WASHINGTON STATE UNIVERSITY

CASAS
Center for Advanced Studies in Adaptive Systems

St. Luke's Rehabilitation Institute
INLAND NORTHWEST HEALTH SERVICES

Designing Wearable Sensor-based Analytics for Quantitative Mobility Assessment

Gina Sprint, Diane Cook, and Doug Weeks

IEEE SmartComp Conference
5/19/16

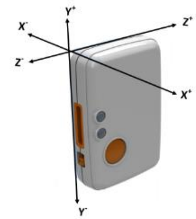
Mobility Monitoring

- Age, injury, or health-related impairments can decrease mobility
- Beneficial to monitor mobility
  - Insights into movement abilities
  - Longitudinal tracking
  - Motivation
- Technologies for mobility monitoring
  - Wearable sensors (acceleration, angular velocity, etc.)
  - Smartphone/tablet apps
  - Ambient sensors (motion, door, etc.)

Research Hypothesis

Wearable sensor data can be analyzed using machine learning techniques to provide insights on mobility changes related to rehabilitation

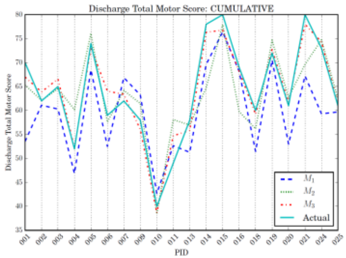
Collect Data



Data Analysis

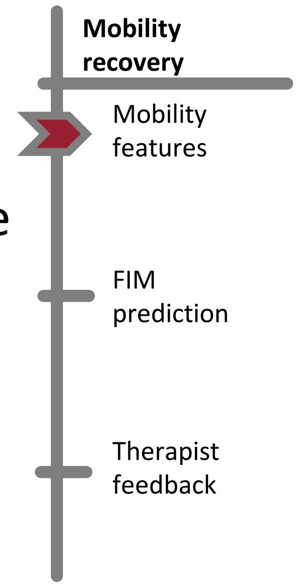
Timestamp	Gyro X	Gyro Y
1465.729	1.328	0.840
1485.352	1.237	1.160
1504.974	1.252	0.916
1524.597	1.450	1.130
1544.220	1.389	1.099
1563.843	1.496	1.221
1583.466	1.344	0.931

Results



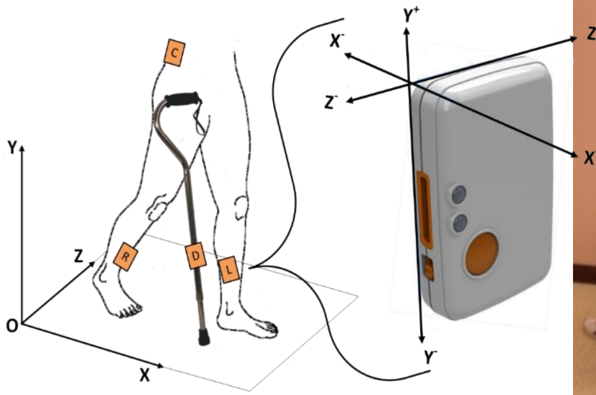
Hypothesis Validation Overview

- Wearable sensor data collected during rehabilitation
  - Mobility feature extraction
  - Predicting patient functioning at discharge
  - Physical therapy provider interviews
    - Utility of features
    - Usefulness of predictions
    - Evaluation of sensor data visualizations

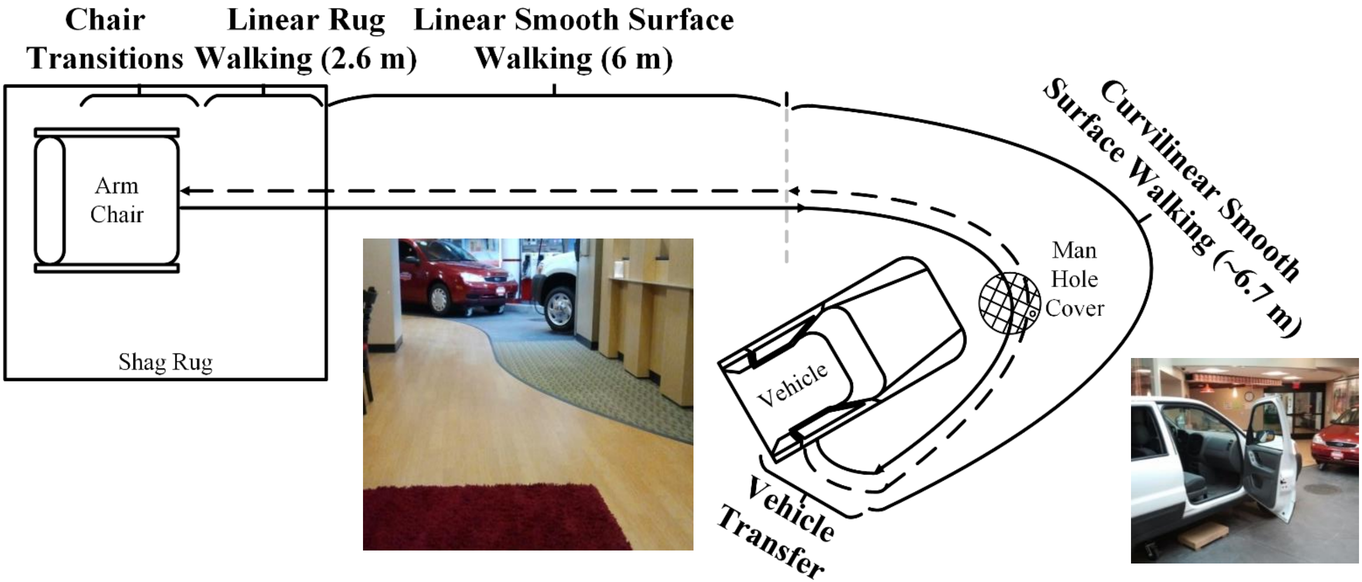


Data Collection

- Participants
  - N=20 (M=14, F=6)
  - 71.55 ± 10.62 years of age
  - Stroke, brain injury, debility, cardiac, etc.
- 2 Testing sessions (S1 and S2 one week later)
  - Ambulation circuit (AC)
- 4 Inertial measurement units
  - C: center of mass
  - L/R: left and right shank
  - D: assistive device (cane or walker)

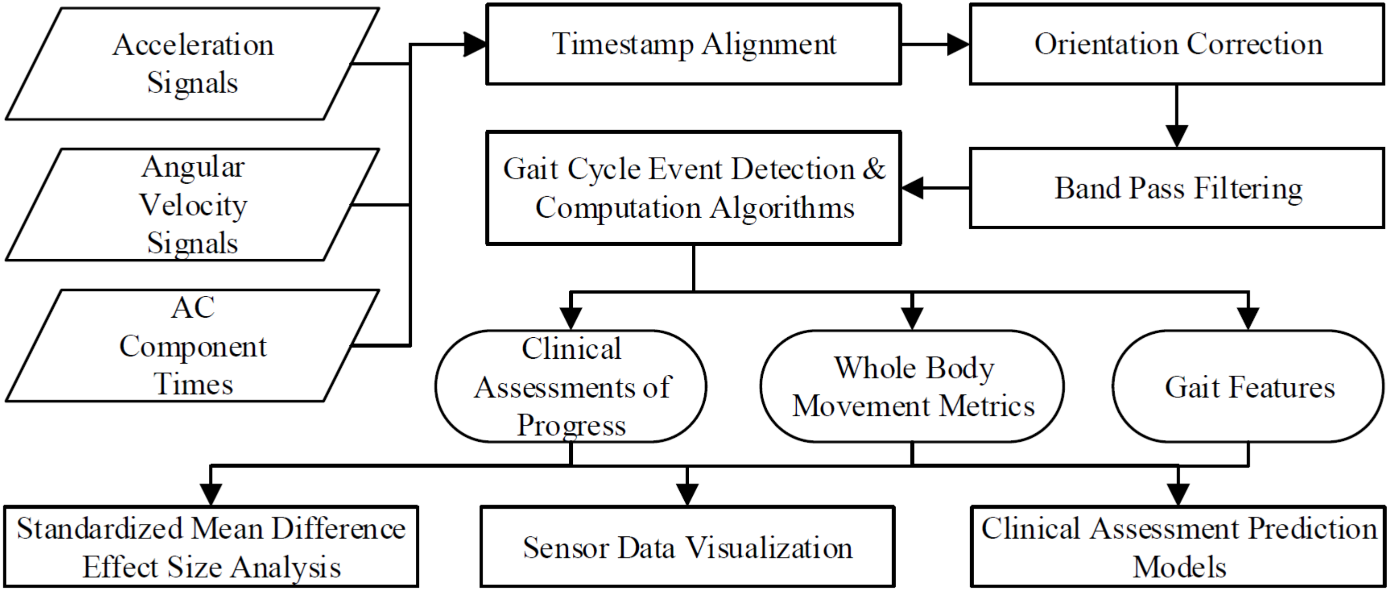


Ambulation Circuit (AC)



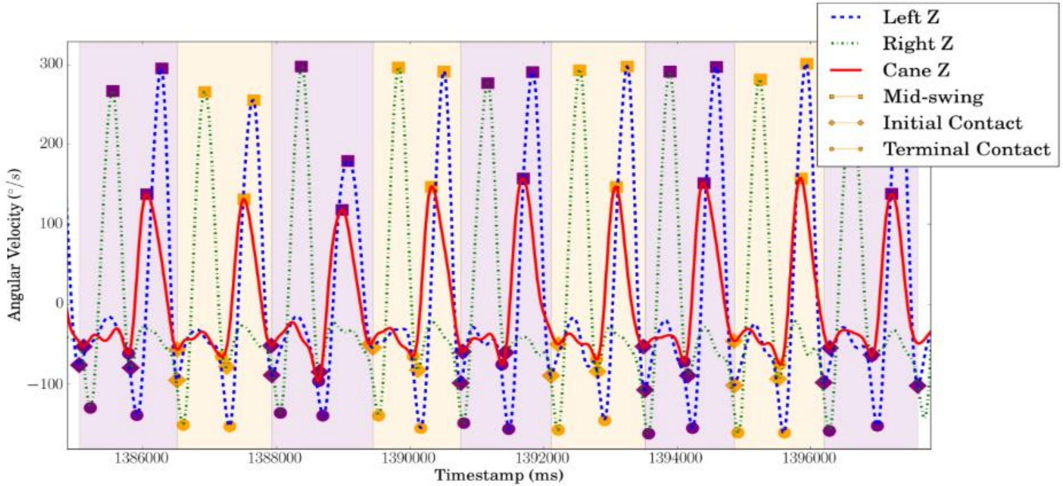

YOGA
SPOKANE
WENDLE
WENDLE

Data Processing



Gait Cycle Event Detection

- Identify gait events in gyroscope Z-axis signals for left/right shank and cane
  - Mid-swing, initial contact, and terminal contact



Participant 015's gait cycles

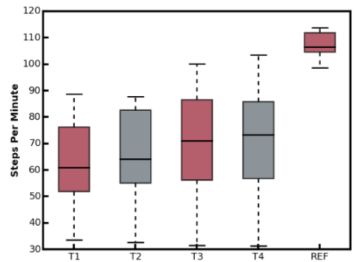
Sensor-based Mobility Features

- Clinical assessments of progress (CAP)
- Whole body movement metrics (WBM)
- Gait features (GF)

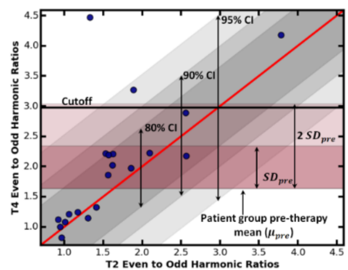
Category	Feature	Units
CAP	Duration	s
	Floor surface speed ratio	
	Walking speed	m/s
WBM	COM peak angular velocity	
	Root mean square (RMS)	$m/s^2/s$
	Smoothness index (harmonic ratio)	
	Smoothness of RMS	$m/s^3/s$
GF	Cadence	$steps/min$
	Double support percent	%
	Gait cycle time	s
	Number of gait cycles	
	Shank peak angular velocity	$^\circ/s$
	Shank range of motion (ROM)	$^\circ$
	Step length	m
	Step regularity	%
	Stride regularity	%
	Step symmetry	%

Mobility Changes

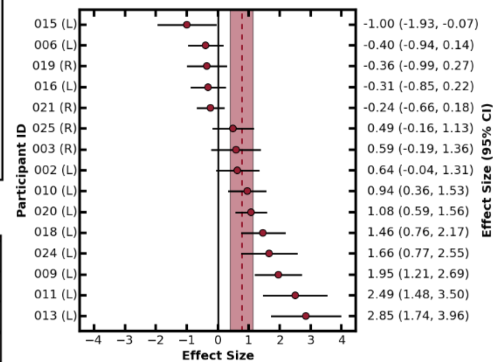
- Changes in performance features
- Group level
  - Boxplot analysis
  - Standardized mean difference effect size
- Individual level
  - Reliable change index
- Several changes detected
  - AC duration, gait features, stroke-affected side improvements, etc.



Cadence (steps/minute)



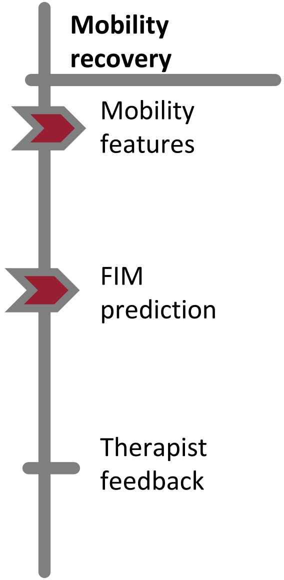
Walking smoothness index



Stroke-affected side shank range of motion

Clinical Outcome Prediction

- Hypothesis: More accurate clinical outcome predictions are possible w/sensor-based features over clinical features alone
- Clinical outcome to predict
  - Discharge Functional Independence Measure (FIM) scores



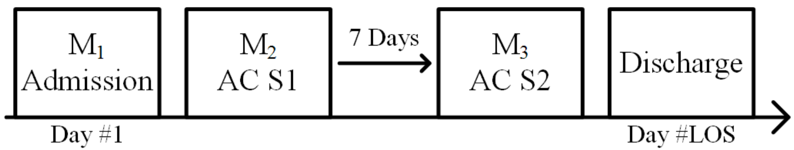
Target Prediction Variable: FIM

- Functional Independence Measure
- Measured at admission and discharge
- 13 Motor tasks
  - Transfers
  - Locomotion
- 5 Cognitive tasks

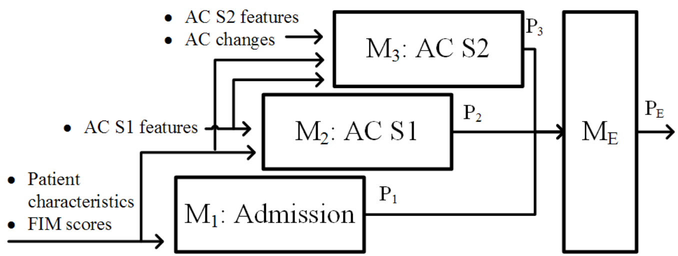
Task Type	#	Task
Motor	1	Eating
	2	Grooming
	3	Bathing
	4	Upper body dressing
	5	Lower body dressing
	6	Toileting
	7	Bladder management
	8	Bowel management
	9	Bed to chair transfer
	10	Toilet transfer
	11	Shower transfer
	12	Locomotion (ambulatory or wheelchair level)
	13	Stairs
Cognitive	14	Cognitive comprehension
	15	Expression
	16	Social interaction
	17	Problem solving
	18	Memory

Prediction Approach

- Train prediction models M_1 (admission), M_2 (AC S1), and M_3 (AC S2)



- Cumulative model construction
  - Utilize features from previous points in time



Feature Selection

- Recursive feature elimination with cross validation (RFECV)
  - Linear SVM
  - 10-fold CV w/mean squared error scoring
- Top 10 ranked features shown

M_1	Rank	M_2	Rank	M_3	Rank
Admission upper body dressing*	1	COM acceleration stand to sit Z peak angular velocity*	1	COM acceleration stand to sit Z peak angular velocity*	1
Admission memory*	1	Admission memory*	1	Admission memory*	1
RIC	1	COM acceleration stand to sit RMS*	1	Range of motion SMD (lesser side)	1
Admission bladder*	1	Shank range of motion average (greater side)*	1	Step length average*	1
Admission grooming*	1	Admission grooming*	1	Admission grooming*	1
Admission problem solving*	1	Double support percent CV	1	COM vehicle unload Z peak angular velocity percent change	1
Admission tub/shower transfer	1	Admission upper body dressing*	1	Admission upper body dressing*	1
Admission lower body dressing	1	Admission bed to chair transfer*	2	S2 peak angular velocity average (lesser side)*	1
Reciprocal admission total motor score*	2	Swing percent CV	3	Cycle duration CV percent change	1
CMG relative weight*	3	Limp average	4	S2 double support percent CV	1

CMG = case mix group, COM = center of mass, CV = coefficient of variation, M = model, RIC = rehabilitation impairment category, RMS = root mean square, S2 = session 2, SMD = standardized mean difference, * = listed in Table 5.3

Discharge FIM Motor Prediction

- Results from leave-one-out-cross validation

	Model	Linear SVM RMSE	Linear SVM NRMSE	Linear SVM r	Linear Regression RMSE	Linear Regression NRMSE	Linear Regression r	Random Forest RMSE	Random Forest NRMSE	Random Forest r
M_1	M_1 (w/o NAC)	4.66	11.65%	0.89**	6.07	15.19%	0.87**	8.14	20.36%	0.61**
	M_1	7.36	18.41%	0.82**	7.95	19.87%	0.80**	10.86	27.14%	0.73**
Separate	M_2	8.55	21.38%	0.60*	9.82	24.55%	0.55*	10.18	25.45%	0.25
	M_3	5.54	13.86%	0.85**	5.43	13.57%	0.86**	10.70	26.76%	0.07
	M_{avg}	5.54	13.86%	0.87**	5.27	13.18%	0.89**	8.04	20.09%	0.69**
	M_E	5.50	13.74%	0.84**	5.69	14.22%	0.84**	9.38	23.46%	0.44
Cumulative	M_2	5.43	13.57%	0.86**	6.59	16.47%	0.78**	8.51	21.27%	0.59*
	M_3	3.40	8.50%	0.95**†	3.59	8.96%	0.94**†	9.78	24.46%	0.31
	M_{avg}	3.66	9.15%	0.96**†	3.91	9.78%	0.93**†	7.38	18.46%	0.77**†
	M_E	3.24	8.11%	0.95**†	4.29	10.72%	0.91**†	9.30	23.24%	0.45*

avg = average, E = ensemble, M = model, NAC = non-ambulation circuit, NRMSE = normalized root mean square error, r = Pearson correlation coefficient, RMSE = root mean square error, SVM = support vector machine, * = $p < 0.05$, ** = $p < 0.01$, † = significantly ($p < 0.05$) improved results from M_1.

Therapists' Feedback

- 7 Physical therapists and assistants interviewed
- Interview content
  - General topics related to technology
    - Measuring gait and transfer ability
  - Usefulness of sensor-based metrics (1 not useful to 5 very useful scale)
    - Providing therapy services
    - Indicator of the FIM discharge motor score
      - RFECV did not select any CAP metrics as top-ranked features
  - Evaluation of three sensor data visualizations
    - Task duration bar plot
    - Gait cycle bar plot
    - Effect size forest plot

Therapists' metric ratings

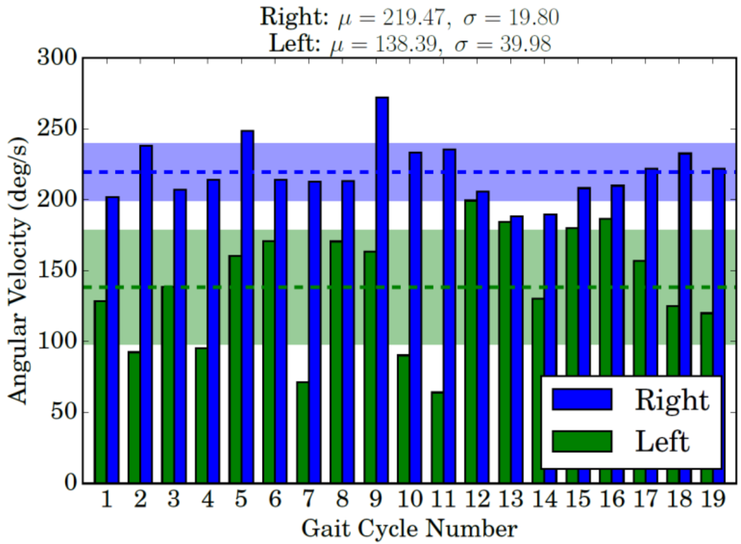
Metric	Usefulness	FIM Indicator
Sit-to-stand duration	4.14 (1.46)	3.29 (1.70)
Walking speed	4.00 (1.41)	3.29 (1.89)
Stand-to-sit duration	3.86 (1.46)	3.29 (1.60)
Curvilinear walking duration	3.71 (1.38)	3.29 (1.38)
Total ambulation circuit duration	3.71 (1.38)	2.71 (1.11)
Floor surface speed ratio	3.57 (1.27)	3.14 (1.35)
Vehicle load duration	3.14 (1.07)	2.43 (1.13)
Vehicle unload duration	3.14 (1.07)	2.43 (1.13)
Walking smoothness	3.71 (1.25)	2.71 (1.60)
Center of mass movement intensity	3.14 (1.07)	2.57 (1.40)
Center of mass peak angular velocity	2.86 (1.07)	2.29 (1.25)
Cadence	4.00 (1.00)	2.86 (1.21)
Single support percent	3.86 (1.35)	2.71 (1.60)
Gait cycle duration	3.71 (1.38)	2.71 (1.50)
Number of gait cycles	3.71 (1.25)	2.71 (1.60)
Shank range of motion	3.71 (1.38)	2.43 (1.27)
Step length	3.71 (1.25)	2.43 (1.27)
Stride length	3.71 (1.25)	2.43 (1.27)
Stride regularity	3.71 (1.25)	2.43 (1.27)
Step regularity	3.57 (1.27)	2.29 (1.38)
Double support percent	3.43 (1.40)	2.29 (1.25)
Shank peak angular velocity	3.43 (1.40)	2.14 (1.07)

FIM Prediction Usefulness

- 7/7 Therapists are interested in using wearable technologies for their patients
- 6/7 Therapists said they would consider FIM predictions for patients useful
  - *“It would be very useful, it could help with discharge planning if we needed to steer one way or another.”*
  - *“I would make use of [the predictions] as an adjunct.”*
- 1/7 would not consider FIM predictions useful
  - *“I probably wouldn’t [use FIM predictions], mostly because patients are really variable.”*

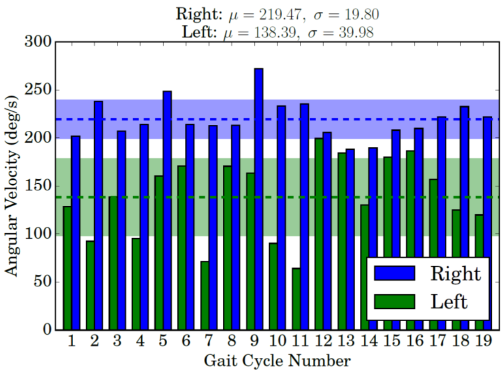
Gait Cycle Bar Plot

- Scale
  - 1 (strongly disagree)
  - 5 (strongly agree)
- I think that I would use this plot frequently
  - (2.57 ± 0.98)
- I thought the plot was easy to understand
  - (2.86 ± 0.90)
- I would imagine most patients would learn to use this plot very quickly
  - (1.43 ± 1.13)

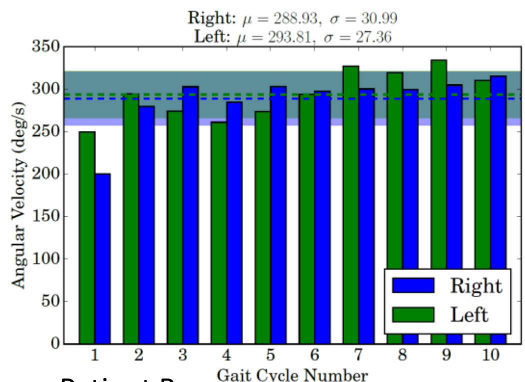


Gait Cycle Analysis

- 7/7 classified patient A's paresis correctly
- Noticed differences in variability between A and B
- 4/7 would use gait cycle bar plots
- *"It would be for my own personal measures to see where they are at. The ankle is really tough to assess when you are by their shoulders."*



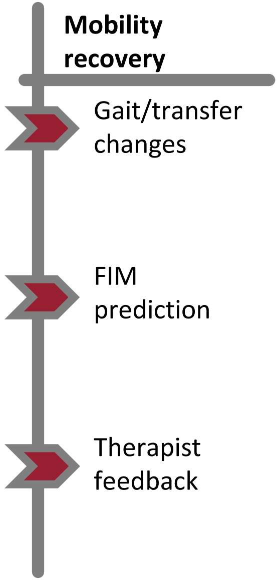
Patient A



Patient B

Mobility Recovery Conclusions

- Our algorithms offer several insights into the recovery process
  - Objectively tracking changes in patient performance
  - Improving clinical outcome predictions with our sensor-based features
- Therapy providers are interested in utilizing our prediction models
- AC study limitations
  - Low sample size
  - Human-operated stopwatch times segment AC components



Future Work

- Increasing sample size
- Improve prediction results
- Interface therapist and patient into data
- Large scale evaluation of sensor-based techniques for health care providers

References

1. G. Vincent and V. Velko. The Next Four Decades-the Older Population in the United States: 2010 to 2050, 2010.
2. Center for Disease Control, 2015
3. M.B. Buntin, C.H. Colla, P. Deb, N. Sood, J.J. Escarce. Medicare spending and outcomes after postacute care for stroke and hip fracture. Med Care. 2010;48:776–784.
4. A. Salarian, F. B. Horak, C. Zampieri, P. Carlson-Kuhta, J. G. Nutt, and K. Aminian. iTUG, a Sensitive and Reliable Measure of Mobility. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 18(3):303-310, 2010.
5. B. R. Greene, D. McGrath, R. O'Neill, K. J. ODonovan, A. Burns, and B. Caulfield. An Adaptive Gyroscope-Based Algorithm for Temporal Gait Analysis. Medical & biological engineering & computing, 48(12):1251-1260, 2010.
6. K. Ben Mansour, N. Rezzoug, and P. Gorce. Analysis of Several Methods and Inertial Sensors Locations to Assess Gait Parameters in Able-Bodied Subjects. Gait & Posture, 42(4):409-414, October 2015.
7. J. W. Tukey. Exploratory Data Analysis. 1977.
8. L. Wolff Smith and S. N. Beretvas. Estimation of the Standardized Mean Difference for Repeated Measures Designs. Journal of Modern Applied Statistical Methods, 8(2):600-609, 2009.
9. N. S. Jacobson and P. Truax. Clinical Significance: A Statistical Approach to Defining Meaningful Change in Psychotherapy Research. Journal of consulting and clinical psychology, 59(1):12, 1991.
10. H. Liu, J. Eaves, W. Wang, J. Womack, and P. Bullock. Assessment of Canes Used by Older Adults in Senior Living Communities. Archives of Gerontology and Geriatrics, 52(3):299-303, May 2011.
11. The Inpatient Rehabilitation Facility-Patient Assessment Instrument (IRF-PAI) Training Manual, 2012.
12. S. Sonoda, E. Saitoh, S. Nagai, Y. Okuyama, T. Suzuki, and M. Suzuki. Stroke Outcome Prediction Using Reciprocal Number of Initial Activities of Daily Living Status. Journal of Stroke and Cerebrovascular Diseases: The Official Journal of National Stroke Association, 14(1):8-11, 2005.
13. R. Kohavi and G. H. John. Wrappers for Feature Subset Selection. Artificial Intelligence, 97(12):273-324, 1997.
14. T. Hielscher, M. Spiliopoulou, H. Volzke, and J. Kuhn. Using Participant Similarity for the Classification of Epidemiological Data on Hepatic Steatosis. In 2014 IEEE 27th International Symposium on Computer-Based Medical Systems (CBMS), pages 1-7, May 2014.
15. B.-r. Chen. LEGSys: Wireless Gait Evaluation System Using Wearable Sensors. In Proceedings of the 2nd Conference on Wireless Health, page 20. ACM, 2011.
16. S. Liu, M. Yamada, N. Collier, and M. Sugiyama. Change-Point Detection in Time-Series Data by Relative Density-Ratio Estimation. Neural Networks, 43:72-83, July 2013.

Thank You

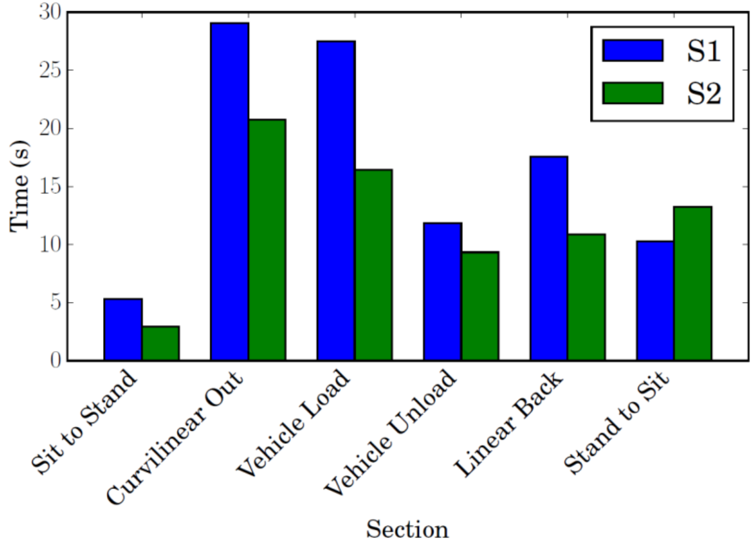
- Questions?
- Contact information
  - gsprint@eecs.wsu.edu
  - www.eecs.wsu.edu/~gsprint
- Acknowledgements
  - Physical therapist collaborators at St. Luke's
  - Vladimir Borisov
  - NSF Grant DGE-0900781

Measuring Gait and Transfer Ability

- Observation
  - Memory to compare previous observations
  - *"I kinda compare and contrast step lengths. I will do speed. I will do trunk deviation. If there's any toe drags. If they are using an assistive device or not. If they are using orthoses or not."*
- Estimate of physical assistance required
- Do not use visualizations, plots, graphs, or drawings

Task Duration Bar Plot

- Scale
  - 1 (strongly disagree)
  - 5 (strongly agree)
- I think that I would use this plot frequently
  - (3.14 ± 0.90)
- I thought the plot was easy to understand
  - (4.43 ± 0.53)
- I would imagine most patients would learn to use this plot very quickly
  - (3.29 ± 0.95)



Task Duration Bar Plot

- *“It may have been an improvement in a safety factor, whereas they may have sat down due to a loss of balance.”*
  - Context is needed to determine improvement/regression
- Therapists think patients could understand
  - 3.29 ± 0.95
- *“[The plot] would be helpful to get the patient more involved in seeing their progress.”*

Effect Size for Repeated Measures

$$d_{RM} = \frac{\bar{X}_{post} - \bar{X}_{pre}}{S_D}$$

[Wolff Smith and Beretvas, 2009]

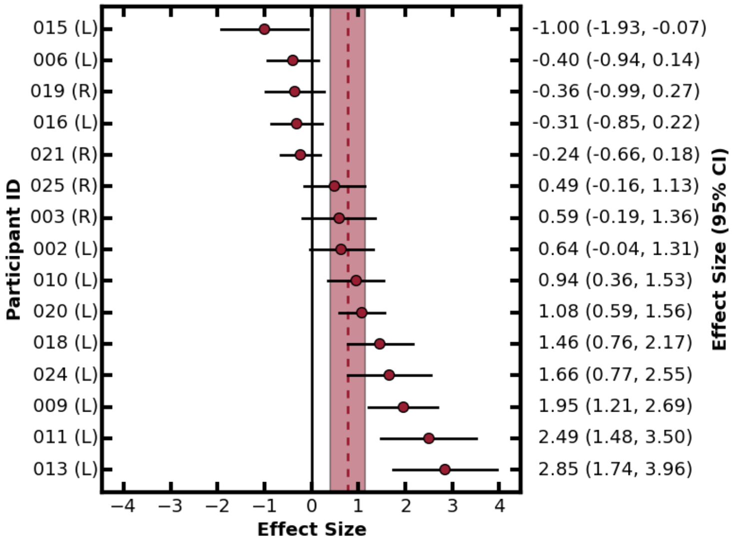
$$d_{RM} \pm CS * \hat{\sigma}_d^{2\,(L1)}, \hat{\sigma}_d^{2\,(L1)} = \sqrt{\frac{2(1-\hat{\rho})}{n} + \frac{{d_{RM}}^2}{2(n-1)}}$$

[Viechtbauer, 2007]

Metric	$\bar{X}_{pre}$	CV_{pre}	$\bar{X}_{post}$	CV_{post}	***ES Category***	d_{RM}	$d_{RM}\ CI_L$	$d_{RM}\ CI_H$
Duration	174.91	0.81	133.22	0.59	Moderate	-0.72	-1.01	-0.43
Cadence	65.08	0.26	70.46	0.28	Moderate	0.67	0.38	0.97
Velocity	0.51	0.51	0.57	0.51	Small	0.39	0.10	0.68
Involved Range of Motion	45.76	0.27	49.54	0.21	Large	0.81	0.45	1.16
Uninvolved Range of Motion	49.90	0.24	53.49	0.17	Moderate	0.63	0.30	0.97

Effect Size Visualization

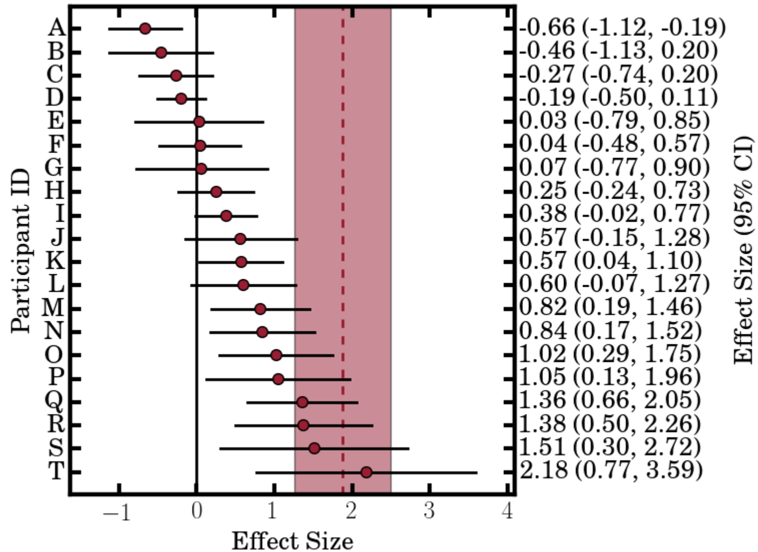
- Each individual as an experiment
- SMD ES for each participant
- S1 *gait cycles* vs. S2 *gait cycles*



Involved side range of motion (ROM)

Effect Size Forest Plot

- Scale
  - 1 (strongly disagree)
  - 5 (strongly agree)
- I think that I would use this plot frequently
  - (1.86 ± 0.90)
- I thought the plot was easy to understand
  - (2.00 ± 1.00)
- I would imagine most patients would learn to use this plot very quickly
  - (1.43 ± 0.79)



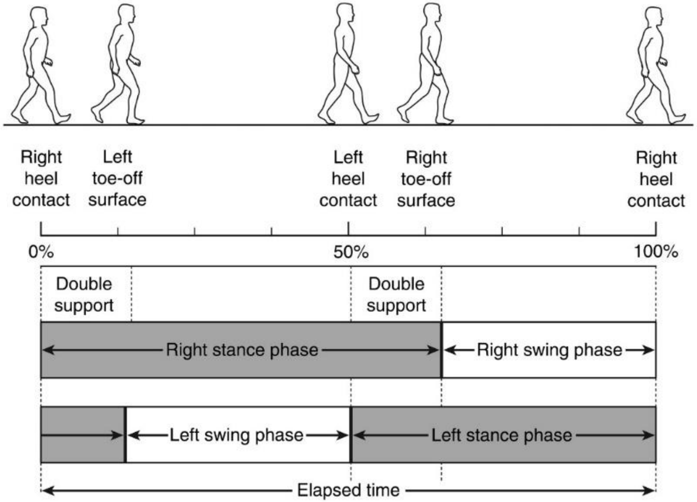
Walking Smoothness Metric

Effect Size Forest Plot

- Lowest rated visualization
- 2/7 acknowledged the usefulness for research
  - *"If I got into a research study to justify what I was doing then yes, but not for direct patient care."*

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)



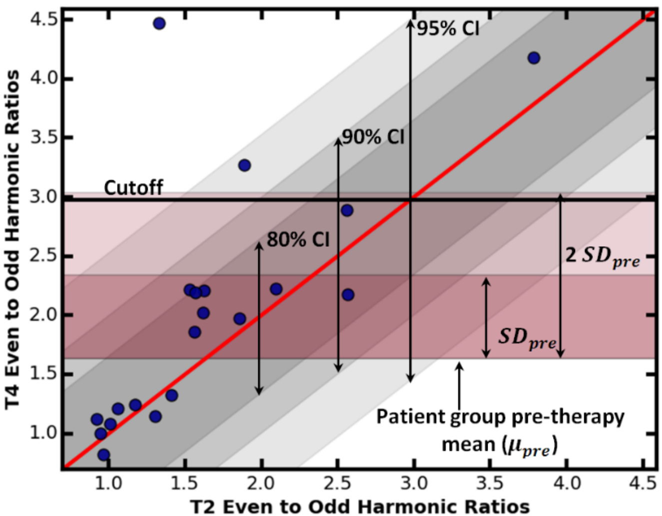
AC Participant Characteristics

PID	RIC	Involved Side	Gender	Age	Comorbi-dities	LOS	#Days $A \rightarrow S1$	#Days $S2 \rightarrow D$	$FIM_{A\text{-cog}}$	$FIM_{D\text{-cog}}$	$FIM_{A\text{-motor}}$	$FIM_{D\text{-motor}}$	Total RER
001	Stroke	L	M	73	N	31	16	8	23	34	25	70	1.81
002	Cardiac	N/A	M	84	Y	14	4	3	26	30	33	62	2.36
003	Misc	N/A	M	68	Y	19	8	4	32	33	37	65	1.53
004	Stroke	L	M	75	Y	21	14	0	15	26	24	52	1.86
005	Stroke	No paresis	M	63	Y	23	15	1	25	33	44	74	1.65
006	Stroke	L	F	82	Y	29	18	5	21	27	25	59	1.38
007	NTBI	N/A	M	52	Y	22	8	7	21	31	43	62	1.32
009	Stroke	No paresis	F	85	Y	20	8	5	22	30	46	58	1.00
010	NTBI	N/A	F	67	N	24	17	0	16	28	25	40	1.13
011	Stroke	L	M	74	N	20	11	2	16	23	28	49	1.40
013	NTSCI	N/A	M	76	N	15	7	1	25	30	26	58	2.47
014	Stroke	No paresis	M	55	Y	17	9	1	16	25	45	78	2.47
015	Stroke	L	M	85	N	13	4	2	32	33	55	80	2.00
016	Stroke	L	M	54	N	21	13	1	23	29	37	69	1.81
018	Stroke	L	M	88	N	29	19	3	26	32	27	60	1.34
019	Stroke	R	M	65	N	14	5	2	30	31	49	72	1.71
020	Misc	N/A	M	74	Y	28	17	4	21	30	31	61	1.39
021	Stroke	R	F	74	N	16	9	0	24	33	40	80	3.06
024	Stroke	L	F	63	N	18	9	2	29	31	38	73	2.06
025	Stroke	R	F	74	N	21	12	2	19	22	37	61	1.29
Mean	-	-	-	71.55	-	20.75	11.15	2.65	23.10	29.55	35.75	64.15	1.752
SD	-	-	-	10.62	-	5.35	4.75	2.25	5.20	3.43	9.27	10.51	0.53

A = admission, cog = cognitive, D = discharge, F = female, FIM = functional independence measure, L = left, LOS = length of stay, M = male, N = no, N/A = not applicable, NTBI = non-traumatic brain injury, NTSCI = non-traumatic spinal cord injury, PID = patient identification, R = right, RER = rehabilitation efficiency ratio, RIC = rehabilitation impairment category, SD = standard deviation, Y = yes.

Reliable Change Index

- Individual-level change
- “Statistical measure of category membership”
- Clinical significance for small samples
  - [Jacobson and Traux, 1991, Gibbons et al., 1993, Zahra and Hedge, 2010]

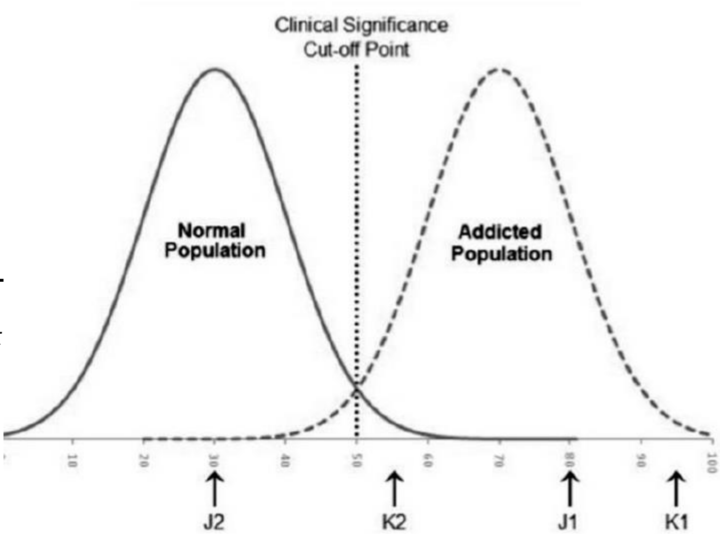


Smoothness Index

RCI Details

- $\mathrm{RCI} = \frac{x_{post} - x_{pre}}{\sqrt{2S_D{}^2}}$
  - $S_D^{=} = s_{pre}\sqrt{2(1-r)}$
  - $S_D^{\neq} = \sqrt{s_{pre}^2 + s_{post}^2 - 2rs_{pre}s_{post}}$

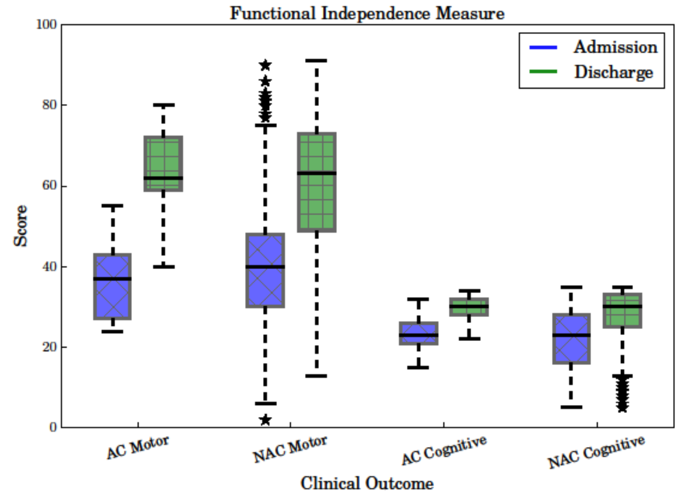
$$midpoint = \frac{(M_1 + M_0)}{2} \equiv \frac{s_0 M_1 + s_1 M_0}{s_0 + s_1}$$



[Zahra, 2010]

FIM Distribution

- AC participants (N=20)
  - FIM_{motor}: 35.75 ± 9.27 → 64.15 ± 10.51
  - FIM_{cog}: 23.10 ± 5.20 → 29.55 ± 3.43
- Utilize additional patient medical records (N=4936) for training (NAC data)
  - FIM_{motor}: 38.58 ± 12.98 → 59.53 ± 16.91
  - FIM_{cog}: 22.12 ± 7.67 → 28.46 ± 6.27



Individual Predictor Correlations

- Pearson correlations with discharge FIM motor score
- Top 10 highest correlations for Admission, AC S1, AC S2

Admission	r	AC S1	r	AC S2	r
Reciprocal admission total motor score	-0.68**	COM acceleration stand to sit Z peak angular velocity	0.62**	S2 peak angular velocity average (lesser side)	0.65**
Admission bladder	0.62**	Shank range of motion average (greater side)	0.62**	S2 vehicle challenge duration	-0.60**
Admission upper body dressing	0.61**	Step length average	0.59**	S2 range of motion average (lesser side)	0.59**
CMG relative weight	-0.60**	Vehicle challenge duration	-0.56**	S2 number of gait cycles	-0.56**
Admission grooming	0.60**	Shank range of motion average (lesser side)	0.55*	Cadence percent change	0.51*
Admission problem solving	0.59**	Number of gait cycles	-0.51*	S2 swing percent CV	-0.50*
Admission memory	0.56*	Shank peak angular velocity average (greater side)	0.48*	Peak angular velocity SMD (greater side)	0.50*
Admission bed to chair transfer	0.53*	COM acceleration vehicle unload RMS	0.47*	S2 duration	-0.49*
Admission toilet transfer	0.50*	COM acceleration stand to sit RMS	0.46*	S2 COM acceleration RMS	0.48*
Admission comprehension	0.46*	Walking speed	0.44	S2 COM acceleration RMS jerk	0.46*

AC = ambulatory circuit, CMG = case mix group, COM = center of mass, CV = coefficient of variation, r = Pearson correlation coefficient, RMS = root mean square, S1 = session 1, S2 = session 2, SMD = standardized mean difference, * = $p < 0.05$, ** = $p < 0.01$.