



Generative adversarial networks to create synthetic motion capture datasets including subject and gait characteristics

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ABSTRACT

Resource-intensive motion capture (mocap) systems challenge predictive deep learning applications, requiring large and diverse datasets. We tackled this by modifying generative adversarial networks (GANs) into conditional GANs (cGANs) that can generate diverse mocap data, including 15 marker trajectories, lower limb joint angles, and 3D ground reaction forces (GRFs), based on specified subject and gait characteristics. The cGAN comprised 1) an encoder compressing mocap data to a latent vector, 2) a decoder reconstructing the mocap data from the latent vector with specific conditions and 3) a discriminator distinguishing random vectors with conditions from encoded latent vectors with conditions. Single-conditional models were trained separately for age, sex, leg length, mass, and walking speed, while an additional model (Multi-cGAN) combined all conditions simultaneously to generate synthetic data. All models closely replicated the training dataset (<8.1 % of the gait cycle different between experimental and synthetic kinematics and GRFs), while a subset with narrow condition ranges was best replicated by the Multi-cGAN, producing similar kinematics (<1°) and GRFs (<0.02 body-weight) averaged by walking speeds. Multi-cGAN also generated synthetic datasets and results for three previous studies using reported mean and standard deviation of subject and gait characteristics. Additionally, unseen test data was best predicted by the walking speed-conditional, showcasing synthetic data diversity. The same model also matched the dynamical consistency of the experimental data (32 % average difference throughout the gait cycle), meaning that transforming the gait cycle data to the original time domain yielded accurate derivative calculations. Importantly, synthetic data poses no privacy concerns, potentially facilitating data sharing.

1. Introduction

Application of deep learning approaches in analysing human movement data is hampered by time-consuming and expensive motion capture (mocap) systems that require specialized equipment and expertise to collect large and diverse datasets for performance and generalization (Halilaj et al., 2018; Knudson, 2017; Robinson et al., 2021). Dataset sizes have been artificially augmented by various techniques, such as simple numerical methods (Mundt et al., 2020; Sharifi Renani et al., 2021). A recent approach, involving the use of generative adversarial networks (GANs), showed promise in producing synthetic

data mimicking the characteristics of real-world data, leading to improved predictive performance in deep learning models (Bicer et al., 2022). However, the diversity of the synthetic trials remains limited, suggesting that enhancing this diversity could further boost performance. Additionally, the synthetic dataset was time-normalized by design and, it could not be used for calculating dynamic quantities of interest for biomechanical applications, such as body accelerations. Overcoming these restrictions is possible using conditions, such as walking speed or anthropometric characteristics, that control how the data is generated by GANs. This approach is implemented in a class of deep learning models called conditional GANs (cGANs), that introduce

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conditional information to the GAN framework (Armanious et al., 2020; Esteban et al., 2017; Mirza and Osindero, 2014; Xu et al., 2019). Unlike traditional GANs, which generate data samples from random noise, cGANs take additional inputs, associated with the real/experimental samples, as conditions to guide the data generation process.

The objective of this study is employing cGANs to develop generative models capable of producing realistic synthetic mocap data of human walking, accounting for subject-specific conditions. In the context of mocap data, meaningful conditions should be factors affecting the gait kinematics and kinetics. We identified five key factors or conditions, encompassing demographic (age, sex) and anthropometric (mass, leg length) subject information, and most importantly walking speed as a spatiotemporal parameter, which are typically reported in publications (Bruening et al., 2015; Chehab et al., 2017; Kerrigan et al., 1998; Kouyoumdjian et al., 2012; Nigg et al., 1994; Røislien et al., 2009; Rowe et al., 2021; Schwartz et al., 2008; Weinhandl et al., 2017). We developed five distinct single-conditional models, each addressing a specific condition, alongside an additional multi-conditional model designed to incorporate all conditions simultaneously. We tested if the inclusion of these parameters enables the generation of diverse synthetic data, extending beyond the scope of the training dataset. Furthermore, the walking speed information was used to derive time-denormalized mocap data, hence leading to a description of the gait dynamics.

The developed models were used to synthesise mocap trials that aimed to 1) replicate the characteristics of the entire training data including its dynamical consistency, 2) replicate the findings of previous studies (Bruening et al., 2015; Nigg et al., 1994; Weinhandl et al., 2017) that investigated the effects of some of our selected conditions on the kinematics and kinetics of human walking and 3) predict mocap data for three individual subjects who were excluded from the training process. All synthetic data were compared to corresponding experimental data by various statistical methods to assess models' performances and realistic data generation.

In addition to GANs utility in augmenting existing datasets (Bicer et al., 2022), we believe that creating realistic synthetic datasets can be a powerful approach to make datasets publicly accessible without privacy or confidentiality concerns, thereby expanding the pool of data available to fellow researchers.

2. Methods

2.1. Experimental data

The experimental data used in this study is taken from a publicly available dataset of walking trials collected on the same participants at different speeds (Schreiber and Moissenet, 2019). The dataset was curated following the design principles outlined in Bicer et al. (2022). Marker trajectories and the calculated kinematics of pelvis and right leg, and ground reaction forces (GRFs) on the right leg were extracted from gait cycles and time-normalized to a standardized 0–100 % range, eliminating any variability in time frames across the dataset. The curated dataset was divided into two groups for training and testing generative models. The training data consisted of 733 trials from 46 subjects (21/25 females/males, 37.2 ± 13.4 years, 72.0 ± 12.4 kg, 1.74 ± 0.09 m) at various walking speeds ranging from 0.18 m/s to 2.04 m/s. The test data included 47 trials from three test subjects. The test subjects were selected to represent extreme cases with maximum walking speed of 2.36 m/s, falling outside the distribution of the training data, for a comprehensive assessment of our generative models' performance.

2.2. Conditional neural network architecture and hyperparameters

The cGAN architecture was based on the one previously used to generate mocap data (Bicer et al., 2022). The cGAN consisted of a generator and a discriminator network, both fully connected neural networks with two hidden layers. The generator functioned as an

autoencoder, comprising an encoder that compressed the input data into a latent vector and a decoder that reconstructed the original input from the latent vector. The discriminator's role was to distinguish between the latent vectors derived from the training data and random vectors. To incorporate conditional information into the generative process, modifications were made by concatenating the latent vectors with condition (s) of the corresponding experimental trials and subjects. In case of more than one condition, the latent vector was appended simultaneously. Each condition was added to the latent vector independently from the remaining conditions as an appended vector component. By this addition, the decoder learnt how to reconstruct experimental data according to the provided condition(s). After training, the decoder was detached from the architecture and served as the synthetic mocap dataset generator. The selected conditions in the generator were age, sex, mass, leg length, and walking speed. All conditions were treated as continuous variables except sex, which was encoded as 1 for male and 0 for female.

To optimize the performance of the network, a grid search was conducted to tune the hyperparameters, including the length of the latent vector, hidden dimension, and batch size. The tuning process was initially performed in a plain GAN without using any conditions, where multiple such models were trained, and their synthetic data was evaluated using the statistical tests explained in the subsequent section. The set of hyperparameters that generated synthetic trials with the least statistically significant differences compared to the experimental data were selected as the best-performing set and used for the remainder of this study. To account for conditions, a conditional model included the length of the latent vector plus the number of conditions that is one for single conditional models and five for the multi conditional model.

Using the best-performing set of parameters, five cGANs were trained using age (A-cGAN), sex (S-cGAN), mass (M-cGAN), leg length measured from the right anterior superior iliac spine marker to the right lateral malleolus marker (LL-cGAN) and walking speed (WS-cGAN), alongside an additional model, Multi-cGAN, designed to incorporate all conditions simultaneously and independently. All synthetic data generated by the cGANs were time-normalised as the experimental training data. Denormalization was achieved only for cGANs having walking speed condition (WS-cGAN and Multi-cGAN) by calculating the step time by dividing the step length by the walking speed.

2.3. Evaluation of synthetic data

The trained cGANs were evaluated in three different scenarios.

First, we assessed their ability to replicate the experimental training dataset using its subjects and trials conditions. The experimental static trial of each subject was used to scale a generic right-leg skeletal model (Rajagopal et al., 2016) and the joint kinematics and kinetics were then computed using the inverse kinematics and inverse dynamics tools available in OpenSim 4.1 (Seth et al., 2018). The marker trajectories in the synthetic trials were used to scale the same generic skeletal model. As joint kinematics were already generated for the synthetic trials, they were used with their GRFs to compute joint kinetics again using the inverse dynamics tool. We compared the joint angles and GRFs waveforms of the synthetic trials to those of the experimental trials. For each component, a non-parametric 1D two-tailed paired *t*-test ($\alpha = 0.05$) was performed using the *spm1d* package (Pataky et al., 2013). We calculated the average percentage of the gait cycle that exhibited statistically significant differences between the synthetic and experimental waveforms. Additionally, we used the results of the inverse dynamics analyses from the experimental and synthetic gait trials to quantify the difference in the residual forces and moments acting on the pelvis segment. These quantities, compared using the 1D *t*-test, were used to assess the synthetic mocap data's dynamic consistency. Another assessment was carried out using a subset of the training dataset representative of only a portion of the experimental ranges for all conditions selected randomly (only females, age: 26–40 years, mass: 57–74 kg, leg length 868–931 mm with walking speed 0.80–1.70 m/s). The selection of these ranges

was random because the goal of the evaluation was to assess the models' adaptability to a constrained condition setting, rather than to focus on any specific range. Synthetic data generated for the subjects/trials that fall into the given range was compared to that of the experimental data using the 1D statistical test, similarly to the previous assessments. Another comparison to the experimental dataset was carried out using dimensionless walking speed (Hof, 1996) and averaging the kinematics and GRFs by dividing trials into walking speed groups, similarly to Schwartz et al. (2008). Since computing the dimensionless speed, defined as walking speed divided by the square root of the product of the gravitational acceleration and the leg length, already involved two conditions, this assessment tested only the multi-conditional model's ability to produce synthetic trials by independently controlling conditions.

Second, we investigated how well our generative models could capture the relationship between gait parameters and selected conditions beyond our training dataset. For this purpose, we used the Multi-cGAN to generate conditions-matching synthetic datasets replicating those of previous research studies investigating the effects of age and sex (Nigg et al., 1994), sex (Bruening et al., 2015), and walking speed (Weinhandl et al., 2017) on kinematics and GRFs. To create these synthetic datasets, we constructed normal distributions using the means and standard deviations reported in the cited research for demographics, anthropometrics, and walking speed. We then sampled these normal distributions to obtain the necessary conditions, which were used to generate synthetic data reflecting the number of subjects who participated in these studies. To assess the synthetic data generation capabilities of our models, we compared the results obtained from our models against the published findings in the corresponding works. These included ankle range of motion (ROM) and peak vertical GRFs for Nigg et al. (1994), sagittal plane joint angles ROM for Bruening et al. (2015) and peak vertical GRFs for Weinhandl et al. (2017).

Third, we left out three test subjects from the training phase and used their specific conditions to generate synthetic data that intended to be "subject-specific" with the aim of testing the predictive limits of the generative model. We generated 10 synthetic trials for each trial in the test data. The root mean square error (RMSE) and the Pearson's product-moment correlation coefficient (R) were calculated for all lower limb joint angles, sagittal plane joint angles and GRFs to test the validity of the subject-specific synthetic data. Average and standard deviation of these metrics were presented.

3. Results

3.1. Reproducing training dataset characteristics

The best-performing hyperparameters, obtained by the plain GAN without using any conditions, were a latent vector length of 20, hidden dimension of 512, and batch size of 128.

All generative models yielded comparable results (maximum difference of 8.1 ± 4.4 % and 7.9 ± 1.0 on average for joint angles and GRFs

respectively, see Table 1), with the S-cGAN producing the most similar synthetic data to the experimental data (2.4 % difference on average, also in Fig. S1). The forces and moments exerted by the pelvis actuators in the OpenSim model exhibited statistically significant differences from the simulations based on experimental data reaching up to 32.8 % of the gait cycle for WS-cGAN and 32.6 % for Multi-cGAN (Fig. S2 and Table S1). When considering only the stance phase, these numbers dropped to 12.6 % and 14.5 %, respectively. Testing within the constrained dataset (females, 26–40 years, 57–74 kg, leg length: 868–931 mm) with walking speeds ranging from 0.80 to 1.70 m/s resulted in Multi-cGAN outperforming other models (7.0 % difference on average, Table 1, Fig. S3).

The RMSE between the kinematics and vertical GRFs of the synthetic trials generated by the Multi-cGAN and experimental trials from Schreiber and Moissenet (2019), averaged after being grouped according to their dimensionless walking speed, were less than 1° and 0.02 BW, respectively, with R of over 0.99 for both (Fig. 1).

3.2. Reproducing literature findings using condition-matched synthetic datasets

Synthetic data generated from subject conditions in Nigg et al., (1994) showed comparable results to the published findings (Table 2). Both the prior study and our findings indicated that ankle dorsiflexion ROM was significantly lower in males than females for young subjects ($p < 0.05$) but not for older subjects. Females exhibited 2.8 % and 3.4 % of BW smaller force during the loading response and 2.3 % and 3.0 % of BW higher force in the terminal stance for the synthetic and experimental dataset, respectively.

Table 3 showed that differences in angle ROM between the previous work (Bruening et al., 2015) and our synthetic data ranged from 1.3° (male's hip ROM) to 7.4° (male's knee ROM). Only ankle ROM was significantly lower in males than females in both the reference study and our synthetic data.

The differences between the previously published data (Weinhandl et al., 2017) and our synthetic data were less than 0.06 and 0.02 BW for the first and second peak vertical GRFs, respectively (Table 4). Both the previous study and our synthetic data showed a significant speed effect for the first peak vertical GRF ($p < 0.05$) but not for the second peak vertical GRF ($p > 0.05$). Post-hoc comparisons indicated that only the first peak vertical GRFs in our slow synthetic trials were significantly lower than those in the fast synthetic trials.

3.3. Subject-Specific predictions

Overall, the left-out test data was best predicted by the generative model conditioned by walking speed with RMSE of $4.7 \pm 1.2^\circ$ and R of 0.76 ± 0.10 for the kinematics and with 0.06 ± 0.03 BW and R of 0.81 ± 0.11 in GRFs (Fig. 2 and Table 5). 21.8 % (for kinematics) and 1.4 % (for GRFs) of the gait cycle were statistically different between the experimental test data and the predictions (Fig.S4).

Table 1

Percentage of the gait cycle with significant differences in kinematics (IK) and ground reaction forces (GRF) between synthetic and experimental data across different generative models. Results for both the entire experimental dataset and a constrained subset of this dataset were presented. Values are averages across all synthetic gait trials for each condition. Bold values indicate the columns with the lowest mean differences..

Condition	Network Name	% of gait cycle with significant differences					
		Entire Experimental Dataset			Constrained Subset of the Experimental Dataset		
		IK	GRF	Average	IK	GRF	Average
Sex	S-cGAN	2.8 ± 1.1	1.5 ± 0.4	2.4 ± 0.6	18.8 ± 2.8	7.3 ± 1.4	15.0 ± 2.0
Age	A-cGAN	3.4 ± 3.9	7.9 ± 1.0	4.9 ± 2.7	47.8 ± 3.9	13.3 ± 1.6	36.3 ± 2.5
Leg Length	LL-cGAN	6.3 ± 3.6	1.7 ± 1.5	4.7 ± 2.1	22.3 ± 2.4	4.2 ± 3.1	16.2 ± 2.3
Mass	M-cGAN	8.1 ± 4.4	2.9 ± 1.0	6.4 ± 2.9	29.7 ± 7.2	3.8 ± 1.8	21.0 ± 5.0
Walking Speed	WS-cGAN	5.3 ± 3.3	3.5 ± 1.6	4.7 ± 2.0	36.0 ± 3.4	16.4 ± 3.3	29.4 ± 3.2
Multi	Multi-cGAN	0.5 ± 1.0	7.5 ± 1.0	2.8 ± 0.6	10.1 ± 2.8	0.9 ± 0.7	7.0 ± 2.0

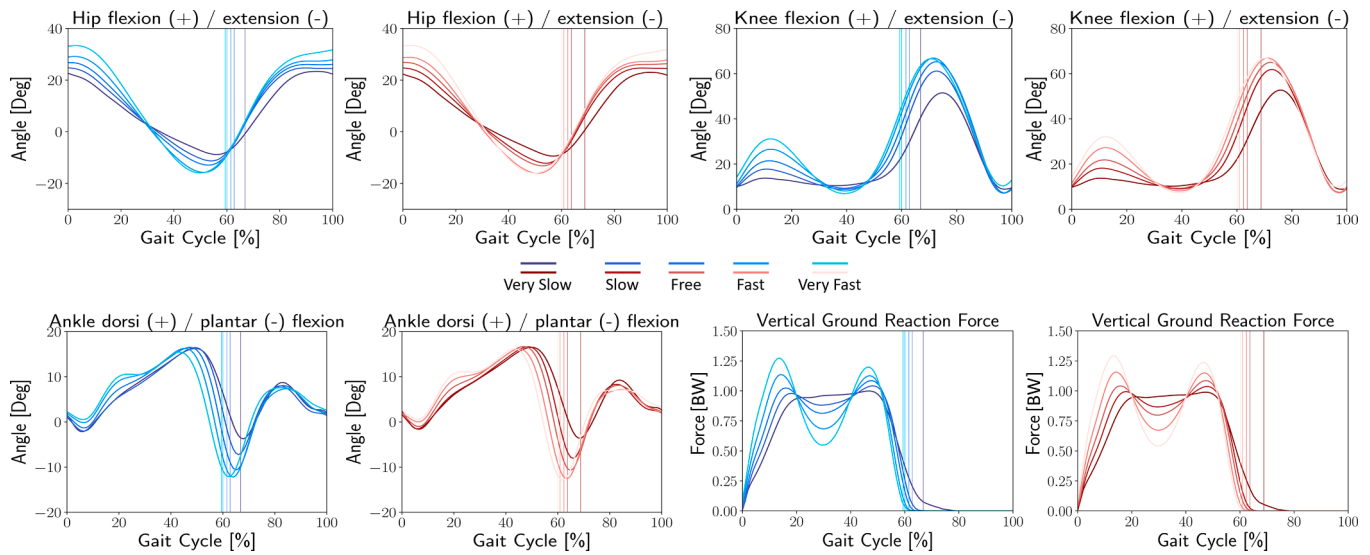


Fig. 1. Sagittal plane kinematics and body-weight (BW) normalized vertical ground reaction forces, averaged according to the dimensionless walking speed of the trials. The experimental data from [Schreiber and Moissenet \(2019\)](#) (blue) was divided into five walking speed ranges based on their average walking speed. The same technique was applied for the same number of synthetic data (red) generated by the Multi-cGAN.

Table 2

Average range of motion (ROM) of ankle dorsiflexion for older/younger males and females, average vertical ground reaction force peaks for males and females considering all age groups. Our data was synthesized using the Multi-cGAN model by randomly sampling conditions using the mean and standard deviation information of the subject cohort given in the reference paper by [Nigg et al. \(1994\)](#). The reference paper reported the peaks of vertical ground reaction forces as differences between genders.

	Ankle Dorsiflexion ROM [deg]				Vertical Ground Reaction Force [%BW]			
	Young (20–39 years)		Older (70–79 years)		1st Peak		2nd Peak	
	Male	Female	Male	Female	Male	Female	Male	Female
Nigg et al. (1994)	28.8 ± 3.7	31.2 ± 4.0	25.0 ± 3.1	25.4 ± 3.9	–	–	–	–
Multi-cGAN	27.0 ± 4.3	29.5 ± 5.0	25.9 ± 4.7	24.7 ± 4.3	117.8 ± 12.1	114.9 ± 9.8	106.0 ± 12.4	108.3 ± 8.2

Table 3

Average range of motion of joint angles for females and males. Our data was synthesized using the Multi-cGAN model by randomly sampling conditions using the mean and standard deviation information of the subject cohort given in the reference paper by [Bruening et al. \(2015\)](#).

	Range of Motion [deg]					
	Hip		Knee		Ankle	
	Female	Male	Female	Male	Female	Male
Bruening et al. (2015)	45.7 ± 4.5	44.1 ± 3.9	67.2 ± 3.2	68.1 ± 4.5	34.6 ± 3.5	32.4 ± 4.5
Multi-cGAN	42.6 ± 1.3	42.8 ± 1.1	61.3 ± 1.8	60.7 ± 1.9	30.0 ± 2.1	28.5 ± 1.6

Table 4

Mean and standard deviation of peak vertical ground reaction force reported at different speeds (slow, medium, and fast). Our data was synthesized using the Multi-cGAN model by randomly sampling conditions using the mean and standard deviation information of the subject cohort given in the reference paper by [Weinhandl et al. \(2017\)](#).

	Vertical Ground Reaction Force [BW]					
	1st Peak			2nd Peak		
	Slow	Medium	Fast	Slow	Medium	Fast
Weinhandl et al. (2017)	1.08 ± 0.04	1.11 ± 0.05	1.12 ± 0.05	1.10 ± 0.03	1.11 ± 0.04	1.12 ± 0.04
Multi-cGAN	1.07 ± 0.08	1.10 ± 0.06	1.16 ± 0.08	1.09 ± 0.08	1.11 ± 0.07	1.14 ± 0.07

4. Discussion

This work aimed to develop a conditional synthetic mocap data generation approach using generative deep learning. Six models generating synthetic mocap data, including marker trajectories, GRFs and lower limb joint angles, based on various subject and trial conditions were developed. Five of these models generated data using a single condition, including subject age, sex, mass, leg length and walking speed. The last model (Multi-cGAN) generated data controlling all conditions simultaneously and independently. We compared the joint angles and GRFs of the experimental and synthetic trials for all models. Our models could generate synthetic, yet realistic, walking trials statistically similar to the experimental trials. Furthermore, we demonstrated that, using the Multi-cGAN, we could successfully generate synthetic datasets matching the participants' conditions described in three previous publications, obtaining statistically similar relationships between gait-related parameters to those obtained from experimental data. This means that our generative models were able to replicate complex interdependencies between the conditions used to control the data generation. Finally, although the aim of this work was generating population-wide mocap trials rather than predicting individual trials, we tested our models' performances on experimental data of three subjects that were not included in training the generative models to explore the potential of this approach. It was found that conditioning with walking speed best replicated the data unseen in training.

Despite generative models' popularity in various fields, especially in computer vision, natural language processing and medical imaging ([Armanious et al., 2020](#); [Goodfellow et al., 2014](#); [Choi et al., 2017](#); [Isola et al., 2017](#); [Karras et al., 2019](#); [Nie et al., 2017](#); [Ramesh et al., 2022](#)),

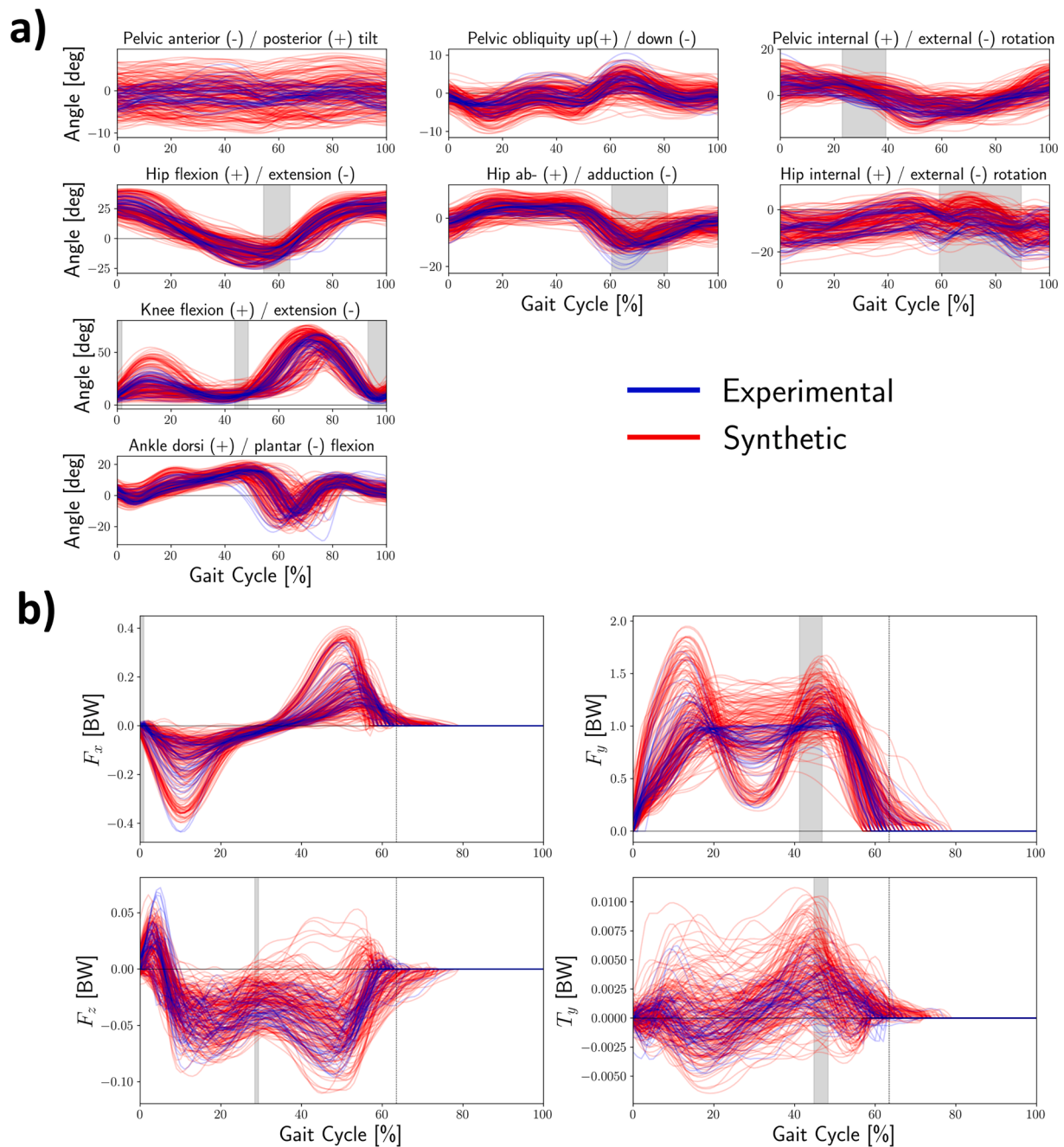


Fig. 2. Lower limb kinematics (a) and ground reaction forces (b) of experimental (blue) and synthetic (red) trials of a representative test subject excluded from the training dataset. The synthetic trials were generated by the WS-cGAN, based on walking speed conditions from the individual trials of the test subject. For each experimental trial, 10 synthetic trials were produced under the same walking conditions by varying the randomly sampled latent vector. Grey shaded areas indicate statistically significant differences between the experimental and synthetic trials.

evaluation of the quality of the synthetic datasets remains challenging when the data is not an image for which quantitative approaches exist in computer vision literature (Salimans et al., 2016; Zhou et al., 2019). To address this issue in the mocap dataset, we have examined the synthetic datasets to validate their realism through rigorous testing procedures. First, the synthetic datasets were compared to the experimental dataset for the entire dataset range and a subset corresponding to restricted conditions' ranges. All models showed reasonable average differences, with Multi-cGAN outperforming the others for the subset evaluation, in which it was reasonable to expect multiple conditions to have a substantial influence on the gait patterns. Furthermore, a measure of dynamical consistency for the synthetic dataset was considered in the form of a statistical comparison of the residual forces and moments

calculated by inverse dynamics on the pelvis against those for the experimental dataset. WS-cGAN and Multi-cGAN outperformed other models in this task, with differences as low as 12.6 % in the stance phase of the gait cycle. The differences in the generative models without walking speed as a condition were at least 40 % of the gait cycle during only the stance phase, mainly because of inaccurate calculation of derivatives of time-normalised data. Multi-cGAN was further compared to the experimental dataset by averaging kinematics and GRFs, using dimensionless walking speed to group the trials. The groups' averaged data showed remarkable agreement with less than 1° and 0.02 BW RMSE for the kinematics and GRFs, respectively, suggesting that the Multi-cGAN's data was not only realistic but also in accordance with multiple conditions simultaneously. We conducted additional tests using the

Table 5

Root mean square error and coefficient of correlation between the experimental and synthetic data of three subjects that are left out from model training. 10 synthetic trials were generated for each experimental trial and the calculated metrics are reported as mean and standard deviations. The values are reported for all lower limb kinematics (three angles for pelvis and hip, and one angle for knee and ankle), as well as sagittal plane kinematics and body-weight (BW) normalized ground reaction forces.

Conditions	Model	Lower Limb Kinematics		Sagittal Plane Kinematics		Ground Reaction Forces	
		RMSE [°]	R	RMSE [°]	R	RMSE [BW]	R
Sex	S-cGAN	5.2 ± 1.3	0.68 ± 0.13	7.3 ± 2.4	0.86 ± 0.12	0.07 ± 0.03	0.77 ± 0.14
Age	A-cGAN	5.7 ± 1.5	0.66 ± 0.14	7.7 ± 2.5	0.85 ± 0.13	0.08 ± 0.03	0.78 ± 0.13
Leg Length	LL-cGAN	5.8 ± 1.4	0.67 ± 0.12	8.1 ± 2.5	0.86 ± 0.11	0.06 ± 0.03	0.80 ± 0.12
Mass	M-cGAN	6.0 ± 1.5	0.68 ± 0.15	8.4 ± 2.6	0.85 ± 0.13	0.06 ± 0.03	0.77 ± 0.13
Walking Speed	WS-cGAN	4.7 ± 1.2	0.76 ± 0.10	6.1 ± 1.9	0.93 ± 0.06	0.06 ± 0.03	0.81 ± 0.11
Multiple	Multi-cGAN	5.5 ± 0.8	0.72 ± 0.09	6.8 ± 1.5	0.90 ± 0.08	0.04 ± 0.01	0.66 ± 0.15

Multi-cGAN model to replicate, using only condition-matched synthetic datasets, the results of previous publications investigating the effects of age and sex (Nigg et al., 1994), and only sex (Bruening et al., 2015). We found similar ROM in sagittal plane angles and vertical GRF peaks together with similar statistical conclusions given in the studies. Investigating the effects of walking speed on the vertical GRF peaks in Weinhandl et al. (2017), the differences in the peak forces between synthetic and experimental datasets were found to be lower than 0.06 BW. Furthermore, we have shown that our models could reasonably predict joint kinematics and GRFs when tested with experimental data from subjects who were not included in model training. Conditioning with walking speed significantly outperformed others, suggesting that walking speed was the most influential factor affecting gait kinematics and GRFs, which was in line with previous studies (Chehab et al., 2017; Moissenet et al., 2019). However, Multi-cGAN model was the best in producing synthetic datasets with smaller standard deviations for a certain subject and walking speed, meaning that when multiple characteristics of the subject have been defined, the trial generation is more constrained, as expected. For example, for a specific mass, the mass-conditioned model generated GRFs with a notably high standard deviation due to the generation of data for a wide range of uncontrolled walking speeds. The Multi-cGAN, on the other hand, generated the data for a specific mass with a very low standard deviation by controlling the walking speed and other conditions.

The presented study is not without limitations. First, although having similarities between the kinematics and GRFs of the experimental and synthetic datasets, every single synthetic data is not necessarily dynamically consistent as our approach was solely data-driven. Whilst statistical similarities existed between the dynamical inconsistencies in the experimental and synthetic datasets, the forces and moments exerted on the pelvis were over the acceptable limits (Hicks et al., 2015), mainly due to the skeletal model which comprised only the pelvis and right leg. These high forces and moments accounted for unmodelled parts of the body. This issue could be further investigated and quantified by generating full-body data and processing it with a full-body model. If there are still dynamical inconsistencies in synthetic data, dynamics of the movement could be included in framing the problem to achieve dynamically consistent trials, for example using physics-informed neural networks (Raissi et al., 2017). Additionally, care must be taken interpreting our results about replicating previous works because we did not have individual subject and gait characteristics, instead we sampled those conditions from normal distributions constructed using reported averages and standard deviations in the corresponding works.

In conclusion, our approach represents a unique effort in synthetic mocap dataset generation, which allows us to specify subject-specific conditions to generate synthetic data. Because diverse and distinct datasets enhance predictive model performances, our approach has the potential to accelerate the ongoing development of standard deep learning applications within the biomechanics domain. Moreover, the synthetic datasets can easily be made publicly available as they do not raise any privacy concerns, allowing our approach to be an effective way

of sharing mocap datasets.

CRediT authorship contribution statement

Metin Bicer: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Andrew T.M. Phillips:** Writing – review & editing, Supervision. **Alessandro Melis:** Writing – review & editing, Methodology. **Alison H. McGregor:** Writing – review & editing, Resources. **Luca Modenese:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Our models are deployed as a web application (<https://thisgaitdoesnotexist.streamlitapp.com>), where users can generate, animate and download synthetic walking trials with desired conditions using any models presented in this study. This tool can be used to create large synthetic mocap datasets. Additionally, the codes for training and testing such generative models will be made available at <https://github.com/metinbicer/generative-mocap>.

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jbiomech.2024.112358>.

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