Accurate telemonitoring of Parkinson's disease symptom severity using nonlinear signal processing and statistical machine learning

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Project background

- Neurological disorders claim lives at an epidemic rate worldwide
- Parkinson’s disease (PD) is the second most common neurodegenerative disorder to Alzheimer
- Incidence rate: 20/100,000 annually
- 1% affected over the age of 60 years (age most important risk factor)
- Aging population more PD patients
- Drugs & surgery can alleviate symptoms but there is no known cure
What we already know

- Speech impairment is common in PD (90%)
- Evidence suggests degradation with PD progression
- Disease symptom tracking: costly, subjective, time-consuming, requires patient’s physical presence.
- Symptoms clinician maps to clinical metric (inter-rater variability)
- Unified Parkinson’s Disease Rating Scale (UPDRS)
- Range: motor-UPDRS 0 – 108, total-UPDRS 0 – 176 (44 sections)
What this study adds

- Novel mapping of speech dysphonias to UPDRS
- Accurate telemonitoring of PD progression
- Objective machine learning implementations
- Remote monitoring, less time-consuming
- Technology enabling large scale clinical trials
- Facilitates design and testing of novel drug treatments
Telemedicine: the dawn of a new era

1. Parkinson’s patient speaks into microphone
2. Home telemonitoring device (AHTD) records speech
3. Speech signals transferred to USB stick
4. Signals copied to patient’s computer via USB stick
5. Signals copied to dedicated clinic server via internet
6. Predicted UPDRS report to clinical staff
7. Statistical mapping of algorithms to UPDRS
8. Speech signal processing algorithms

Speech data transmitted through internet

Patient’s home  Medical centre
Methodology of this work

- Speech signal
- Extract feature vector
- Feature selection
- Statistical machine learning (mapping features \( \rightarrow \) UPDRS)
- Report results
Features

- Classical dysphonia measures (Tsanas et al. IEEE TBME 2010a) (capture fundamental frequency changes, amplitude, variability...)

- Improved classical dysphonia measures (Tsanas et al. ICASSP 2010b) (power transformation of classical schemes leads to improved results)

- Wavelets, Entropies & Energy (Tsanas et al. NOLTA 2010c) (wavelet decomposition and application of entropy and linear/nonlinear energy concepts)

- Nonlinear dynamical systems theory (Tsanas et al. JRSI 2010d)
Novel features (background)

- Pathological voices exhibit high frequency noise
- Asynchronous excitation due to incomplete vocal fold closure
- Loss of signal power & increase of noise power signal to noise ratio concepts
- Unstable control of voice production mechanism, not confined only to vocal folds
- Tentative belief that voice disorders affect differently frequency bands
- **Nonlinearities in voice production**
Novel features (algorithms)

- **Empirical mode decomposition excitation ratio** (first components represent noise, the rest components the signal)

- **Vocal fold excitation ratio** (detect glottal pulses and scan the frequency range using 500 Hz bands, then 1 Hz – 2.5 kHz denotes signal, the rest is noise - heuristic finding in this study)

- **Glottis quotient** (use DYPSA algorithm to detect glottal pulses and quantify periodicity – concept invoked from the classical dysphonia measures)
Feature selection

- Curse of dimensionality
- Reducing number of features enables a) improved performance, b) more accurate inference of the underlying characteristics of the modelled system
- LASSO, elastic net …
- 3 November (tomorrow!) co-organizing a workshop on FS
Statistical mapping

- $y = f(X)$, $X$ $\rightarrow$ Features and $y$ $\rightarrow$ UPDRS

- **Random forests**, powerful nonparametric learner

- Input into Random Forests the feature subsets selected by the feature selection algorithms

- One standard error rule to select **parsimonious** model
Results

- Data partitioning: 4,010 signals for males and 1,865 signals for females
- Use 10-fold cross validation with 100 repeats
- Report $\text{MAE} = \frac{1}{L} \sum_{Q} (y_i - f(x_i))$, $L$ is number of samples denoted by $Q$ which contains the indices of samples in each cross validation repeat

Table 1: Out of sample mean absolute error (MAE) for motor UPDRS and total UPDRS

<table>
<thead>
<tr>
<th>Motor – UPDRS (males)</th>
<th>Total – UPDRS (males)</th>
<th>Motor – UPDRS (females)</th>
<th>Total-UPDRS (females)</th>
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<tbody>
<tr>
<td>1.62 ± 0.17</td>
<td>1.96 ± 0.23</td>
<td>1.72 ± 0.16</td>
<td>2.20 ± 0.21</td>
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Results

6-month tracking for a male and a female subject

Motor UPDRS tracking for a male subject

- Baseline: 25
- 3-month: 27
- 6-month: 21
- MAE: $1.69 \pm 1.82$

Motor UPDRS tracking for a female subject

- Baseline: 18
- 3-month: 35
- 6-month: 18
- MAE: $2.34 \pm 1.75$

Total UPDRS tracking for a male subject

- Baseline: 30
- 3-month: 35
- 6-month: 25
- MAE: $1.93 \pm 3.03$

Total UPDRS tracking for a female subject

- Baseline: 24
- 3-month: 41
- 6-month: 28
- MAE: $3.13 \pm 2.83$

Legend:
- Clinicians' assessment
- Interpolated UPDRS
- Predicted UPDRS
- 25-75 percentile confidence interval
- 5-95 percentile confidence interval
Conclusions

- Speech signals convey clinically useful information
- **Fast, accurate, remote, objective** monitoring of PD is shown to be possible using simply speech
- Results are better than the **inter-rater variability** (which is about 5 UPDRS points).
- Potentially these results could be further improved in conjunction with other PD recorded signals (e.g. tremor data).
References


