Additionally, various movement tests have been developed to assess balance such as the Berg Balance Scale [14], the Timed Up and Go Test [17] and the Single Limb Stance Test [6,10,16]. Among them, the Single Limb Stance Test (SLST) is one of the most common and reliable tests. To assess SLST performance, a subjective three-level performance assessment (good, moderate, poor) is frequently implemented in clinical settings, but this classification level has not yet been compared to any quantitative score. The Balance Error Scoring System (BESS) is a combined subjective and quantitative SLST assessment method and has been validated by comparison with centre of pressure sway [18]. The BESS assesses six main SLST balance performance issues (balance error events) including a hip angle of more than 30 degrees, stepping with the contra-lateral foot, opening the eyes, lifting part of the fore- or hindfoot from the ground, arm swing, and remaining out of posture more than 5 seconds. According to the guideline, this procedure allows assessors to evaluate the SLST performance in a more quantitative manner.

While the BESS allows for quantification of SLST performance, the

* Corresponding author.
E-mail addresses: ylee2@uni-muenster.de (Y.Y. Lee), lena.fennen@uni-muenster.de (L. Fennen), r.dubbeldam@uni-muenster.de (R. Dubbeldam).

https://doi.org/10.1016/j.gaitpost.2025.04.015
Received 6 May 2024; Received in revised form 14 January 2025; Accepted 15 April 2025
Available online 2 May 2025

rating process is time-consuming and remains subjective. To mitigate such subjective biases in balance assessment, alternatively sophisticated equipment such as a marker-based motion capture system or force plates for quantifying movement can be used. However, these tools are costly and not readily accessible to the general population. Therefore, a quantitative and accessible tool to assist with SLST assessment is needed.

A few researchers have automated the BESS rating process of the SLST by using different technology devices. Napoli et al. and Zhu et al. have utilized the Microsoft Kinect sensor to calculate the BESS total score and compared the BESS total score to human assessments. The agreement levels ranged from 88 % to 100 % and the correlation coefficients ranged from 82 % to 93 %. Although the Microsoft Kinect sensor is a reliable tool and relatively affordable compared to a marker-based motion capture system, it is still not widely used [12,21].

Currently, video-based motion capture systems are widely utilized in both research and industry [7]. The video-based pose estimation is developed based on deep learning techniques to enable the quantification of the recorded motion. While it is an accessible and affordable analysis tool, the accuracy of estimated motion remains a topic of debate. Some studies have pointed out a high accuracy of these systems compared to a marker-based motion capture system with correlation coefficients ranging from 89 % to 99 % [8,20], while others have shown low accuracy during certain scenarios [15].

The objective of this study is to validate an accessible video-based motion capture system for assessing SLST performance based on the BESS. Also, the subjective classification of good, moderate or poor SLST balance performance will be related to the corresponding BESS total score. To achieve this, we will compare the BESS assessments from human assessors, a marker-based motion capture system, and a video-based motion capture system. Throughout this process, a threshold-based rating algorithm based on the BESS will be developed to process the recorded kinematic data from both motion capture systems. We hypothesize that the BESS error event scores computed using the video-based motion capture system are highly correlated and not significantly different from those assessed from the human assessors and the marker-based motion capture system.

2. Methodology

2.1. Participants

In total, 23 participants with and without complaints to their foot and ankle were included. The participant's age ranged from 20 to 35 years. Participants without impairments to their lower extremities were recruited from the student and lecturer population at the Institute for Sport and Exercise Sciences. Participants with chronic or acute ankle instability were recruited using flyers and multi-media platforms at the Institute for Sport and Exercise Sciences and through the orthopaedic surgeons at the University Hospital. This latter participant group underwent physiotherapy with follow-up measurements. Participants with (other) impairments to the lower extremities or back in the last 6 months, and macro-vascular, neurological, metabolic, or systemic diseases that could hinder walking and balance task were excluded. The study was approved by the local ethical committee and all participants provided a written consent before participation.

2.2. Measurement protocol

The dataset is part of a larger study, in which two repetitions (trials) of various movements were conducted to assess balance, gait and jump performance of healthy participants and those with acute or chronic ankle instability. During the measurements, participants were asked to perform two trials of a 75-second SLST with eyes closed on each limb. For participants without ankle instability, the dominant limb was defined as their strong limb and the non-dominant limb as their weak limb. For participants with ankle instability, the strong limb is the non-injured limb.

The study employed a detailed foot and ankle kinematic segment model. To ensure precise capture of, especially, the foot markers during dynamic movements, we utilized 18 infra-red cameras with a recording rate of 200 Hz (Oqus cameras, Qualisys AB, Sweden). Reflective markers placed on the sternum, wrist, hip, thigh, ankle, heel, and distal metatarsal I (Fig. 1-A) were used for calculating the BESS sub-scores. An iPad (7. generation) camera was used to record the whole-body movement. Pilot testing with cameras placed at different angles showed that kinematic signals were minimally affected, provided the camera could accurately capture the full-body segments. To better account for variability in camera positioning and replicate real-world assessment conditions, cameras were systematically positioned either anteriorly or posteriorly relative to the participant. These video inputs were then processed using Mediapipe 0.10.9, a deep learning-based pose estimation algorithm. Mediapipe, unlike other algorithms, offers detailed skeletal estimation, including heel and forefoot (as shown in Fig. 1-B), crucial for accurate assessment of SLST using the BESS.

To validate the BESS results from the Qualisys and video recordings, three human assessors evaluated the participant's SLST performance using the BESS after a 45-min training to familiarize themselves with the assessment process and to ensure consistent scorings. The mean BESS (sub-)score values of the three assessors is used as reference values. Furthermore, a subjective balance assessment was performed by the human assessors: SLST performance was rated as good (scored as 1), moderate (2), or poor (3). The subjective reference value was then assessed by calculating the average of the three assessors and rounded to determine the subjective balance level (good, moderate, or poor).

2.3. Error detection algorithms

A threshold-based codes were developed to calculate the BESS score. The BESS score is a cumulative measure, assessing five distinct error events that can occur during SLST (Table 1). The error events were detected by analysing the kinematic information: In Qualisys the positions of the markers were used, and Mediapipe decoded the raw videoframe into 33 3-dimensional body key points where the ratio of a frame is 275 × 487 x 3. First, a low pass filter was applied to smooth the kinematic signals with a cut-off frequency of 2 Hz. Then, each error event was counted when it occurred during the trial. In both codes, a threshold-based error detection approach was utilized for each error event (Equation 1). Since there is no reference regarding the threshold value, we manually fine-tuned the threshold value based on a portion of the kinematic data and applied it throughout the study. The threshold for hip motion was defined as the mean angle of the first five seconds plus 15 degrees. Instead of using the one-fit for all value (30 degrees), setting the threshold through averaging the mean of the first five seconds allows the algorithm to detect error events more personalized. Examples of the threshold calculations are given in Fig. 2.

Equation 1 shows the threshold-based error detection equation. With t, time; Output (x, t), the value of the output signal at t; Input (x, t), the value of the input signal at t; Threshold, the threshold value that determines whether the signal is considered as Foreground Value or Background Value; 1, the value that pass the threshold value; and 0, the value that does not pass the threshold value.

$$Output(x,t) = \begin{cases} 1, Input(x,\ t) > Threshold, Input(x,\ t+1) \leq Threshold \\ 0, Otherwise \end{cases} \tag{1}$$

2.4. Data analysis

A priori power analysis was conducted using G*Power (version 3.1.9.7) to determine the required sample size for a repeated measures ANOVA. The analysis assumed a medium effect size (f = 0.25) based on previous studies, a significance level of 0.05, a power of 0.95, 3

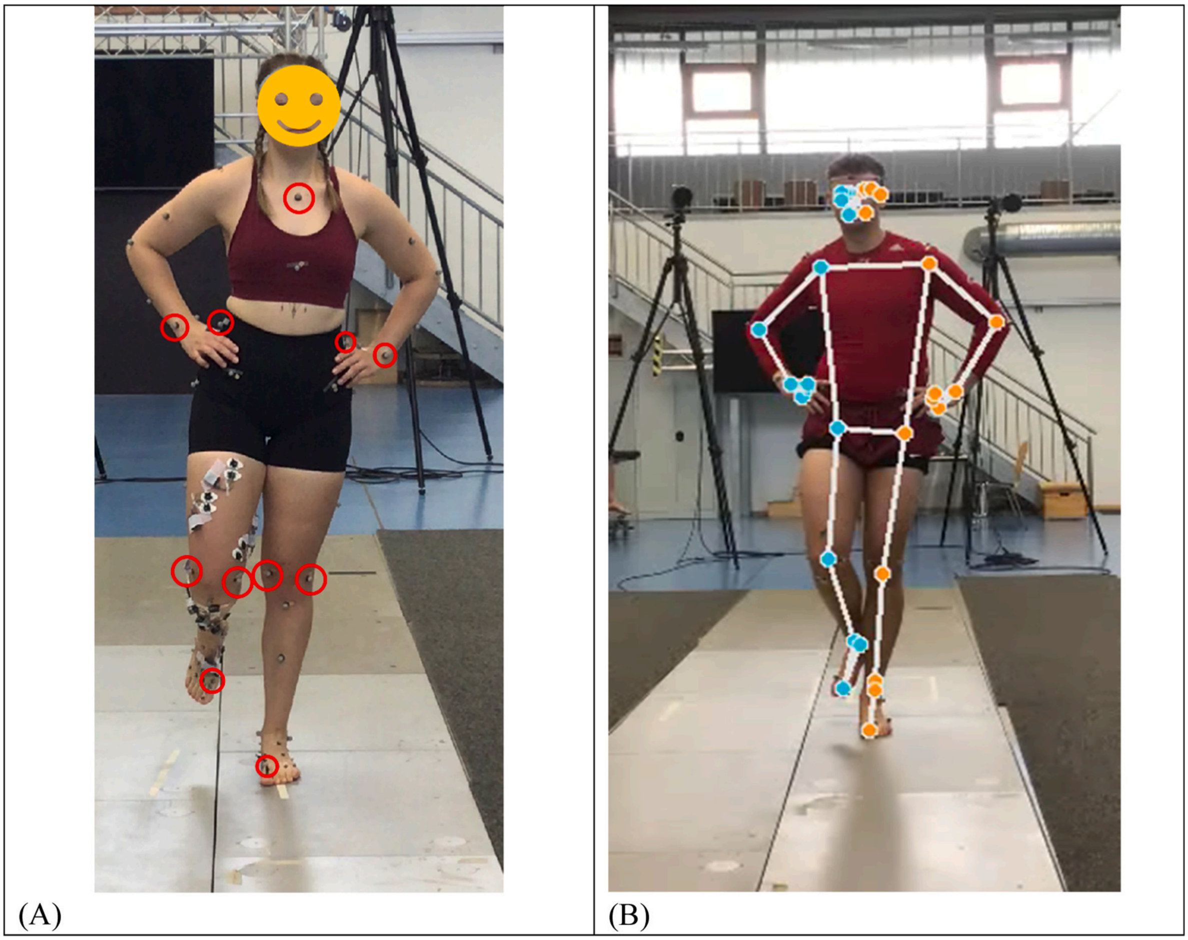

Fig. 1. (A) Utilized markers for the marker-based motion capture system. (B) Pose estimation skeleton based on Mediapipe.

Table 1
Balance Error Scoring System items, Feature List [18] and Error detecting approach. With cm, centimeters; 3D, three-dimensional.

BESS error items	Targeted signals	Threshold	Detection
Lifting forefoot or heel	Distance between landing toe/heel to the ground	Mean of whole signal + 3.5 times standard deviation	Threshold-based peak detection
Moving the hip to more than 30 degrees of flexion or abduction	3D Angle between trunk and thigh	Mean of first 5 seconds + 15 degrees	Threshold-based cut off
Stepping, stumbling, or falling	Distance between right toe and left toe	1.5 cm	Threshold-based cut off
Lifting hands off iliac crests	Distance between right wrist and left wrist	Mean of first 5 seconds + 20 cm	Threshold-based cut off
Remaining out of position for more than 5 seconds	The remaining duration and the occurrence of any of the four events mentioned above		Threshold-based cut off

measurement methods, a correlation among repeated measures of 0.7 and a non-sphericity correction factor of 0.5 was applied. The analysis indicated a minimum total observation of 44 to detect significant difference between measurements.

To synchronize the motion capture systems, signals were time-indexed in seconds to account for differences in recording rates between devices. During data collection, video recording was stopped simultaneously with the Qualisys system, and the final 60 seconds of the measurement were selected for analysis. Particularly unstable SLST trials, were manually reviewed using Qualisys Track Manager and video footage to ensure that the movement patterns were accurately captured and synchronized. Firstly, the mean plus one standard deviation was used to determine the upper BESS score boundary for each level of the three-level subjective assessment. The upper boundary was used as the lower boundary for the next performance level. A repeated measure ANOVA with $p < 0.05$ as the significance level was implemented to examine whether there was a significant difference in the BESS total score and sub-scores between the three different assessment methods. Tukey post-hoc tests were conducted to examine the pairwise differences between the assessments. Additionally, Pearson's correlation coefficient tests were performed to examine the correlation in BESS scores between all assessments.

3. Results

10 participants (6 male, 4 female) had no impairments to their lower extremities and 13 participants (6 male, 7 female) suffered from ankle instability were included in this study. They performed a total of 51 eyes-closed SLST trials which meet the required number of sample size: Five participants with ankle instability were repeatedly measured during a 12-week period resulting in 24 trials (performed on strong limb, weak limb or both limbs included). The other 18 participants were measured once and performed the SLST on the weak limb (13) or the strong limb (14), resulting in 27 trials.

Among the 51 trials, six trials were classified as poor, 15 as moderate and 30 as good subjective balance performance respectively. The mean BESS total score and corresponding standard deviation for good balance is 1.66 ± 1.32, for moderate balance 6.53 ± 1.75, and for poor balance 13.44 ± 5.12. Based on these values, the BESS total score boundaries

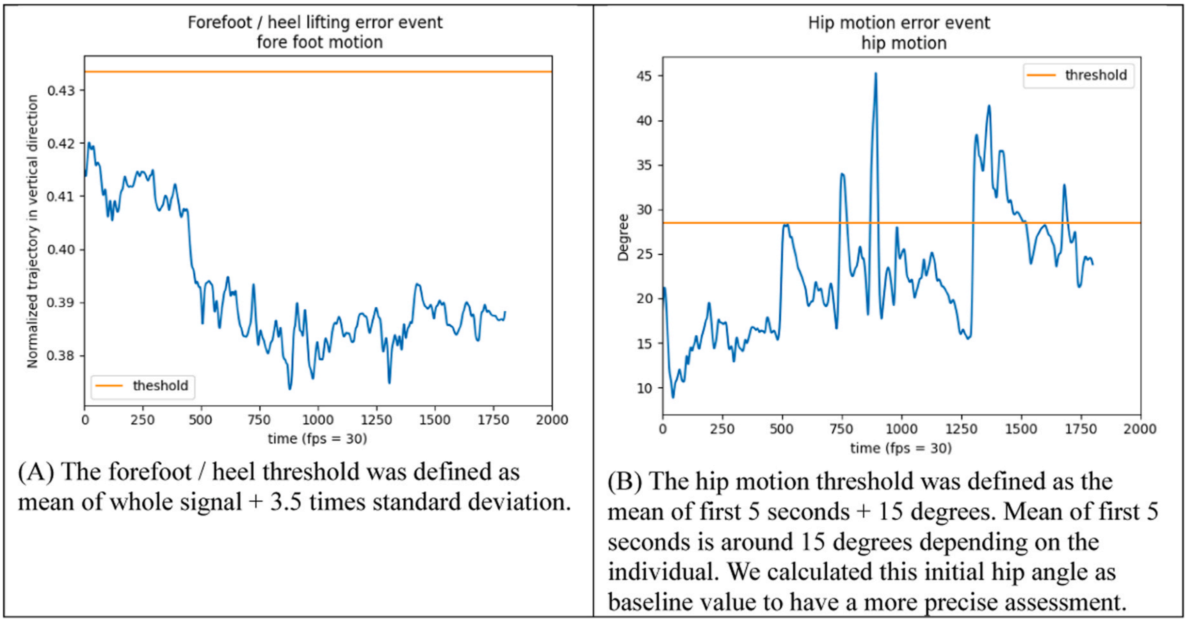

Fig. 2. Visualization of (A) the forefoot kinematic trajectory and (B) the calculated hip angle motion in blue. In orange the corresponding estimated threshold levels.

ranged from 0.00 to 2.98 (1.66 + 1.32), from 2.98 to 8.28 (6.53 + 1.75) and larger than 8.28 for good, moderate, and poor balance respectively (Fig. 3).

In Table 2 and Fig. 4, an overview of all group average BESS scores of the human, marker-based and video-based assessment are presented. The most occurring BESS error events were forefoot or heel lifting, hip motion and stepping. Among these error events, the video-based motion capture system was not able to detect the forefoot or heel lifting and over-counted the hip motion error event (2.25 ± 4.40) compared to the other assessments (human reference: 1.00 ± 1.41, Qualisys: 1.29 ± 3.51).

Based on the repeated measure ANOVA, there was no significant difference in BESS total score, stepping score, hand motion score and out of position score between the video-based method, the marker-based method and the human reference value. However, significant differences in forefoot or heel lifting score were observed. Also, more hip motion error events were detected by the video-based assessment compared to the other two assessment methods (Fig. 4). Although, there was significant difference in hip motion score based on a repeated measure ANOVA, there was no significant difference between the groups according to the post hoc test.

Lastly, the Pearson Correlation tests suggest moderate (CC 0.5–0.69) to strong (CC > 0.7) correlations in BESS total score between the assessment methods (Table 2). The CC's between the human assessors ranged from 0.88 to 0.98. For the BESS total score, the CC between the human reference and the marker-based assessment is 0.77 and between the marker-based and the video-based assessment the CC is 0.72. Additionally, the lowest correlation 0.69 in BESS total score was found for comparison of the video-based approach and the human reference score.

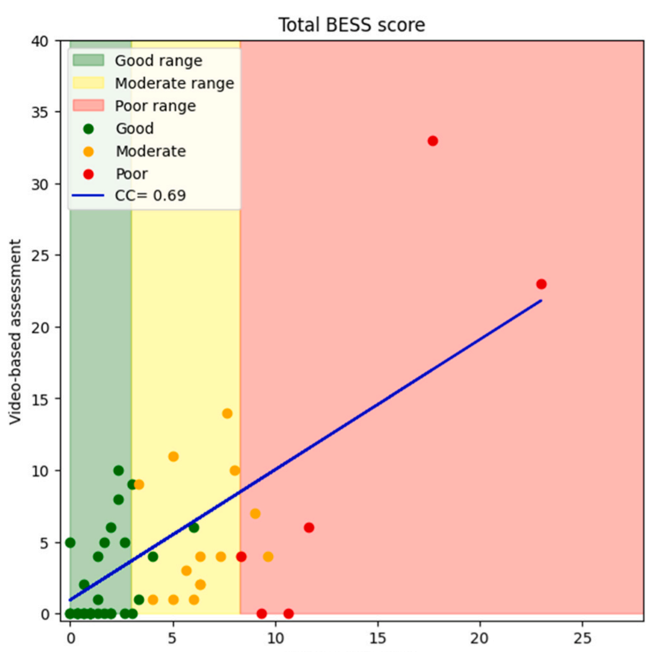

Fig. 3. Visualization of the subjective (Good, Moderate, Poor) and corresponding objective BESS total score for SLST performance assessment by the video-based system and human reference.

Table 2
The BESS total and sub-scores from the three different assessment methods. With H1, H2, H3 the assessments of the three human assessors.

BESS	H1	H2	H3	Average Human Reference	Video-based	Marker-based
Total score	4.90 ± 4.78	4.59 ± 5.13	3.94 ± 4.26	4.48 ± 4.57	4.10 ± 6.12	5.00 ± 5.41
Foot lifting score	1.67 ± 1.63	1.41 ± 1.82	0.75 ± 0.98	1.27 ± 1.25	0.00 ± 0.00	1.88 ± 1.16
Hip motion score	1.29 ± 1.74	0.84 ± 1.64	0.86 ± 1.22	1.00 ± 1.41	2.25 ± 4.40	1.29 ± 3.51
Stepping score	1.94 ± 2.4	2.31 ± 2.89	2.29 ± 2.94	2.18 ± 2.66	1.59 ± 2.71	1.80 ± 2.55
Hand motion score	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.14 ± 0.69	0.02 ± 0.14
Out of position score	0.00 ± 0.00	0.02 ± 0.14	0.04 ± 0.20	0.02 ± 0.10	0.12 ± 0.71	0.00 ± 0.00

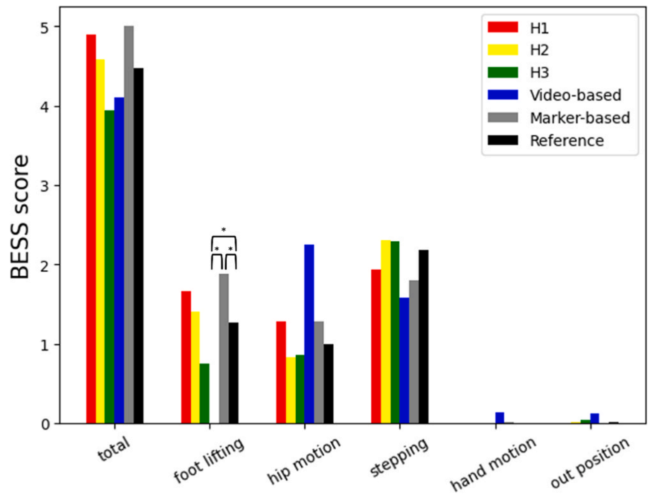

Fig. 4. The average BESS total and sub-scores from 51 trials of SLST based on the different assessing methods where "Reference" was the average value based on H1, H2, H3. * Represents significant difference between groups ($p < 0.05$).

4. Discussion

This is the first study providing a comprehensive validation of a video-based digital assessment of the BESS score. Furthermore, the BESS total score was related to subjectively rated SLST balance performance (good, moderate, poor). Regarding the BESS error events, only forefoot/heel lifting was significantly different between the video-based, the marker-based and human assessment. No significant differences were observed for the other BESS error events, although a higher BESS error score in hip motion was calculated based on the video-based method compared to the other methods. We confirmed that the video-based pose estimation system is a reliable and accessible method, which can be used to examine and speed up SLST assessment using the BESS total score. However, Mediapipe was not able to detect forefoot and heel lifting during postprocessing of the recorded video data.

4.1. Correlations

The results indicated a moderate CC of 0.69 between the video-based assessment and the human reference for the BESS total score. On the contrary, a low CC (0.38) between the video-based motion capture system and the human reference score was reported by Dave et al., while Napoli et al. reported a high agreement (0.99) and Zhu et al. a high correlation (0.82–0.92) in BESS total score between the Kinect system and a human reference [3,13,21]. First, differences in CC's may be explained by differences in levels of balance performance by the recruited participants. In the previous studies, only young and healthy adults, who usually have a better balance performance compared to participants with ankle instability, were recruited. In line with this, previous studies reported that the more challenging balance tasks lead to more inconsistencies between the assessments: i.e., the correlation between the digital assessment and the human reference when performing SLST on a firm underground was 89–93 % but only 82–87 % when performing on foam. Second, in the study by Zhu et al. two video cameras were used and calibrated to detect the BESS scores [21]. Using two video cameras might allow the system to produce a more precise kinematic signal than single video-based recordings. Accordingly, Dave et al. who only used one Kinect camera to assess BESS, reported 38 % correlation between the video-based system and the reference [3]. This indicates that the number of video-cameras could influence the accuracy of the assessment.

4.2. Forefoot and heel lifting

The largest deviations in BESS error events between the digital and human assessment methods were observed for forefoot and heel lifting. Not only between the three assessment methods but also between the three human assessors. Although there was no significant difference between the human assessors, the CC's ranged from 0.41 to 0.7 in forefoot lifting score which is much lower than other error event scores. The main reason is the lack of a clear guidance to define foot lifting. In this study, the forefoot or heel lifting threshold was set to 3.5 times standard deviation of the marker's motion in perpendicular direction, which allowed the marker-based motion capture system to detect the error. Unlike the Kinect system used in previous studies [3,12,21], Mediapipe was utilized in this study since it provides a more comprehensive skeletal marker set including heel and forefoot. However, Mediapipe still failed to detect forefoot and heel lifting error events overall since the video camera resolution was too low to capture the lifting motion of the foot, or the algorithm is not robust enough to detect the small range of movement motion. Future solutions could include, among others, improvement of the current pose estimation algorithm, training a novel foot motion capture algorithm or making use of an additional video camera to specifically capture the foot motion during SLST.

4.3. Threshold-based approach

Finally, as mentioned by Zhu et al. a threshold-based error detection method is sensitive to the chosen threshold. At present, the algorithms are fine-tuned using an arbitrary threshold based on kinematic data since there is no guideline available. Although we considered an individual reference value when setting the hip motion threshold, the hip motion error event was overestimated by the video-based motion capture system due to mis-estimation of in-depth information. Especially when using a video-based motion capture system, the performance is not only influenced by the threshold but also by the filming angle and the resolution of the recording frame. To solve this problem, a data-driven approach can be utilized in future to conduct a more generalized and precise detecting algorithm.

4.4. Limitations

In this study, five participants (19 %) performed poor balance (represented by 6 of 51 trials, 12 %). Although this study recruited more participants with poor or moderate balance performance than previous studies, future studies analysing the BESS should include a larger proportion of participants with moderate to poor balance. Furthermore, in the BESS, the eye condition is assessed as an error event. However, this error event was not included in this study because assessing eye condition is not possible from the rear-view SLST video and Qualisys.

5. Conclusions

This study aimed to validate the assessment of the BESS of SLST by using an affordable and accessible video-based method and to relate the BESS total score to subjectively rated balance performance. Based on the 60-second SLST trials, BESS total score boundaries could be determined for good (0–3), moderate (4–8), and poor (>8) balance, respectively. The results confirmed that it is feasible to assess the BESS total score for SLST performance using one video camera and postprocessing the data using Mediapipe. Although Mediapipe can precisely detect the hip motion and stepping error events, it failed to detect forefoot and heel lifting error events. Hence, an improvement of the accuracy on capturing foot motion is needed when using this system. Future studies should investigate the possibilities of improving the pose estimation algorithm by using various datasets and neural network. Also, large variation in the scoring of forefoot and heel lifting error event was observed between the human and marker-based assessment methods. Therefore, further research into threshold values and development of a consistent and clear guideline for forefoot and heel lifting error events would benefit the reliability and repeatability of the BESS assessment.

CRediT authorship contribution statement

Dubbeldam Rosemary: Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Fennen Lena:** Writing – review & editing, Software, Data curation, Conceptualization. **Lee Yu Yuan:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

All authors contributed to the writing or revision of the manuscript. The authors agree to be accountable for all aspects of the work and gave approval to the final manuscript version. The authors have no potential competing interests. In the appendix, please find the authors' information. All related data, figures, and tables have not been previously published and the manuscript is not under consideration elsewhere. No conflicts of interest to report Dr. Iylad Obeid and Dr. Yinlin Li have been suggested as referees based on their expertise and their lack of conflicts of interest with this manuscript.

References

[1] I.G. Amiridis, F. Arabatzi, P. Violaris, E. Stavropoulos, V. Hatzitaki, Static balance improvement in elderly after dorsiflexors electrostimulation training, Eur. J. Appl. Physiol. 94 (4) (2005) 424–433, https://doi.org/10.1007/s00421-005-1326-3.

[2] R.A. Da Silva, M. Bilodeau, R.B. Parreira, D.C. Teixeira, C.F. Amorim, Age-related differences in time-limit performance and force platform-based balance measures during one-leg stance, J. Electromyogr. Kinesiol. 23 (3) (2013) 634–639, https://doi.org/10.1016/j.jelekin.2013.01.008.

[3] P. Dave, I. Obeid, C. Tucker, Automated system for balance error scoring, BIODEVICES 2014 - 7th Int. Conference on Biomedical Electronics and Devices, Proceedings; Part of 7th International Joint Conference on Biomedical Engineering Systems and Technologies, BIOSTEC 2014 (2014) 329–333, https://doi.org/10.5220/0004951403290333.

[4] B. Dingenen, B. Malfait, S. Nijs, K.H.E. Peers, S. Vereecken, S.M.P. Verschueren, L. Janssens, F.F. Staes, Postural stability during single-leg stance: a preliminary evaluation of noncontact lower extremity injury risk, J. Orthop. Sports Phys. Ther. 46 (8) (2016) 650–657, https://doi.org/10.2519/jospt.2016.6278.

[5] C. Doherty, C. Bleakley, J. Hertel, B. Caulfield, J. Ryan, E. Delahunt, Balance failure in single limb stance due to ankle sprain injury: An analysis of center of pressure using the fractal dimension method, Gait Posture 40 (1) (2014) 172–176, https://doi.org/10.1016/j.gaitpost.2014.03.180.

[6] A.G. Drusini, G.P. Eleazer, M. Caiazzo, E. Veronese, N. Carrara, C. Ranzato, F. Businaro, R. Boland, D. Wieland, One-leg standing balance and functional status in an elderly community-dwelling population in Northeast Italy, Aging Clin. Exp. Res. 14 (1) (2002) 42–46, https://doi.org/10.1007/BF03324416.

[7] K.J. Eveleigh, K.J. Deluzio, S.H. Scott, E.K. Laende, Principal component analysis of whole-body kinematics using markerless motion capture during static balance tasks, J. Biomech. 152 (2023), https://doi.org/10.1016/j.jbiomech.2023.111556.

[8] J.L. Garrido-Castro, R. Medina-Carnicer, R. Schiottis, A.M. Galisteo, E. Collantes-Estevez, C. Gonzalez-Navas, Assessment of spinal mobility in ankylosing spondylitis using a video-based motion capture system, Man. Ther. 17 (5) (2012) 422–426, https://doi.org/10.1016/j.math.2012.03.011.

[9] J. Howcroft, E.D. Lemaire, J. Kofman, Prospective elderly fall prediction by older-adult fall-risk modeling with feature selection, Biomed. Signal Process. Control (2018), https://doi.org/10.1016/j.bspc.2018.03.005.

[10] J.V. Jacobs, F.B. Horak, V.K. Tran, J.G. Nutt, Multiple balance tests improve the assessment of postural stability in subjects with Parkinson's disease, J. Neurol., Neurosurg. Psychiatry 77 (3) (2006) 322–326, https://doi.org/10.1136/jnnp.2005.068742.

[11] Mancini, M., & Horak, F.B. (n.d.). The relevance of clinical balance assessment tools to differentiate balance deficits.

[12] A. Napoli, S.M. Glass, C. Tucker, I. Obeid, The automated assessment of postural stability: balance detection algorithm, Ann. Biomed. Eng. 45 (12) (2017) 2784–2793, https://doi.org/10.1007/s10439-017-1911-8.

[13] A. Napoli, S.M. Glass, C. Tucker, I. Obeid, The automated assessment of postural stability: balance detection algorithm, Ann. Biomed. Eng. 45 (12) (2017) 2784–2793, https://doi.org/10.1007/s10439-017-1911-8.

[14] P.D. Neuls, T.L. Clark, N.C. Van Heuklon, J.E. Proctor, B.J. Kilker, M.E. Bieber, A. V. Donlan, S.A. Carr-Jules, W.H. Neidel, R.A. Newton, Usefulness of the berg balance scale to predict falls in the elderly, J. Geriatr. Phys. Ther. 34 (1) (2011) 3–10, https://doi.org/10.1097/JPT.0b013e3181ff2b0e.

[15] Ong, A., & Sujae, I.H. (n.d.). The efficacy of video-based marker-less tracking system in gait analysis.

[16] H. Pauliina Hämäläinen, J.H. Suni, M.E. Pasanen, J.J. Malmberg, S.I. Miilunpalo, Predictive value of health-related fitness tests for self-reported mobility difficulties among high-functioning elderly men and women, Med. Sci. Sports Hels. 18 (3) (2004).

[17] J.D. Podsiadlo, S. Bscpt, M.D.J. Richardson, The Timed "Up & Go": a Test of Basic Functional Mobilitv for Frail Elderlv Persons, J. Am. Geriatr. SOC 39 (1991).

[18] B.L. Riemann, K.M. Guskiewicz, E.W. Shields, Relationship Between Clinical and Forceplate Measures of Postural Stability, *Orig. Res. J. Sport Rehabil.* 8 (1999).

[19] P. Wagman, C. Håkansson, Introducing the occupational balance questionnaire (OBQ), Scand. J. Occup. Ther. 21 (3) (2014) 227–231, https://doi.org/10.3109/11038128.2014.900571.

[20] M. Windolf, N. Götzen, M. Morlock, Systematic accuracy and precision analysis of video motion capturing systems-exemplified on the Vicon-460 system, J. Biomech. 41 (12) (2008) 2776–2780, https://doi.org/10.1016/j.jbiomech.2008.06.024.

[21] M. Zhu, Z. Huang, C. Ma, Y. Li, An objective balance error scoring system for sideline concussion evaluation using duplex kinect sensors, Sensors (Switzerland) 17 (10) (2017), https://doi.org/10.3390/s17102398.