Modeling and Analyzing Human Motion

Trung-Hieu Hoang and Minh N. Do

Department of Electrical and Computer Engineering

University of Illinois at Urbana-Champaign

Collaborators and Sponsors

Dr. Chris Zallek, MD
Neuromuscular Medicine, OSF

Dr. Mona Zehni, PhD
former UIUC PhD student

George Heintz
HCESC, UIUC

Dr. Minh Ho, MD
Orthopedics, Vinmec

Our research has been funded by the Jump ARCHES endowment through the Health Care Engineering Systems Center (HCESC)

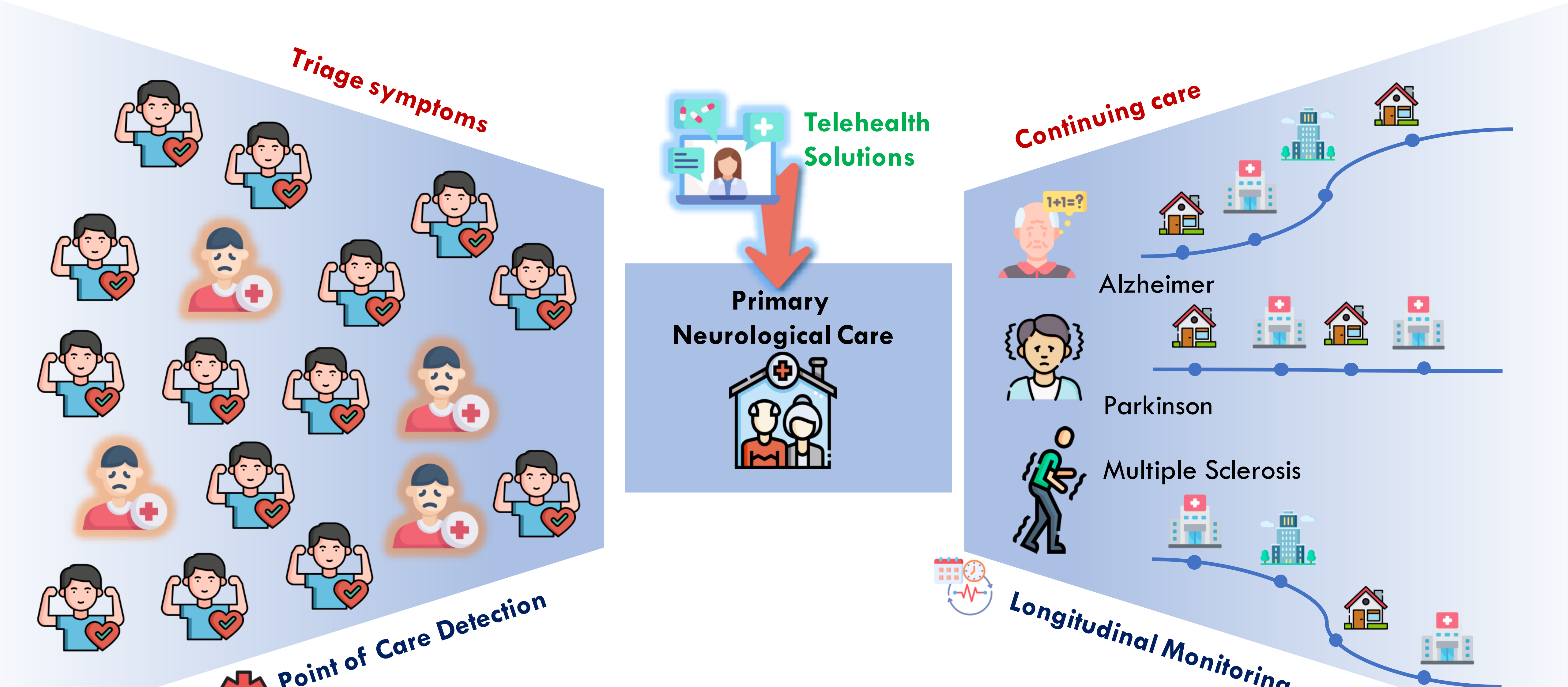
jump | ARCHES

The Grainger College of Engineering
Health Care Engineering Systems Center

“Life requires movement” – Aristotle

“To move is to live. To live is to move” – Toni Sorenson

Primary Neurological Care Bottleneck



Population aging is **increasing**
19% **shortage** of neurologist

1 in 3 people affected
Leading cause lost quality of life
Second leading cause of death

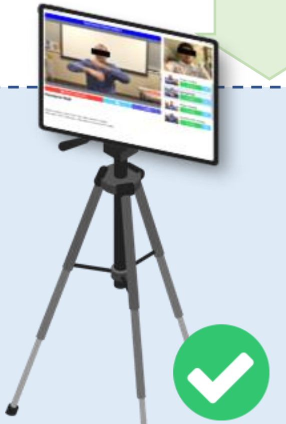
Today: Smartphone-based Telehealth Applications

Exponential growth of computing power + Cloud computing

High-resolution Cameras

Advanced lab equipment is required (Mocap, 3D cameras, etc.)

Lack of automated assessment



Using any available smartphone device, easy-to-use software installation

Computer aided telehealth and documentation solution

<u>Aim:</u> Empowering computer vision perception for telehealth applications

Our Proposal: Digitized Neurological Exam (DNE) System

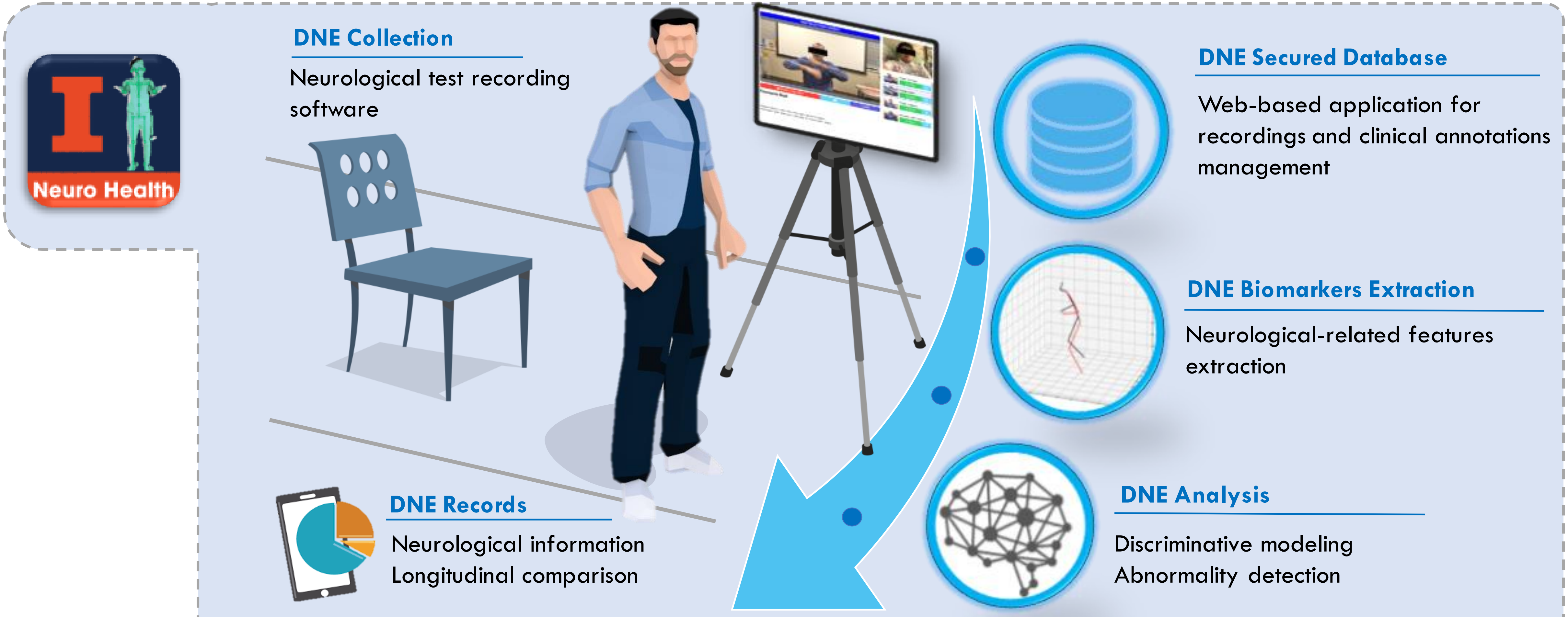


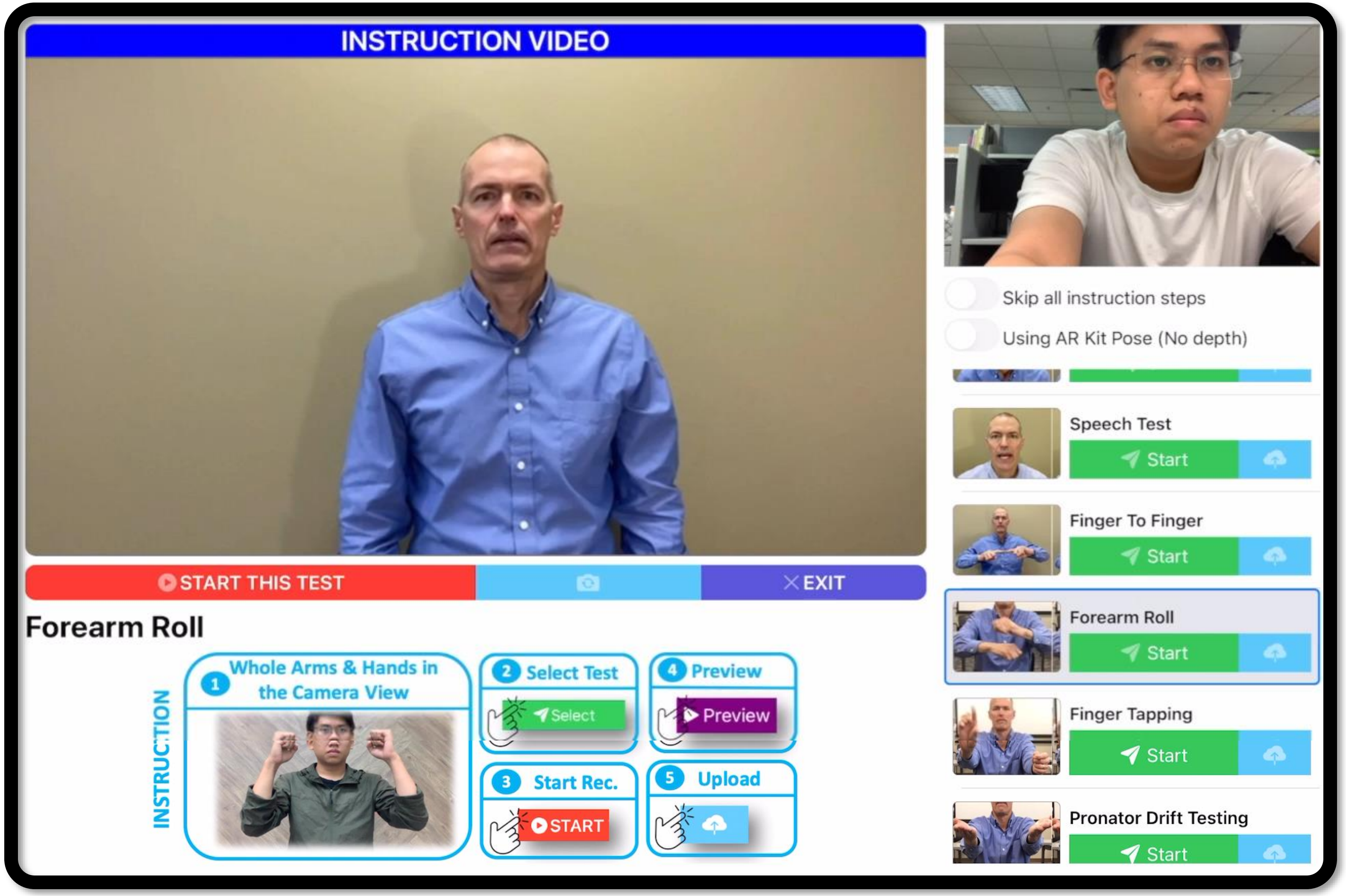
Illustration of the DNE system. A smartphone-based teleneurology solution analyzes clinically relevant biomarkers from multiple video-recorded neurological examinations

Trung-Hieu Hoang* and Mona Zehni* *et al.*, "Towards a Comprehensive Solution for a Vision-based Digitized Neurological Examination", *IEEE JBHI, 2022*

Trung-Hieu Hoang *et al.*, "Smartphone-Based Digitized Neurological Examination Toolbox for Multi-test Neurological Abnormality Detection and Documentation", *Under Review at IEEE-JBHI*, 2024

* *Authors contributed equally*

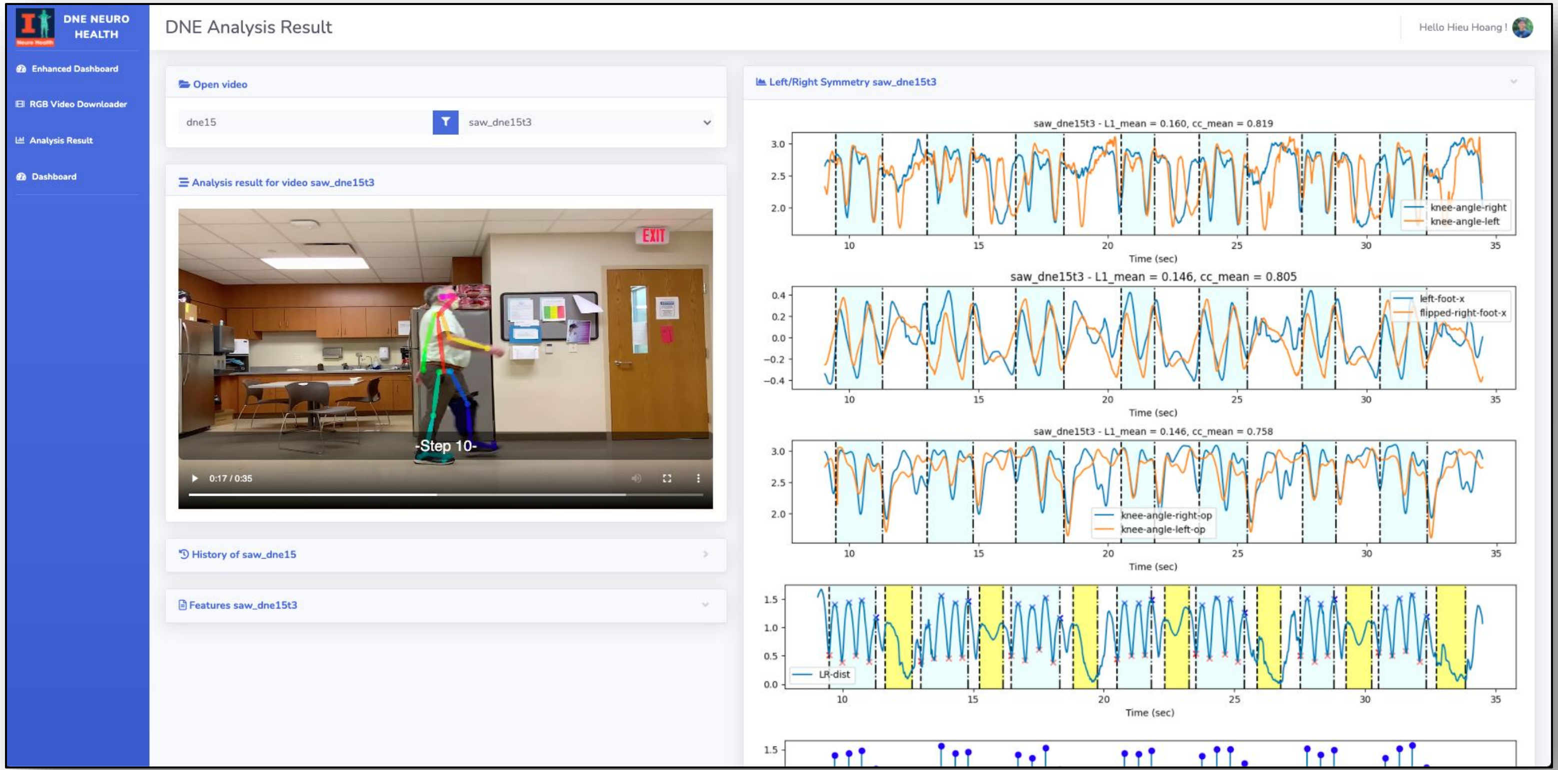
DNE Neuro Health Recorder

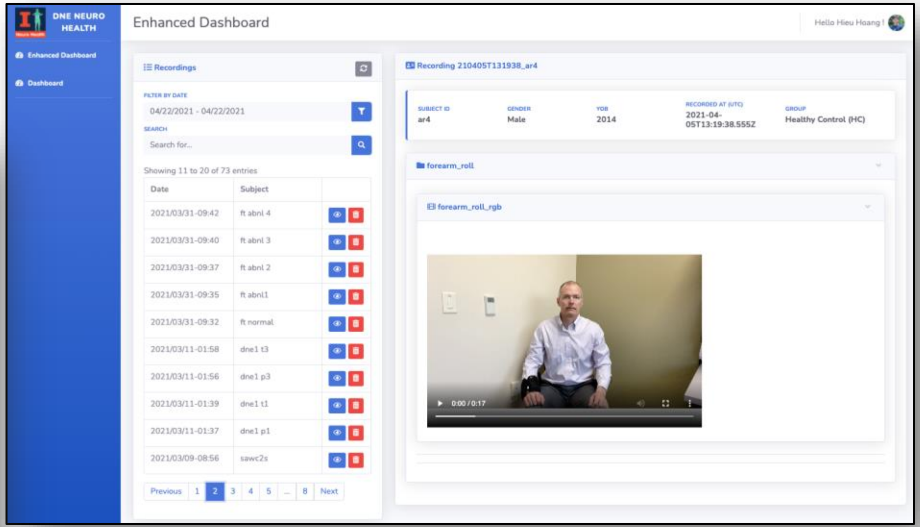


Neuro-Health Recorder

An iOS application providing an accessible solution for remote neurological recordings collection

DNE Neuro Health Viewer





Neuro-Health Viewer

A secure web application for managing video recordings, previewing and visualizing the analysis results

A Multi-test DNE Record

Finger to Finger (FTF)

Finger Tapping (FT)

Forearm Roll (FR)

Stand-up and Walk (SAW)

DNE Dataset. We provide **the first** vision-based dataset consisting of multiple neurological tests. Our dataset has **334 normal** *(green box)* **and impairment-simulating** *(red box)* **video recordings of 21 subjects**

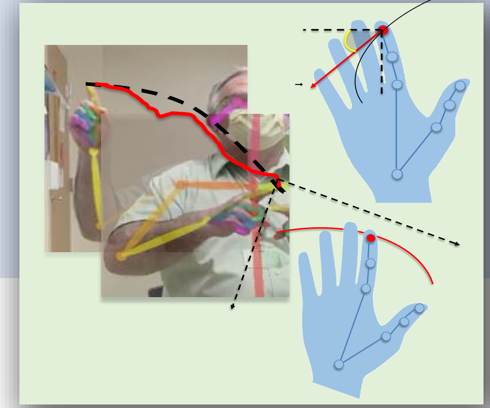
*The subject in these videos gave us permission to show his videos in this presentation

DNE - Vision-based Analysis Module

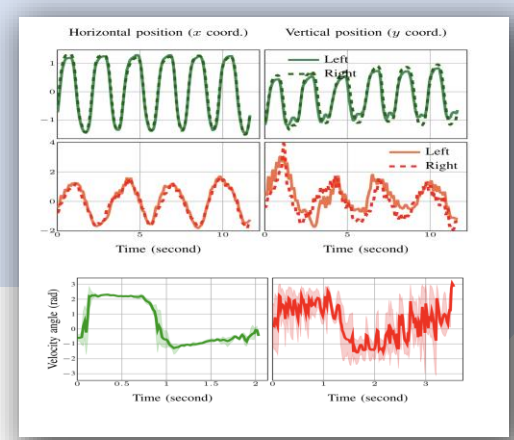
RGB Video

2D/3D Pose Estimation*

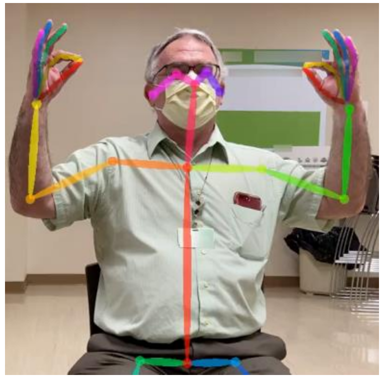
Kinematic/Spatio-temporal Feature Extraction



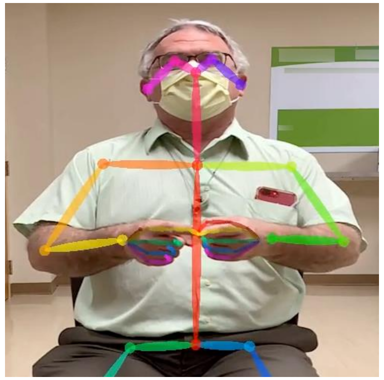
Feature Visualization & Abnormality Detection



Human pose estimation

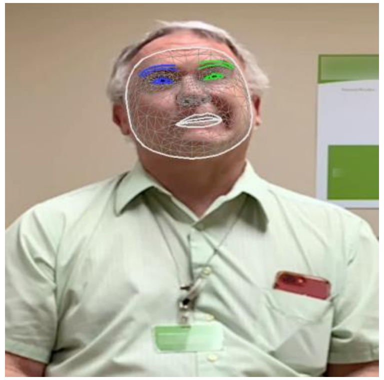


Finger tapping



Finger to finger

Forearm roll

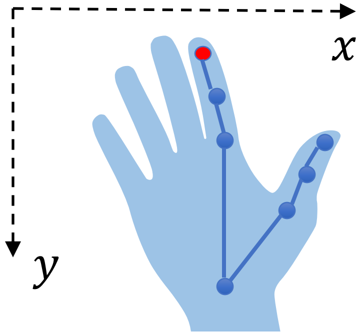


Facial activation

Stand-up and walk

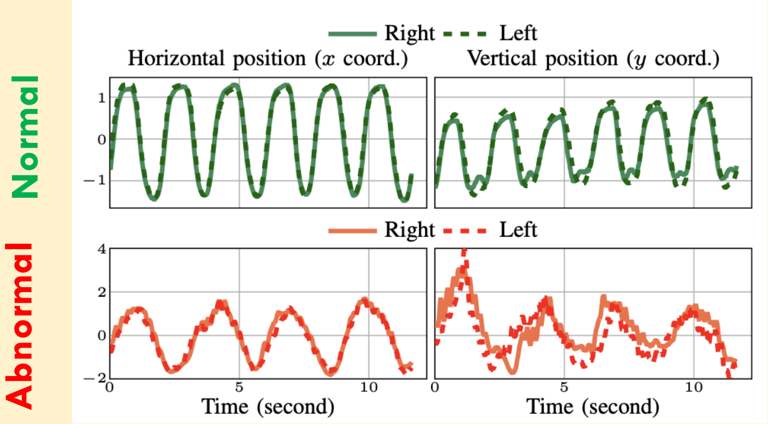
(*) 2D pose estimation from OpenPose [Cao, 2019], MediaPipe [Lugaresi, 2019]

Finger to Finger (FTF) Spatio-temporal DNE Biomarkers



Locations of the index fingertip of the right (s^{right}) and the left hand (s^{left})

Horizontal and Vertical Left/Right (L/R) Symmetry



Locations of joint index finger (s)

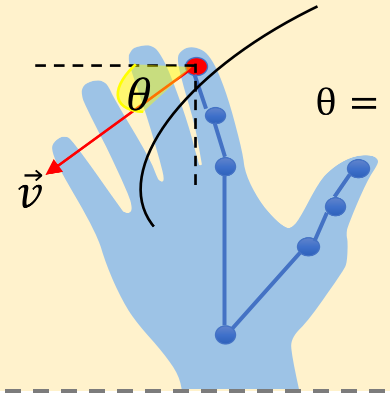
Pearson Cross-correlation coefficient (CC):

$$\mathrm{CC}(\boldsymbol{x}_1, \boldsymbol{x}_2) = \frac{(\boldsymbol{x}_1 - \overline{\boldsymbol{x}_1})^T (\boldsymbol{x}_2 - \overline{\boldsymbol{x}_2})}{\|\boldsymbol{x}_1 - \overline{\boldsymbol{x}_1}\|_2 \|\boldsymbol{x}_2 - \overline{\boldsymbol{x}_2}\|_2}$$

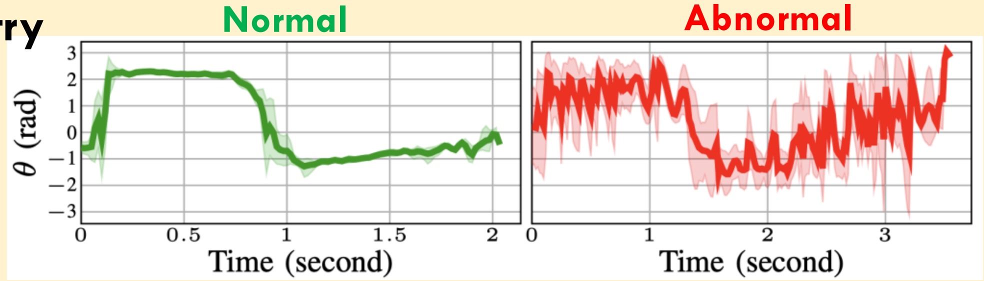
Return: The CC of the horizontal/vertical trajectory of the right ($\boldsymbol{s}^{right}$)/ left ($\boldsymbol{s}^{left}$) index finger:

$$S_{ftf}^{x} = CC\left(\left[\boldsymbol{s}^{left}\right]_x, \left[\boldsymbol{s}^{right}\right]_x\right)$$
$$S_{ftf}^{y} = CC\left(\left[\boldsymbol{s}^{left}\right]_y, \left[\boldsymbol{s}^{right}\right]_y\right)$$

Cycle-wise Velocity Angle Symmetry



$$\theta = \mathrm{atan2}\left(\frac{\frac{d[\boldsymbol{s}^*]_y}{dt}}{\frac{d[\boldsymbol{s}^*]_x}{dt}}\right)$$



Mean and STD of the velocity angle across multiple cycles

Return: Mean/STD of the pairwise CC between the angle velocity series of any two cycles

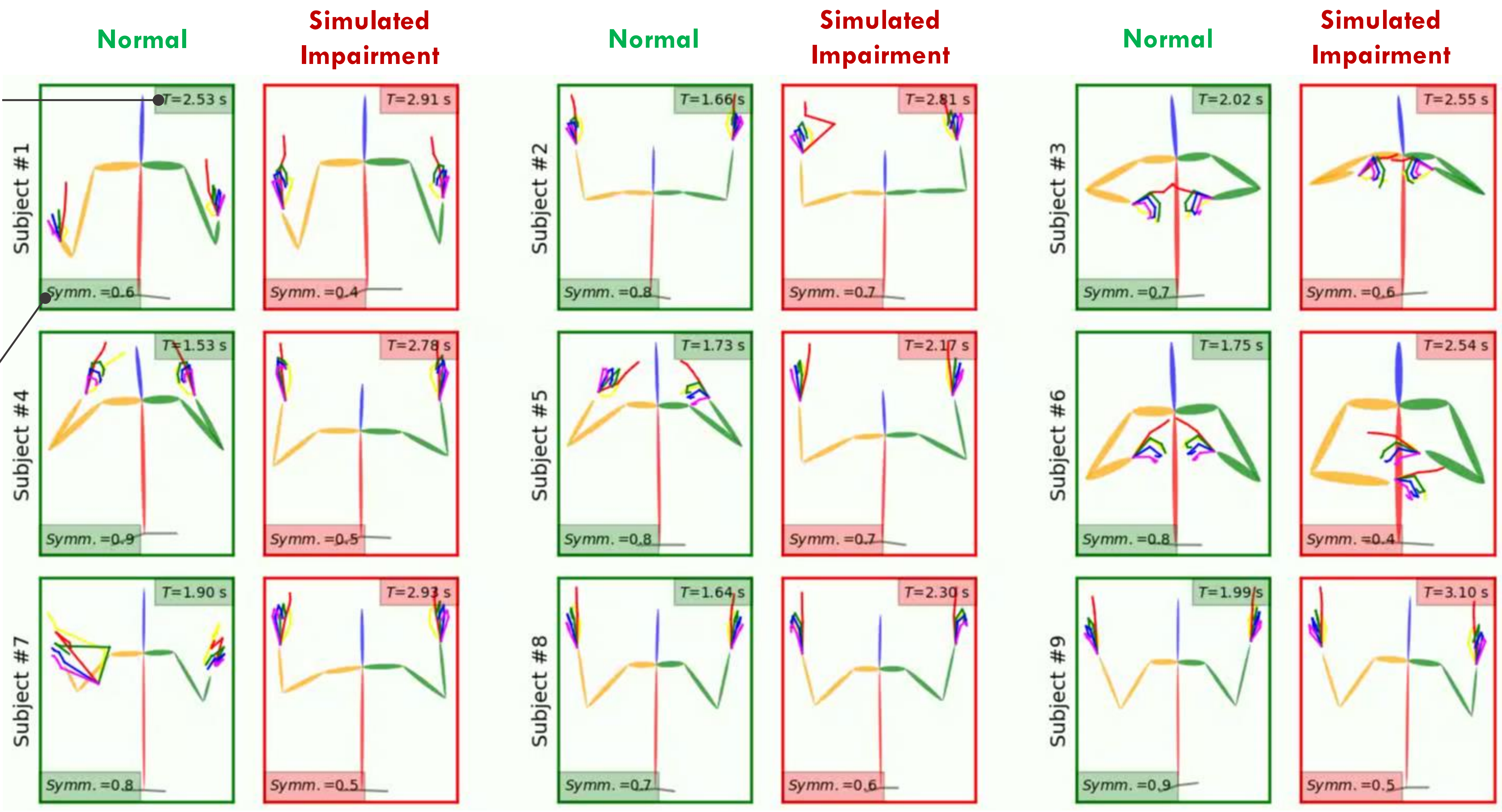
Other features: movement period, average speed, path smoothness

Green: normal, red: abnormal (simulated impairment)

Finger to Finger (FTF) - Visualization

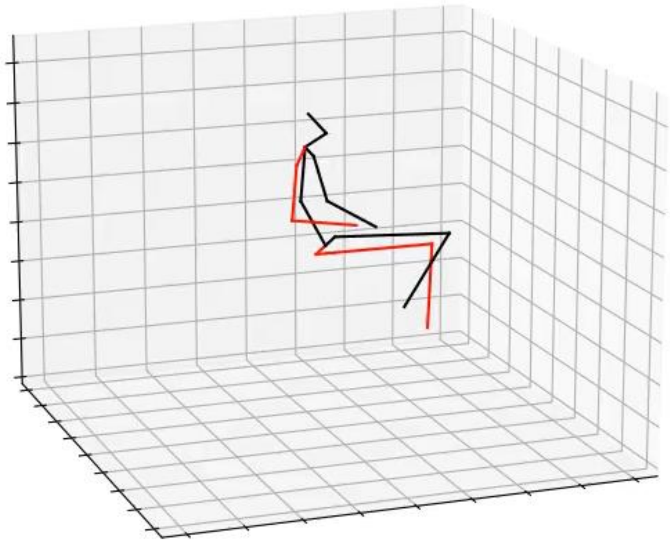
Average period (sec)
Total time taken for one complete cycle (moving from the highest to the lowest vertical position and back) on each side

Horizontal L/R Symmetry
The CC of spatial trajectory of the R/L index finger



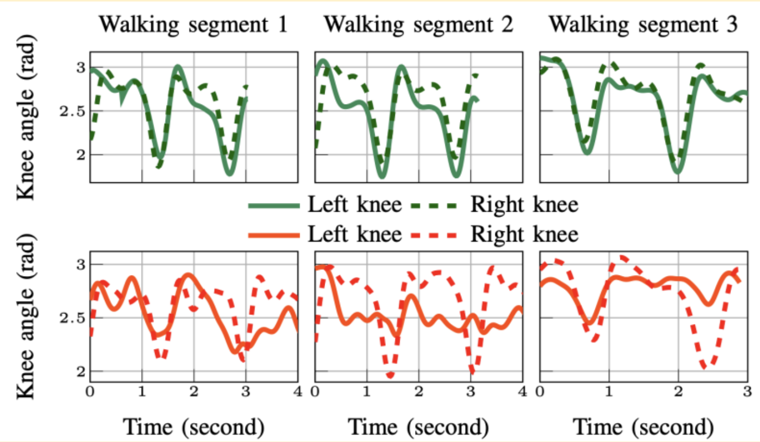
Stand-up and Walk (SAW) Spatio-temporal Features

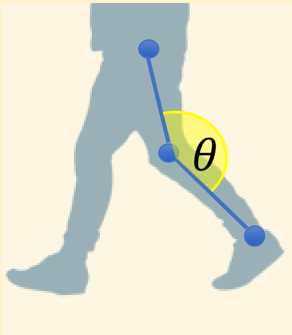
2D pose estimation from OpenPose [Cao, 2019]



3D pose reconstruction from 2D frames using VideoPose 3D [Pavllo, 2019]

Knee Angle Symmetry

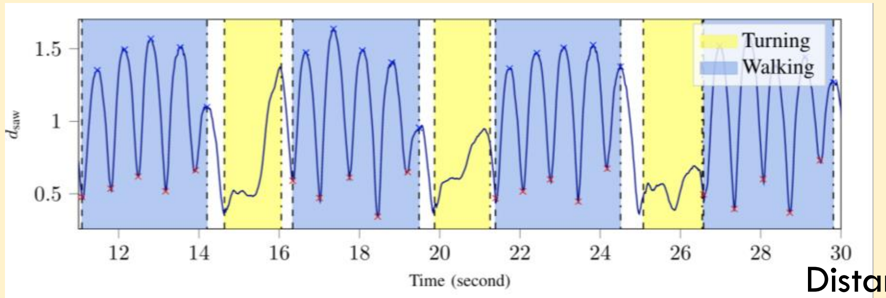


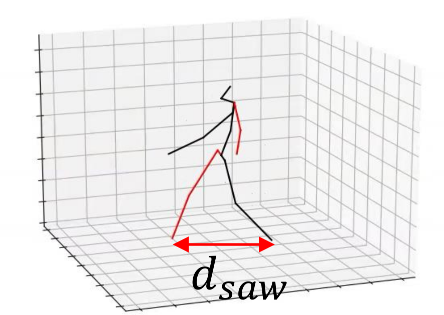


Knee angle series for three walking segments

Return: The CC of the aligned R/L knee angle series within a walking segment (a full pass of the room length)

Spatio-temporal Gait Parameters





Distance between two feet (d_{saw})

- Step time
- Turing time, time to stand
- Walking speed, cadence
- Step length/step width
- Step symmetry

Green: normal, red: abnormal (simulated impairment)

Stand-up and Walk (SAW) - Visualization

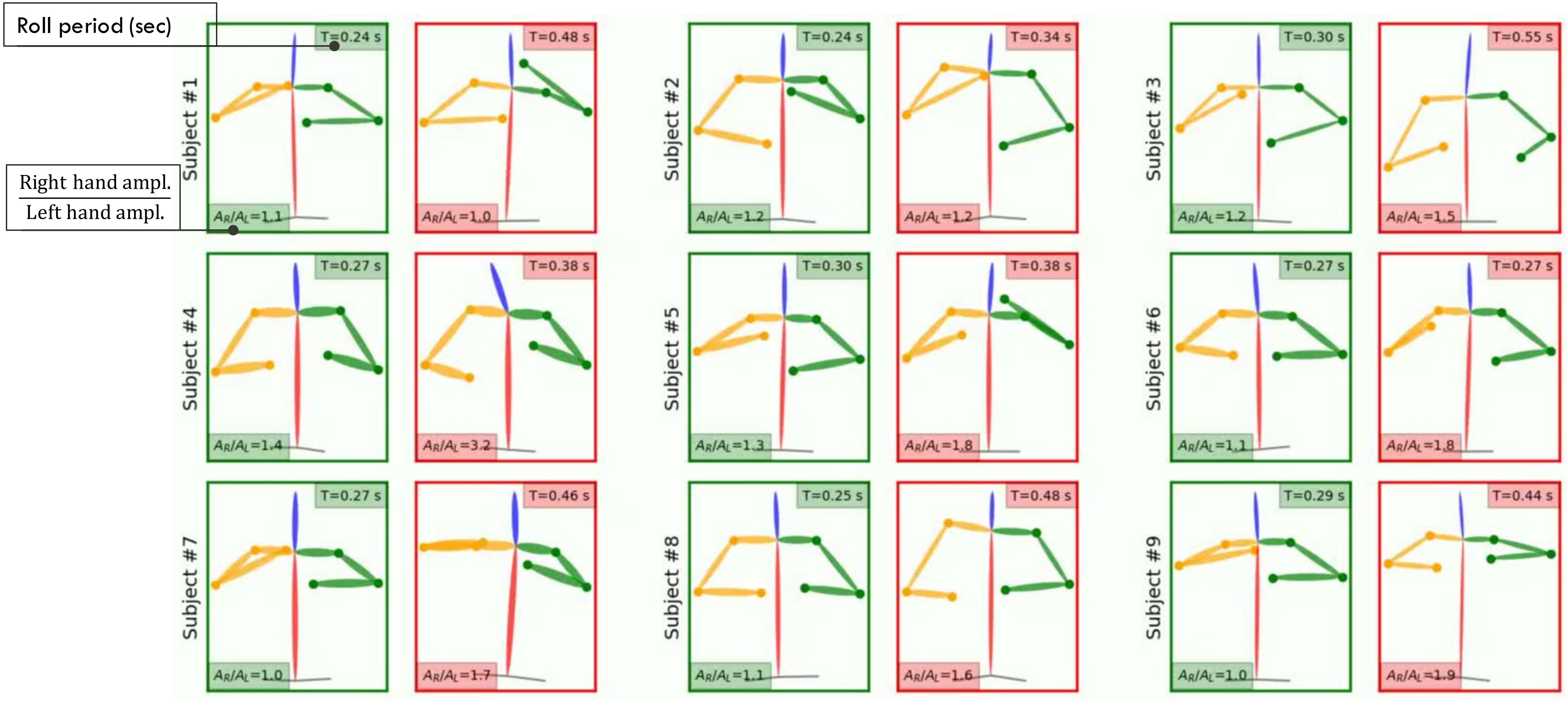
Normalized step length

The furthest distance between two feet within each step

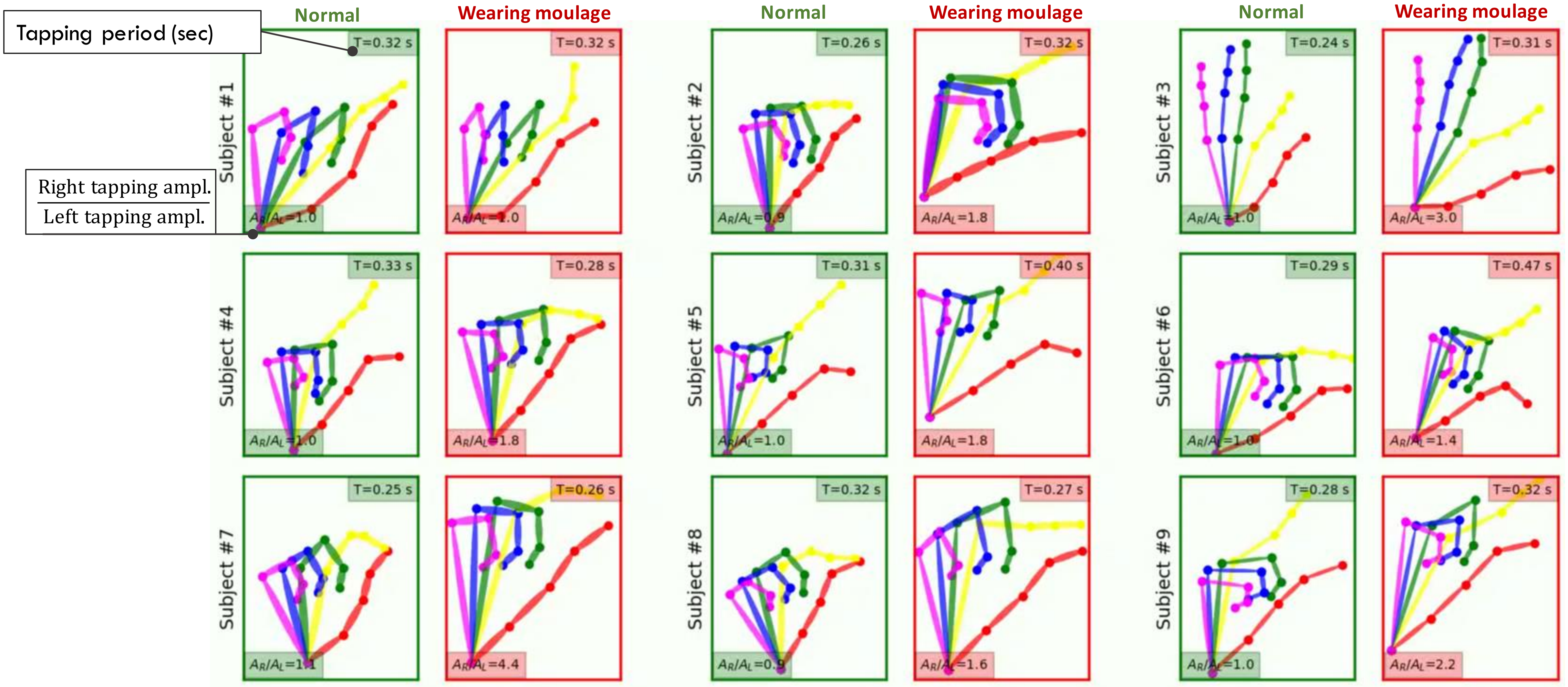
Knee angle symmetry

The correlation coefficient of the aligned R/L knee angle series within a walking segment (a full pass of the room length)

Forearm Rolling

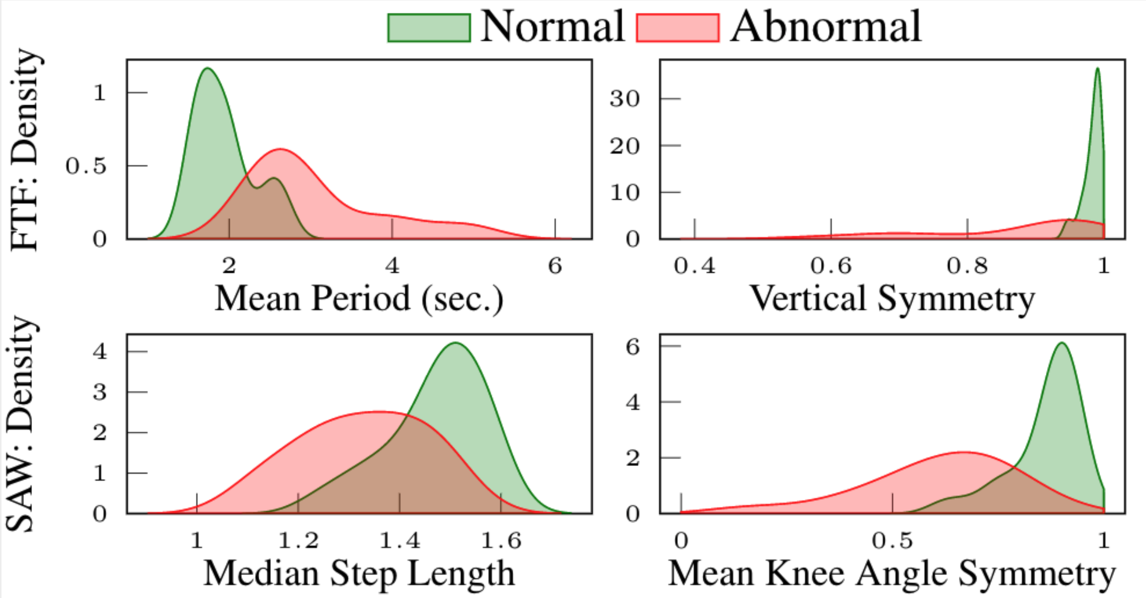


Finger Tapping



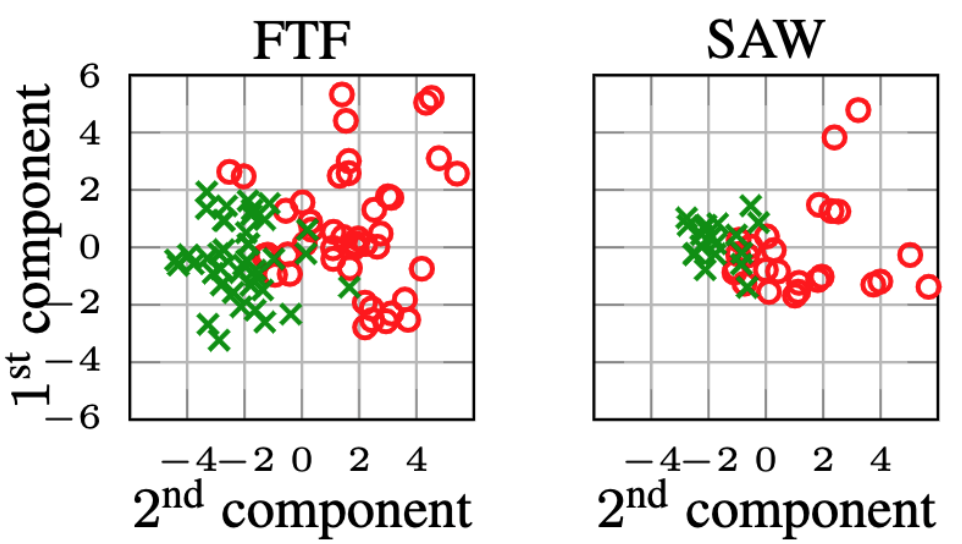
Qualitative Results

Distribution of Normal/Abnormal Features



- Normal features are concentrated in a specific range
- Abnormal features are often less regular and have a higher standard deviation

PCA Analysis for Different Tests



Two classes are separated in a lower dimensional feature space, implying the discriminative power of our constructed features set

Green (X): normal, red (O): abnormal/simulated impairment

Classification Performance

Subject-based: 21 subjects are divided into train/test sets, videos belonging to the same subject are used correspondingly

Video-based: 361 videos from all subjects are divided independently into train/test sets

Test	Model	Subject Based							Video Based						
		Acc	Precision	Recall	Specificity	F1 Score	AUC	AP	Acc	Precision	Recall	Specificity	F1 Score	AUC	AP
FTF	RF	0.8625	0.9232	0.8250	0.9000	0.8510	0.8625	0.8357	0.9623	0.9550	0.9818	0.9400	0.9666	0.9609	0.9473
	GBM	0.9125	0.9378	0.9000	0.9250	0.8993	0.9125	0.8878	**0.9895**	0.9800	**1.0000**	0.9800	**0.9895**	**0.9900**	**0.9800**
	XGBOOST	**0.9250**	0.9278	**0.9250**	0.9250	**0.9249**	**0.9250**	**0.9028**	0.9684	0.9800	0.9636	0.9800	0.9704	0.9718	0.9647
	LR	0.8375	0.9378	0.7500	0.9250	0.8004	0.8375	0.8128	0.8930	0.9314	0.8805	0.9200	0.8988	0.9003	0.8853
	RSVM	0.8875	0.9378	0.8500	0.9250	0.8708	0.8875	0.8628	0.9579	0.9600	0.9636	0.9600	0.9599	0.9618	0.9447
	MLP	0.8625	0.8788	0.8750	0.8500	0.8619	0.8625	0.8218	0.9789	0.9778	0.9778	0.9800	0.9778	0.9789	0.9686
	LSTM	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.9723
	CNN	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.9770
SAW	RF	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.8270
	GBM	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.8139
	XGBOOST	0.8261	0.8250	0.8542	0.8036	0.8240	0.8289	0.7677	0.8200	0.8317	**0.9333**	0.6300	0.8670	0.7817	0.8106
	LR	0.8189	0.8375	0.8542	0.7946	0.8250	0.8244	0.7802	0.7800	0.8762	0.7810	**0.7867**	0.8097	0.7838	0.8257
	RSVM	**0.8606**	0.8500	**0.9375**	0.7946	**0.8740**	**0.8661**	0.8187	**0.8400**	**0.8929**	0.8714	**0.7867**	**0.8685**	**0.8290**	**0.8514**
	MLP	0.8189	0.8500	0.8542	0.7946	0.8240	0.8244	0.7771	0.7800	0.8179	0.8714	0.6467	0.8277	0.7590	0.7860
	LSTM	0.7372	0.8333	0.6250	0.8393	0.6778	0.7321	0.6950	0.7800	0.7833	0.8648	0.6700	0.8139	0.7674	0.7541
	CNN	0.7877	0.8542	0.7292	0.8393	0.7643	0.7842	0.7452	0.7800	0.8267	0.8076	0.7500	0.8063	0.7788	0.7962

We achieve an accuracy beyond 90% for upper limb tests and 80% for the stand and walk test

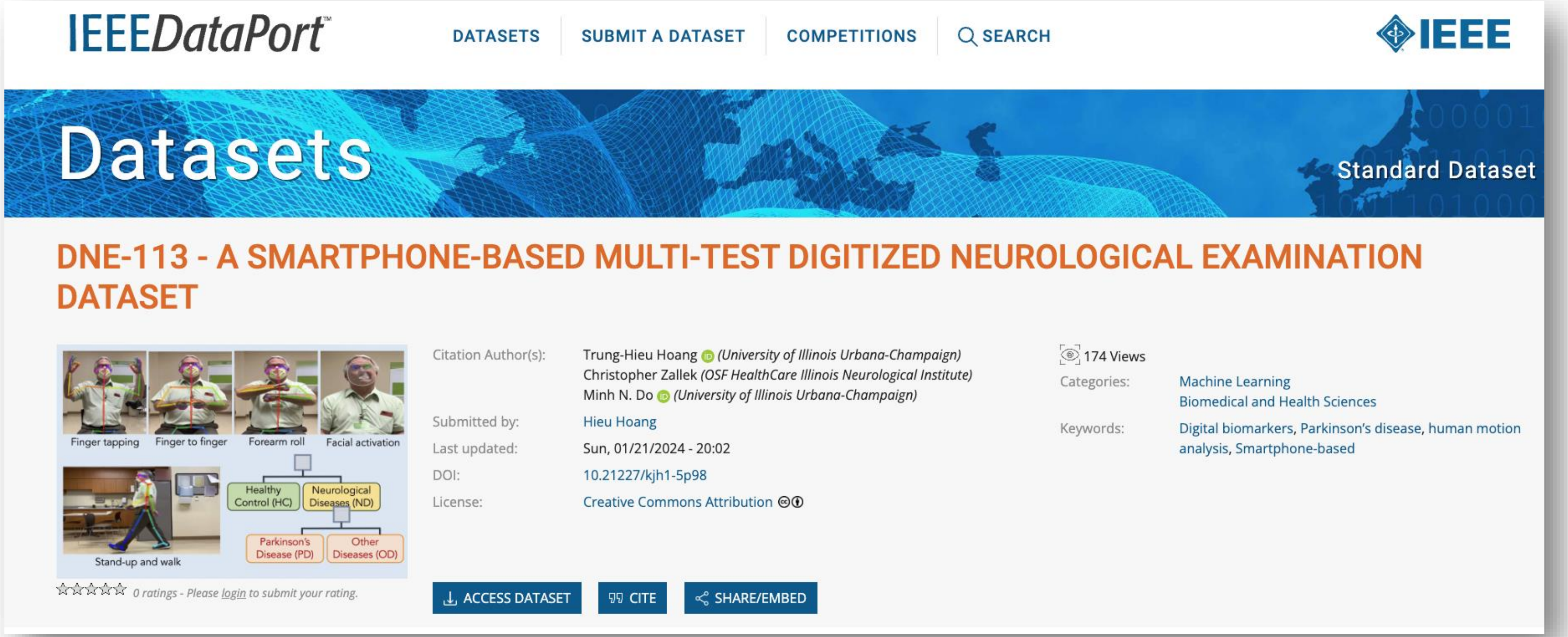
We perform classification using various machine learning models – *base classifier*:

Tree-based methods:
- Random Forest (RF)
- Gradient-Boosting Machine
- XGBoost

Parametric models trained using gradient-descent:
- Logistic Regression (LR),
- Support Vector Machine (SVM)
- Multi-layer Perceptron (MLP)

Deep learning-based models:
- Bidirectional LSTM
- Temporal Convolution Neural Network

DNE-113 Dataset – Smartphone-based - Multi-test DNE Database



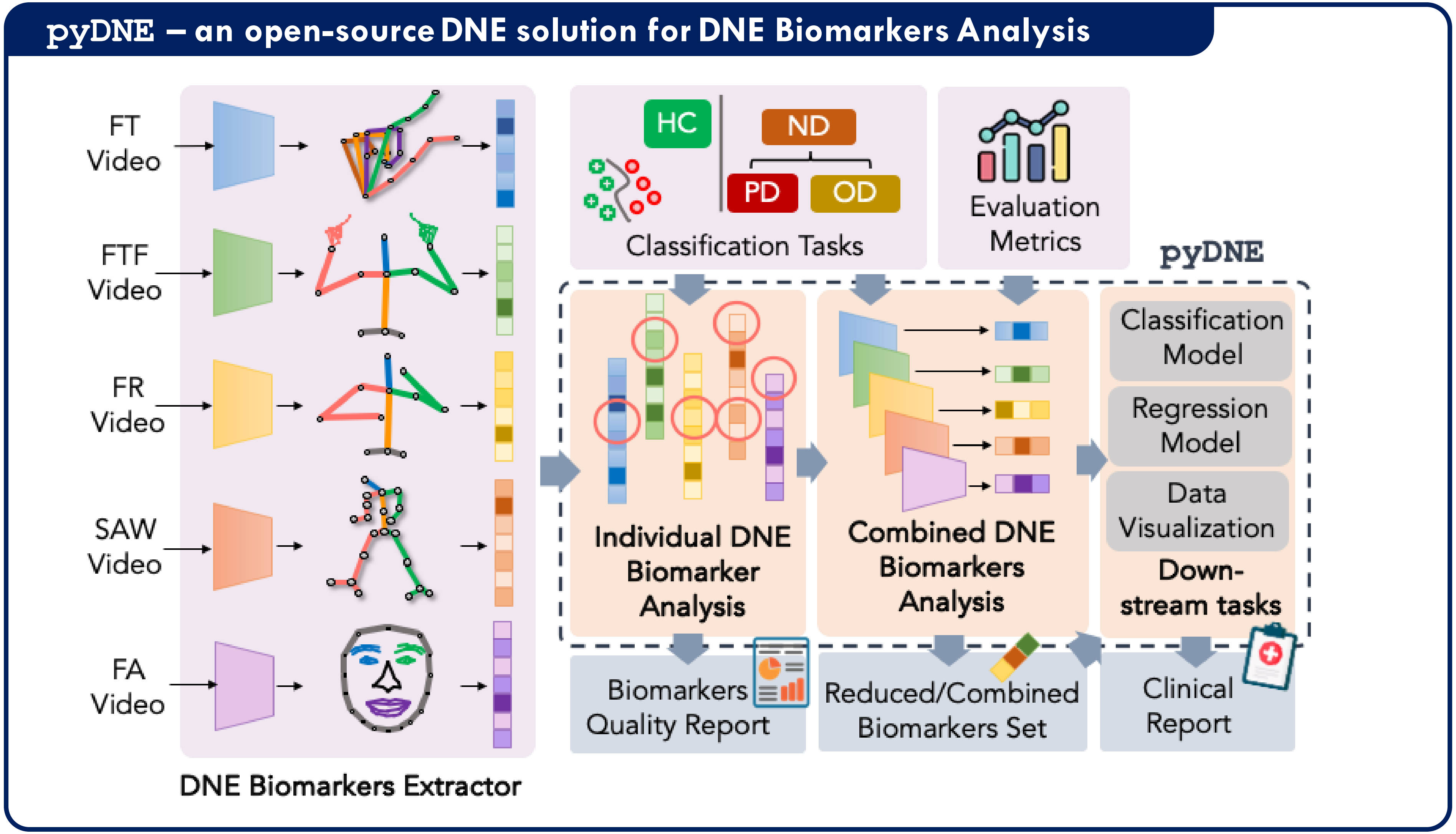
DNE 113 is made publicly available as a dataset on IEEE DataPort

Cohort	Demographic				Number of	Number of Videos per Test				
	Size	Age	Male/Female	Disease Duration	Records	FT	FTF	FR	SAW	FA
Healthy Control (HC)	34	54.9 ± 13.6	8/26	-	65	52	53	60	32	53
Parkinson's Disease (PD)	33	73.0 ± 9.1	22/11	1.6 ± 3.5	35	35	35	35	30	35
Other Diseases (OD)	46	64.5 ± 14.0	25/21	2.6 ± 6.0	47	45	46	46	39	47
Total	113	64.1 ± 14.3	55/58	2.2 ± 5.1	147	132	134	141	101	135

Demographic characteristics and the statistics of our DNE-113 Dataset

- ✓ Multi-test
- ✓ Smartphone-based
- ✓ Broader range of neurological abnormalities

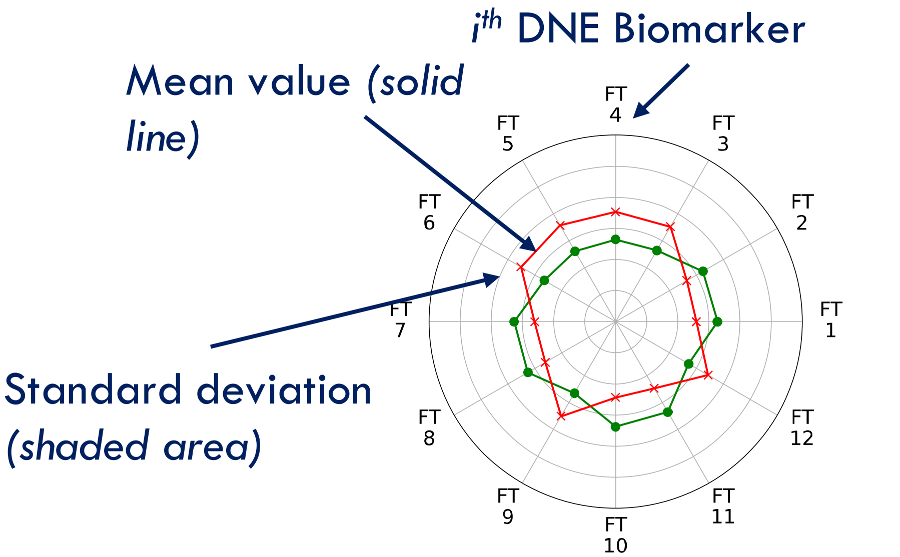
pyDNE: Software Toolkit for DNE Biomarkers Analysis

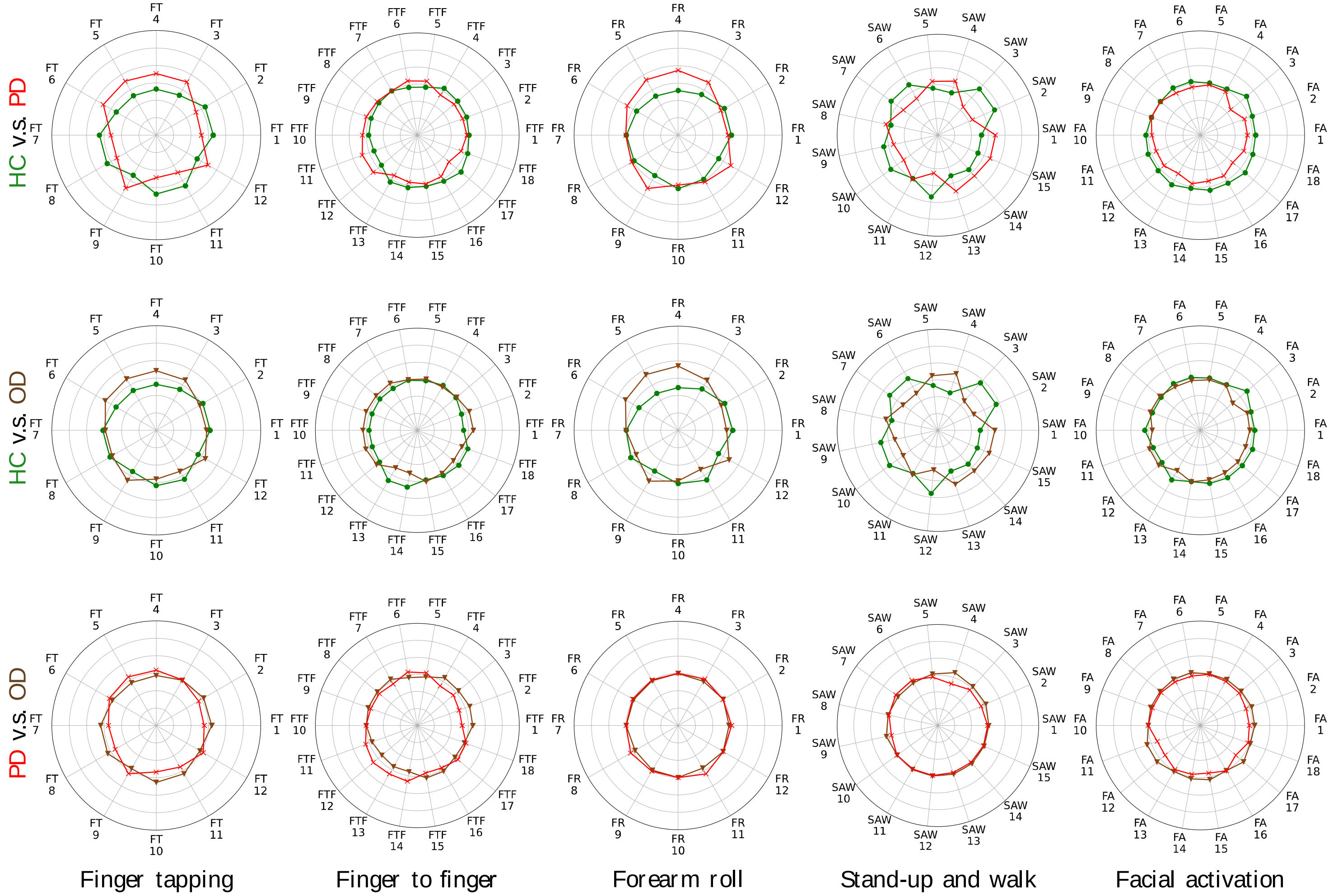


Overview of our Python open-source DNE solution and the proposed pyDNE toolbox.

Individual DNE Biomarkers Analysis

We provide a *qualitative assessment* comparing the *discrimination* of DNE biomarkers across three groups of subjects:





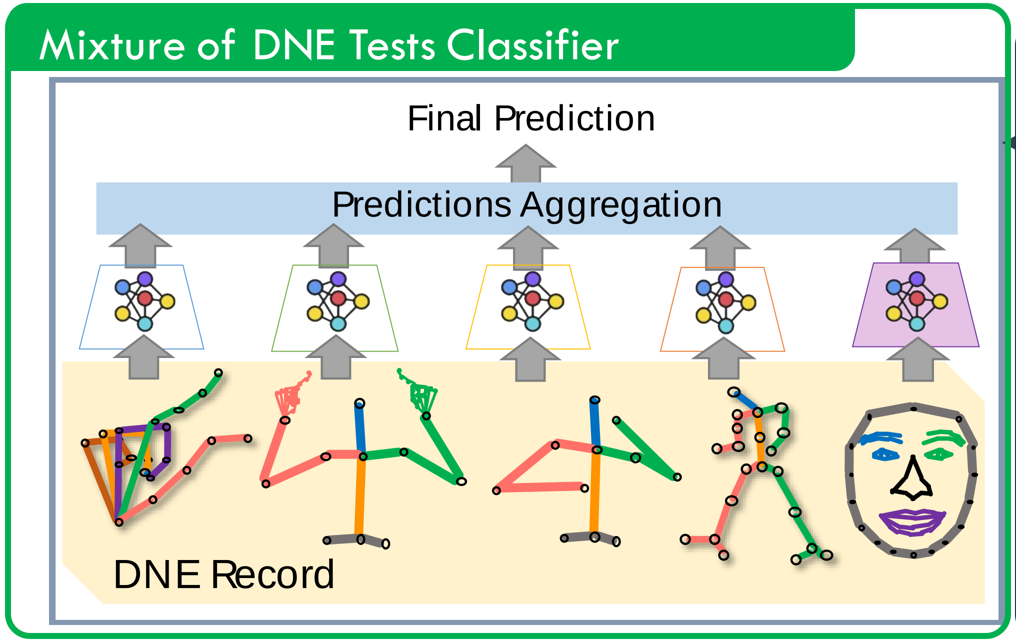
A clear differentiation is observed on DNE biomarkers captured between healthy control (HC) and patients with Parkinson's Disease (PD) or other neurological disorders (OD)

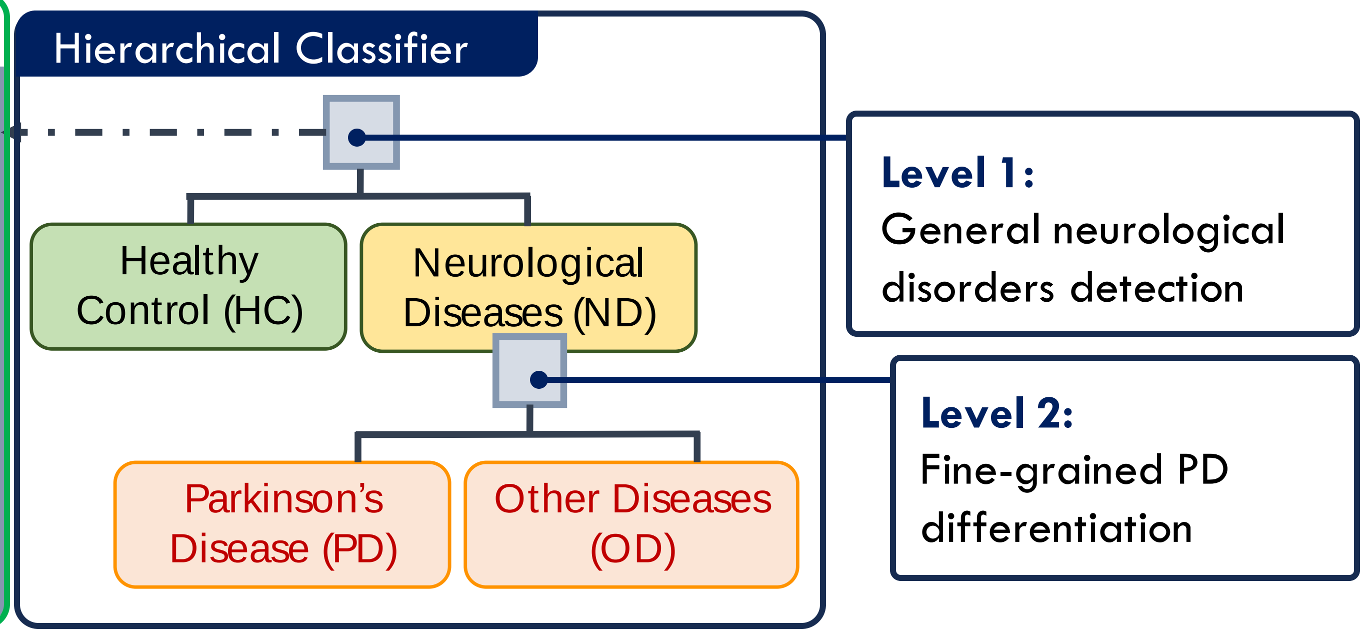
(—●—) Healthy Control (HC) | (—×—) Parkinson's Disease (PD) | (—▼—) Other Diseases (OD)

Combining DNE Biomarkers for Classification Tasks

Settings: DNE biomarkers can be used for classification with various machine learning models.

- *Mixture of DNE tests classifier:* combining information from multiple DNE tests
- *Hierarchical classifier:* utilizing *the* hierarchy of categories in DNE-113 dataset





- The *mixture of DNE* tests classifier aggregates the prediction results from multiple base estimators, each trained separately for classifying a single DNE test
- The categories in DNE-113 can be structured hierarchically

: Binary classifier

Multi-class classification on DNE-113

Confusion Matrix: the best model on the three-class (HC, PD, and OD) classification problem

True label

	HC	PD	OD
HC	0.79	0.00	0.21
PD	0.11	0.40	0.49
OD	0.29	0.16	0.56

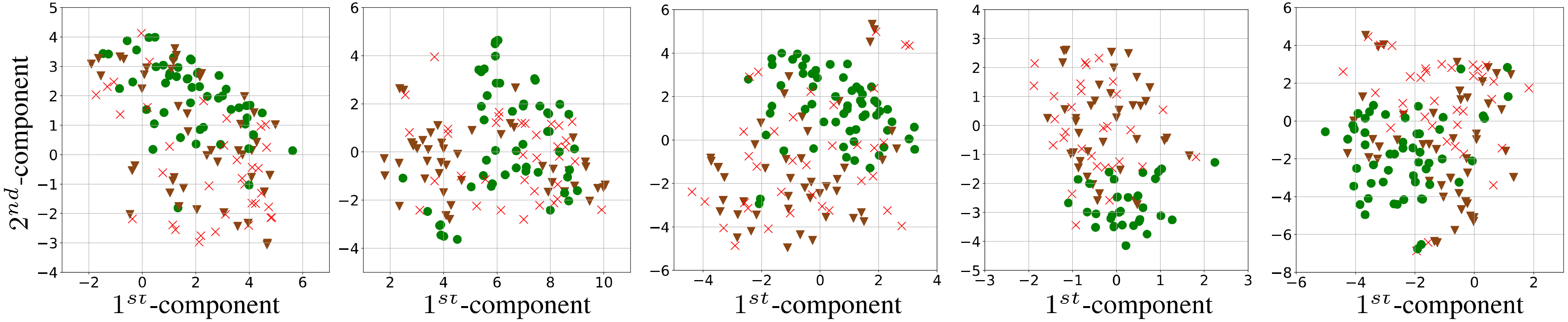
	HC	PD	OD
HC	0.57	0.25	0.19
PD	0.00	0.63	0.37
OD	0.09	0.20	0.72

	HC	PD	OD
HC	0.87	0.02	0.12
PD	0.31	0.20	0.49
OD	0.17	0.15	0.67

	HC	PD	OD
HC	0.78	0.12	0.09
PD	0.07	0.43	0.50
OD	0.13	0.33	0.54

	HC	PD	OD
HC	0.72	0.04	0.25
PD	0.09	0.46	0.46
OD	0.17	0.23	0.60

t-SNE Dimensionality Reduction: projection of concatenated DNE biomarkers on 5 neurological tests



Finger tapping | **Finger to finger** | **Forearm roll** | **Stand-up and walk** | **Facial activation**

(●) Healthy Control (HC) | (×) Parkinson's Disease (PD) | (▼) Other Diseases (OD)

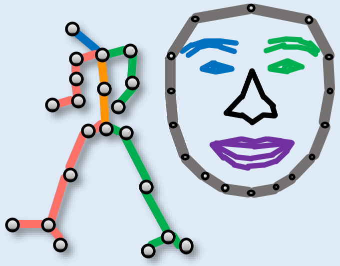
Conclusion – Digitized Neurological Examination (DNE)

- Aims:
  - Constructing a comprehensive *vision-based* (contactless) DNE solution
  - Providing a toolbox for neurological disorders *detection* and *documentation*
- Contributions:

Phase 1: A Comprehensive DNE Solution [IEEE-JBHI, 2022]

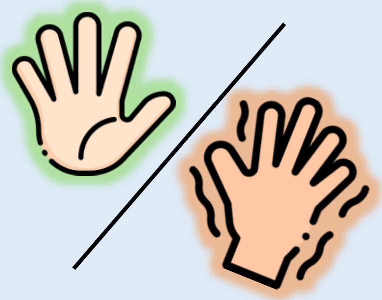
Smartphone-based DNE *recording*
Web-based app for *visualization*

DNE Platform



75 kinematic *digital biomarkers* representing 5 neurological tests

DNE Biomarkers



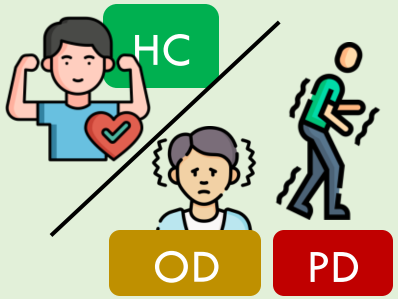
Normal/simulated impairment movements classification of 21 healthy-control (HC) subjects

HC Validation

Phase 2: Validation & Analysis [U/Review, 2024]

Data collection on 92 *real-patients* with Parkinson's diseases (PD) or other neurological disorders (OD)

Real-patient Data Collection



Hierarchical *differentiation/ classification* between HC and OD/PD

DNE Biomarkers Validation

Phase 3:

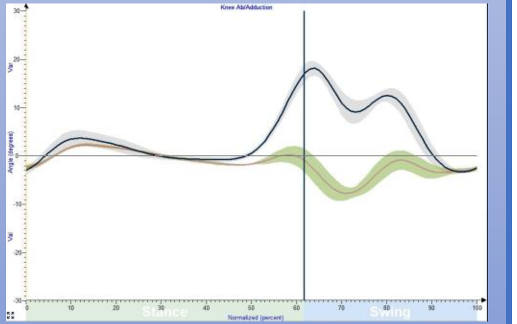
(Future work)

Neuromusculoskeletal Modeling via Digital Twin

Goal: Using optimization methods for predicting muscles activation for explaining observed motion and predicting motion in unseen scenarios.

Observing human motion

Motion Kinematic & Dynamic



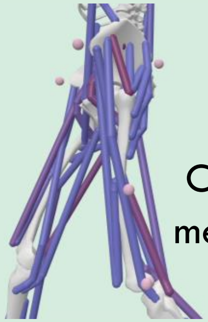
Inverse Dynamic

Forward Dynamic

Computational Framework

Explaining human motion

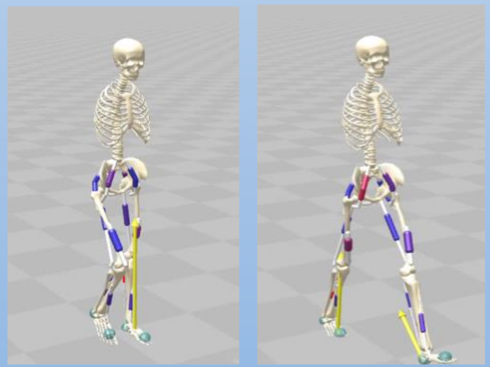
Muscle Activation Estimation



Computational method for measuring individual muscle force generation

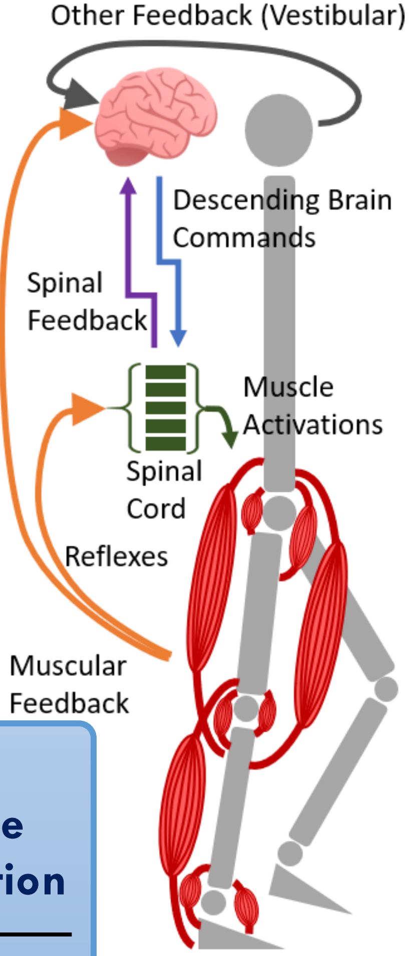
Initial Control

Predicting human motion

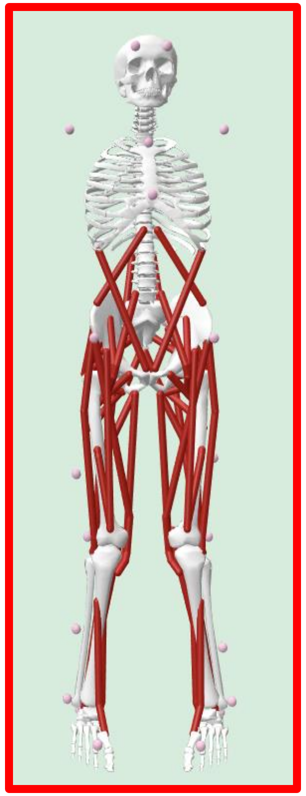


Answering the "what-if" question

Predicting possible clinical outcomes



Example Recording

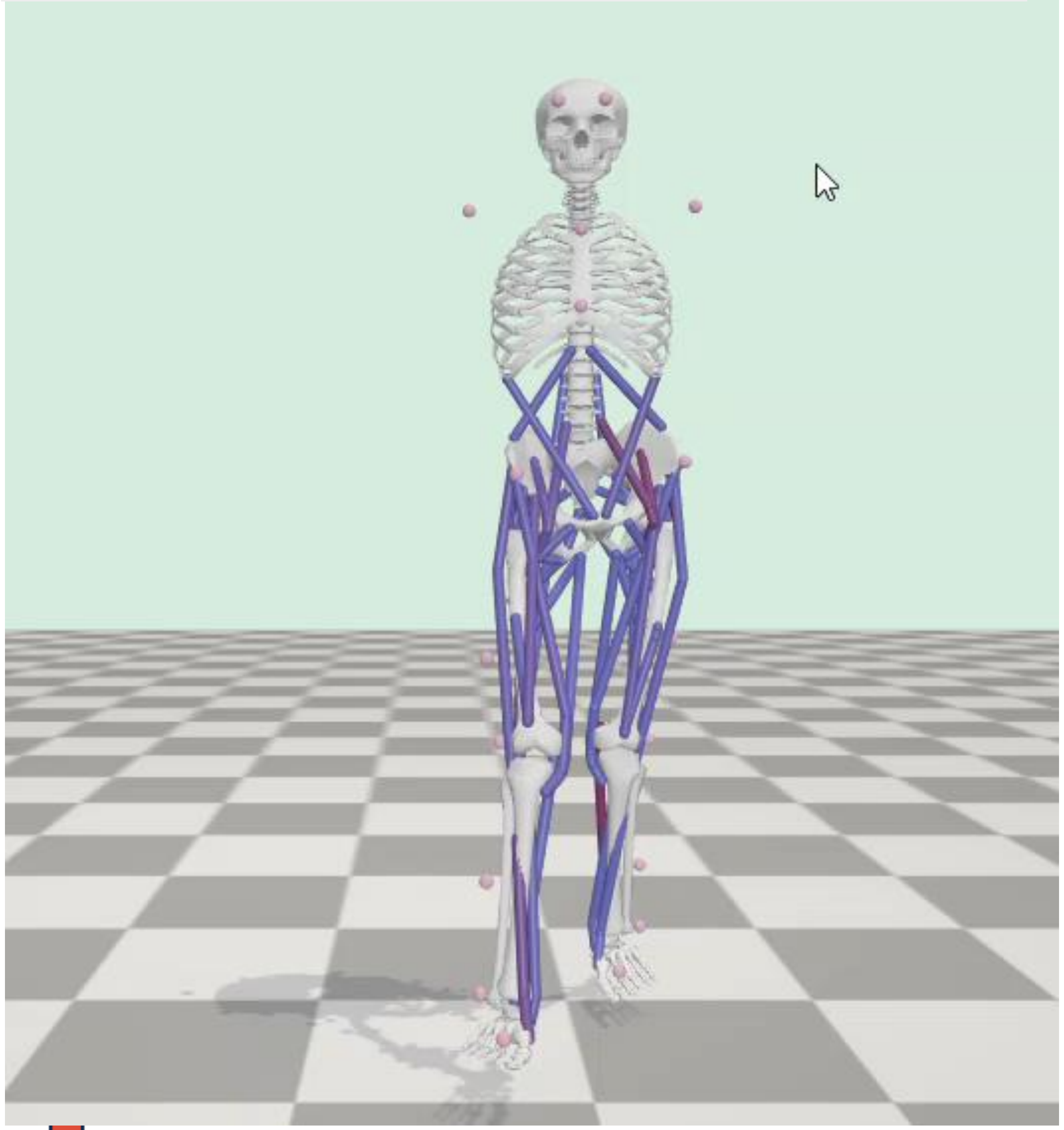


A patient-specific 3D-model with the knee valgus

A recording of one subject with abnormal knee valgus at VinMec Motion Analysis Laboratory on June 2nd, 2023

Estimate Muscle Control from Observed Motion

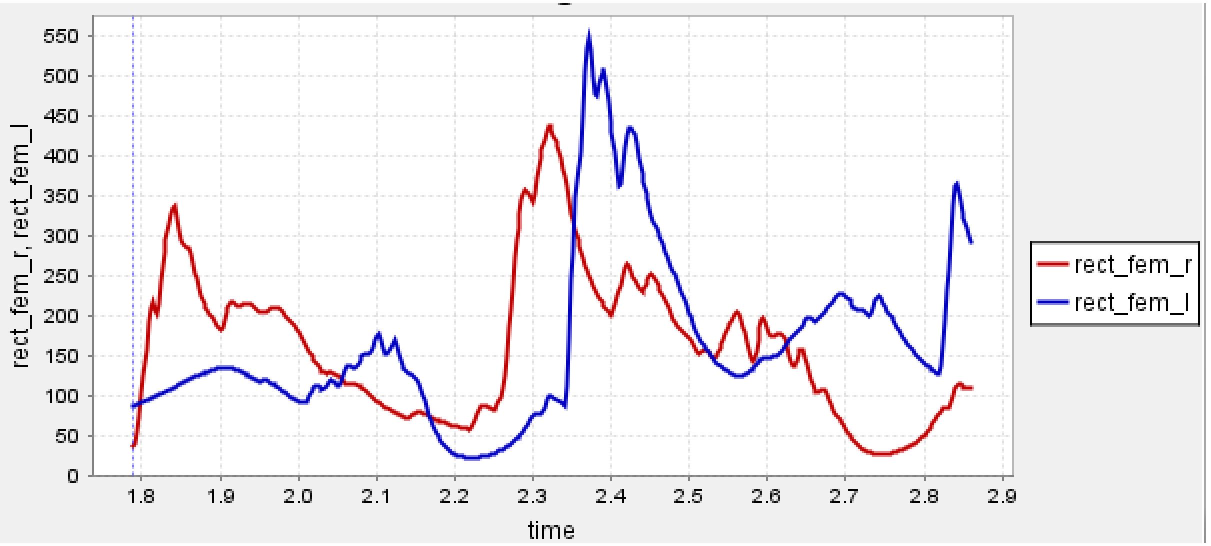
Frontal view of the video in the previous slide



To compensate for the abnormal anatomical structure (knee valgus):

→ the neural control of this subject was **activated asymmetrically** (e.g., one side was activated more than the other)

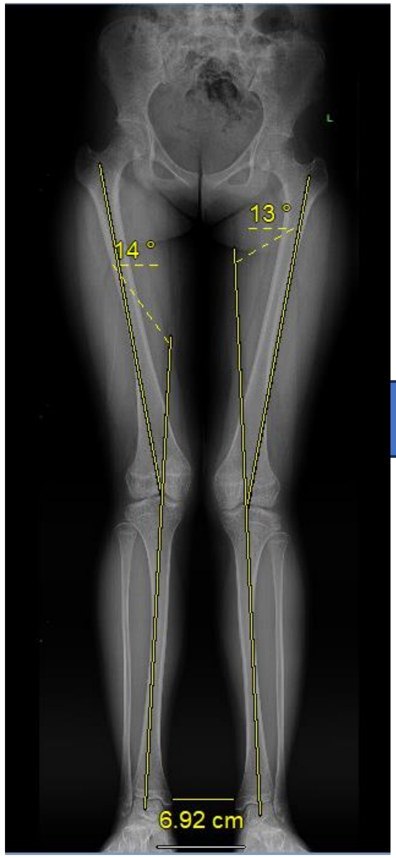
→ even with abnormal legs, the gait of this subject remains highly balanced as observed in the experimental data (looking at the shoulder key-points)



Estimated force generated by the rectus femoris muscle on the left (rect_fem_l) and right (rect_fem_r) leg. The magnitude of the peak force generated by the left leg is larger.

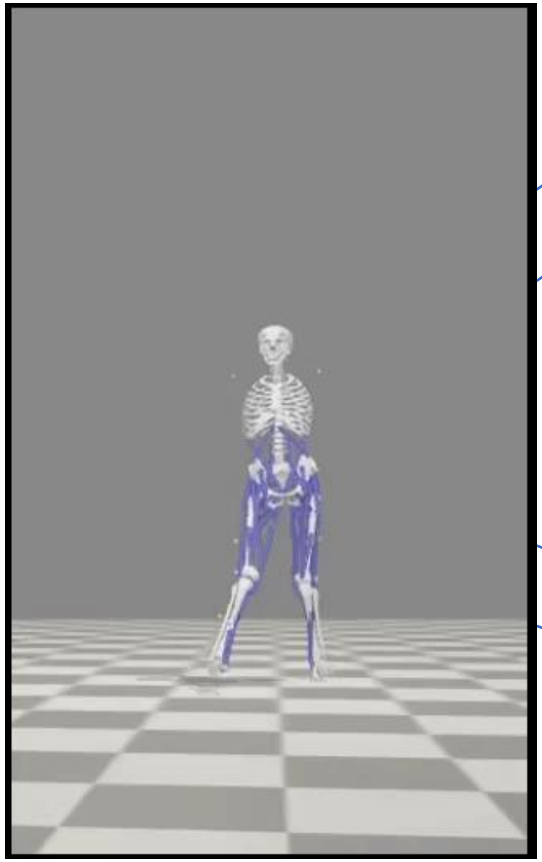
Subject-Specific Musculoskeletal Models from CT Scans

CT Scan



Motion data

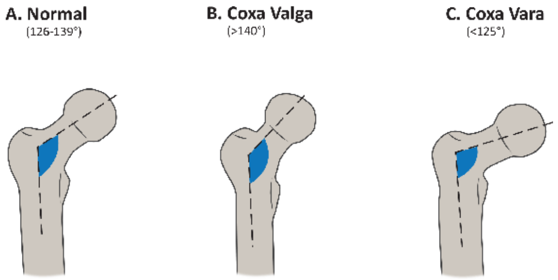
OpenSim Simulation/ Prediction



Short Hamstring

OR

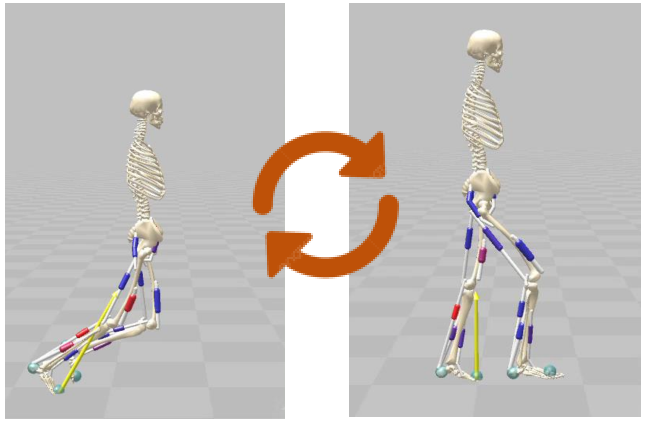
Abnormal Femur



Computational Methods for Modeling & Analyzing Human Motion

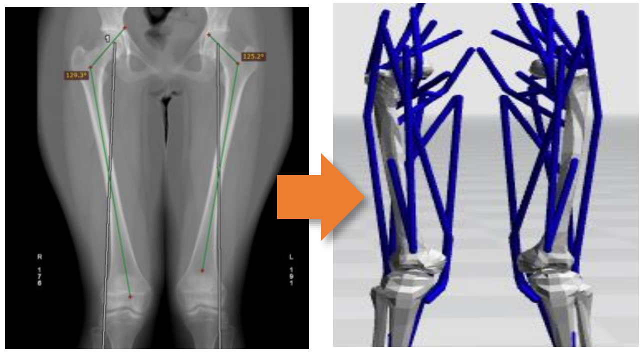
Toward a comprehensive computational methods for modeling and analyzing human motion

Computational Approach for Muscle Control Estimation and Simulation

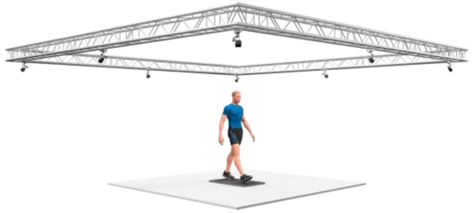


Step 0 → Step 700

AI Toolbox for Automated Patient's Digital Twin Construction

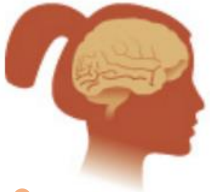


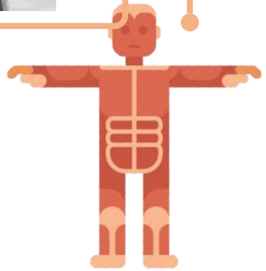
Machine Learning/Signal Processing for Time-series Data Analysis

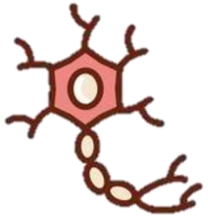


Motion Kinematic & Dynamic Results

Smartphone-based Motion Analysis







Initial Control → **Neural Command** (Controllers) → **Muscoloskeletal System** (Actuators) → **Sensory Processing** (Measurements)

Biofeedback (Controller feedbacks)