Identifying Dyskinesia Periods in Parkinson's Disease

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Why Identify Dyskinesia?

- IGERT aim: Develop smart environments and technologies to improve human health.
- Dyskinesia in Parkinson's disease (PD) is characterized by unintentional and uncoordinated movements.
  - A side effect of PD therapies used to improve motor function due to overmedication or overstimulation.
  - Assessment is done by infrequent visits to clinic and unreliable patient self-report.
- In general, in-home monitoring systems are effective for identifying and quantifying disease symptoms, and optimizing treatments [1].

We hypothesized that we could classify body-worn accelerometer data into dyskinesia and non-dyskinesia periods using signal analysis, feature extraction, and machine learning algorithms with observed dyskinesia periods as training classes.

Meeting Patient and Clinician Acceptance Criteria

Body-Worn Sensor Acceptance Criteria	
Patients:	Clinicians:
High acceptance rate	Requires no technology training
Not affect bodily behavior	Simple interface
Not replace the clinician	Low cost
Easy to use	Minimal upkeep
Small	Low time demand.
Unobtrusive	

Table 1. Design constraints for body-worn sensor systems, based upon [2].

To meet patient and clinician criteria (Table 1):

- We chose a sensor (Figure 1) that:
  - Looks like an ordinary watch
  - Is inexpensive and simple to use
- The system output must have clinical relevance
- We tested that the algorithm is able to generalize across participants

Figure 1. Geneactiv Accelerometer on Left Wrist

References

1. Cunningham *et al.*, 2009, 2. Bergmann *et al.*, 2011, 3. Patel *et al.*, 2011, 4. Tsipouras *et al.*, 2012, 5. Keijsers *et al.*, 2003, 6. Mera *et al.*, 2012

Engineering Meets A Clinical Need

Overview of System Design (Figure 2).

- **Collect Sensor Data:** 19 PD Participants wore accelerometers on wrists, ankles, and right hip.
- **Observe Dyskinesia:** Trained observer recorded times when dyskinesia occurred over 1.5 hours.
- **Signal Analysis:** Band-pass filtered accelerometer signals and transformed them into the frequency domain with a fast Fourier transform (FFT).
- **Derive Features:** Calculated features in the frequency bands identified in the literature [3-4]: Dyskinesia (1-3.5 Hz), PD Tremor (5-8 Hz), High (3.5-8 Hz), and Full (1-13 Hz) frequency.
- **Classify Features onto Observed Dyskinesia**: Combined features into a "Feature Vector" and classified into dyskinesia and non-dyskinesia periods with a decision tree classifier. [3-6]

Deriving Features

- Calculated for each sensor location
- Calculated for 1-minute moving time window instances
- Feature Vector Matrix: all features from 5 sensor locations
- WEKA software classifies feature instances onto dyskinesia class

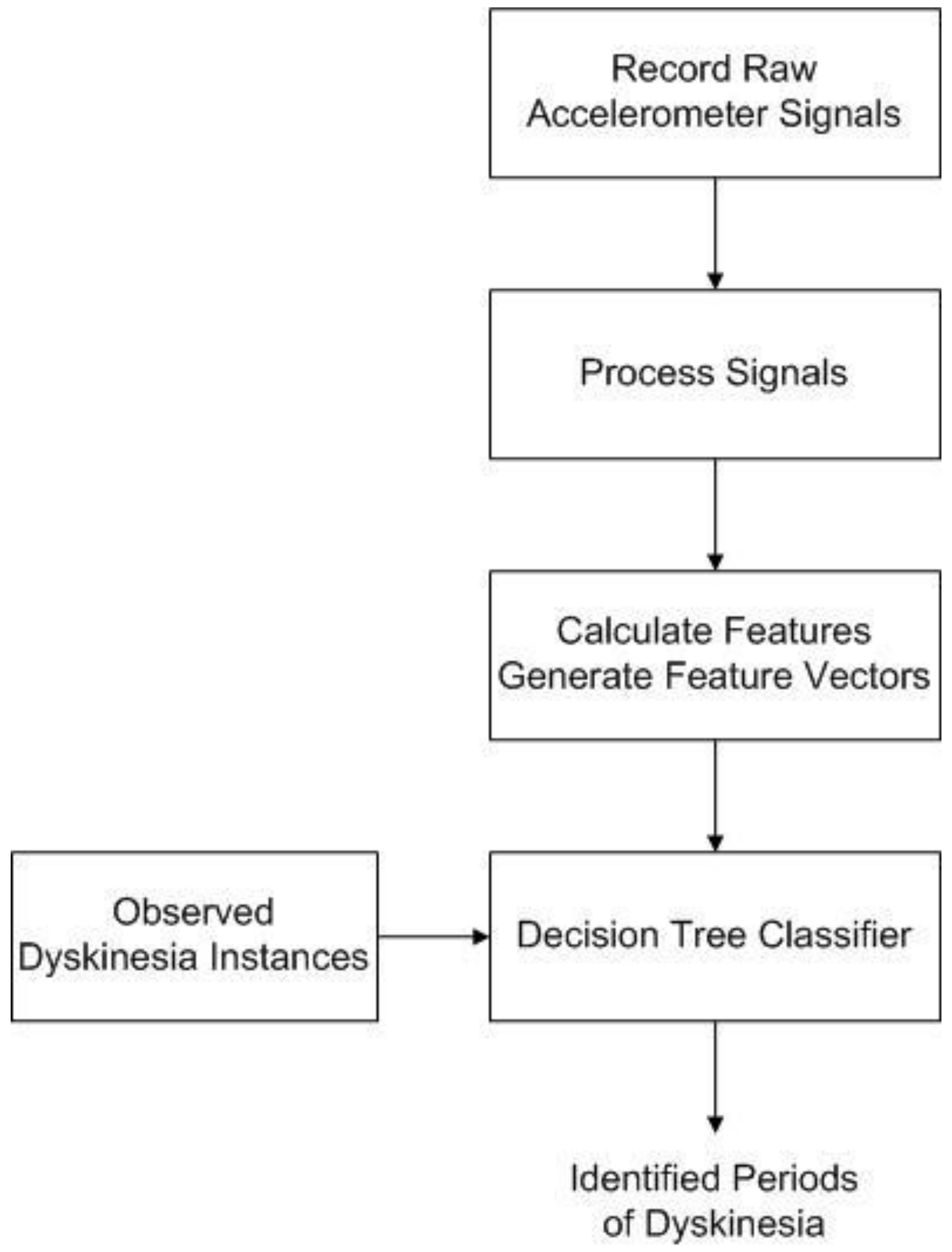


Figure 2. System Overview. Periods of dyskinesia are identified from classification of features derived from the data recorded by the accelerometers worn on the wrists, ankles, and hip.

How well does our system identify dyskinesia?

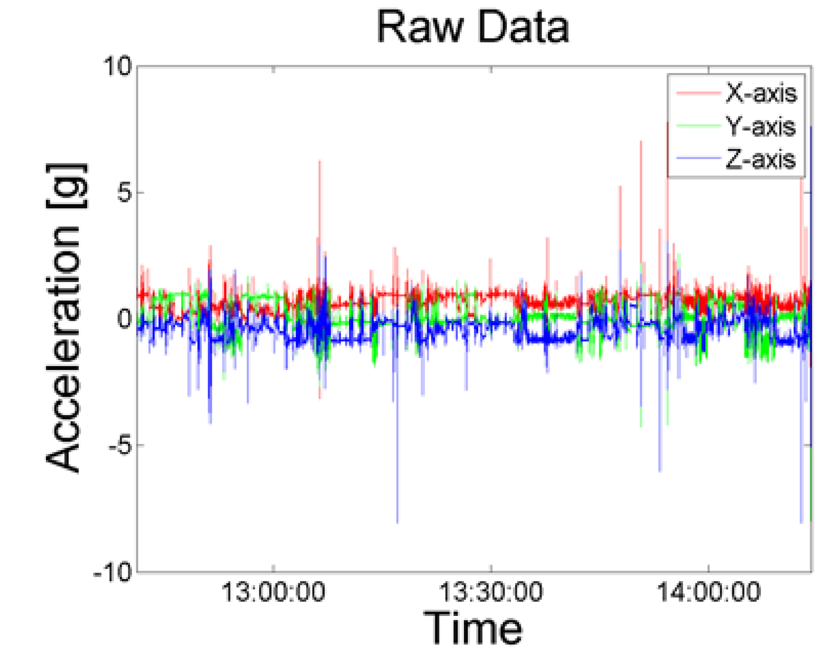


Figure 3. Non-Dyskinesia raw accelerometer signal

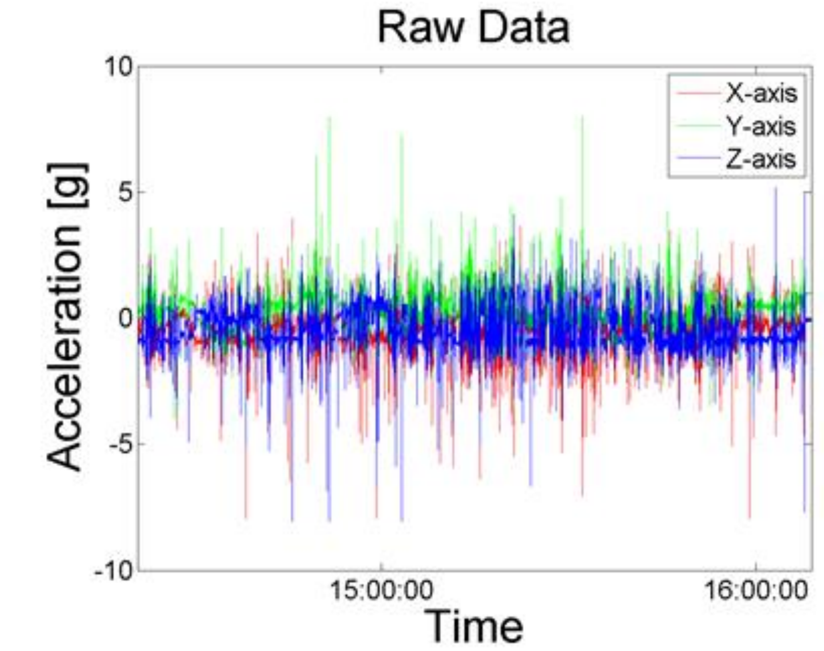
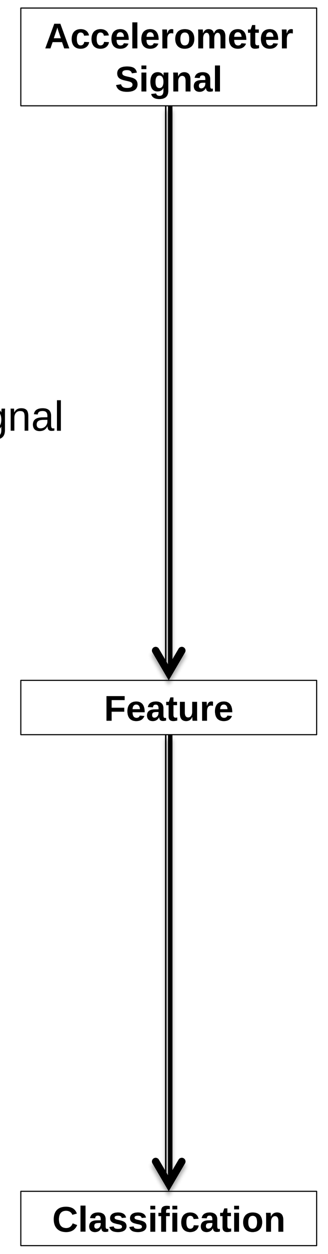


Figure 4. Dyskinesia raw accelerometer signal



The decision tree classifier ranked the feature, "Energy in Freq. Bands," as most important in identifying dyskinesia.

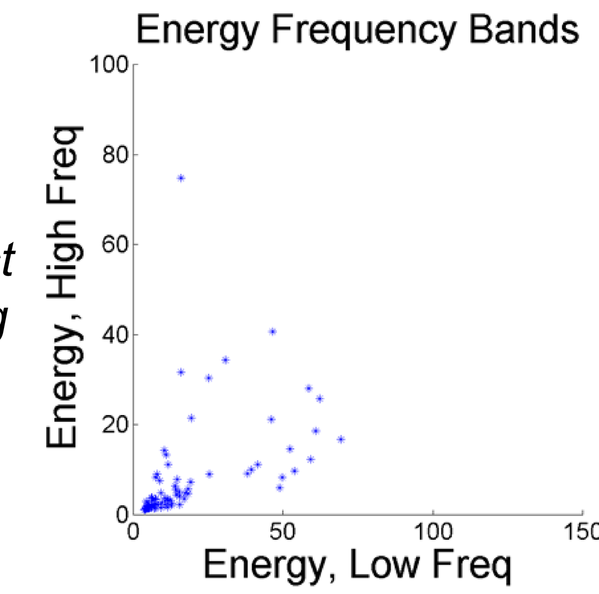


Figure 5. Non-Dyskinesia feature: Energy in frequency bands

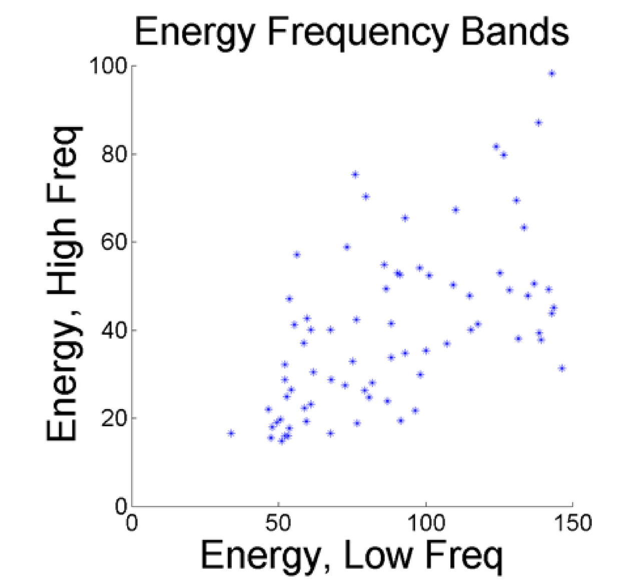


Figure 6. Dyskinesia feature: Energy in frequency bands

Dyskinesia Classification: 95.9% accuracy.

Impact for Patients and Clinicians

- **Patients wear wristwatch-like sensors** which provide data to determine automatically when dyskinesia occurs.
- **Clinicians can track dyskinesia** fluctuations of their patients with this system, which assists them in optimizing treatment of PD symptoms while minimizing dyskinesia.
- We are expanding this system to track dyskinesia, on (functional), and off (nonfunctional) motor states of PD over 7 days and automatically generate a symptom timeline (Figure 7).

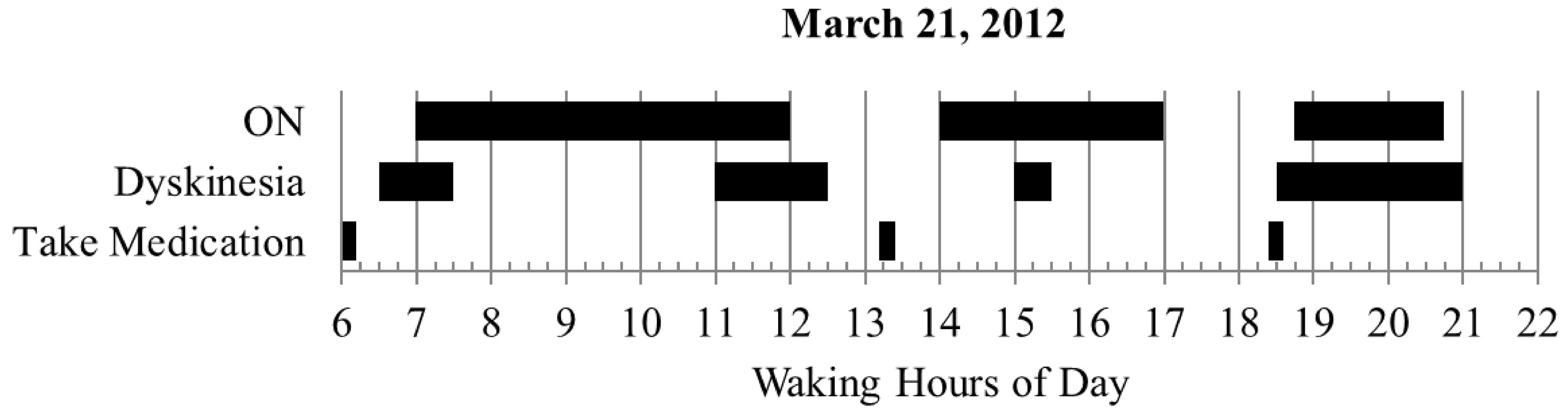


Figure 7. Example timeline. We aim to provide clinicians with an timeline of the daily fluctuations in dyskinesia and on/off motor states.

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