WASHINGTON STATE UNIVERSITY

St. Luke's Rehabilitation Institute
INLAND NORTHWEST HEALTH SERVICES

Quantitative Assessment of Lower Limb and Cane Movement with Wearable Inertial Sensors

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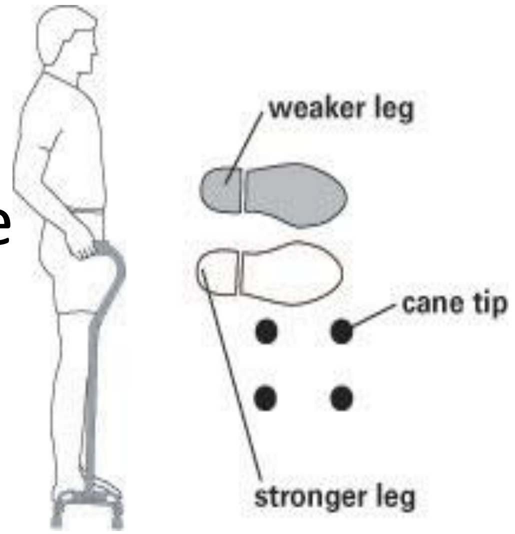
IEEE BHI 2016

Mobility Impairments

- Functional Independence
  - Age, injury, or disease-related impairments
- Assistive devices
  - Canes, walkers, and wheelchairs
  - Increase base of support

Assistive Devices: Canes

- 16% of adults 65 years and older use a cane
- Used incorrectly
  - 28% of cane users incorrectly hold the cane on their weak side
  - 11% occasionally swing the cane with the ipsilateral leg
  - 14% occasionally hold the cane in the air for multiple steps

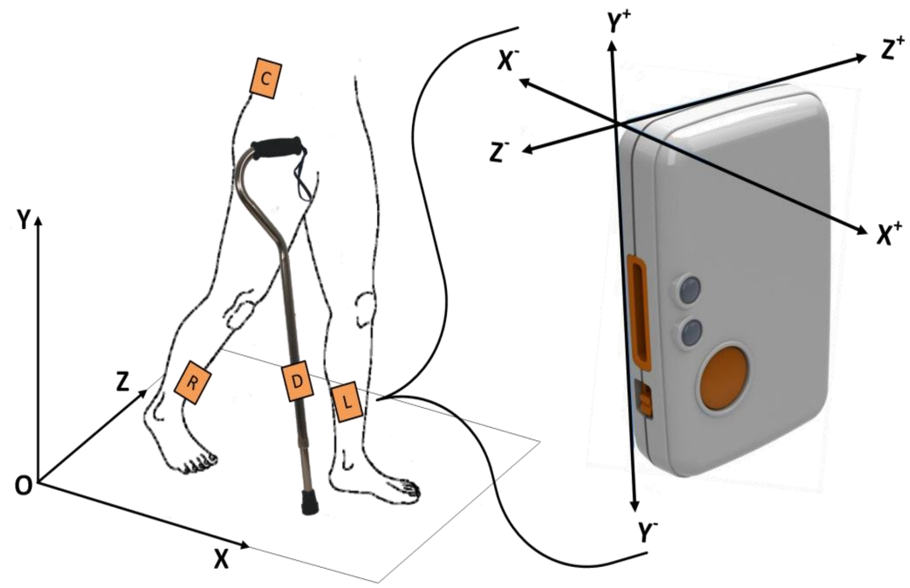


Assessing Physical Movement

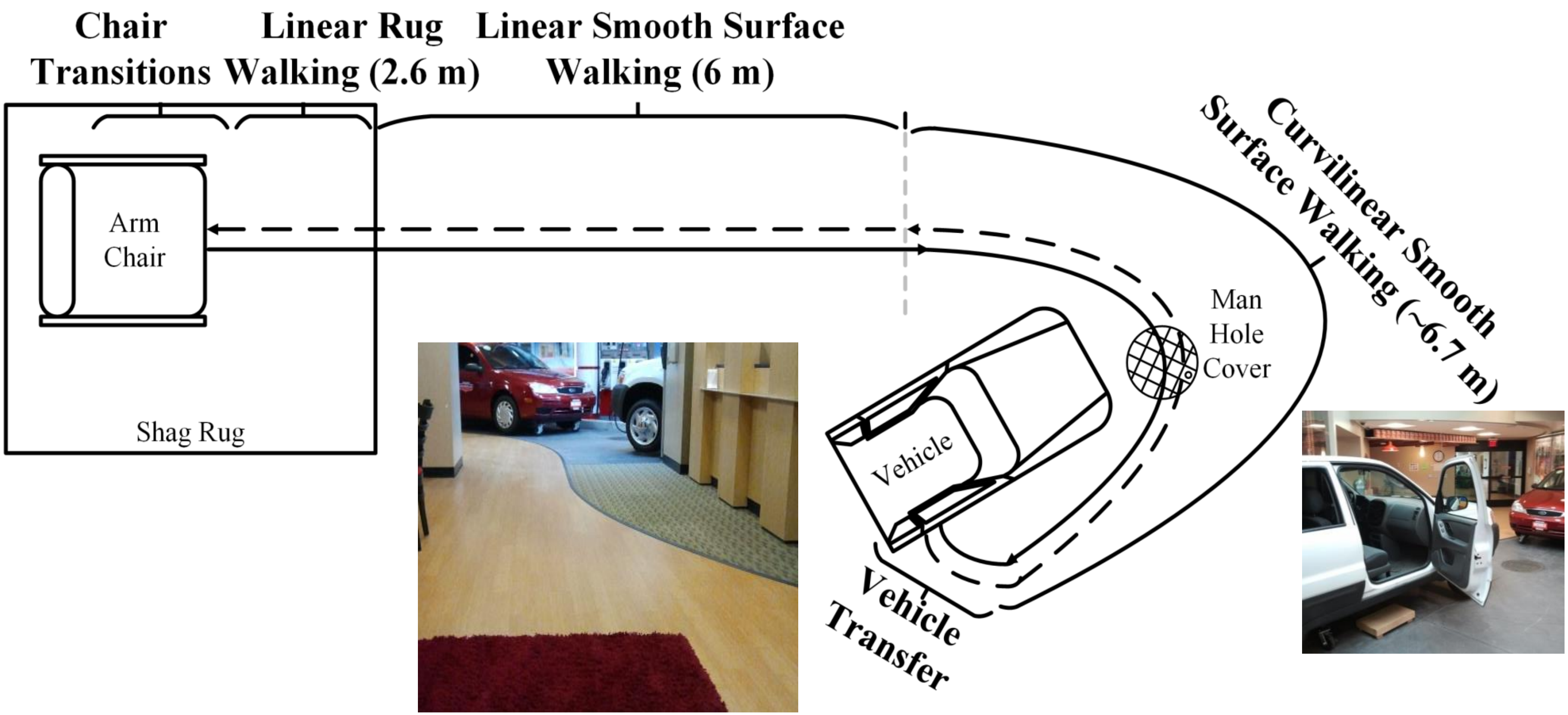
- Evaluation of motor recovery and physical movement
  - Observation
- Wearable technology for monitoring
  - Fine-grained, objective data
  - Portable, inexpensive, unobtrusive sensors
  - Usage information/insights for users, clinicians, caregivers

Study Design

- 4 Inertial measurement units
  - C: center of mass
  - L/R: left and right shank
  - D: assistive device (cane or walker)
- Ambulatory circuit (AC)
  - 2 Testing sessions (S1 and S2)
  - One week apart



Ambulatory Circuit (AC)



AC Study Participants

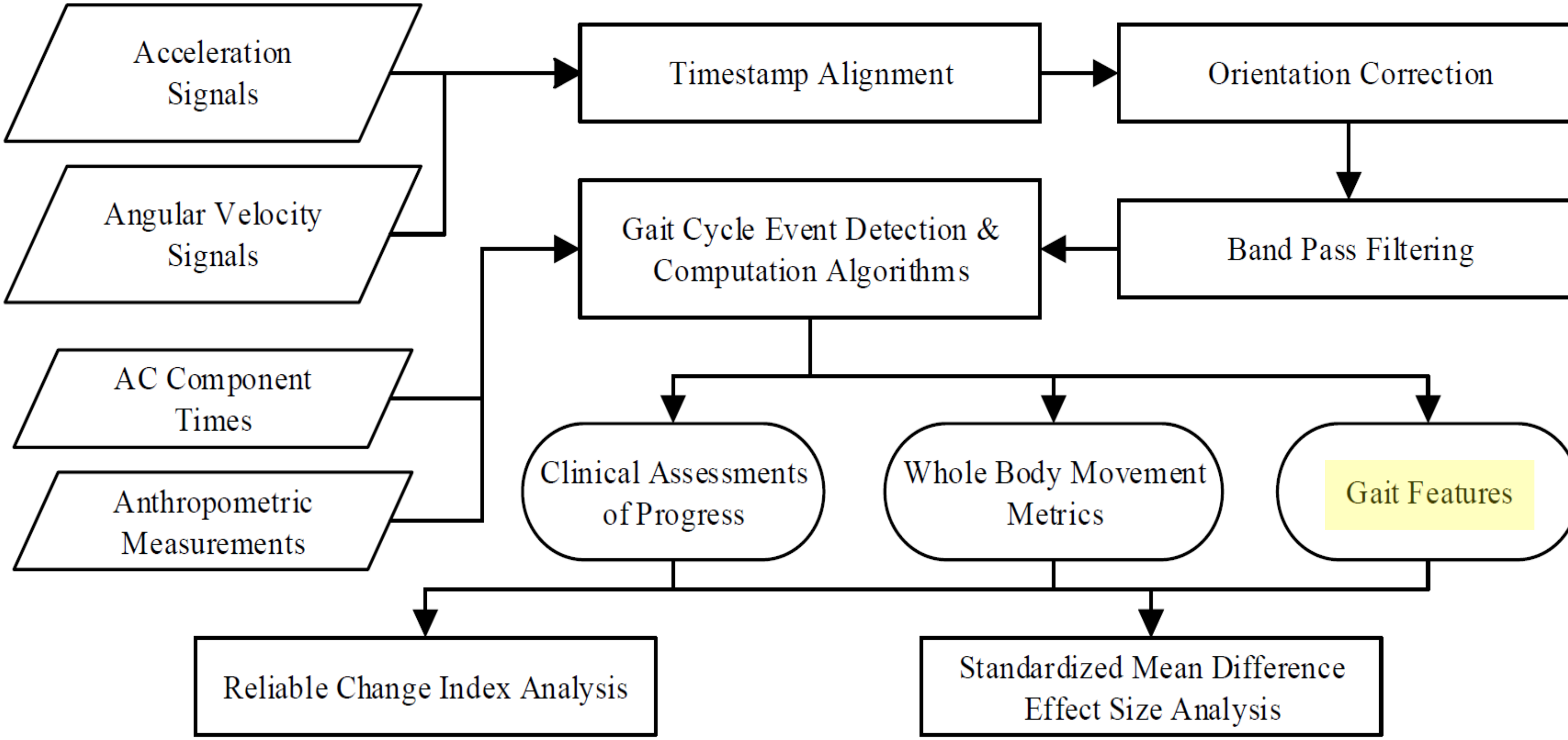
- N=35 to date, N=2 used cane at S1 and S2

TABLE I
PARTICIPANT CHARACTERISTICS

ID	Etiology	Sex	Age (years)	Device	Dominant Side	Affected Side	FIM_A	FIM_D
P1	Stroke	Male	85	Cane	Right	Left	87	113
P2	Stroke	Male	63	Cane	Right	No paresis	69	107

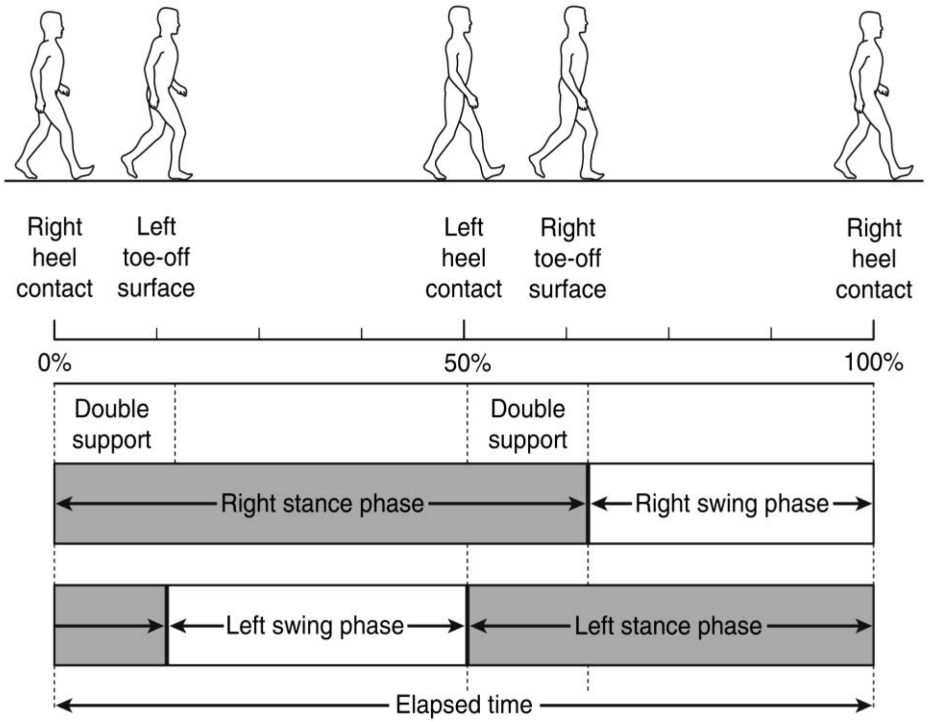
FIM_A = admission total FIM, FIM_D = discharge total FIM.

Data Processing



Gait Analysis

- Gait cycle events
  - Initial contact (IC)
  - Terminal contact (TC)
  - Mid-swing (MS)
- Support periods
  - Single (one limb)
  - Double (both limbs)
  - Triple (both limbs + cane)



Gait Cycle Event Detection

Algorithm 1 GaitCycleEventDetection($lead_Z$, $other_Z$, $cane_Z$)

```
Input: lead_Z, other_Z, cane_Z Gyroscope Z-axis signals
Output: IC, TC, MS event timestamp vectors for lead_Z, other_Z, cane_Z
Detect and store lead_Z IC, TC, MS events
Identify gait cycles based on lead_IC events
for each gait cycle do:
    Detect and store other_Z and cane_Z IC, TC, MS events
end foreach
Perform validity checks
return IC, TC, MS event timestamp vectors for lead_Z, other_Z, cane_Z
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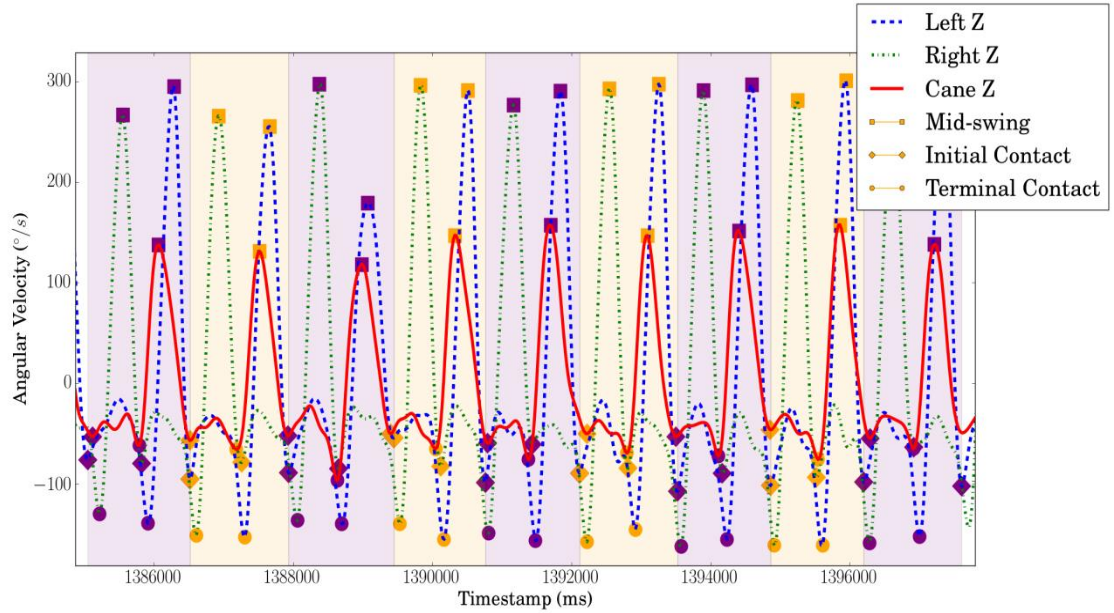


Participant P1's gait cycles

Gait Cycle Features

- Note: each trial t has N_t gait cycles
- For each gait cycle GC_i $(\mathrm{i} = 0; \mathrm{i} < N_t; i++)$:
  - Compute and store:
    - Cycle duration: $\mathrm{Lead\_IC_{i+1}} - \mathrm{Lead\_IC_i}$
    - Stance %
    - Mid-swing °/s
    - Cane stance percent ratio: $\frac{\mathrm{Contralateral\_Stance_i}}{\mathrm{Cane\_Stance_i}}$
    - Cane swing temporal offset: $|\mathrm{Cane\_MS_i} - \mathrm{Contralateral\_MS_i}|$
    - Double support %
    - Triple support %
- For each feature:
  - Compute mean and coefficient of variation for all N_t gait cycles

Gait Feature Results

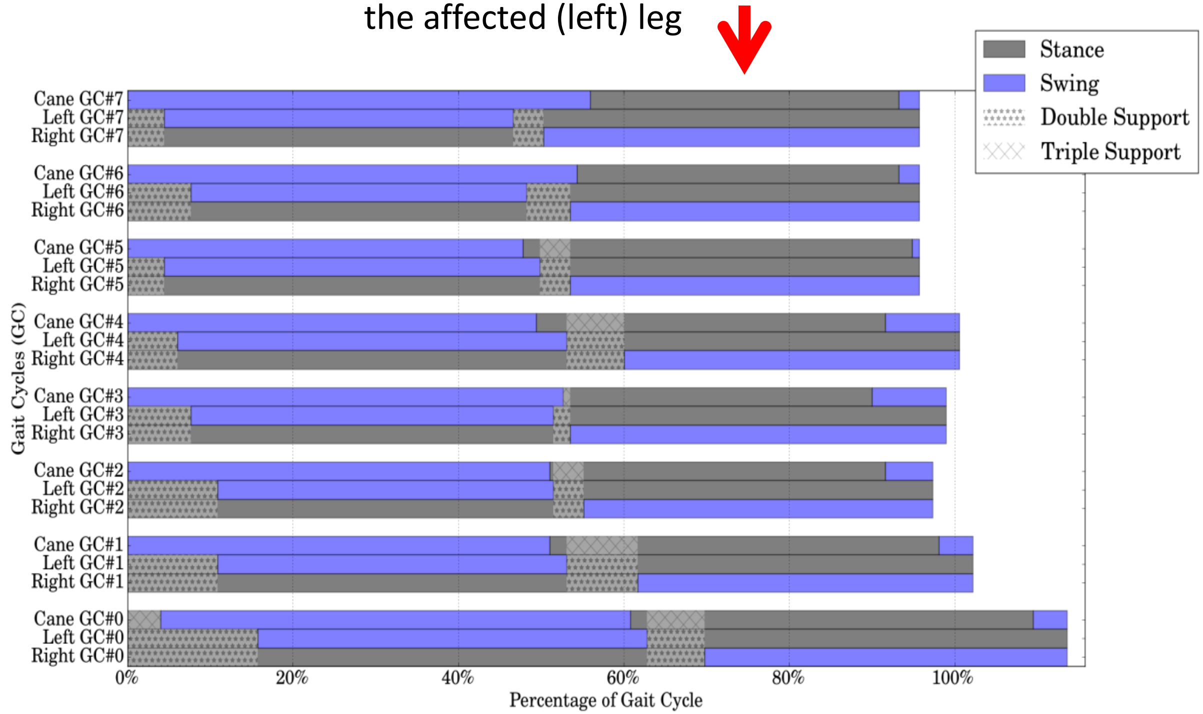
Metric	P1 μ_{S1} (P1 CV_{S1})	P1 μ_{S2} (P1 CV_{S2})	P1:	P2 μ_{S1} (P2 CV_{S1})	P2 μ_{S2} (P2 CV_{S2})
Number of cycles per trial	8, 7	8, 7	Fewer GCs	14,12	9,9
Cycle duration in milliseconds	1377.79 (4.04%)	1221.33 (5.18%)	Shorter GCs	1398.95 (5.29%)	1308.21 (7.68%)
Left stance %	57.67% (4.45%)	56.44% (3.73%)		63.08% (7.37%)	59.03% (4.53%)
Right stance %	58.82% (4.73%)	58.18% (5.34%)		58.82% (5.58%)	59.26% (6.41%)
Cane stance %	46.91% (6.11%)	43.60% (8.48%)		46.33% (23.04%)	40.26% (13.23%)
Left mid-swing °/s	282.86 (9.79%)	321.70 (14.71%)	Swings w/higher velocity	249.76 (18.74%)	292.47 (9.93%)
Right mid-swing °/s	286.91 (6.66%)	320.81 (7.53%)		240.43 (14.76%)	276.11 (12.51%)
Cane mid-swing °/s	140.88 (7.94%)	153.24 (13.19%)		58.45 (27.88%)	66.61 (26.38%)
Cane stance ratio	1.24 (7.26%)	1.30 (9.17%)	Lower variability	1.33 (22.88%)	1.49 (13.20%)
Cane swing offset	112.59 (39.43%)	164.21 (30.92%)		94.20 (103.72%)	110.90 (59.80%)
Double support %	16.49% (23.89%)	14.62% (29.08%)	Less time in support	21.90% (16.16%)	18.34% (30.07%)
Triple support %	6.50% (41.04%)	5.72% (74.28%)		7.99% (78.43%)	6.54% (87.39%)

CV = coefficient of variation, P1 = participant 1, P2 = participant 2, S1 = session 1, S2 = session 2, and μ = mean.

Stance and Swing Phase Plots

- Visualizes the variability of timing between both legs and a cane
- Stance (gray) and swing (blue) phases
- Y-axis groups sensor location
- X-axis shows an estimate of the percentage of the gait cycle
- Overlaid hatch are support periods of:
  - Double (star hatch)
  - Triple (cross hatch)

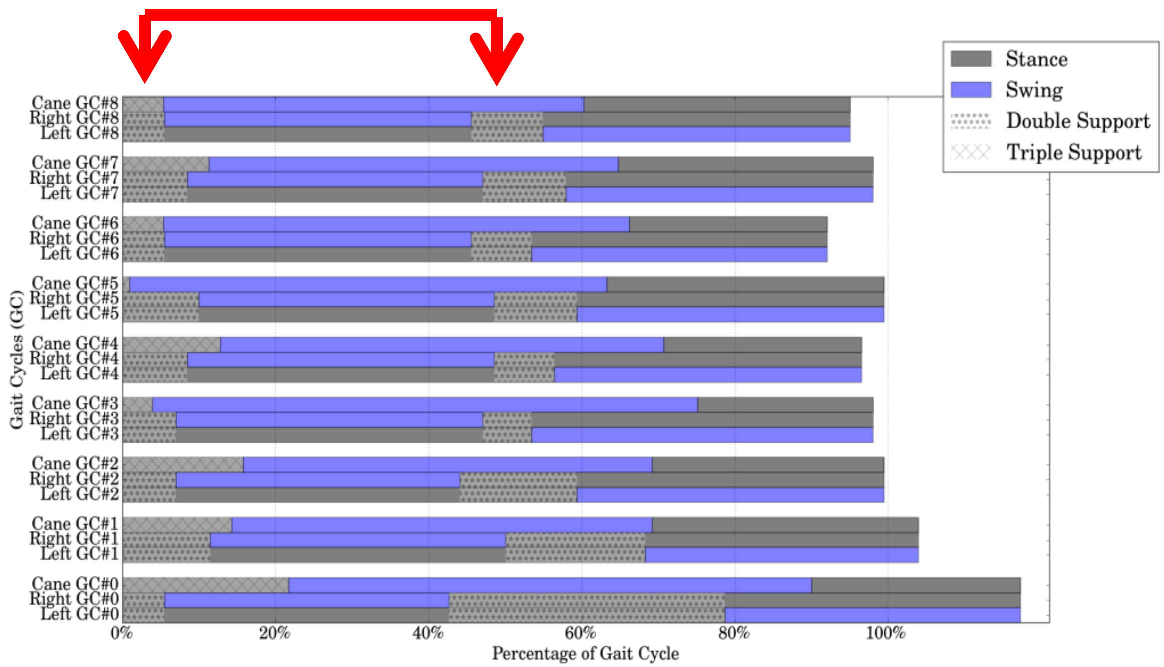
Cane correctly swings in phase with the affected (left) leg



Participant P1's S2 stance and swing phase plot

P2 Cane Movement

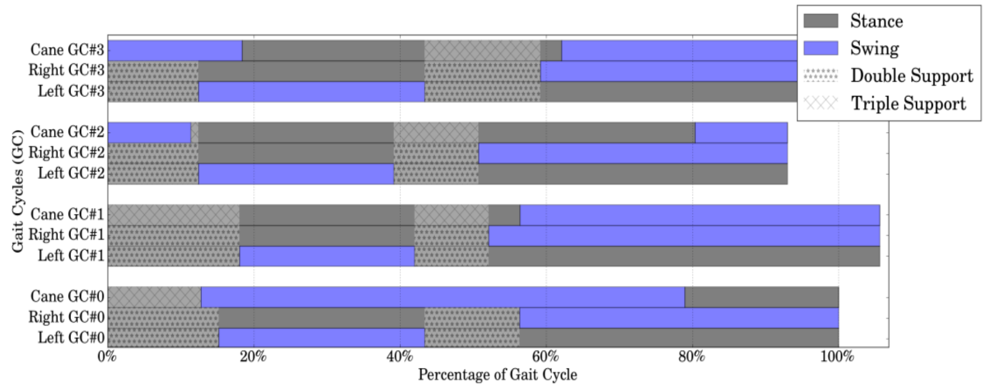
- More variable gait
- Only one period of triple support each cycle
  - Different behavior at S1 testing



Participant P2 (S2)

Detecting Incorrect Cane Usage

- Incorrect cane use [2]
  - Swinging the cane in phase with the ipsilateral leg (GC #0)
  - Holding the cane in the air for multiple steps
    - Missing cane IC within a gait cycle



Participant P2 (S1)

Closing Thoughts

- Limitations
  - Low sample size (N=2)
  - Gait cycle event detection algorithm has not been laboratory validated
- Future work
  - Collecting data from additional participants using different assistive devices
  - Designing a real-time system monitoring system

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- Images courtesy of:
  - St. Luke’s Rehabilitation Institute, Spokane, WA
  - http://www.upmc.com/patients-visitors/education/PublishingImages/P-S/QuadCane-1.jpg
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Thank You

- Questions?
- Contact information

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- Funded in part by National Science Foundation grant 0900781