A Novel Dataset Augmentation Approach Using Generative Deep Learning in Motion Analysis Settings

Mattia Perrone[1], Steven P. Mell[1], John Martin[1], Scott Simmons[2], Shane J. Nho[1], Philip Malloy[1, 3]

[1]Rush University Medical Center, Chicago, IL, [2]Drury University, Springfield, MO, [3]Arcadia University, Glenside, PA
Email of Presenting Author: mattia_perrone@rush.edu

Author Disclosure Information: M.P., S.P.M., J.M., S.S., P.M. (N) S.J.N. (Allosource, American Orthopaedic Society for Sports Medicine, Arthrex Inc., Arthroscopy Association of North America, Athletico, DJ Orthopaedics, Linvatec, OSSÜR, Smith & Nephew, Springer, Stryker).

INTRODUCTION: Motion analysis is a valuable tool to help understand the impact of musculoskeletal conditions on joint function during everyday activities. However, a major challenge in motion analysis clinical trials is the ability to enroll an adequate sample size to obtain statistical power to draw strong inferences from the study's results to help meaningfully inform clinical practice. A number of reasons are behind this challenge of enrollment including, the time commitment involved in study participation, the requirement of multiple testing sessions, and the burden on patients to perform repeated trials while experiencing discomfort from their condition. Considerable interest in generative deep learning has evolved with the development of applications such as Chat GPT. However, generative deep learning can also be used to potentially overcome this challenge human motion analysis research by augmenting time series datasets through data generation. Therefore, the aim of the current paper is to introduce a deep learning approach for data augmentation of a time series motion analysis dataset.

METHODS: A total of twenty-nine individuals diagnosed with femoroacetabular impingement syndrome (FAIS) and twenty-four healthy individuals participated in three-dimensional motion capture assessments while performing single-leg squat trials. Out of these, eighty-eight trials were excluded due to dropout markers and biomechanical inconsistencies, leaving a total of two-hundred thirty valid observations (n=115 from controls and n=115 from patients). Marker data was acquired at 100 Hz with a twenty camera motion capture system and, simultaneously, force plate data was acquired at 1000 Hz. Marker trajectories were tracked in Motive and Visual3D software was used to calculate sagittal plane hip joint angles (HJA), knee joint angles (KJA), hip joint moments (HJM) and knee joint moments (KJM). Therefore, each observation of the dataset consisted in four time series, corresponding to each of biomechanical variables processed in Visual3D. These variables represent the gold standard for comparison the current study. The dataset was augmented using a variational autoencoder, which is a type of neural network that learns to encode and decode data, reconstructing the input data by learning a compressed representation of it (**Fig.1.1**). Since the input data consist of multivariate time series, long term-short memory (LSTM) layers were included in both the encoder and the decoder architecture to capture the temporal dependencies within the data more effectively. Grid search hyperparameter tuning was performed, selecting the best hyperparameters assessing the loss function, which is the mean squared error. The VAE was trained separately on two datasets: one including healthy controls (n=86 observations) and the other including patients (n=86 observations). In both scenarios, the number of samples generated is 1.5 time the real data, resulting in the generation of one hundred twenty-nine samples for both controls and patients. The synthetic data generated by the VAE were compared with the gold standard using statistical parametric mapping (SPM) in python, using an alpha level of 0.05 to define statistical significance (**Fig.1.2**).

RESULTS: SPM revealed no differences between real and synthetic data for controls and patients. **Fig.2** shows a comparison between V3D and generated data in terms of the four biomechanical variables for controls.

DISCUSSION: This method demonstrated the ability to generate biomechanical data that are consistent with what would be obtained in a motion analysis study. Investigating the impact of the generative model training sample size on the quality of synthetic data, as well as applying the proposed pipeline also to other motion tasks to assess its applicability and generalizability, could be valuable paths for future research.

SIGNIFICANCE: The deep learning framework described could prove valuable given the growing trend of employing deep learning to predict biomechanical variables in motion analysis[1,2]. The proposed approach holds the potential to enhance the performance of such predictive models by enabling training on larger datasets created by these generative deep learning models. This methodology could also be employed to understand the impacts of pathology and disease on movement, leveraging expanded motion analysis datasets.

REFERENCES: 1. W. S. Low et al., A review of machine learning network in human motion biomechanics. 2. M. Mundt et al., Prediction of lower limb joint angles and moments during gait using artificial neural networks.

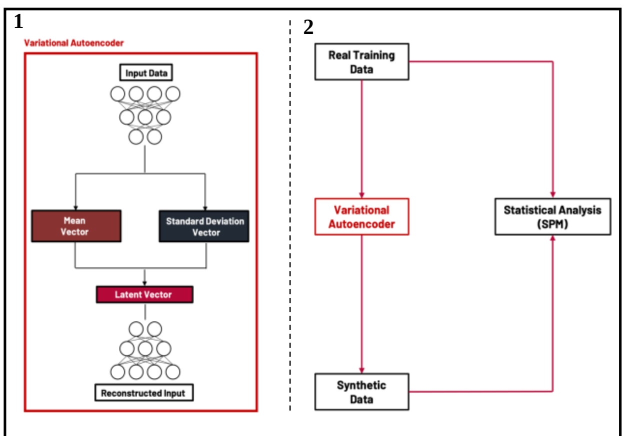

Fig. 1.1 Schematic of the variational autoencoder architecture. **Fig. 1.2** Pipeline followed to generate synthetic data and assess their quality. This was done separately for patients and controls.

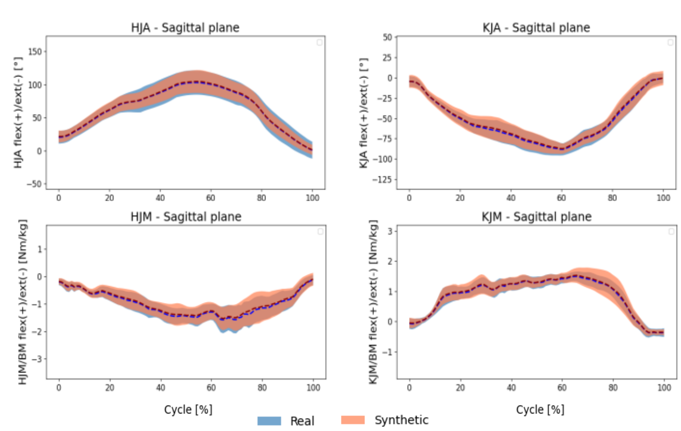

Fig. 2 Graphs showing waveforms of all the biomechanical variables analyzed for controls. Dashed lines show the mean of the variables of interest and shaded areas represent standard deviation of real (blue) and synthetic (red) data.