

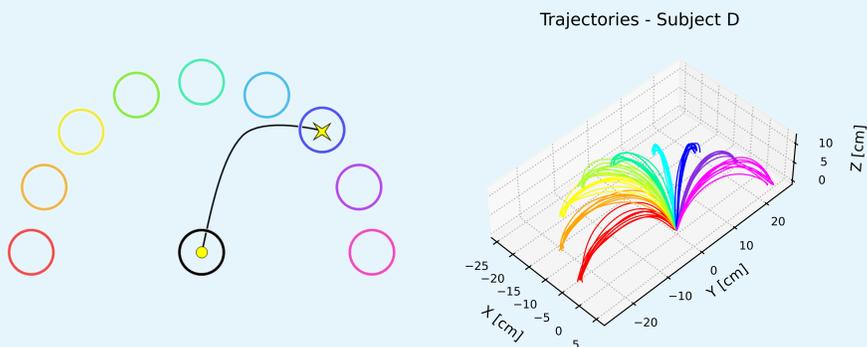
## Motivation

- Neurological conditions are a major source of disabilities, such as in movement disorders like Parkinson's disease
- Variability may serve as indicator for pathological movements (Stergiou and Decker, 2011)
- In the VAFES project (Virtual-Reality-based Machine Learning for Arm-Hand Function Evaluation and Support System), a portable glove to diagnose hand and arm dysfunctions is developed
- To achieve this goal, we need to develop a systematic understanding of the generation and variability of human upper-limb motion, and propose a transport trajectory model (Attractor Dynamics Approach, Rañó and Iossifidis, 2013)
- For this, trajectory data is captured by sensors which are to be embedded into the diagnosis system in a later step for clinical as well as ambulant pathological analysis

## Introduction

- Former studies of upper-limb transport motion mainly conducted under constrained settings (2D configurations)
- Moreover, no specific analysis of the variability of transport movement available
- The data (acceleration, velocity, position) will be needed for parameter fitting of nominal trajectories and variance in the dynamical systems model
- Requiring embedded applicability: high portability, fast setup, constrained physical dimensions, energy supply
  - Infrared/optical sensors would provide higher precision but require external reference
  - Networks of multiple IMUs not suitable when solely focusing on hand trajectories

## Experimental Setup



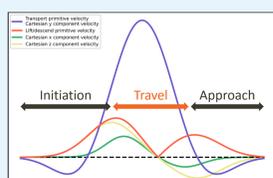
- Tasks:
  - Reaching tasks with targets at a distance of 25 cm aligned on a semicircle
  - Center of start circle positioned at 6 cm from edge of table
  - 9 tasks (to each target): task 1 to task 9 from left to right
  - 10 trials per task
  - Transported cylinder: diameter 5.0 cm and height 2.5 cm; weight 22 g
  - Docking start block to ensure fixed zero time coordinates
- Measurements:
  - Single wireless IMU sensor from state-of-the-art motion capture system at 100 Hz
  - So far: measurements with 5 participants (3 male, 2 female, age  $27.6 \pm 2.8$  years) without known movement disorders/impairments, to be continued
- Measurement session:
 

Target presentation	Variable time	Target reaching	Return to start position
1.5 seconds	1-2 seconds	3.5 seconds	3 seconds

  - Random delays introduced between visual target cue and acoustic start signal to avoid rhythmic movement patterns and timing effects (Tsunoda and Kakei, 2011)

## Data Processing

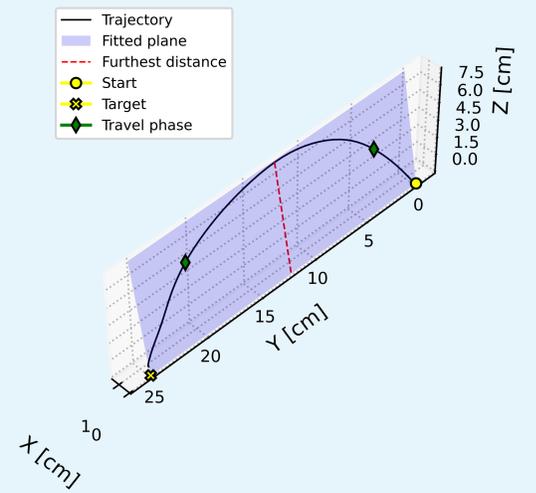
- General Pipeline:
  - Low-pass Butterworth filtering of accelerometer data
  - Drift correction: zero-velocity update (ZUPT)
  - Integration to obtain velocity and position data
  - Rotation to map the connection line between start and target onto the y-axis
- Decomposition (Grimme et al., 2012):
  - Transport primitive  $y(t)$
  - Lift/descend primitive  $\sqrt{x(t)^2 + z(t)^2}$
- Movement phases:
  - Initiation, travel, and approach phase
  - Transition at the lift/descend extrema



## Data Analysis

- Introduction of a neurologically inspired variability measure deduced from the finding of planarity of end-effector paths (Soechting and Terzuolo, 1987 and Grimme et al., 2012)
  - Angle of the plane that best describes the trajectory
  - Extent of deflection of the movement
- Derivation from measured trajectories
  - Plane fitting of the travel phase path
  - Furthest distance from the connection line between start and target position

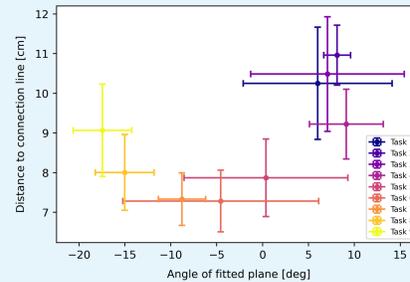
### Fitted Plane - Subject D Task 4 Trial 8



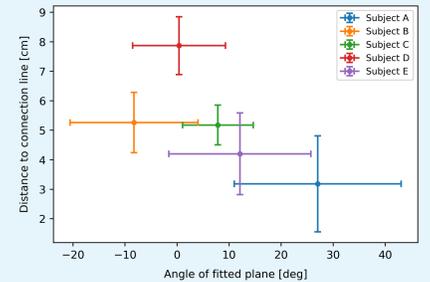
## Results

Left: Example course of angles and distances over different target directions for subject D. Right: Example of subject-specific differences of angles and distances for task 5.

Angle against furthest distance for each task - Subject D

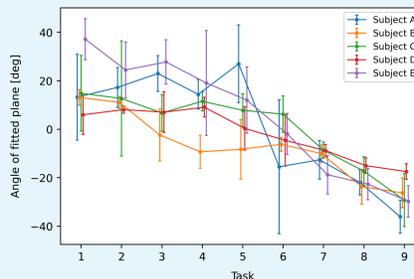


Angle against furthest distance - Task 5

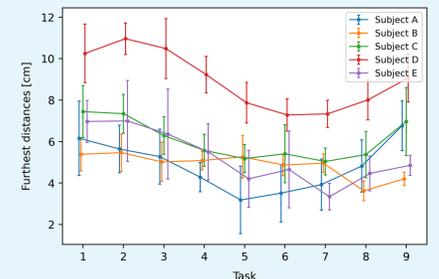


Complete comparison over all tasks and subjects for angles and distances separately:

Angles for each task and subject



Distances for each task and subject



## Literature

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## Acknowledgement

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