Breakout Session 7: Track B

WalkVIZ: Development of a Comprehensive Tool to Process and Visually Analyze Gait Data

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WalkVIZ: Development of a Comprehensive Tool to Process and Visually Analyze Gait Data




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Problem Statement

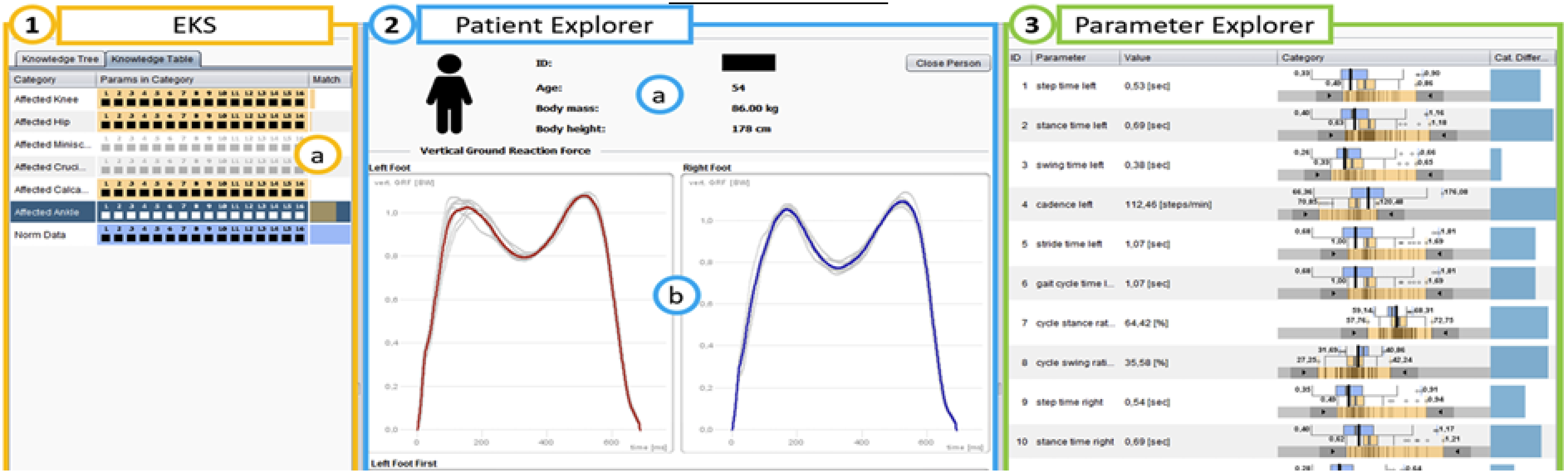
- Complexity in analyzing gait data.
- Diversity and integration of gait data collection tools.
- Multifaceted challenge in gait data analysis workflow.
- Step-time detection.
- Fall risk prediction.
- Lack of open-access Tools.
- User interface and usability challenges.

Summary of project

- **Aim 1:** To create a common metadata schema through datawrangling and harmonization capabilities following FAIR data principles (findability, accessibility, interoperability and reusability).
- **Aim 2:** To leverage harmonized data sets from Aim 1 to create scientific workflows for biomechanical data utilization (GaitVis library), which would include data visualization, and cleaning and analysis functionalities to enable future AI/ML researchers access to this data through a centralized website (Walkviz).
- **Aim 3:** To demonstrate an initial use case of the transformed data to develop an AI/ML fall risk predictive model for people with chronic stroke (PwCS) using the transformed and corrected data along with clinical measures.

Related Work and Challenges

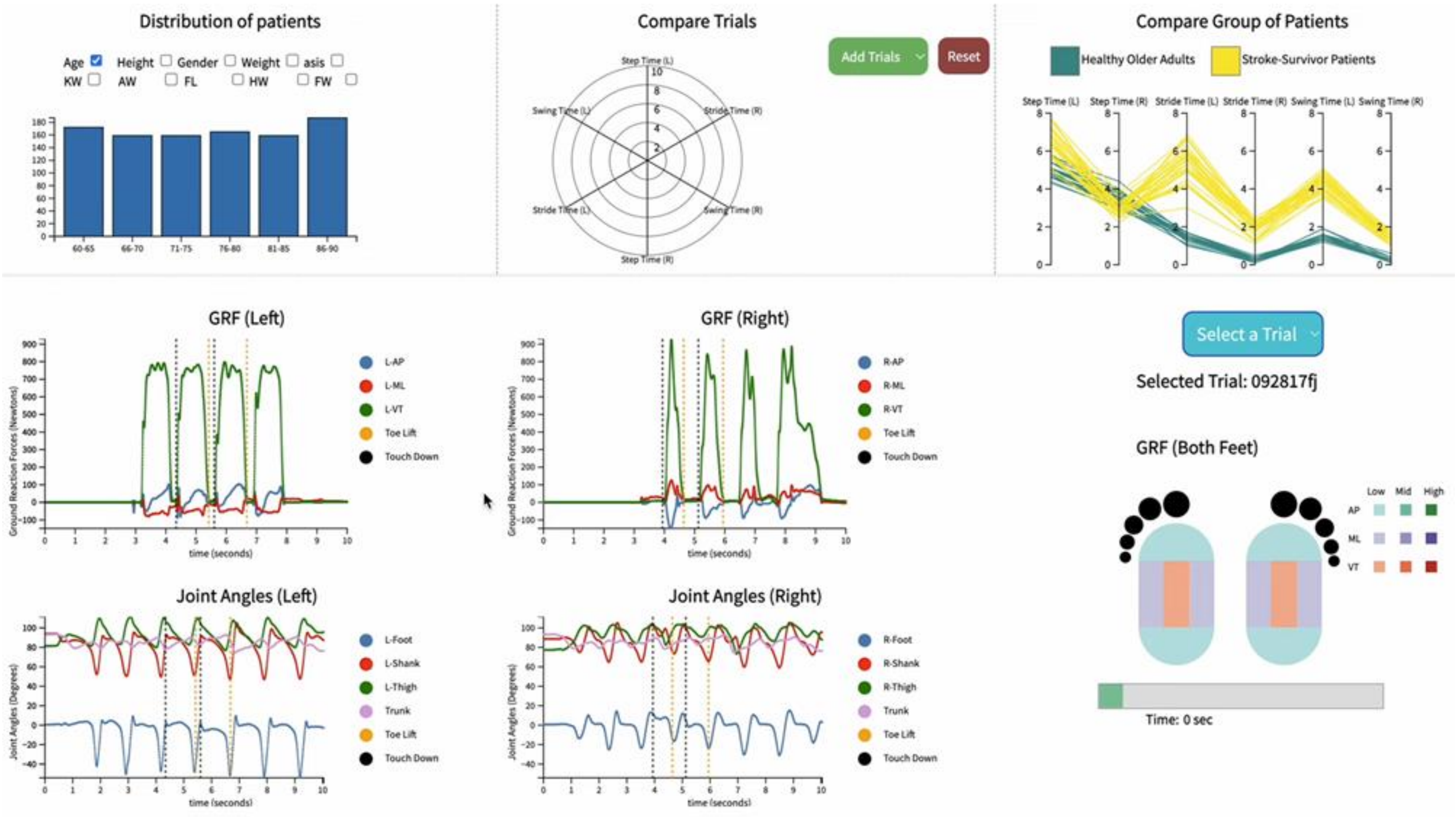
KAVAGait



- Kinematic and kinetic data can be collected with different methods and saved in different formats based on third party instrumentation and software. Computational expertise and programming skills would be required to import these data for AI/ML model development.
- Data loss is a common issue for motion capture systems, especially wireless systems, which could greatly affect the performance of AI/ML models.
- Step time detection is time consuming, especially for perturbed walking trials.

Wagner, Markus, et al. "KAVAGait: Knowledge-assisted visual analytics for clinical gait analysis." *IEEE transactions on visualization and computer graphics* 25.3 (2018): 1528-1542.

Initial Prototype



Survey

Survey Question (Q)	Responses	Requirements
Q1: What target population do you collect data from?	• Healthy older adults (68.2%) • Stroke patients (54.5%) • Cognitive impaired patients (36.4%) • Healthy young adults (31.8%)	• Organize patient data in groups.
Q2: What is the primary goal of your data collection?	• Understand biomechanics of gait (65.2%). • Develop rehabilitation strategies (60.9%). • Compare gait features between trials/patients (52.2%). • Predict future injury or fall risk (47.8%). • Monitoring disease progression over time (39.1%). • Finding gait anomalies in a trial (30.4%).	• Analyze rehabilitation/disease progression of patients. • Compare different groups of gait trials. • Predict fall risk using gait features • Analyze artifacts/outliers in the data.
Q3: What type of gait data do you typically work with?	• Spatiotemporal parameters (85%). • 3D marker trajectories (45%). • Ground reaction forces (40%). • Electromyography (40%). • Joint segment angles (35%).	• Analyze different gait characteristics of patients.
Q4: What are the formats of data you collect?	• CSV (73.7%). • MAT (42.1%). • DAT (31.6%). • TXT (31.6%).	• Compatibility with multiple data formats.

Requirement Analysis

- Compatibility with multiple data formats.
- Organize and access patient data in groups.
- Facilitate analysis of a subset of data.
- Data processing (gap filling, filtering).
- Analyze different gait characteristics of patients.
- Analyze statistical measures, artifacts/outliers in the data.
- Compare different groups of gait trials.
- Analyze rehabilitation/disease progression of patients.

Workflow

Computational Notebook

1

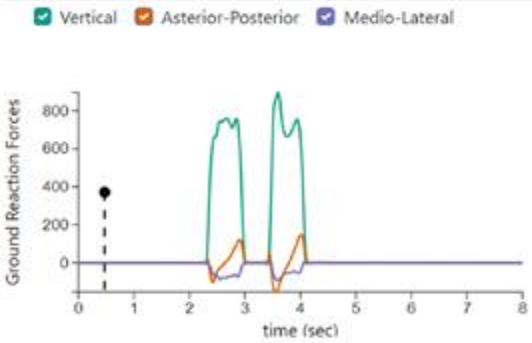
```
In [2]: df_raw_trajectory = c3dToCSV('data/input/022318xz0004.c3d')
        df_grf = pd.read_csv('data/input/022318xz0004.csv')

        df_raw_trajectory = impute_missing_values(df_raw_trajectory)
        df_grf = impute_missing_values(df_grf)

        df_raw_trajectory = filter_noise(df_raw_trajectory, 'bandpass')
        df_grf = filter_noise(df_grf, 'bandpass')
```

2

```
In [5]: mark_step_times(df_grf)
```



3

```
In [3]: df_angle = motionToJointAngle(df)
        df_moment = computeJointMoment(df_angle, df_grf)
        df_spatiotemporal = extractSpatiotemporal(df_grf)
```

4

```
In [4]: df_angle = normalizeByGaitCycle(df_angle)
```

5

```
In [11]: predictFallRisk(df_raw_trajectory, df_angle, df_grf)
Out[11]: '70%'
```

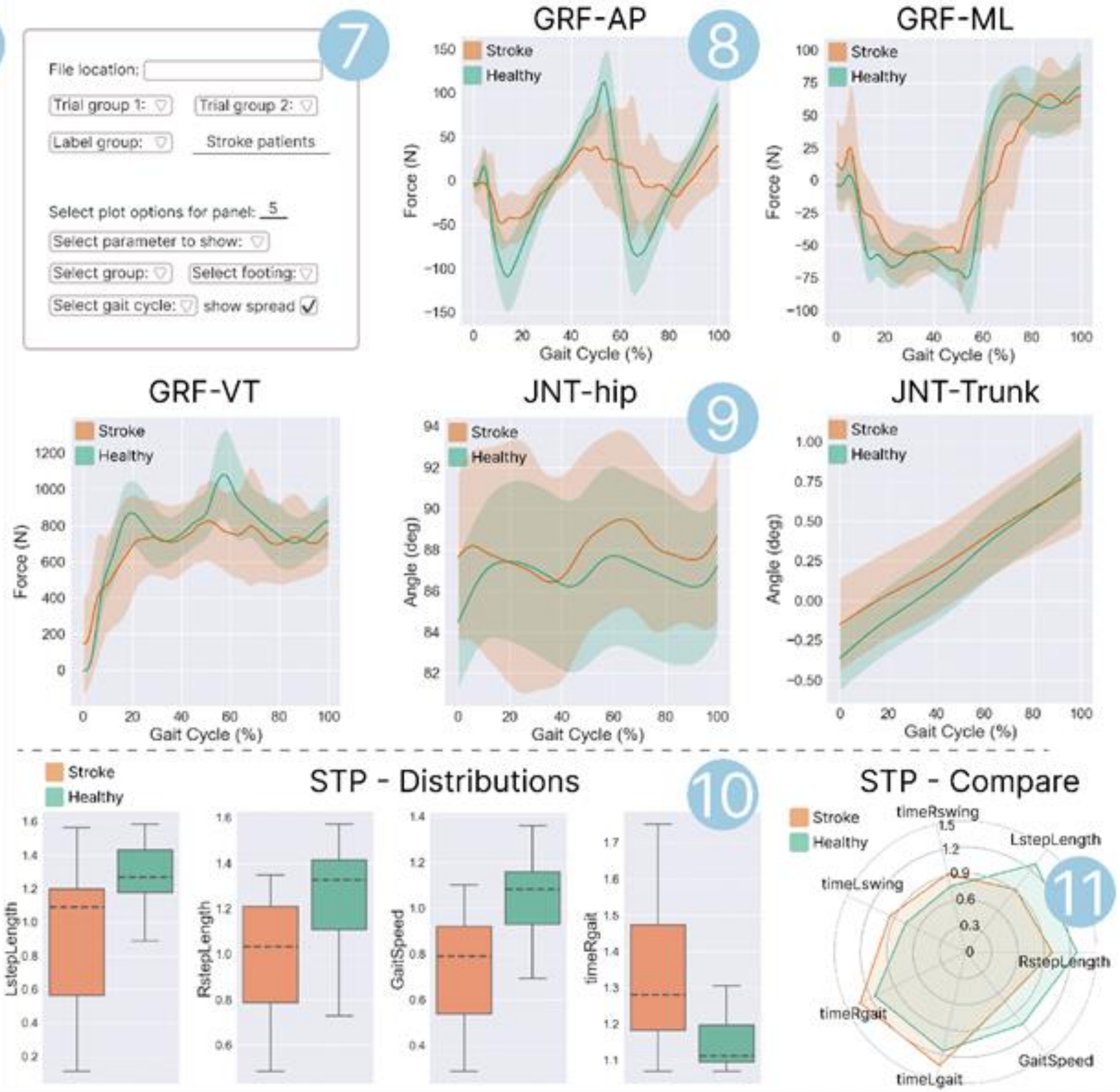
6

```
In [6]: createPatientGroup('Healthy Adults')

        patient_id = '022318'
        trial_id = '022318xz0004'

        upload_data('Healthy Adults', patient_id, trial_id)
```

Visualization Portal



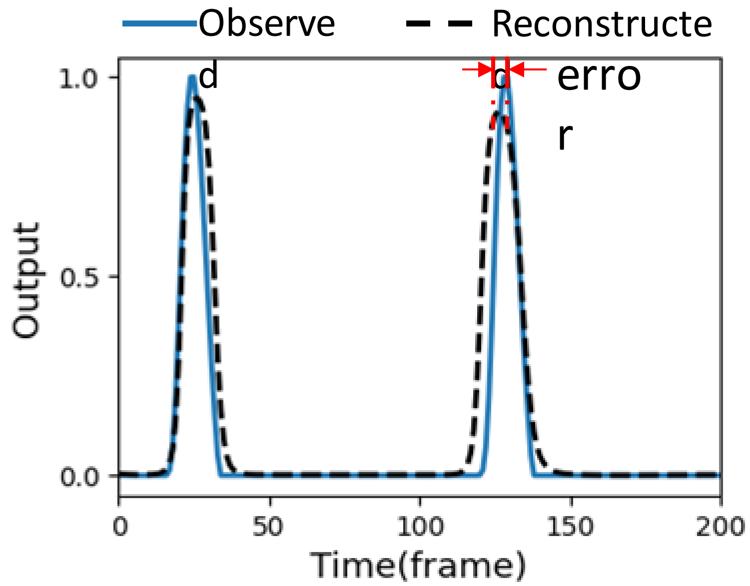
Step-time automatic detection method

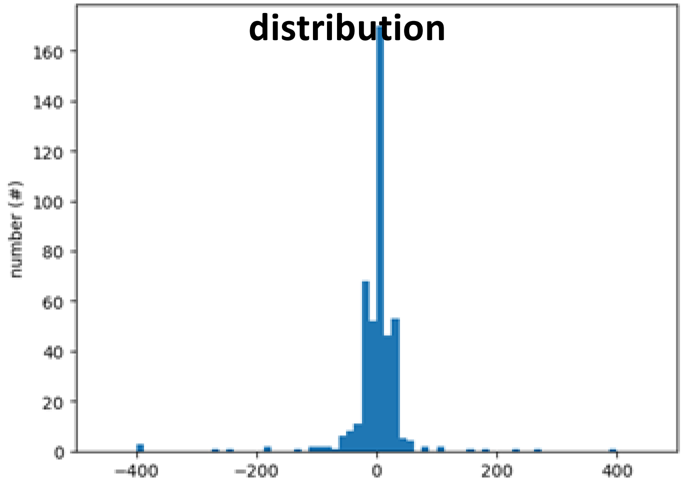
inputs → **outputs**

Lower limb angles → **Well-Trained models** → **Reconstruct Gait event curves** → **Peaks detection** → **Step times**

Bidirectional GRU
Bidirectional GRU
Batch Normalization
Dropout 10%
Dense

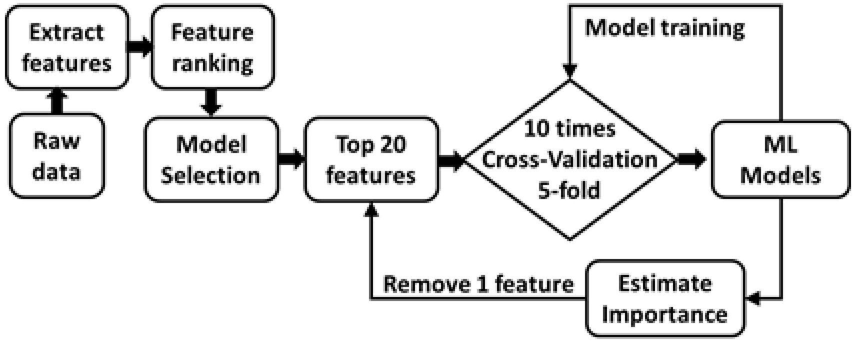
Model architecture





Model	Mean error (ms)	Error SD (ms)	% of error <50ms	% of error <30ms
Angle-model	16.76	84.52	96.6%	93.2%

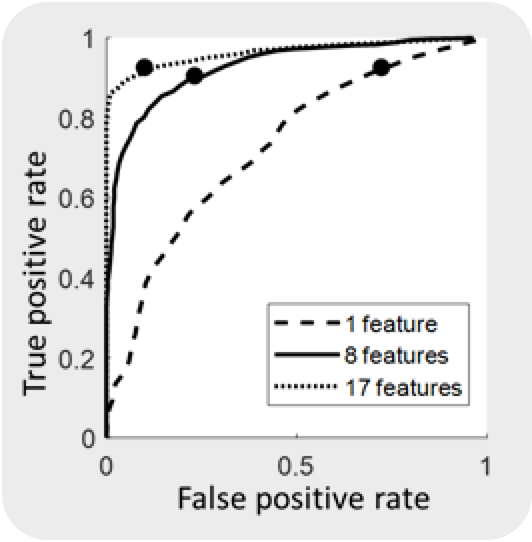
Fall-risk prediction models



Flow chart of model training

Include gait features

Feature #	New Feature
1	COM velocity at LO
2	L hip angle at Post-TD
3	Gait speed in gait cycle
4	Max knee flexion in swing phase
5	R foot angle at Post-TD
6	L knee angle at Post-TD
7	Toe clearance
8	Max trunk flexion in gait cycle
9	COM velocity at pre-TD
10	R hip angle at Post-TD
11	Trunk angle at Post-TD
12	Max Hip flexion in swing phase
13	R knee angle at Post-TD
14	L hip angle at LO
15	Max Gait speed in gait cycle
16	R knee angle at LO
17	L foot angle at TD



ROC curve for fall-risk prediction models (Acc > 80%)

Your
Trip-fall-risk is 15%
Slip-fall-risk is 75%

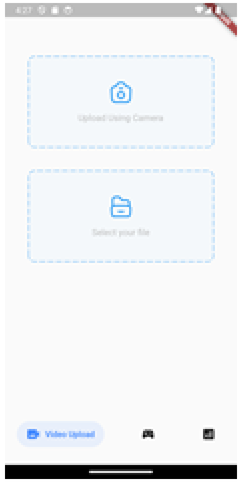
Outcome example

Validation of fall-risk model using video-based

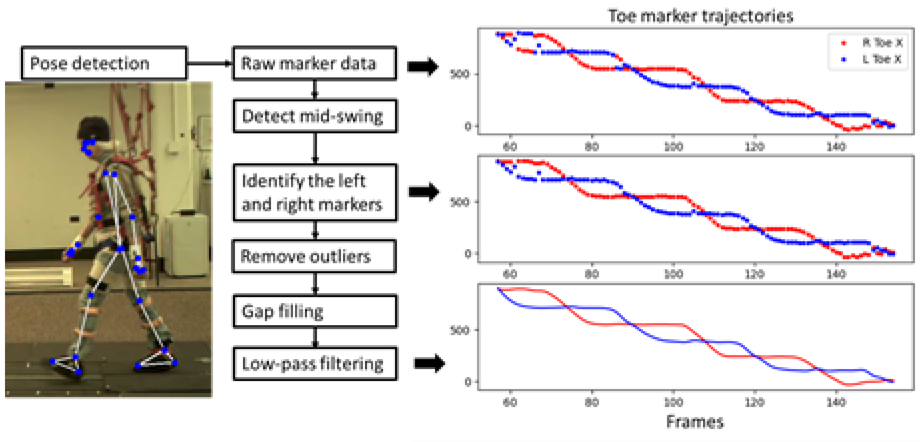
inputs

Gait video → **Marker coordinates** → **Post processing** → **Well-Trained Fall-risk models** → **Estimated fall risk**

outputs

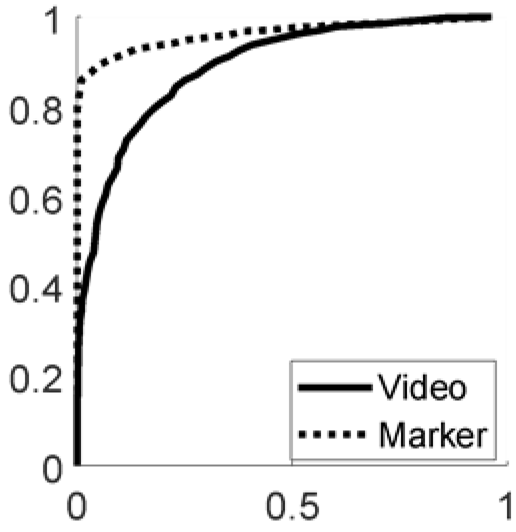


FRATS
UI



motion
detection

data post-
processing



Comparison of ROC curves between video-based gait features and marker-based gait features. The accuracy reduced by ~10%.

Future Work

- Perform comprehensive user studies across different research labs and clinical settings.
- Support comparison of more than two patient groups.
- Include additional statistical tests (ie., ANOVA, chi-square) to the comparison results.
- Include demographics and clinical measures to further improve the prediction accuracy of fall-risk.
- Add video-based gait data to the current training dataset to enhance the model.

Highlights of the Ongoing Work

- Omar et al. “eMoGis: Enabling Motion and Gait Visual Analytics with the Support of Exploratory Notebooks and Multivariate Data Analysis.” *Computer Graphics Forum* (**Under review**)
- Wang et al. “Automatic Step Time Detection In Older Adults During Perturbed Walking.” ASB 2024 Meeting Registration (**Accepted**)
- Wang, S., Nguyen, T. K., & Bhatt, T. (2023). Trip-related fall risk prediction based on gait pattern in healthy older adults: a machine-learning approach. Sensors, 23(12), 5536.
- Omar et al. “Comprehensive Requirement Analysis for Data Processing and Visual Analysis of Multivariate Gait Data” (In preparation)

Acknowledgements

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