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Data Augmentation by Synthesizing IMU Data of Physiotherapeutic Exercises using Musculoskeletal Models

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Abstract:
This study presents a novel approach to augment physiotherapeutic exercise datasets by synthesizing realistic Inertial Measurement Unit (IMU) data. The augmented dataset is used to improve the performance of a deep learning based exercise evaluation system. The approach is demonstrated using the deep squat exercise from the Functional Movement Screening (FMS) protocol. By integrating musculoskeletal simulation and leveraging knowledge of potential movement errors based on FMS evaluation criteria, we aim to produce synthetic data that closely mimics human movement. Our evaluation demonstrates that training a combination of a Convolutional Neural Network with a Long-Short-Term-Network (CNN-LSTM) with both real and synthesized data significantly improves the model's performance, especially in generalizing to unknown subjects. However, limitations such as the approach's specificity to the deep squat exercise suggest the need for a more adaptable method. Future work will focus on refining the synthesis process to ensure a broader applicability to various exercises. This research contributes to advancing automated physiotherapeutic exercise evaluation, highlighting the importance of synthetic data in achieving better performing and more generalizable models.

Keywords: IMU Data Synthesis; Musculoskeletal Models; Automatic Exercise Evaluation; Deep Learning

1 Introduction

Many physiotherapy treatments require patients to perform specific exercises regularly and accurately at home, which is crucial for their recovery [1]. However, ensuring proper exercise execution in an unsupervised environment is challenging, as patients receive no feedback on their form. Incorrect execution can delay recovery and, in the worst case, cause additional injuries [2].

To address this issue, we have developed a deep learning framework capable of automatically evaluating physiotherapy exercises utilizing Inertial Measurement Unit (IMU) data, and recorded a suitable dataset to train this algorithm [3]. Our approach achieved competitive results, but we aim to further improve performance by increasing the quantity and diversity of the dataset. However, collecting and labeling suitable data is costly, time-consuming, and at times unfeasible due to the unavailability of subjects with specific movement patterns. In order to generate new examples of human motion with reasonable effort, computer based simulation methods can be utilized. In this context the use of musculoskeletal models is particularly advantageous, as they ensure the generated motion adheres to human movement constraints.

Renani et al. use musculoskeletal models to generate synthetic IMU data to train a Neural Network on joint angle prediction during walking [4]. Their method uses motion capture data mapped to a musculoskeletal model to compute and subsequently augment joint kinematics, thereby generating IMU data from the modified kinematics. However, this approach requires motion capture data of the selected movement, which is expensive to obtain. In addition, the joint angles are synthesized independently rather than in relation to another. This limitation could impact the adaptability of the method to complex exercises where the dependency between the individual joint angles must be considered, potentially resulting in examples that do not align with the original exercise.

These kinematic dependencies were considered by Dorschky et al., who generated synthesized IMU data to train a Neural Network on predicting sagittal plane joint angles, moments and ground reaction forces during walking [5]. They approached the generation of movement pattern as an optimal control problem, where new movement sequences are created by prescribing random trajectories to the individual body segments. These trajectories are drawn from distributions, which are created from an existing walking IMU dataset. However, this method requires considerable computational effort, to solve the optimization problem. Furthermore, the random creation of trajectories may result in infrequent generation of movement sequences that deviate considerably from the mean of the underlying dataset. Especially, these atypical sequences could be important for enhancing the diversity within the dataset.

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Building on previous work, we propose a synthesis approach adapted to the domain of physiotherapeutic movement exercises. This approach is based on a musculoskeletal simulation and enables the augmentation of an existing dataset by synthesizing diverse and realistic movements. In addition to established methods, we aim to use existing knowledge about common movement variations, to ensure a meaningful addition to the variance of the dataset. Using the deep squat exercise from the FMS, we will investigate how the performance of a Neural Network tasked with the evaluation of movement exercises improves, when trained with real and synthetic data. Our approach focuses on the following key aspects:

– Data Augmentation of an existing dataset by synthesizing physiotherapeutic movement exercises using exclusively IMU data in combination with a musculoskeletal simulation, reducing computational cost as much as possible.
– Targeted variation of relevant movement aspects, to enhance the diversity within the dataset.
– Automatic labeling of synthetically generated movement patterns for exercise evaluation tasks.

2 Materials and Methods

The synthesization approach is demonstrated using an existing dataset of squatting movements (see chapter 2.1). Initially, segment orientations are computed from raw IMU data (acceleration, gyroscope), which are subsequently used to control the movement of a musculoskeletal model (see chapter 2.2). This movement is systematically varied during the synthesis process (see chapter 2.3) and subsequently automatically evaluated (see chapter 2.4). Finally, chapter 2.5 outlines the Neural Network architecture, while chapter 2.6 details the use of synthesized data for the training of the Neural Network.

2.1 Dataset

The synthesization method is demonstrated using the deep squat movement pattern, which is part of the Functional Movement Screening (FMS) program [6]. Each movement within the FMS protocol, is evaluated based on a set of defined performance criteria. These criteria are essentially binary, meaning that for a given exercise performance, each criterion is either met or not met. The FMS employs a decision tree to derive the final assessment based on the fulfillment status of these criteria. The scoring system ranges from 3 (optimal execution) to 1 (fundamentally flawed execution). Detailed definitions of the individual criteria and their impact on the scoring can be found in [6].

For this publication we use IMU data collected by Spilz et al. [3], which includes approximately 600 repetitions from 18 subjects of the described deep squat movement. This data was recorded using 17 IMUs distributed on the subjects body. The IMU data has been converted into a standardized coordinate system to ensure consistency across measurements. For a detailed description of this process and the dataset see Spilz et al. [3].

2.2 Musculoskeletal simulation

The used musculoskeletal simulation is developed in OpenSim (version 4.3), an open source software tool for simulating and analyzing human movement [7]. We utilized the full-body musculoskeletal model by Rajagopal et al. [8], which includes detailed formulations of the upper and lower extremities as well as a simplified torso.

To transfer the recorded movement to the model, first the orientations of the individual IMUs were calculated using a Madgwick Orientation Filter (beta=0.033) [9]. This filter utilized data from the tri-axial accelerometers and gyroscopes. Next, we used OpenSense [10], an open-source toolbox within OpenSim, to map the generated orientations onto the skeletal model.

2.3 Synthesization process

Our study's synthesis approach manipulates the prescribed movement of the musculoskeletal model to either meet or violate specific evaluation criteria for the deep squat exercise. To illustrate this process, we consider the "Femur below horizontal" criteria as an example. It assesses whether the hip joint descends below the knee at the squat's lowest point.

For each criterion, we define a measurable evaluation parameter. In the current example, this parameter is the angle between the femur and the longitudinal axis. Based on the criteria definition and anatomical thresholds, two distinct value ranges are established for each evaluation parameter: one where the criterion is fulfilled and one where it is not. Depending on whether the criterion is to be met or not, a new value is sampled uniformly from the corresponding range.

To adapt an existing movement to a drawn evaluation parameter value, the movement of the body segments involved is transformed by scaling the joint angles so the desired value is achieved. Care is taken to ensure that these changes do not affect the movement of the remaining body segments and thus influence other evaluation criteria. Applied to our example, this implies that only the movement of the femur and the

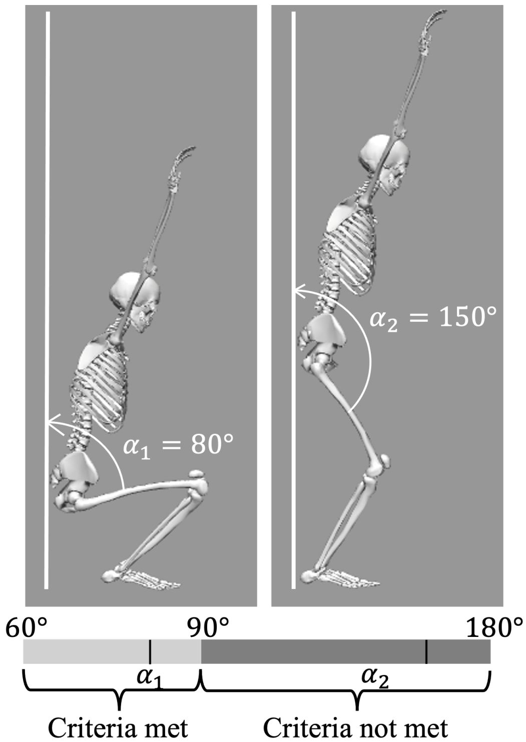

Fig. 1: Illustrative example of how the deep squat exercise is adjusted based on the FMS evaluation criterion "Femur below horizontal" [6], which can be evaluated using the angle between the femur and the longitudinal axis. The left image depicts an example where the defined angle a_1 is 80° at the squat's lowest point, adhering to the FMS criteria. Conversely, the right image displays an example, where the femur is raised above the horizontal line ($a_2 = 150$), thereby not meeting the FMS criterion.

tibia is adjusted. Two examples of the resulting movement are shown in Figure 1.

This method allows us to use a recorded example to generate numerous variants of movements, which also differ in their assigned label due to disparate combinations of fulfilled or violated evaluation criteria. Since the modified joint angles curves are still applied to the musculoskeletal model, it can be ensured that the biomechanical constraints are adhered to. The existing dataset can be supplemented with the synthesized movements through the extraction of segmental orientation over time, a process readily facilitated by OpenSim.

Using this approach, a computing time of approx. 10 seconds is required to synthesize a repetition (AMD Ryzen 5 3600X, Windows 10, no GPU acceleration).

2.4 Automatic evaluation

The synthesized movements must now be evaluated automatically. For this purpose, the positions, orientations of individual segments and joint angles are exported from the simulation in OpenSim. Utilizing these parameters, it is possible to automatically review the defined evaluation criteria and assign the corresponding label to the repetition.

2.5 Neural Network architecture

In this study, we utilize a model architecture that combines a Convolutional Neural Network (CNN) with a Long-Short-Term-Network (LSTM), called CNN-LSTM, to derive and analyze both the spatial and temporal features of the presented data. Following the CNN and LSTM layers, dense layers are integrated to classify the FMS rating. The detailed structure and parameters of this model, including the rationale for the architectural choices and the optimization process, are described in detail in a previous publication by the authors [3].

The training dataset consists of individual repetitions of the deep squat exercise, whereby each sample contains the orientations of the IMUs represented as quaternions. These orientations are organized in a 2D matrix that resembles an image, with the quaternion components arranged as columns within the matrix. A graphical explanation and further preprocessing steps are provided in the publication mentioned [3].

2.6 Evaluation

We will now compare how the network's performance varies when trained with both real and synthetic data, as opposed to real data only. To conduct this test, we generated a synthetic dataset with 6000 repetitions which were automatically labeled. For each of the three possible classes, 2000 synthetic examples were generated. The performance was evaluated using the Leave-One-Subject-Out (LOSO) method, i.e. all real repetitions of a given subject were removed from the training dataset and used as the test dataset. In addition, all synthetic repetitions based on examples from that subject were removed from the training dataset. The data from the remaining subjects was used for the training (80%) and validation (20 %) dataset, stratified by label and subject. This procedure was repeated for each of the 18 subjects in the dataset. Only real repetitions were used for the test dataset, while both real and synthetic repetitions were used for the training and validation dataset. The remaining training parameters are identical to the procedure outlined in [3].

3 Results

This chapter presents the results of the performance evaluation of the Neural Network when trained with both real and synthetic data, as opposed to real data only. We analyze the results using the weighted / macro F1-score, as the datasets of the individual LOSO splits feature notable class imbalances.

The performance evaluation results of the CNN-LSTM network for the exercise evaluation classification task are presented in Table 1. The averaged performance metrics indicate that using a combination of synthetic and real data enhances the classification performance on both the test and the validation dataset. Moreover, the standard deviation of the performance metrics suggests that training the network with both synthetic and real data leads to more consistent results.

4 Discussion and Outlook

The observed improvement in model performance emphasizes that the proposed approach, which uses existing knowledge about potential movement variations, to synthesize more diverse and accurate datasets, is a promising research direction. The results presented mark a first step in the development of this approach. Further investigations are necessary to assess the influence of the used method on the dataset and thus on the training of the Neural Network. For example, it is essential to investigate how the network performance changes depending on the number of synthetic examples and the ratio of synthetic to real examples in the training dataset.

Additionally, the current approach is tailored specifically for the deep squat exercise. A lot of manual labor is needed to implement the protocols to adjust the body position due to evaluation criteria, to derive meaningful value ranges and to implement an automatic labeling routine. It is essential to develop a methodology that can be adapted to a random exercise with a minimal amount of additional manual labor. An ideal approach should be able to synthesize a wide range of motion patterns from a minimal set of real repetitions, accurately capturing the nuances of the movement across all possible labels.

In conclusion, the presented approach is a promising research direction to improve the performance of Neural Networks in exercise evaluation. However, future work must focus on overcoming the approach's exercise specificity. Developing a more adaptable and universally applicable methodology will be essential in advancing the field and maximizing the potential of Neural Networks for exercise evaluation.

Tab. 1: Performance of the used CNN-LSTM on an exercise evaluation classification task with and without synthetic training data. Mean and standard deviation are calculated from the results of the 18 LOSO splits

Dataset	Weighted-F1 test set (mean $\pm$ std)	Macro-F1 validation set (mean $\pm$ std)
real data	0.78 $\pm$ 0.35	0.92 $\pm$ 0.1
real + synthesized data	0.89 $\pm$ 0.21	0.98 $\pm$ 0

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