DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING

Quantifying Joint Flexion During Realistic Human Movement: A Deep Learning Approach

Henry Saltzman, Md Asiful Islam, and Asimina Kiourti
ElectroScience Laboratory, Dept. of Electrical and Computer Engineering, The Ohio State University

INTRODUCTION and MOTIVATION

The ability to monitor joint flexion can provide essential information regarding an individual's joint health in many clinical applications.

- Rehabilitation
- Injury Prevention
- Athletics

State-of-the-art motion capture:

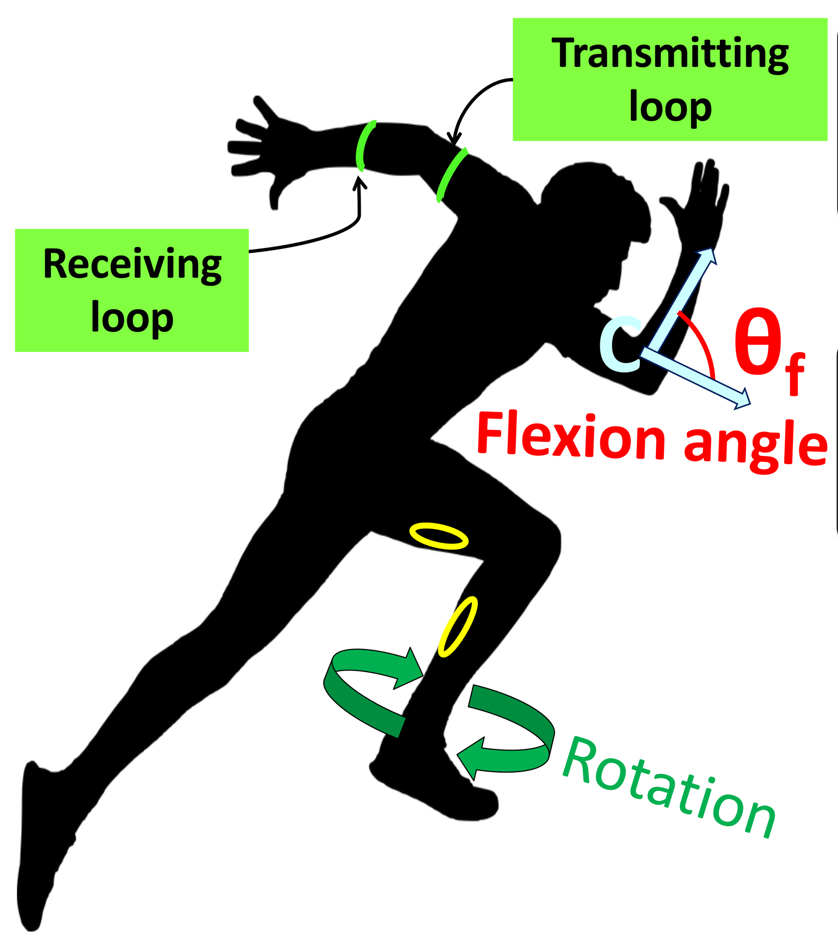
Motion Capture Labs

(+) Highly accurate
(-) Restricted to lab environments

Inertial Measurement Units (IMUs)

(+) Break the lab boundaries
(-) Suffer from integration drift
(-) Obtrusive/bulky
(-) Not injury safe

VISION and OPERATING PRINCIPLE



Wearable sensors integrated in garments

↓

Biomechanical data collected in natural environments (at home, exercising, etc.)

↓

Better understanding of neuromuscular deficits

Operating Principle: Joint flexion/rotation → alters loop coupling via Faraday's law → changes in transmission coefficient, $|S_{21}|$

GOAL OF THIS RESEARCH

- Previous works have quantified the relationship between transmission coefficient ($|S_{21}|$) and flexion angle in **static settings**.

- In this work, we take a major leap forward and model the relationship between flexion angle and transmission coefficient ($|S_{21}|$) in a **dynamic environment**.

EXPERIMENTAL SETUP

Wearable Electrically Small Loop Antennas (ESLAs) are embedded (sewn) in fabric sleeves in a planar manner.

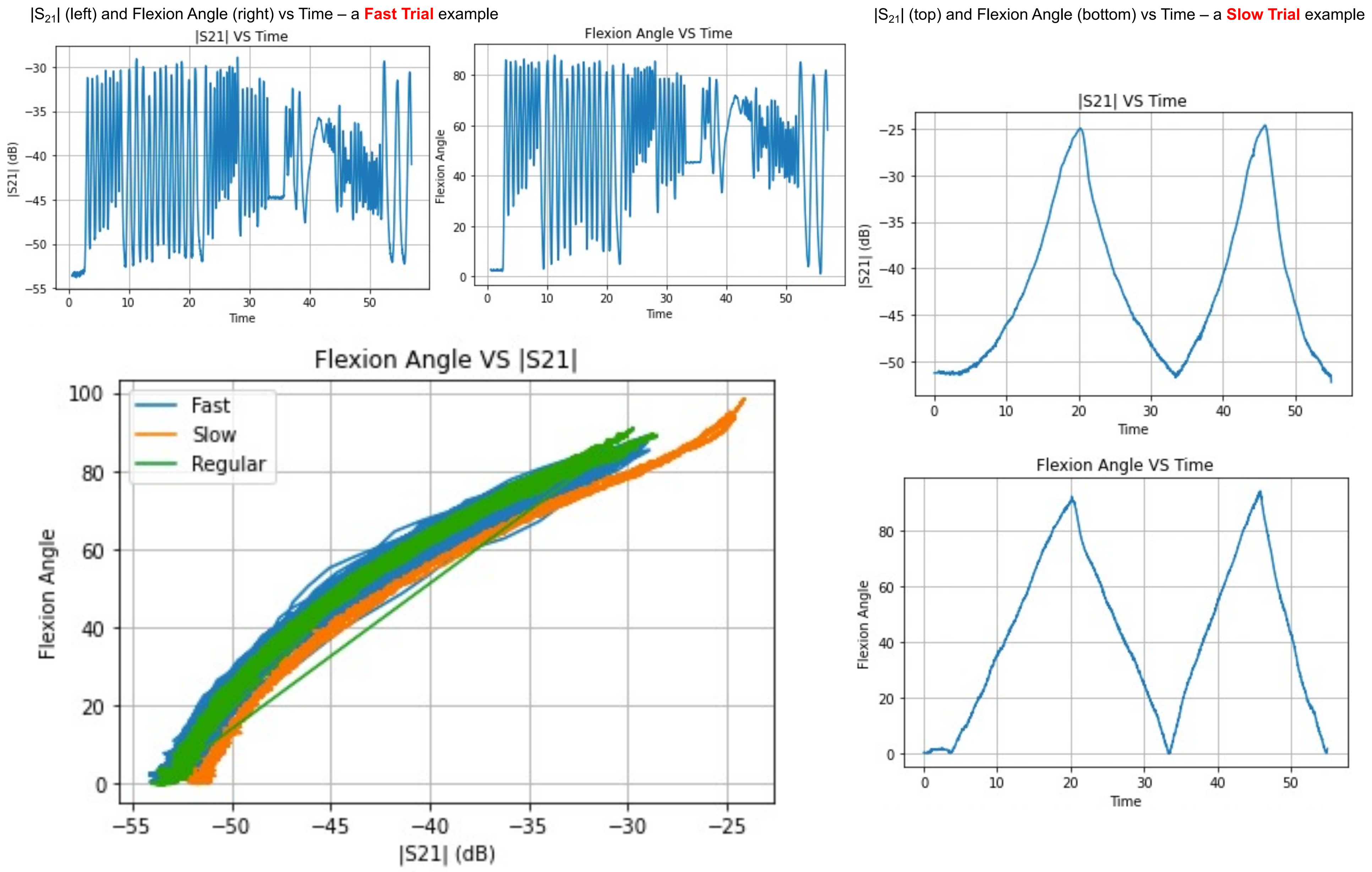
A cylindrical phantom limb is utilized to simulate dynamic motion at 3 categorized speeds (slow, regular, fast).

Using a Keysight PNA-L Network Analyzer, the transmission coefficient is measured at varying dynamic flexion angles.

Simultaneously, with an interfacing tool and an Intel Realsense 2 depth perception camera, "gold standard" angles are recorded.

3 trials are recorded for each task.

CHALLENGES with DYNAMIC DATA CAPTURE



- **Speed of motion influences the $|S_{21}|$ vs. Flexion Angle relationship.**
- There is a logarithmic relationship between $|S_{21}|$ and Flexion Angle in a time domain.

DEEP LEARNING MODEL

- Interpolation is used to achieve ($|S_{21}|$, flexion angle) time series in a synchronous domain.

Feature Engineering Process

1) Moving average with window size 75 elements applied to ($|S_{21}|$, flexion angle) data for every trial.

2) Averaged data are separated into matrices containing length 4 vectors.

- $|S_{21}|$ coefficient signal matrix contains (rows: 3 tasks x 3 trials x 3000 time-steps; columns: 4 $|S_{21}|$ elements).

- Corresponding flexion angle matrix contains (rows: 3 tasks x 3 trials x 3000 time-steps; columns: 4 flexion angle elements).

- Deep neural network is trained to learn the relationship between $|S_{21}|$ coefficient vector inputs and flexion angle vector targets.

DNN Structure

- 4 nodes in input layer and 4 nodes in output layer.
- 2 Hidden Layers; 1500 nodes in each layer.
- Connections between layers consisted of rectified linear unit activation functions.
- Mean square error loss function.
- Adam optimizer algorithm – learning rate = 0.001.
- Evaluation completed with 10-fold cross validation.

PRELIMINARY RESULTS

Motion Speed	RMSE (degrees)	rRMSE	R
Slow	4.56 +- 0.410	0.09 +- 0.008	0.99 +- 0.0002
Regular	2.61 +- 0.406	0.05 +- 0.008	0.99 +- 0.0005
Fast	3.16 +- 0.182	0.06 +- 0.004	0.98 +- 0.0026
Mean	3.49 +- 0.106	0.07 +- 0.002	0.99 +- 0.0004

Root-mean-square error, relative root-mean-square error, Pearson Correlation Coefficient (R).

The relationship between transmission coefficient ($|S_{21}|$) and flexion angle can be quantified and predicted in dynamic settings.

ACKNOWLEDGEMENT

This work was supported by NSF under grant #2042644.