Motor Symptoms Detection and Analysis of Parkinson's and Huntington's Disease by Hidden Markov Models Based Activity Recognition

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Outline

- Introduction and Study Setup
- Methodology
  - Motor Symptoms Analysis for Parkinson's and Huntington's Disease
  - Hidden Markov Models Based Activity Recognition
- Experimental Results
- Conclusion

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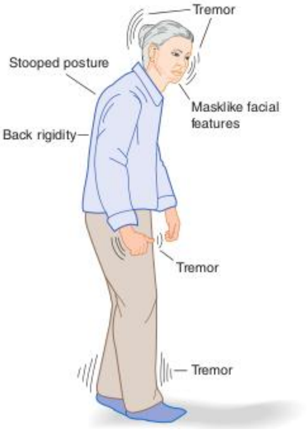
Parkinson's Disease (PD)

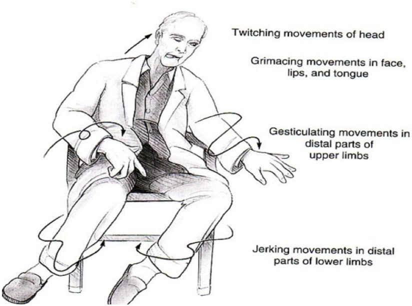
- Progressive neurological disorder characterized by
  - Tremors and Rigidity
  - Freeze of Gait
  - Postural Instability
- Rhythmic motor symptoms (Tremor)
- UPDRS - Scale for assessment of severity
- Approximately 1 million people suffering in USA



Source: http://body-disease.com/parkinson-disease/

Huntington's Disease (HD)

- Progressive and inherited neurological disorder characterized by
  - Chorea
  - Unsteady Gait
  - Cognitive Impairment
- Erratic motor symptoms (Gait)
- UHDRS - Scale for assessment of severity
- Approximately 30k people living with HD



Source: http://slideplayer.com/slide/7992667/

Motor Symptoms: Subjective vs Objective Assessment

- Motor symptoms is inherent in both diseases
- UPDRS and UHDRS are short term, subjective assessments
- Wearable sensors have emerged as suitable alternative
- Hence, in this project, we want to recognize the movement/non-movement activities and do motor symptoms analysis in the detected activity duration for PD and HD

Body-affixed Sensors: BioStampRC (MC10 Inc.)

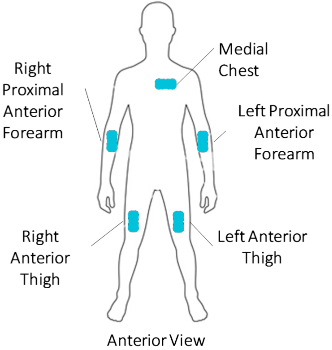
- Lightweight(7grams)
- Unobtrusive,body-affixable
- Low power
- Long recording time

Body-affixed Sensors: BioStampRC Key Specifications

Mode	Sampling Rate	Dynamic Range	Recording Time (Max)
Accelerometer (Accel.)	31.25, 50, 100, 200 Hz	2, 4, or 8 g	8-35 hours
ECG	125, 250 Hz	0.2 V	17-35 hours
EMG	250 Hz	0.2 V	17 hours
Accel.+ECG	50 Hz(accel) 125, 250 Hz (ECG)	2, 4, or 8 g (accel) 0.2 V (ECG)	11-22 hours
Accel.+EMG	50 Hz(accel) 250 Hz(EMG)	2, 4, or 8 g (accel) 0.2 V (EMG)	11 hours
Gyro.+Accel	25, 50, 100, 250 Hz	2, 4, 8, 16 g (accel) Off, 250, 500, 1000, 2000 /sec (gyro)	2-4 hours

Source: https: //www.mc10inc.com/our-products/biostamprc

Pilot Study



- 10 HD, 16 PD, and 15 Controls enrolled
- Five accelerometers for each participant
- In-clinic assessment + two day in-home recording

Gait Analysis in HD: Aim

- Gait analysis in HD is characterized by
  - Cross-correlation analysis to parameterize the lack of co-ordination between the legs to differentiate between HD and controls
  - Auto-correlation analysis to parameterize the step duration variability that is higher in HD when compared to controls

Characterization of Lack of Coordination (Joint Utilization of Sensors)

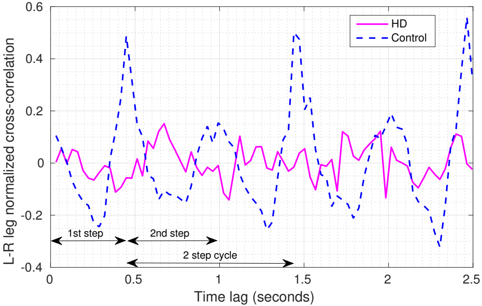
- Three in-clinic 10 meter walk tests were conducted for 10 HD and 15 controls
- To parameterize the lack of co-ordination between legs, we use normalized vector cross correlation of the data obtained from the sensors attached to the left and right leg.

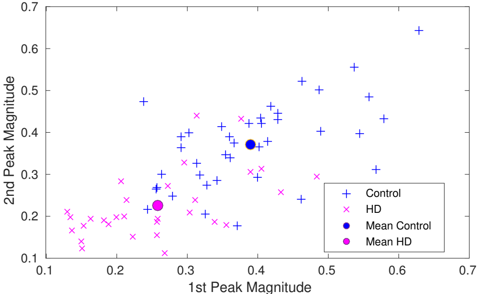
Normalized Vector Cross-Correlation of Left and Right Leg Sensors

$$R_{LR}(m) = \frac{\sum_{n=1}^{N-m} (\mathbf{a}_L(n)\mathbf{a}_R(n+m))}{\left(\sum_{n=1}^{N-m} \|\mathbf{a}_L(n)\|^2\right)^{1/2} \left(\sum_{n=1}^{N-m} \|\mathbf{a}_R(n+m)\|^2\right)^{1/2}}$$

where,
$\mathbf{a}_L(n) \rightarrow$ left leg sensor , $\mathbf{a}_R(n) \rightarrow$ right leg sensor
N $\rightarrow$ total samples , m $\rightarrow$ time lags

Lack of Co-ordination: HD vs Control





Characterization of Step Duration (Individual Sensor Utilization)

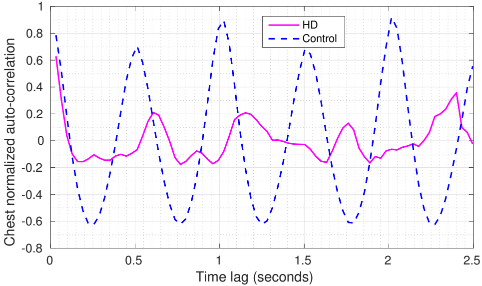
- Lack of co-ordination also results in variability in step duration, which can be visualized but not quantified by cross-correlation of leg sensors
- We perform auto-correlation of chest sensor, which captures movement from both legs

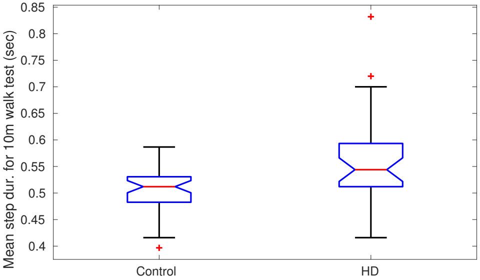
Normalized Vector Auto-Correlation of Chest Sensor

$$R_{CC}(m) = \frac{\sum_{n=1}^{N-m} \left(\mathbf{a}_C(n)\mathbf{a}_C(n+m)\right)}{\left(\sum_{n=1}^{N-m} \|\mathbf{a}_C(n)\|^2\right)^{1/2} \left(\sum_{n=1}^{N-m} \|\mathbf{a}_C(n+m)\|^2\right)^{1/2}}$$

where,
$\mathbf{a}_C(n) \rightarrow$ chest sensor
N $\rightarrow$ total samples , m $\rightarrow$ time lags

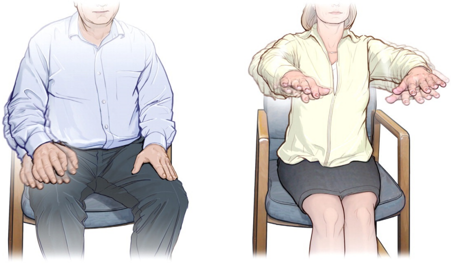
Step Duration: HD vs Control





Tremor Analysis in PD: Aim

- Analyze the tremor and differentiate PD from control
- Tremors have typical frequency band: 4-7 Hz
- Hence, spectrogram analysis to characterize the tremor



Source: https://quizlet.com/63838614/ecr-3-flash-cards/

Frequency Characterization for Tremor in PD: Spectrograms

- We perform Principal Component Analysis (PCA) on the tri-axial data and choose dominant acceleration component for analyzing tremor
- We divide the data into segments and analyze the spectrogram of each segment

Spectrogram Analysis using Short Term Fourier Transform (STFT)

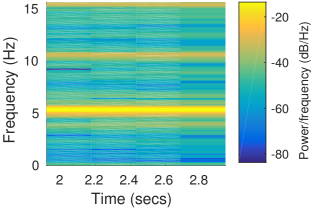
$$A_{SI}(k,\omega) = \sum_{n=-\infty}^{\infty} a_{SI}^{pc}(n) w(n-k) e^{-j\omega n},$$

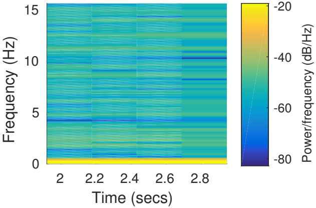
$$A_{SI}(k,p) = A_{SI}(k,\omega)\ , at\ \omega = \frac{2\pi}{M} p,$$

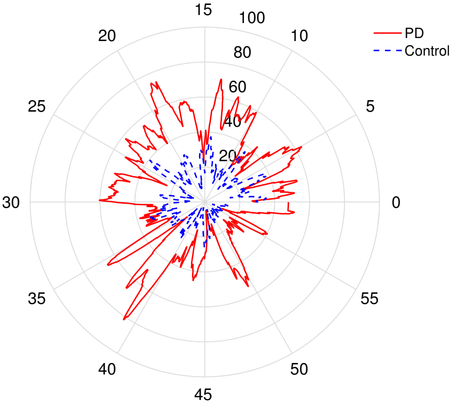
$$S(k,p) = \left| A_{SI}(k,p) \right|^2 .$$

where,
$a_{SI}^{pc}(n) \rightarrow I^{th}$ segment of the PC data, $w(n) \rightarrow$ window function of length M, $k \rightarrow$ overlap, $A_{SI}(k,\omega) \rightarrow \mathrm{STFT}(a_{SI}^{pc}(n))$, $S(k,p) \rightarrow$ Spectrogram

PD vs Control







Why Activity Recognition?

- Till now we were manually picking the movement and non-movement duration.
- We need to automate the process of extracting the moving and non-moving duration from the data

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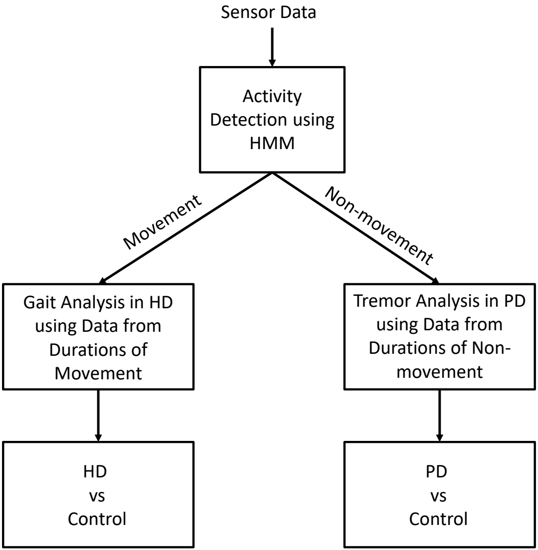
Schematic Diagram of Proposed Model

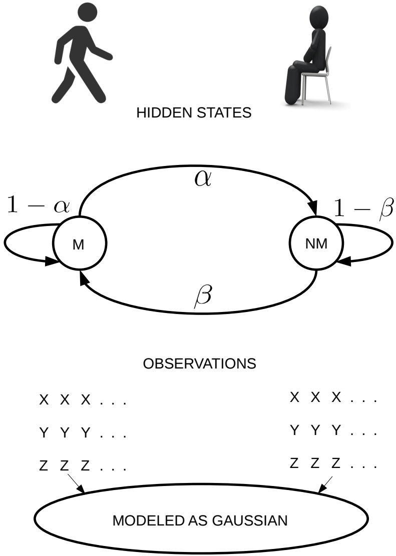


Motivation for Using HMM

- The accelerometer data is the observation and the activity causing the accelerometer reading is the state which is HIDDEN
- The data is time series which has inherent dependency which can modeled as MARKOVian
- Hence, HIDDEN MARKOV model

Hidden Markov Model: Assumptions and Initializations

- Hidden States:- We consider 2 states: Moving and Non-moving
- The observation in each state is modeled as multivariate Gaussian $\mathcal{N}(\mu_1, \Sigma_1)$ and $\mathcal{N}(\mu_2, \Sigma_2)$
- We have 2×2 transition matrix $T = \begin{bmatrix} 1-\alpha & \alpha \\ \beta & 1-\beta \end{bmatrix}$
- We start with stationary distribution $\pi = [\pi_0 \quad \pi_1]$



State and Parameter Estimation: Baum-Welch Iteration

- Parameters $\theta = [\pi, \alpha, \beta, (\mu_1, \Sigma_1), (\mu_2, \Sigma_2)]$
- Current parameter estimate $\theta^t = [\pi^t, \alpha^t, \beta^t, (\mu_1^t, \Sigma_1^t), (\mu_2^t, \Sigma_2^t)]$
- Data: $X = \begin{bmatrix} x_1 & y_1 & z_1 \\ x_2 & y_2 & z_2 \\ . & . & . \\ . & . & . \end{bmatrix}$
- States: $Z = [M, NM]$
- Step1: Obtain MAP estimate of the state sequence

$$\hat{Z} = arg \max_{Z} \; p(X, Z \mid \theta^t)$$

- Step 2: Update the parameter

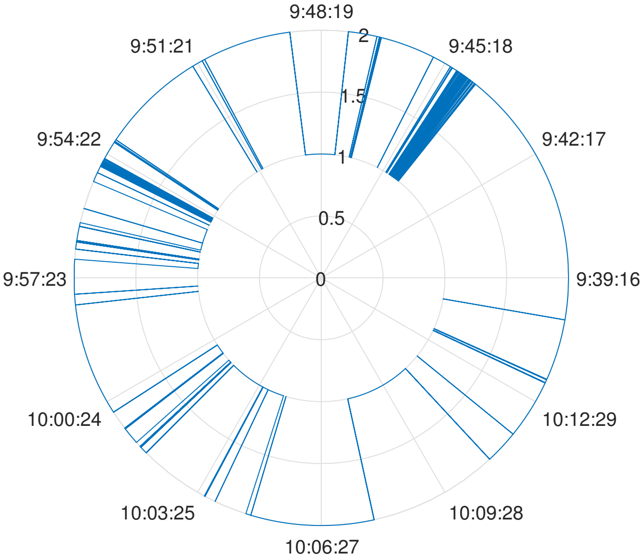
$$\theta^{t+1} = arg \max_{\theta} \; p(X, \hat{Z} \mid \theta)$$

Activity Prediction (AP)

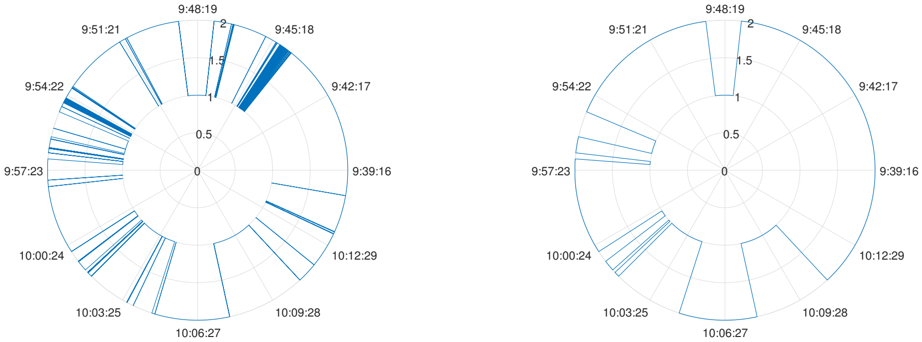
- We obtain the Baum-Welch parameter estimate for all participants
- Since each participants estimate are independent, we average the (μ,Σ) across all participants
- Use the aggregate (μ,Σ) to calculate the Mahalanobis distance of each point from the parameter estimate for each state

$$D_M(\vec{x}) = \sqrt{(\vec{x}-\vec{\mu})^T \Sigma^{-1} (\vec{x}-\vec{\mu})}$$

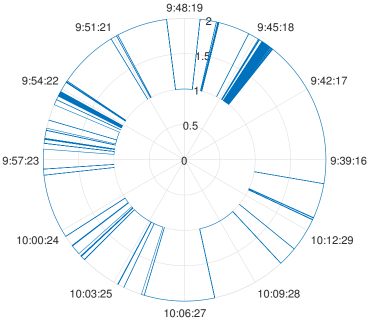
HMM Activity Recognition Result

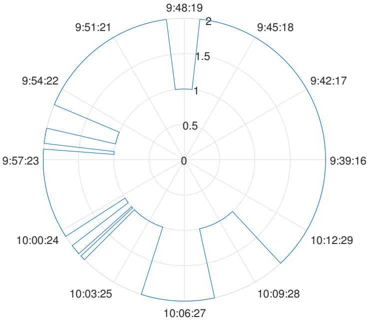


HMM Activity Recognition Result: Smoothing



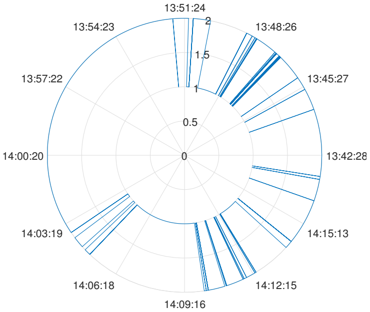
Control: HMM Smoothing Pre vs Post with Validation

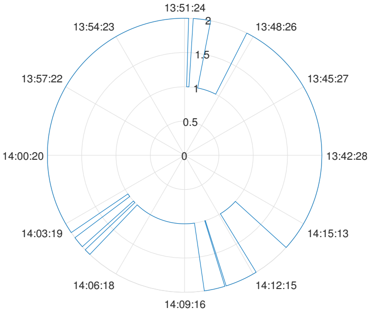




8/10/2016, 9:45:05 AM EDT	UHDRS 9 - Arm Rigidity	0:00:06
8/10/2016, 9:45:24 AM EDT	UHDRS 9 - Arm Rigidity	0:00:24
8/10/2016, 9:47:46 AM EDT	UHDRS 13 - Gait	0:00:27
8/10/2016, 9:48:20 AM EDT	UHDRS 14 - Tandem Walking	0:00:13

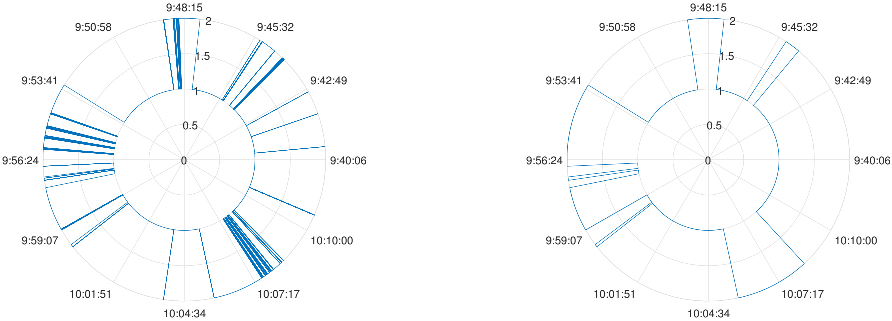
HD: HMM Smoothing Pre vs Post with Validation





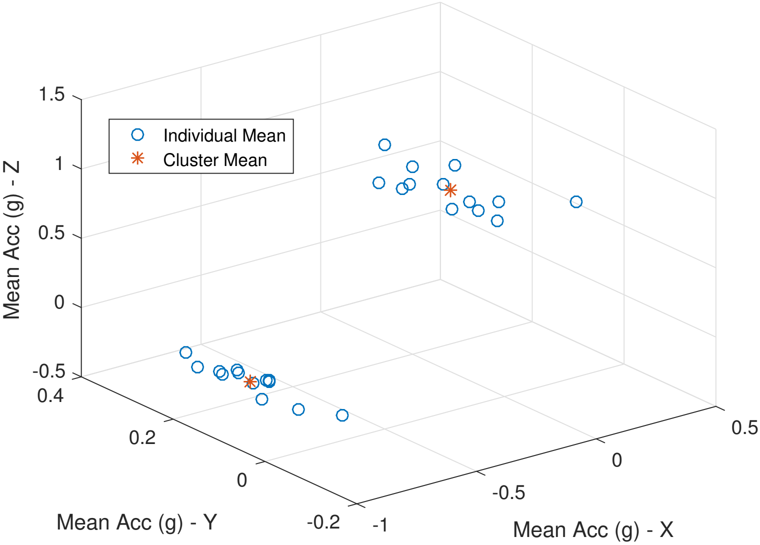
9/21/2016, 1:48:15 PM EDT	UHDRS 12 - Maximal Chorea	0:00:01
9/21/2016, 1:48:28 PM EDT	UHDRS 12 - Maximal Chorea	0:00:01
9/21/2016, 1:48:51 PM EDT	UHDRS 13 - Gait	0:00:11
9/21/2016, 1:49:16 PM EDT	UHDRS 11 - Maximal Dystonia	0:00:01
9/21/2016, 1:49:25 PM EDT	UHDRS 11 - Maximal Dystonia	0:00:01

PD: HMM Smoothing Pre vs Post with Validation

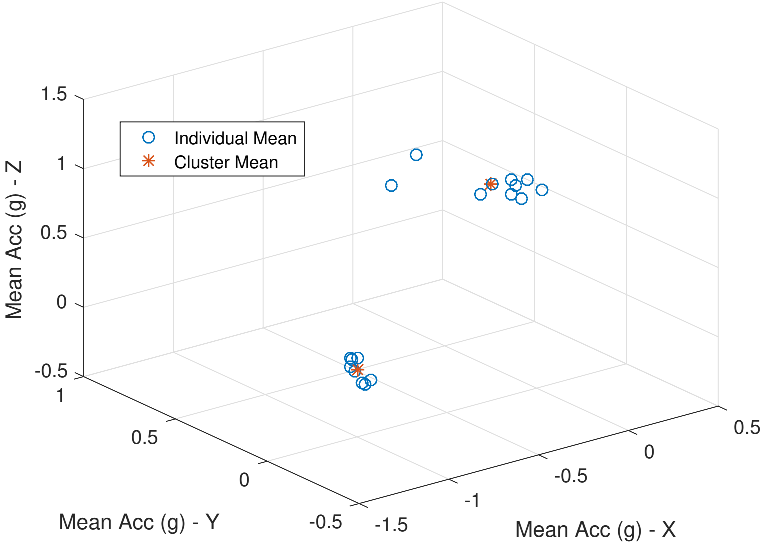


8/17/2016, 9:46:19 AM EDT	UPDRS 3.16 - Kinetic Tremor of Hands	0:00:09
8/17/2016, 9:47:48 AM EDT	UPDRS 3.12 - Postural Stability	0:00:14
8/17/2016, 9:48:30 AM EDT	UPDRS 3.10 - Gait	0:00:15
8/17/2016, 9:54:40 AM EDT	10 Meter Walk Test	0:00:04
8/17/2016, 9:55:31 AM EDT	10 Meter Walk Test	0:00:04

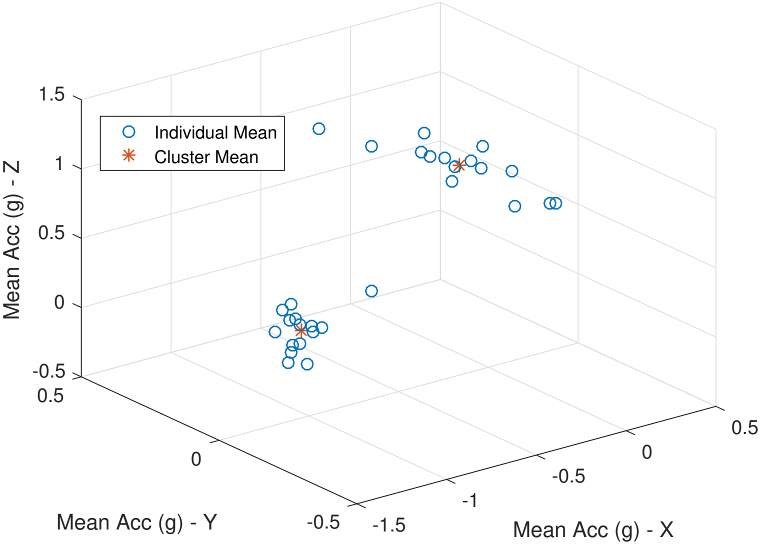
Baum-Welch Parameter Estimates: Control



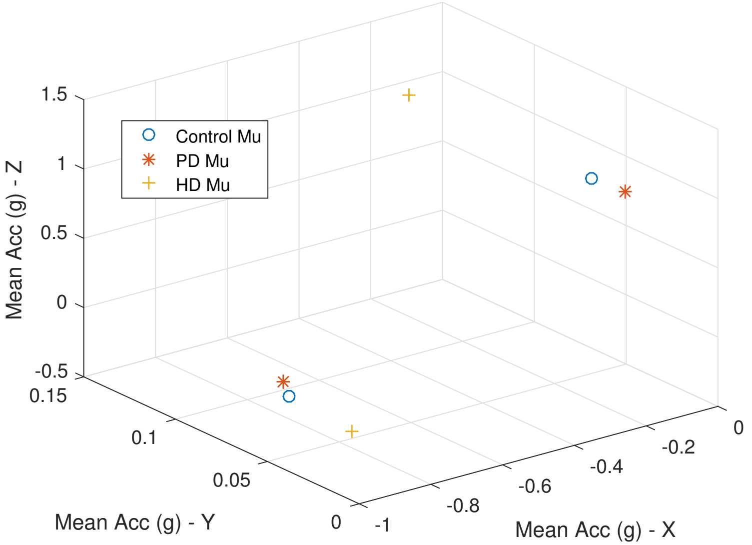
Baum-Welch Parameter Estimates: HD



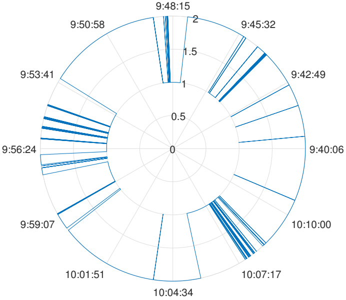
Baum-Welch Parameter Estimates: PD

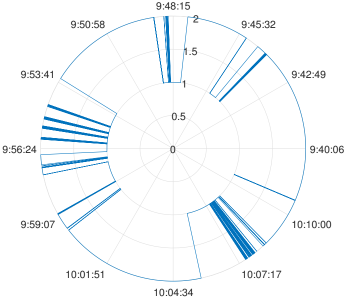


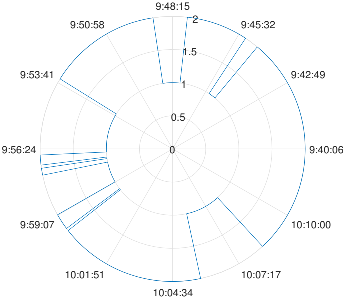
Baum-Welch Parameter Estimates: Aggregate

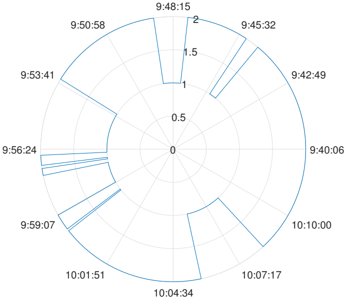


PD: HMM vs Predictor







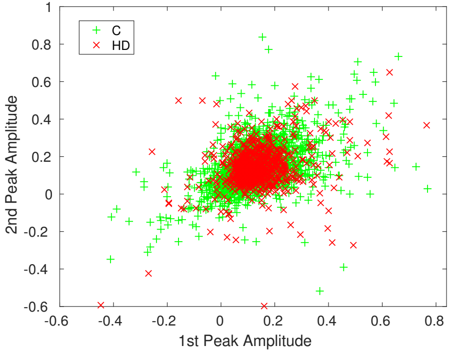


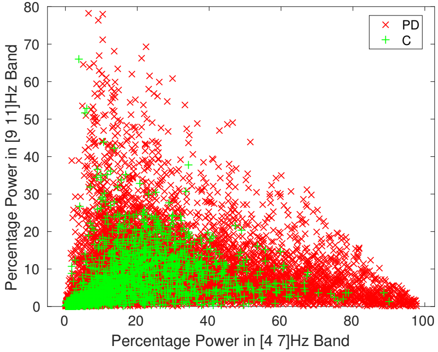
Runtime and Accuracy Statistics

Patient Type	HMM Runtime	AP Runtime	AP Accuracy
Control	3.33 sec	**0.79 sec**	99.67%
Control	4.08 sec	**1.07sec**	99.49%
HD	3.5 sec	**1.1 sec**	98.34%
HD	3.57 sec	**0.94 sec**	99.81%
PD	26.8 sec	**3.5 sec**	99.89%
PD	7.66 sec	**3.8 sec**	99.45%

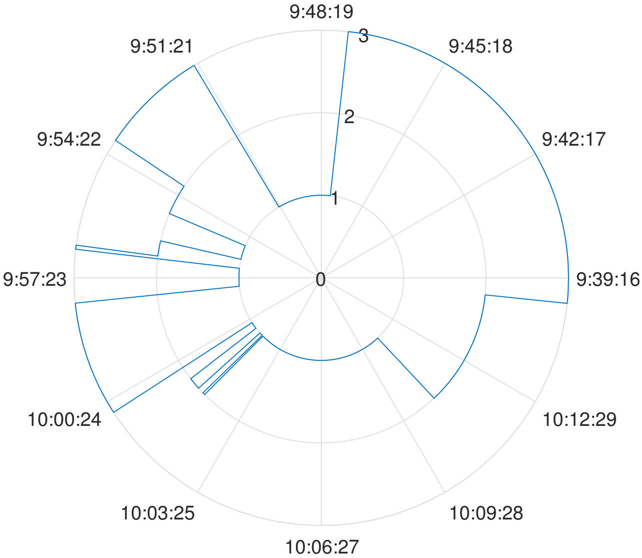
Table: Comparison of HMM and AP Performance

Not So Good Results: HD vs C and PD vs C





Not So Good Results: 3 State Estimation



Conclusion

- Utilization of sensors for PD/HD analysis is advantageous
  - Light weight, body-affixed with low power and long recording capacity
- Preliminary analysis based on manually locating the activity duration helped us come up with features
  - Cross correlation for gait analysis in HD
  - Spectrogram for tremor analysis in PD
- HMM automates the activity prediction process and proves to be useful
  - Succesfully recognized moving and non-moving durations and validated it on the in-clinic data
    - HMM suffers the initialization problem
  - Came up with AP which works on par with HMM in terms of accuracy with better runtime
  - However, further analysis did not give expected results

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Thank You