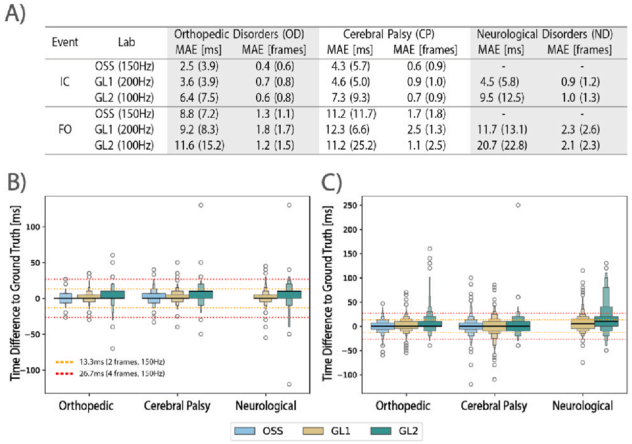
Results

IC events are detected within 10ms on average across all laboratories and pathologies (Figures 1A and 1B), while FO events are detected between 8.8ms and 20.7ms (Figures 1A and 1C).



A)

Event	Lab	Orthopedic Disorders (OD)		Cerebral Palsy (CP)		Neurological Disorders (ND)	
		MAE [ms]	MAE [frames]	MAE [ms]	MAE [frames]	MAE [ms]	MAE [frames]
IC	OSS (150Hz)	2.5 (3.9)	0.4 (0.6)	4.3 (5.7)	0.6 (0.9)	-	-
	GL1 (200Hz)	3.6 (3.9)	0.7 (0.8)	4.6 (5.0)	0.9 (1.0)	4.5 (5.8)	0.9 (1.2)
	GL2 (100Hz)	6.4 (7.5)	0.6 (0.8)	7.3 (9.3)	0.7 (0.9)	9.5 (12.5)	1.0 (1.3)
FO	OSS (150Hz)	8.8 (7.2)	1.3 (1.1)	11.2 (11.7)	1.7 (1.8)	-	-
	GL1 (200Hz)	9.2 (8.3)	1.8 (1.7)	12.3 (6.6)	2.5 (1.3)	11.7 (13.1)	2.3 (2.6)
	GL2 (100Hz)	11.6 (15.2)	1.2 (1.5)	11.2 (25.2)	1.1 (2.5)	20.7 (22.8)	2.1 (2.3)

Figure 1: A) Overall performance as MAE in milliseconds and frames; B) Boxplots for IC performance; C) Boxplots for FO performance.

Conclusions

IntellEvent demonstrates strong generalizability in detecting IC events across both gait laboratories, performing well even on a pathology it was not trained on (cp. ND). For the FO, IntellEvent shows good generalizability across both gait laboratories, but still, displays a higher variance. Overall, IntellEvent shows a higher robustness to variations in setup, marker placement, and capturing frequencies compared to other algorithms [1], [3], providing results that are unlikely to have a significant negative impact on lower body kinematics [4]. Future work will extend the multicenter analysis by incorporating lab-specific fine-tuning to explore potential performance improvements.

References

[1] B. Dumphart, D. Slijepcevic, M. Zeppelzauer, A. Kranzl, F. Unglaube, A. Baca, B. Horsak, (2023), Robust deep learning-based gait event detection across various pathologies, PLoS ONE, p. e0288555, vol. 18, no. 8

[2] M. Lempereur, F. Rousseau, O. Rémy-Néris, C. Pons, L. Houx, G. Quellec, S. Brochard, (2020), A new deep learning-based method for the detection of gait events in children with gait disorders: Proof-of-concept and concurrent validity, Journal of Biomechanics, p. 109490, vol. 98

[3] R. Visscher, S. Armand, D.W.W. Heitzmann, S.I. Wolf, M. Lempereur, F. Leboeuf, M. Grant-Beuttler, R.S. Soangra, M.H. Schwartz, C. Condoluci, M. Galli, F. Camuncoli, M. Gwerder, W. R. Taylor, R. Brunner, N.B. Singh, E. Viehweger, (2021), Standardizing approaches on automatic gait event detection for use in pediatric pathological populations - A multicenter evaluation, Gait & Posture, pp. 300–301, vol. 90

[4] B. Dumphart, S. Djordje, F. Unglaube, A. Kranzl, A. Baca, B. Horsak, (2024), The impact of initial contact events on kinematics in pathological gait - Preliminary results of an ongoing study, Gait & Posture, pp. 54–55, vol. 113

https://doi.org/10.1016/j.gaitpost.2025.01.049

Assessing the Impact of Virtual Reality on Lower Limb Muscle Synergies: A Comparison with Real-World Movement

Johannes Eichwalder [1], Paul Kaufmann [1],
Thomas Mandl [2], Brian Horsak [3], Arnold Baca [1],
Hans Kainz [1]

[1] *University of Vienna, Biomechanik, Bewegungswissenschaft und Sportinformatik, Vienna, Austria*
[2] *University of Applied Sciences Technikum Wien, Department Computer Science, Vienna, Austria*
[3] *University of Applied Sciences St. Pölten, Digital Health and Social Innovation, St.Pölten, Austria*

Background

The concept of muscle synergies is used to explain the neural control of movement. It describes the coordinated patterns of muscle activity that work together to produce voluntary movements [1]. The utilization of immersive virtual reality (VR) in motor rehabilitation is predicated upon the concepts of neuroplasticity and sensorimotor learning [2]. Nevertheless, the precise replication of a movement in VR remains an open question [3].

Methods

Three-dimensional motion capture data (Vicon Motion Systems, Oxford, UK) and electromyography data from 12 lower limb muscles (Cometa, Milan, Italy) were collected from ten participants as they performed walking (in the real world (RW) and in VR) and balancing (beam balancing in the RW and VR and an elevated over 25m) tasks. These tasks were conducted both in the real world (RW) and in VR, participants wore a Meta Quest II headset. Muscle synergies were extracted using non-negative matrix factorization, and the number of synergies (NoS) was identified by the knee-point of the total variance accounted for (VAF) curve across all conditions [4]. A repeated measures ANOVA were employed to compare the tVAF of one synergy (VAF_1) and the VAF of NoS (VAF_N) between the two environments (RW vs. VR) and the tasks (walking vs. balancing. The stance to gait ratio and the step times were determined by force insoles (Novel, Germany).

Results

Over all tasks a mean of four synergies were determined. The VAF_1 and VAF_N showed no significant differences when comparing the balancing tasks between RW and VR conditions (RW balance – VR balance high 0.094 & 0.275 | VR balance – VR balance high 0.492 & 0.677). The stance to gait ratio, as well as the step times were significantly higher in RW balance than VR balance and VR balance high ($p < 0.05$) Comparing balancing in RW to the high exposure balancing in VR led to a higher difference in stance to gait ratio as well as in step time than comparing both VR conditions.

Conclusions

Despite differences in proprioceptive input, VR shows promise as a rehabilitation tool, suggesting its potential to enhance therapeutic interventions. Contrary to the exception that high exposure in VR would result in significant changes in muscle synergies and motor control during gait, the results showed no difference in muscle synergies when comparing the RW balancing task to low exposure balancing task and the high exposure balancing task in. However, the study sheds light on the current limitations of VR technology and highlights the need for further refinement to better replicate RW proprioceptive feedback for greater complexity in the gait task. Current research in the field of VR rehabilitation of the upper extremity is faced with a similar problem, where exercises that represent a higher level of complexity in the RW cannot be reproduced, or only partially reproduced, in VR [5].

References

[1] E. Bizzi and V. C. Cheung, (2013), The neural origin of muscle synergies, Frontiers in Computational Neuroscience, p. 51, vol. 7

[2] K.E. Laver, (2020), Virtual reality for stroke rehabilitation, 9780429351365

[3] B. Horsak, M. Simonlehner, B. Dumphart, und T. Siragy, (2023), Overground walking while using a virtual reality head mounted display increases variability in trunk kinematics and reduces dynamic balance in young adults, S. 3021–3032, Bd. 27, doi: 10.1007/s10055-023-00851-7

[4] Paul Kaufmann, Willi Koller, Elias Wallnöfer, Basilio Goncalves, Arnold Baca, Hans Kainz, (2023), Trial-to-trial similarity and distinctness of muscle synergy activation coefficients increases during learning and with a higher level of movement proficiency, https://doi.org/10.1101/2023.09.19.558460

[5] E. Scalona, J. Taborri, D. R. Hayes, Z. Del Prete, S. Rossi, and E. Palermo, (2019), Is the neuromuscular organization of throwing unchanged in virtual reality? implications for upper limb rehabilitation, Electronics, p 1495, V 8 No. 12

https://doi.org/10.1016/j.gaitpost.2025.01.050

AI-Enhanced Markerless 2D Gait Analysis in Japan and Germany: A Multicenter Study Across Ethnic, Gender, and Age Groups

Boris Feodoroff, Rebekka Lenz

Europäische Fachhochschule Rhein/Erft GmbH, Köln, Germany

Background

Traditional instrumental gait analyses in clinical settings often require significant personnel and equipment, such as reflective markers and cameras for marker-based motion capturing, making gait analyses both costly and time-consuming [1]. Additionally, the analysis and interpretation of the results are complex. The use of artificial intelligence (AI) has the potential to revolutionize these procedures and drive technological advancements [2]. This creates the possibility for gait analyses to be increasingly applied in patient and client settings without the need for markers.

Methods

In 2024, Matsuda and colleagues developed a markerless 2D system using the open-source system OpenPose [3]. This system was further enhanced with VisionPose®, a high-precision AI pose estimation engine (Imasen Electric, Japan).

In this multicenter study, 278 German/Caucasian individuals and, in collaboration with Jutendo University, 303 Japanese/Asian subjects aged between 18 and 79 were measured. All participants were required to be able to walk independently without assistive devices. Their task was to walk back and forth through a calibrated measurement area in three different walking styles (see Fig. 1). The standardized setup included a camera positioned frontally and another in a sagittal view, allowing the investigation of various gait parameters across the three walking styles “normal speed”, “faster walking”, and “walking with larger strides”. Data collected and analyzed included walking speed, cadence, step length-to-height ratio, active range of motion (ROM) of the hip joint (extension and flexion), knee joint angles, and gait index.

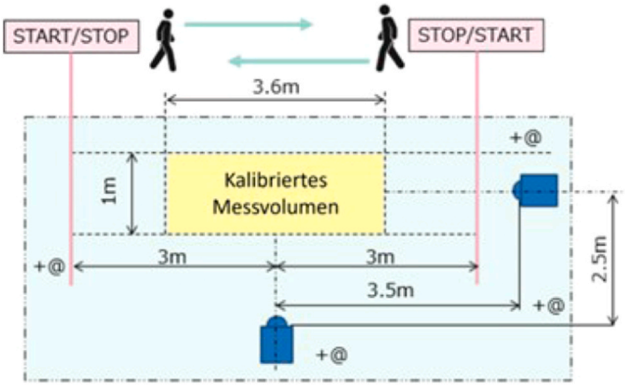


Figure 1: Standardized experimental setup

Results

A mixed-ANOVA was conducted to compare the data of four groups (Ger-male, Ger-female, Jap-male, Jap-female), each divided into three age categories (18-39; 40–59; 60–79 years) across three walking styles. The analysis revealed significant results in gait parameters as well as in the three different walking styles concerning anthropometric data such as ethnicity, gender, height, and age of the participants.

Conclusions

The gait analysis using the 2D system was simple and quick to perform, as markers were not required. The system demonstrated the potential to objectify the analysis process, where data was efficiently processed. The comparison with reference values was understandable for the participants and allowed for immediate feedback, including specific suggestions for improving gait. This enables the possibility of transferring these corrections into daily life.

References

[1] Raab, D. & Kecskeméthy, A., (2023), Stellenwert der instrumentellen Ganganalyse in der klinischen Versorgung [Clinical value of instrumental gait analysis]., Orthopädie, https://doi.org/10.1007/s00132-023-04397-z

[2] van Hooren, B., Pecasse, N., Meijer, K. & Essers, J. M. N., (2023), The accuracy of markerless motion capture combined with computer vision techniques for measuring running kinematics., Scandinavian journal of medicine & science in sports, https://doi.org/10.1111/sms.14319

[3] Matsuda, T., Fujino, Y., Makabe, H., Morisawa, T., Takahashi, T., Kakegawa, K., Matsumoto, T., Kiyohara, T., Torimoto, Y., Miwa, M., Fujiwara, T. & Daida, H., (2024), Validity Verification of Human Pose-Tracking Algorithms for Gait Analysis Capability., Sensors, https://doi.org/10.3390/s24082516

https://doi.org/10.1016/j.gaitpost.2025.01.051