Can Variational Autoencoders detect the underlying gait patterns from data captured using different measurement techniques?

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Abstract This study explores combining joint angles extracted from both Optical Motion Capture (OMC) and Inertial Measurement Units (IMU) data using a Variational Autoencoder (VAE). Gait data from 12 participants walking at three speeds were processed to extract latent features representing gait patterns. Bland-Altman analysis showed high agreement between OMC and IMU-derived features and visual inspection confirmed with a comparable clustering of participants OMC and IMU data in the latent space. The VAE effectively identified individual gait patterns independent of the data collection system. These results highlight the potential of VAEs for integrating data from diverse clinical systems, advancing gait analysis and rehabilitation methods.

Introduction Gait analysis is an important step in gait rehabilitation to evaluate the treatment and track the progess[1,2]. While joint angle assessment is a central part of clinical gait analysis[3], it results in vast amounts of data and the challenge of selecting the key information from it. This is why Artificial Intelligence (AI) options are being explored. AI algorithms generally require vast amounts of data and techniques such as data fusion can therefore be utilized to combine datasets of different measurement types or clinical origin[4,5]. The golden standard for estimating joint angles is OMC[6], but also IMUs[7] are commonly used. The validity and reliability of joint angle estimation from IMUs has been reported extensively and showing a varying error, mainly in the non-sagittal planes[8]. However, deep learning algorithms, such as VAEs aim at capturing the underlying pattern in their most compressed key feature representation (latent space), regardless of small amounts of noise. Therefore, the aim of this study is to explore the reliability of the latent space within participants and thereby test the feasibility of combining data joint angles estimated from OMC and IMUs for future data explorations.

Methods The 3D lower-limb joint angles during treadmill walking (1 m/s, 1.25 m/s and 1.5 m/s) of 12 able bodies participants (24.5 ± 4.5 years) were derived from IMU (MVN Link Suit (Movella Technologies B.V, Enschede, the Netherlands) and OMC data (QTM 2024.1, Qualisys, Göteborg, Sweden). The joint angle data was segmented into four second windows, all initiated from a right heel strike and presented as input data to a VAE pretrained on joint angles from 29 stroke survivors and 42 healthy participants[9] The VAE was symmetrical with 3 convolutional layers, a flatten and dense layer, used Kullback-Leibler divergence loss and was trained for 40 epochs[9]. To test the level of agreement, Bland Altmann statistics were calculated for the 3 latent features derived from the OMC and IMU inputs.

Results and Discussion The Bland Altmann statistics reveal a high level of agreement between the two data sets (figure 1B). No systematic bias is detected, indicating high agreement between the IMU and OMC method.

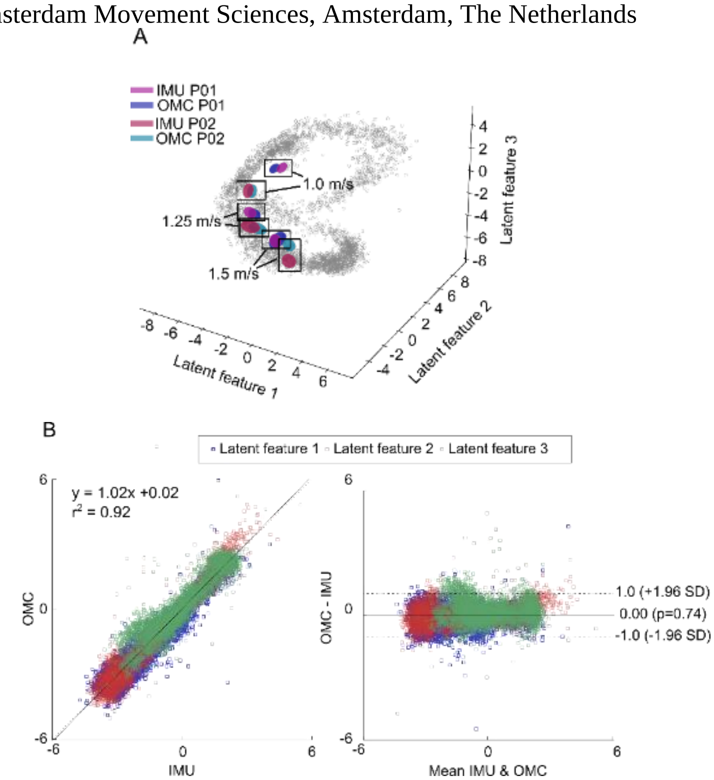

Figure 1: A) *Visual representation of the latent space, with two participants' data clusters, separated into the IMU and OMC data for each of the 3 speeds. Grey circles: original test data.* ***B)*** *The Bland Altmann plot with a linear regression to access the agreement between the features derived from the OMC and IMU data.*

Visual inspection confirmed that the data of the same participant and speed is located in the same area of the latent space (figure 1A), thereby showing, that the VAE identified the same gait pattern from both data sets.

Conclusion The VAE effectively extracts individual gait patterns regardless of the data collection system, enabling future data fusion across clinical sources. This approach can be expanded to other systems like 2D video or markerless motion capture. This may enable the use of AI in clinical settings, supporting objective diagnostic and monitoring of patients.

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