Estimation of Lower Joints Kinematics and Kinetics Using EMG Signals and Deep Learning

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1. Introduction

Research goal: investigate the possibility of mapping EMG signals to knee and ankle angles and moments **ahead of time** using different deep neural network (DNN) time series models.

Motivation: Precisely acquiring lower extremity joints' angles and moments is an important step for a better understanding of joints implementations for the rehabilitation process, and gait analysis. Predicting Joints Kinematics and Kinetics data ahead of time is essential for prothesis control.

EMG signals: Elctro-myography (EMG) sensors are non-invasive instrument that measures the electrical activities in the targeted muscle by placing the sensor on the skin, and they are related to the joint's kinetics.

Kinemaics and Kinetaics data method: Motion Capture systems and force plates are well-known non-invasive instruments for acquiring joints' angles and moments in a limited volume, but because these systems are expensive many clinics cannot afford to buy them.

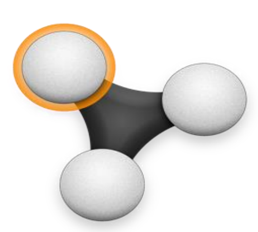
2. Experiment

EMG Data: 14 Delsys Tringo were attached to seven lower extremity muscles on both sides following SENIAM recommendations.

Joints Kinematics and Kinetics: Subject stood on force plates to measure the ground reaction forces (GRF) in a motion capture space with 39 reflective markers attached to the subject.

Experiment procedures: subjects were asked to do squat, pick an object and put it down and sit on chair and stand repeatedly.

3.2 Methodology | Data



14 Delsys Tringo EMG sensors → Preprocessing → Data Windowing

Features

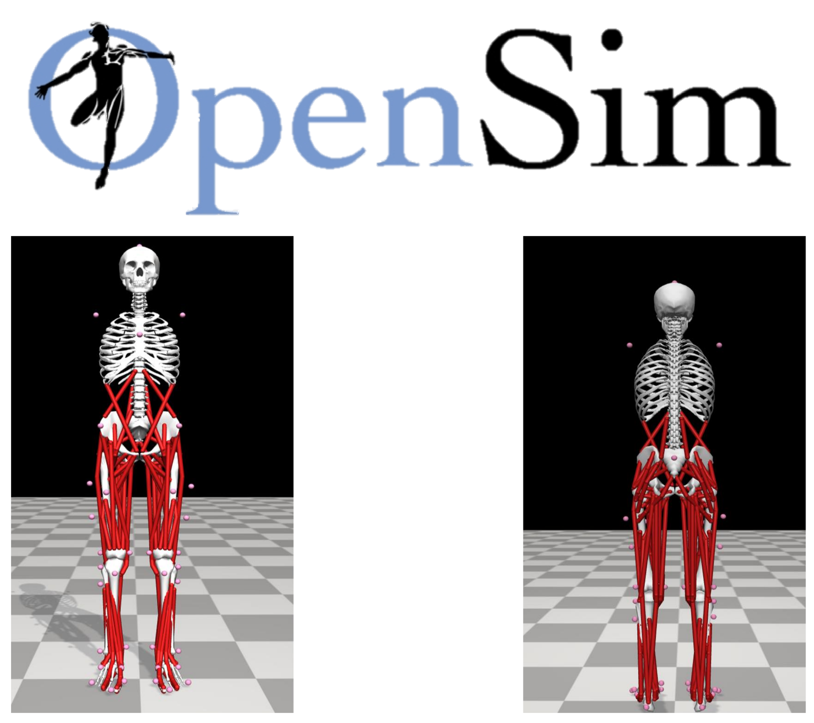
$$\text{MAV} = \frac{1}{N}\sum_{t=1}^{N}|x(t)|$$

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}x(t)^2}$$

$$x(t) = \sum_{p=1}^{P}(a_p x(t-p) + \epsilon)$$

Motion Capture System with → Markers' 3D Trajectories

Two Force Plates → Ground Reaction Forces (GRFs)



Knee & ankle joints' angles & moments → Down sampling → **Dataset**

Training DL model → **Predictions** → **R^2 Evaluation Metric**

3.2 Methodology | DNNs Architectures

CNN Model

Layer	Output shape
Input layer	(None,20,112)
Conv1D Batch Norm ReLU	(None,20,16)
Conv1D Batch Norm ReLU	(None,20,32)
Conv1D Batch Norm ReLU	(None,20,64)
Conv1D	(None,20,8)

CNN + LSTM Model

Layer	Output shape
Input layer	(None,20,112)
Conv1D Batch Norm ReLU	(None,20,16)
Conv1D Batch Norm ReLU	(None,20,32)
LSTM	(None,20,64)
Desne	(None,20,8)

LSTM Model

Layer	Output shape
Input layer	(None,20,112)
LSTM	(None,20,16)
LSTM	(None,20,16)
Desne	(None,20,8)

All layers' shape are (batch size, timestep, features) except last layer (batch size, timestep, joints angles or moments).
All models took 20 timestep point (1 second) and return 20 timesteps points with 5 timesteps (0.25 second) shifting toward the future.

4. Results & Discussion

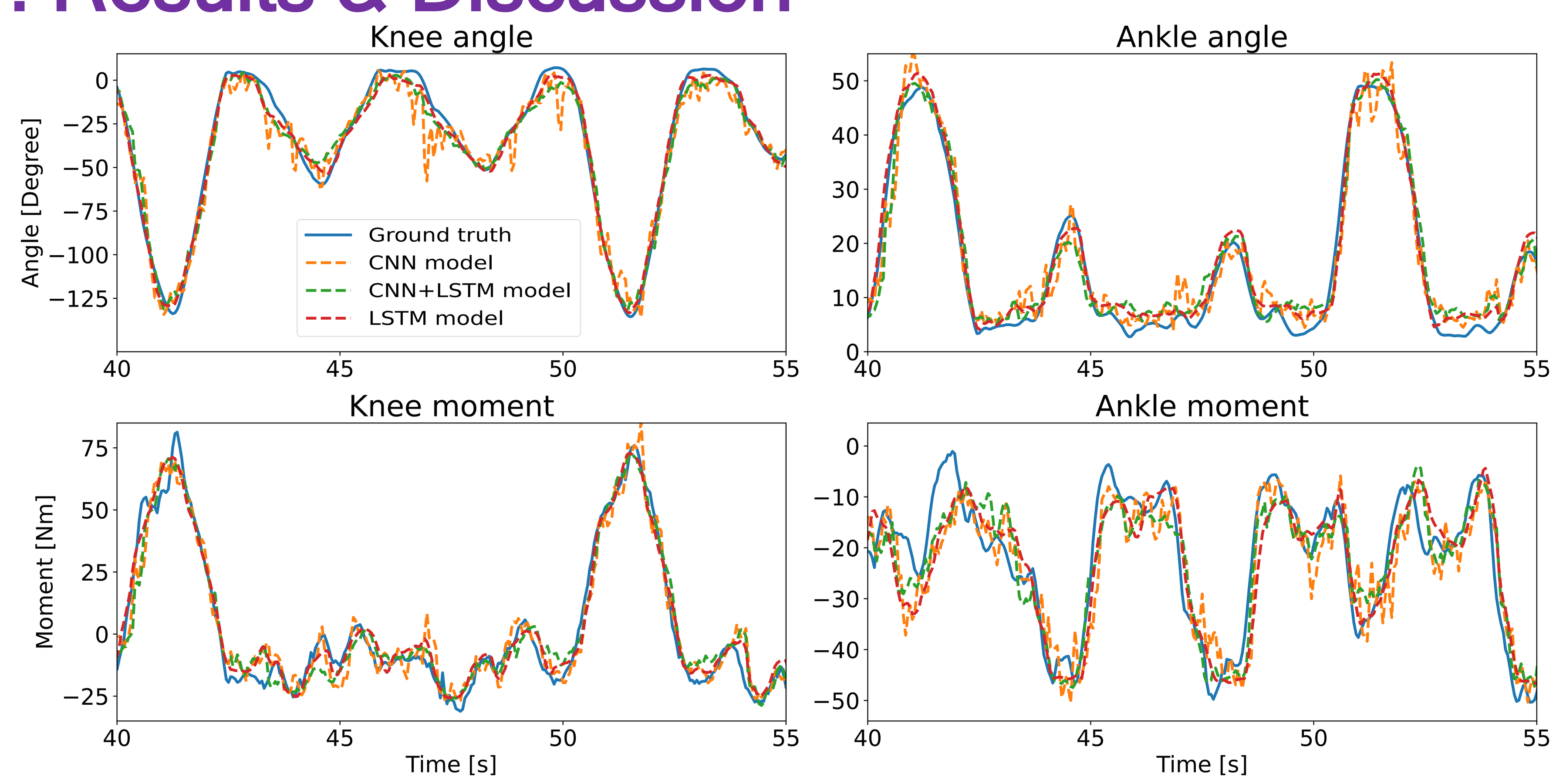


Figure 1 right side ground truth values against predictions (0.25s in the future) using 15 seconds from subject's 6 test set

1. All results are based on the ground truth values and the last timestep point in the predictions.
2. Ground truth values are based on the motion capture system, force plates, and OpenSim are assumed to be accurate and represent the real joints angles and moments values.
2. The table shows different DNN models can predict future joints results from EMG signals.
3. CNN and CNN+LSTM models' performance was lower than LSTM model performance is the best among the 3 models except for subject 7 where the model with the best performance was the CNN model

Subject	CNN	CNN+LSTM	LSTM
01	0.90 ± 0.02	0.93 ± 0.02	0.94 ± 0.02
02	0.77 ± 0.06	0.80 ± 0.09	0.82 ± 0.07
03	0.85 ± 0.07	0.84 ± 0.08	0.88 ± 0.06
04	0.88 ± 0.05	0.90 ± 0.05	0.92 ± 0.06
05	0.83 ± 0.09	0.85 ± 0.07	0.87 ± 0.06
06	0.74 ± 0.11	0.74 ± 0.09	0.84 ± 0.06
07	0.87 ± 0.06	0.77 ± 0.15	0.84 ± 0.09

4. Table 1 and figure 1 show that predicting future joints angles and torques using EMG signals only is feasible.

5. Future work

The results we had suggested that estimating joints' angles and moments ahead of time using EMG signals is feasible. Our next goal is:
1. Designing DNN models that can predict walking.
2. Generalize the walking models to work on a subject that wasn't introduced in the training nor validation.
3. Test the walking models in real-time setups.