Feature Representation of Pathophysiology of Parkinsonian Dysarthria

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Introduction

Parkinson's disease (PD) dysarthria manifests through changes in control of a person's speech production, and affects several speech production subsystems:

- Respiratory: breathing, reduced volume and range.
- Articulation: less control on consonant production.
- Prosody (Rhythm): rate variation/instability, longer pauses, takes longer time to start voicing, slower speech.
- Phonation: monotony of pitch, hoarse.

Database

PC-GITA database was considered [1]. It contains recordings of 50 PD patients and 50 healthy control (HC) speakers. All participants are Colombian Spanish native speakers. The data are age and gender balanced.

Tasks: Each subject performed six diadochokinesis (DDK) tasks: (/pa/, /ta/, /ka/, /pa-ka-ta/, /pa-ta-ka/, /pe-ta-ka/). Three repetititions of sustained vowel /a/ are also considered.

Feature Extraction

Articulation features

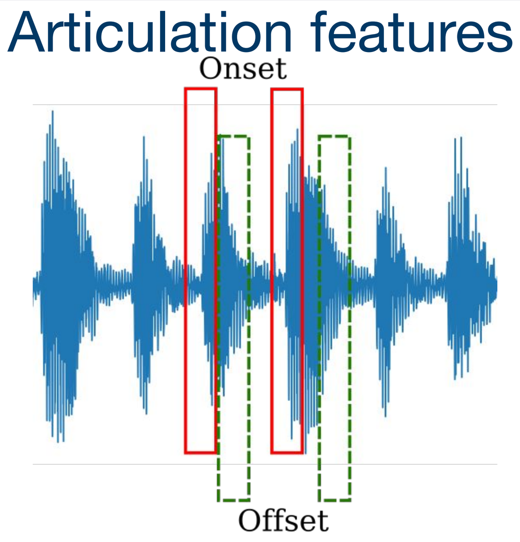

Figure 1: Onset and offset segments.

Empirical Mode Decomposition (EMD) features

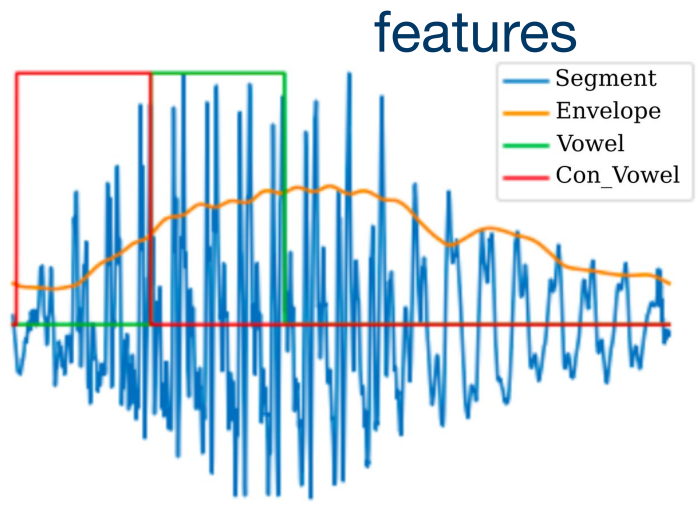

Figure 2: Separating consonant-vowel transition and plain vowel segments.

A total of 3534 features from four feature sets were extracted.

Type	Task	Features	Statistics	Total
Phonation	/a/ 3 times	7	x4	84
Articulation	DDK 6 tasks	53x2	x4	2544
DDK Rhythm	DDK 6 tasks	55	n/a	330
EMD	DDK 6 tasks	24	x4	576

Table 1: Features extracted for each type.

Feature Selection

Stage 1 – KLD Filter:

- Kullback-Leibler Divergence (KLD) is also known as relative entropy.
- Measures the differences between two probability distribution functions.
- Taken PD entropy in relative to HC.

$$KLD(P_{PD}||P_{HC}) = \sum_{x \in X} P_{PD}(X) log \frac{P_{PD}}{P_{HC}}$$

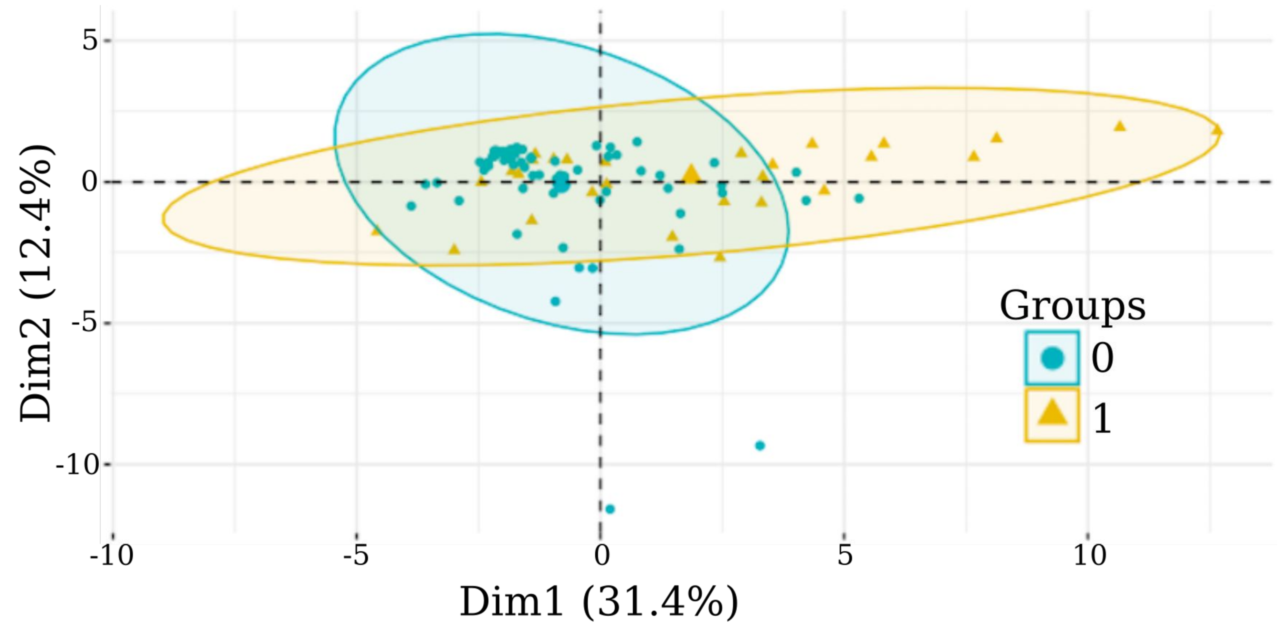

Figure 3: Visualizing the dataset after KLD feature filtering using Principal Component Analysis.

Item	Rel. Feat.	Task	Tent. Feat.	Task
1	dF0 Std	/a/-2	ddF0 Std	/a/-1
2	dF0 Std	/a/-3	Df0 Kurt	/a/-2
3	ddF0 Std	/a/-2	PPQ Std	/a/-1
4	ddF0 Std	/a/-3	Jitter Std	/a/-1
5	PPQ Mean	/a/-1	Jitter Std	/a/-2
6	PPQ Std	/a/-2	Jitter Std	/a/-3
7	PPQ Std	/a/-3	Min V	/pa-ta-ka/
8	P-U ratio	/pa-ta-ka/		

Table 2: Relevant features (Left table) and tentative features (Right table).

Stage 2 – Boruta Wrapper:

Boruta wrapper is used to remove redundant and less relevant features. Boruta algorithm is built-around Random Forest classifier for relevancy determination. For each iteration, the algorithm performs:

- Step 1: Adding shadow features by adding 5 or more features with their values shuffled.
- Step 2: Calculate Z score and find the maximum Z score of the shadow attributes (MZSA).
- Step 3: Features with Z score higher than MZSA are deemed important.

Results

Three traditional classifiers were used to validate the selected features, Support Vector Machine (SVM), Random Forest (RF), and Naïve Bayes (NB). A 10-fold Cross-validation was performed.

	KLD selected features		Boruta confirmed features	
Classifier	Acc.	F1-score	Acc.	F1-score
SVM	69 ± 11	70 ± 14	72 ± 16	71 ± 18
RF	73 ± 17	74 ± 15	73 ± 16	74 ± 14
NB	64 ± 14	67 ± 15	67 ± 13	70 ± 15

Table 3: Classification results with KLD and Boruta selected features.

Conclusions

- Boruta Wrapper works better than using only the KLD filter. Improvements around 2-3% are observed in the classification accuracy.
- The sequence of bilabial, alveolar, and velar stops has more discriminating power than other DDK sequences.
- The features related to voice onset time and stability are more relevant for the addressed problem.
- Future work will include other feature types and different feature selection strategies.

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