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Feature Representation of Pathophysiology of Parkinsonian Dysarthria

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Abstract

This paper focuses on selecting features that can best represent the pathophysiology of Parkinson's disease (PD) dysarthria. PD dysarthria has often been the subject of feature selection and classification experiments, but rarely have the selected features been attempted to be matched to the pathophysiology of PD dysarthria. PD dysarthria manifests through changes in control of a person's speech production muscles and affects respiration, articulation, resonance, and laryngeal properties, resulting in speech characteristics such as short phrases separated by pauses, reduced speed for non-repetitive syllables or supernormal speed of repetitive syllables, reduced resonance, irregular vowel generation, etc. Articulation, phonation, diadochokinesis (DDK) rhythm, and Empirical Mode Decomposition (EMD) features were extracted from the DDK and sustained /a/ recordings of the Spanish GITA Corpus. These recordings were captured from 50 healthy (HC) and 50 PD subjects. A two-stage filter-wrapper feature selection process was applied to reduce the number of features from 3,534 to 15. These 15 features mainly represent the instability of the voice and rhythm. SVM, Random Forest and Naive Bayes were used to test the discriminative power of the selected features. The results showed that these sustained /a/ and /pa-ta-ka/ stability features could successfully discriminate PD from HC with 70% accuracy.

Index Terms: Parkinson's speech, DDK, feature analysis, dimension reduction, discriminative feature selection

1. Introduction

PD was the only neurological disorder with increasing age-specific prevalence between 1990 and 2015 [1] and had the fastest growing prevalence [2]. Speech impairment is a red flag for PD diagnosis. It is not a prodromal PD syndrome [3], nor a cardinal diagnostic criterion [4]. However, if speech impairment can be used as an objective screening tool, it might provide a feasible solution to the growing prevalence.

Little [5] raised the awareness of the possibility of using sustained /a/ for discriminating PD from HC subjects. The challenge lays in the overlapping feature space between PD subjects and HC subject with age-related voice impairment [6]. There is still a lot of room for improvement, including a more objective scoring by PD speech specialists. Recent adoption of the Frenchay dysarthria Assessment (FDA) scale and the modified version (m-FDA) [7, 8, 9, 10] have provided an alternative to the subjective UPDRS-III.1 score.

The goal of this study is to identify the minimal optimal set of speech features that are relevant to discriminating PD subjects from HC subjects. A 2-stage feature selection process is used to determine a set of features that can help represent the physiological aspects of Parkinsonian dysarthria. A set of classical (phonation, articulation, rhythm) and Empirical Mode Decomposition (EMD) features extracted from the sustained vowel /a/ and DDK recordings is reduced into a small set of relevant features and analyzed to determine their representative power.

This paper is organized into the following sections. Section 2 provides an overview of the pathology and physiology of PD and its manifestation to Parkinsonian Dysarthria. Section 3 describes the corpus and method used in this study. The results on the selected feature and their discriminating power using three classifiers are provided in Section 4. Section 5 contains the discussion of the findings followed by conclusions in Section 6.

2. Pathophysiology of PD Dysarthria

PD speech impairment, also known as Parkinsonian dysarthria, is a textbook example of hypokinetic dysarthria [11, 12]. Hypokinetic dysarthria is associated with basal ganglia pathology resulting from depleted dopamine levels in the striatum. The reduced dopamine level is caused by the death of the dopaminergic neurons, or the striatum is not able to receive dopamine. Parkinsonian dysarthria can affect all three main speech production subsystems: respiratory, laryngeal, and supralaryngeal articulation [13, 14]. Like other motor syndromes, speech-organ movements also exhibit voice tremor at 3-7 Hz [13] and bradykinesia [14].

At the supralaryngeal level, the narrowed range of movement inhibits tongue and lip movements, and insufficient function of the soft palate. Functional movements of the laryngeal have also become less flexible with reduced control. The vocal folds do not fully close, and have reduced mobility with slow and irregular vocal fold activities. Respiratory abnormalities such as reduced respiratory muscle strength and endurance can affect loudness and speech prosody. Changes in control and flexibility of the speech production muscles manifested in respiratory, phonatory, resonatory, articulatory, and intelligibility of speech [12, 15].

Perceptually, PD speech characteristic includes decay of loudness, shorter and rush phases separated by pauses, less articulated, pronounce consonant defectively, takes a longer time to produce sound (i.e., increased voice onset time), and slower speech but can have a supernormal rate of repetitive syllables. PD subjects have a longer voice onset time (VOT) than HC subjects since it takes a longer time for a PD to create sound.

The most distinctive characteristics are related to phonatory, articulatory, and abnormalities on prosody Alternating motion rates (AMRs) obtained from DDK. A lot of PD speech analyses have been published in the recent year including using a sustained vowel, DDK tasks, and speech analysis from scientists like Little, Orozco-Arroyave, Arias-Vergara, Rusz, Skodda,

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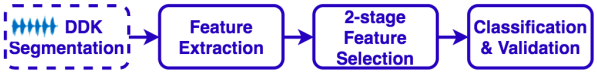

Figure 1: *The process to select discriminating features and validation .*

and others. This paper focuses on sustained vowel /a/ and DDK tasks. The DDK tasks can be used to observe reductions in the range of movement and rate abnormalities [12].

In [16], Novotný used six articulation features to differentiate PD to HC subjects. Rusz used phonation and rhythm features and other vowel features to capture the acoustics characteristics of PD dysarthria [17, 18]. Fischer and Goberman conducted an extensive study on PD VOT [19]. The recent trend in DDK studies has been using /pa-ta-ka/ alone for discriminative studies, as in [16, 9, 20].

With the advancements in signal processing research and machine learning, there are more and more features that can be extracted. The challenge is to find a small set of features that can better represent the physiological aspects of the disease. A more recent one was performed by Rusz in [17] using acoustic measures.

3. Database and Methodology

This study used the DDK recordings from the Spanish GITA Corpus [21] with 50 PD subjects and 50 age- and sex-matching HC subjects. Each group contained 25 male and 25 female subjects. PD subjects age were ranged between 33-81 years old with an average age of 61.02±9.44 years old, and HC subjects age ranged 31-86 years old with an average age of 60.98±9.46 years old. The UPDRS-III score for the PD subjects had a mean of 37.66 and a standard deviation of 18.31. The m-FDA score for the PD subjects had a mean of 28.76 and standard deviation of 8.39. The m-FDA score for the HC subjects had a mean of 8.5 and a standard deviation of 7.46.

Each subject performed a set of DDK tasks by rapidly and repetitively uttering different DDK syllables in one breath, and voiced sustained vowel /a/ three times.

Figure 1 illustrates the overall process that encompasses feature extraction, selection, and validation. Some DDK features required event detection and segmenting each syllable.

3.1. DDK Tasks

All DDK syllables were in the form of obstruent-sonorant pairs. The plosive obstruent consonants (unvoiced) consisted of [p, t, k], and sonorant vowels (voice) [a, e]. The unvoiced consonantal sounds included the voiceless bilabial [p], alveolar [t], and velar [k] stops. There were six DDK tasks, three single-syllables (/pa/, /ta/, /ka/) and three triple-syllables (/pa-ka-ta/, /pa-ta-ka/, /pe-ta-ka/).

3.2. Feature Extraction

A total of 3,534 features from four feature types were extracted from each subject, summarized in Table 1. The four feature types were phonation, articulation, DDK rhythm, and EMD features. EMD features provide a complementary measure that classical features cannot provide, such as nonlinearity. There were seven classical phonation features, two sets of 53 articulation features, 55 DDK rhythm features, and 24 EMD features. Except for DDK rhythm features, statistical measures (mean, standard deviation, skewness, and kurtosis) were extracted for each feature of the other three types.

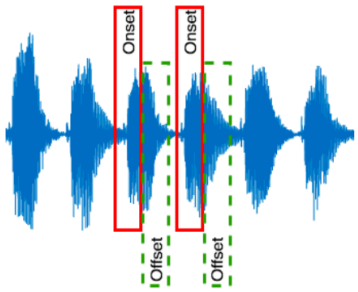

Figure 2: *Separating voice onset and voice offset segments for articulation feature extraction.*

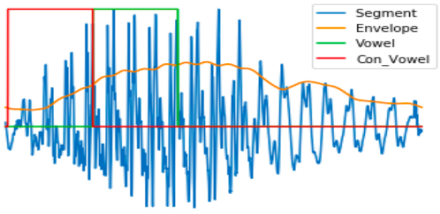

Figure 3: *Separating consonant-vowel transition and plain vowel segments for EMD features.*

Table 1: *Features extracted for each type.*

Type	Task	Features	Statistics	Total
Phonation	/a/ x3	7	x4	84
Articulation	DDK x6	53x2	x4	2,544
DDK rhythm	DDK x6	55	n/a	330
EMD	DDK x6	24	x4	576

Phonation, articulation, and DDK rhythm features were obtained using NeuroSpeech [22]. Phonation features were obtained from the three trails of sustained /a/ recordings. The two sets of articulation features represent voice onset (unvoiced-to-voice transition) and offset (voice-to-unvoiced transition) of the DDK syllables, as shown in Figure 2.

The train of syllables was segmented into single syllables through an Hilbert-transform-based enveloping to detect individual syllable. From each syllable, EMD features were obtained from the transition of the obstruent-sonorant (consonant-vowel transition) segments from plain vowel segments of the DDK syllables, as shown in Figure 3. The segments were then passed to the EMD feature extraction process to obtain energy based features from the Intrinsic Mode Functions (IMF) [23].

After features were extracted, all features were normalized with mean 0 and standard deviation 1. The normalized features were then passed to a 2-stage feature selection process.

3.3. Feature Selection

The goal of the feature selection is to select a subset of features that have the most discriminating factor, and to simplify a high-dimension problem to a minimal optimal problem. Different feature techniques have different strength. This study used a

2-stage feature selection that comprises of a Kullback-Leibler Divergence (KLD) filter and a Boruta wrapper selector.

Stage 1 - KLD Filter: The KLD filter is a thresholding filter. KLD, also known as relative entropy, measures the differences between two probability distribution functions. For every $x \in X$ space of feature X, KLD is calculated as

$$KLD(P_{PD} \parallel P_{HC}) = \sum_{x \in X} P_{PD}(x) \log \frac{P_{PD}(x)}{P_{HC}(x)} \quad (1)$$

The threshold to determine whether there is enough divergence between the two groups was set to a minimum of $KLD = 1$.

Stage 2 - Boruta Wrapper: Dissimilar features are not necessarily relevant to classification. The second stage of feature selection used a Boruta wrapper [24] 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 and vice versa

3.4. Classification and Validation

For such a small subject size, neural network classifiers are not suitable. Three traditional classifiers were used to validate the selected features. These classifiers were Support Vector Machine (SVM), Random Forest, and Naïve Bayes. Cross-validation of 10-fold was used to measure the performance of the classification.

The SVM classifier has a soft-margin constant C and a Gaussian radial basis kernel function. Grid search was used to tune the hyperparameters C in the range of $(10^{-2}, 10^{4})$ and Gaussian kernel width γ in the range of $(10^{-2}, 10^{2})$.

4. Results

4.1. Selected Features

There were 29 features past the first stage of feature filtering with criterion KLD ≥ 1. These features have KLD values range in [1.0026, 2.196]. Twenty out of the 29 features were phonation features extracted from the sustained /a/, and the other nine are DDK rhythms extracted from DDK recordings. DDK rhythm features included 4 pause-duration to unvoiced-duration ratios, and 4 minimum duration of voiced segments for /ta/, /pa-ta-ka/, /pa-ka-ta/, and /pe-ta-ka/, and the maximum duration of voiced segments for /ta/.

With the reduced feature dimension, it is feasible to visualize the datapoints by projecting them onto Principal Component Analysis (PCA) dominate dimensions, as illustrated in Figure 4.

Boruta confirmed 8 relevant features, 7 tentative features, and rejected 14 filtered features. The list of the relevant and tentative features listed in Table 2 was validated through changes in the classification result. Besides the two /pa-ka-ta/ features, the rest of the final feature list were phonation features extracted from sustained /a/. KLD selected features that were rejected by the Boruta wrapper are listed in Table 3.

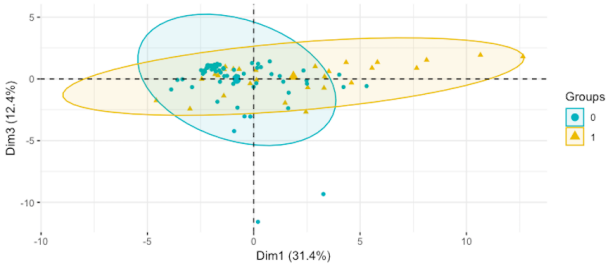

Figure 4: *Visualizing the dataset after KLD feature filtering using PCA. PD subjects belong to Group 0 and HC subjects belong to Group 1.*

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

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/		

Std - Standard deviation
dF0 - 1st Derivative of the fundamental frequency
ddF0 - 2nd Derivative of the fundamental frequency
PPQ - Pitch Perturbation Quotients
Min V. - Minimum duration of voiced segments
P-U ratio - defined as Pause duration/Unvoiced duration (Pause duration is defined as unvoiced period that is greater than 270 ms.)

4.2. Classification Results

Without using a wrapper in the second stage feature selection, the classifiers were tuned using all 29 features to obtain the hyperparameters of C = 9.44 and γ=0.0003 for SVM, and 500 trees for the Random Forest classifier. The classification results with only the KLD filter are summarized in Table 4.

With the second-stage wrapper, the classifiers were tuned using only the 15 selected features. The hyperparameters obtained were C = 204.5 and γ=0.0014 for the SVM classifier, and 500 trees for the Random Forest classifier. The classification results using the 2-stage feature selection are provided in Table 5.

The classification results indicated that not only can the 2-stage feature selection reduce the feature dimension almost by half, it can also slightly improve the classification results.

5. Discussion

EMD is generally used for analyzing non-linear non-stationary signals. Its features can be used as complementary features to the standard signal processing practice. However, the application of EMD depends largely on frame size and normalization to make the decomposition meaningful. In this paper, EMD processed the DDK recordings as in the standard practice by separating the consonant-vowel transition and vowel segments of the voice. It might be better to apply EMD on a fixed length

Table 3: *KLD features that were rejected by Boruta wrapper.*

item	Feat.	Task	item	Feat.	Task
1	dF0 Std	/a/-1	8	P-U ratio	/pa-ka-ta/
2	dF0 Kurt	/a/-1	9	P-U ratio	/pe-ta-ka/
3	dF0 Kurt	/a/-3	10	P-U ratio	/ta-ta-ta/
4	ddF0 Kurt	/a/-2	11	Min V.	/pa-ka-ta/
5	PPQ Kurt	/a/-1	12	Min V.	/pe-ta-ka/
6	PPQ Kurt	/a/-2	13	Min V.	/ta-ta-ta/
7	Jitter Kurt	/a/-2	14	Max V.	/ta-ta-ta/

Max V. - Maximum duration of voiced segments
Please refer to 2 for the rest of the acronyms.

Table 4: *Classification Results from the 29 KLD selected features. Performance measures obtained in accuracy (%), precision (%), recall (%), and F1-score.*

	Acc. (p-value)	Precision	Recall	F1
SVM	69±11	65±18	84±23	70±14
RF	73±17	72±20	78±18	74±15
NB	64±14	62±19	81±24	67±15

window size that is long enough to capture the dynamics of a person's DDK.

The selected features from the KLD filter all belong to sustained /a/, /ta/, /pa-ta-ka/, /pa-ka-ta/, and /pe-ta-ka/. This indicates that changes in syllables is more difficult than repeating the same syllable. However, it was unexpected to see /ta/ on the list instead of /ka/ for Spanish speakers [25].

At the end of feature selection, all features were obtained from sustained /a/ and /pa-ta-ka/. This means the variation of /ta/ between the PD and HC subject is not a discriminating factor. The results suggest /pa-ta-ka/ has more discriminative power than other sequences which agrees with the current trend on DDK studies using /pa-ta-ka/ sequences for PD dysarthria study. At the same time, the results indicate the potential of using sustained /a/. However, further studies are still required.

KLD filter removed overall 3,000 features that have no or low discriminative power. Boruta wrapper further removes another half of the filtered features. The features on the residual list are all related to the stability of the voice. The phonation features include standard deviations of the first and second derivation of the fundamental frequency, jitter, and pitch perturbation quotients. These features measure the stability of the sustained vowel. The two DDK features, the minimum duration of the voiced segment and Pause duration to Unvoiced duration ratio, are considered to be VOT related features.

Even through Boruta is a Random Forest-based wrapper, the improvement in the classification results from all three classifiers support Boruta's selection. There is a small improvement on the classification results after Boruta removed the irrelevant features. Half of the Boruta rejected features are higher order statistics. It is possible that there is insufficient information to form presentable higher order statistics, or they do not contribute to the decision making at all.

6. Conclusions

There is PD caused instability of voice from reduced muscle control in the speech production subsystem is found to be more distinguishable in sustained /a/ and /pa-ta-ka/ sequence. After the 2-stage feature selection process, features from all other DDK sequences were rejected. The findings agree with the current literature studies that the sequence of bilabial, alveolar, and velar stops has more discriminating power than other DDK sequences.

Table 5: *Classification Results from the 15 Boruta confirmed features. Performance measures obtained in accuracy (%), precision (%), recall (%), and F1-score.*

	Acc. (p-value)	Precision	Recall	F1
SVM	72±16	69±21	77±22	71±18
RF	73±16	73±19	78±17	74±14
NB	67±13	62±16	83±22	70±15

Stability features on sustained vowel and VOT related features on DDK sequence are more relevant for PD dysarthria and HC voice discrimination. However, it is not conclusive on the usefulness of high order statistical features.

The feature selection process successfully selected the relevant features that have pathophysiological meaning to PD. Using the 15 selected features, all three classifiers has improved classification accuracy of 2-3%, but with only half of the feature dimension. Both SVM and random forest achieved over 70% accuracy.

There is still much work to be done to understand the physiological presentation of PD dysarthria truly. Future work should include other more sophisticated features and modify the EMD window size.

7. Acknowledgements

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8. References

[1] GBD2015 Neurological Disorders Collaborator Group, "Global, regional, and national burden of neurological disorders during 1990–2015: a systematic analysis for the Global Burden of Disease Study 2015," *The Lancet Neurology*, vol. 16, no. 11, pp. 877–897, 2017.

[2] GDB2016 Parkinson's Disease Collaborators, "Global, regional, and national burden of Parkinson's disease, 1990–2016: a systematic analysis for the Global Burden of Disease Study 2016," *The Lancet*, vol. 17, pp. 939–953, 2018.

[3] D. Berg, R. B. Postuma, C. H. Adler, B. R. Bloem, P. Chan, B. Dubois, T. Gasser, C. G. Goetz, G. Halliday, L. Joseph, A. E. Lang, I. Liepelt-Scarfone, I. Litvan, K. Marek, J. Obeso, W. Oertel, C. W. Olanow, W. Poewe, M. Stern, and G. Deuschl, "MDS research criteria for prodromal Parkinson's disease," *Movement Disorders*, vol. 30, no. 12, pp. 1600–1609, 2015.

[4] R. B. Postuma, D. Berg, M. Stern, W. Poewe, C. W. Olanow, W. Oertel, J. Obeso, K. Marek, I. Litvan, A. E. Lang, G. Halliday, C. G. Goetz, T. Gasser, B. Dubois, P. Chan, B. R. Bloem, C. H. Adler, and G. Deuschl, "MDS clinical diagnostic criteria for Parkinson's disease," *Movement Disorders*, vol. 30, no. 12, pp. 1591–1599, 2015.

[5] M. A. Little, P. E. McSharry, E. J. Hunter, J. Spielman, and L. O. Ramig, "Suitability of dysphonia measurements for telemonitor-

ing of Parkinson's disease," *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 4, pp. 1015–1022, 2009.

[6] T. Arias-Vergara, J. C. Vásquez-Correa, and J. R. Orozco-Arroyave, "Parkinson's disease and aging: Analysis of their effect in phonation and articulation of speech," *Cognitive Computation*, pp. 1–18, 2017.

[7] M. Cernak, J. R. Orozco-Arroyave, F. Rudzicz, H. Christensen, J. C. Vásquez-Correa, and E. Nöth, "Characterisation of voice quality of Parkinson's disease using differential phonological posterior features," *Computer Speech and Language*, vol. 46, pp. 196–208, 2017.

[8] J. C. Vásquez-Correa, J. R. Orozco-Arroyave, R. Arora, E. Nöth, N. Dehak, H. Christensen, F. Rudzicz, T. Bocklet, M. Cernak, H. Chinaei, J. Hannink, P. S. Nidadavolu, M. Yancheva, A. Vann, and N. Vogler, "Multi-view representation learning via gcca for multimodal analysis of Parkinson's disease," in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2017, pp. 2966–2970. [Online]. Available: http://ieeexplore.ieee.org/document/7952700/

[9] T. Arias-Vergara, J. C. Vásquez-Correa, J. R. Orozco-Arroyave, and E. Nöth, "Speaker models for monitoring Parkinson's disease progression considering different communication channels and acoustic conditions," *Speech Communication*, vol. 101, no. June 2017, pp. 11–25, 2018. [Online]. Available: https://doi.org/10.1016/j.specom.2018.05.007

[10] J. C. Vásquez-Correa, T. Arias-Vergara, J. R. Orozco-Arroyave, and E. Nöth, "A multitask learning approach to assess the dysarthria severity in patients with Parkinson's disease," in *Proceedings of the Annual Conference of the International Speech Communication Association, INTERSPEECH*, 2018, pp. 456–460.

[11] F. L. Darley, A. E. Aronson, and J. R. Brown, *Motor speech disorders*. Philadelphia, PA: W.B. Saunders, 1975.

[12] J. R. Duffy, *Motor speech disorders: Substrates, differential diagnosis, and management, 2nd edition*. Boston: Mosby, 2005.

[13] R. D. Kent, G. Weismer, J. F. Kent, H. K. Vorperian, and J. R. Duffy, "Acoustic studies of dysarthric speech: Methods, progress, and potential," *Journal of Communication Disorders*, vol. 32, no. 3, pp. 141–186, 1999.

[14] S. Pinto, C. Ozsancak, E. Tripoliti, S. Thobois, P. Limousin-Dowsey, and P. Auzou, "Treatments for dysarthria in Parkinson's disease," *Lancet Neurology*, vol. 3, no. 9, pp. 547–556, 2004.

[15] S. Pinto, A. Chan, I. Guimarães, R. Rothe-Neves, and J. Sadat, "A cross-linguistic perspective to the study of dysarthria in Parkinson's disease," *Journal of Phonetics*, vol. 64, pp. 156–167, 2017.

[16] M. Novotný, J. Rusz, R. Čmejla, and E. Ržička, "Automatic evaluation of articulatory disorders in Parkinson's disease," *IEEE Transactions on Audio, Speech and Language Processing*, vol. 22, no. 9, pp. 1366–1378, 2014.

[17] J. Rusz, R. Cmejla, H. Ruzickova, and E. Ruzicka, "Quantitative acoustic measurements for characterization of speech and voice disorders in early untreated Parkinson's disease," *The Journal of the Acoustical Society of America*, vol. 129, no. 1, pp. 350–367, 2011.

[18] J. Rusz, R. Cmejla, T. Tykalova, H. Ruzickova, J. Klempir, V. Majerova, J. Picmausova, J. Roth, and E. Ruzicka, "Imprecise vowel articulation as a potential early marker of Parkinson's disease: Effect of speaking task," *The Journal of the Acoustical Society of America*, vol. 134, no. 3, pp. 2171–2181, 2013. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/23967947

[19] E. Fischer and A. M. Goberman, "Voice onset time in Parkinson disease," *Journal of Communication Disorders*, vol. 43, no. 1, pp. 21–34, 2010.

[20] L. Moro-Velazquez, J. A. Gomez-Garcia, J. I. Godino-Llorente, J. Rusz, S. Skodda, F. Grandas, J. M. Velazquez, J. R. Orozco-Arroyave, E. Nöth, and N. Dehak, in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2018, pp. 1404–1407.

[21] J. R. Orozco-arroyave, J. D. Arias-Londoño, J. F. Vargas-Bonilla, M. C. González Rátiva, and E. Nöth, "New Spanish speech corpus database for the analysis of people suffering from Parkinson's disease," in *Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC)*, 2014, pp. 342–347. [Online]. Available: http://www.lrec-conf.org/proceedings/lrec2014/summaries/7.html

[22] J. R. Orozco-arroyave, J. C. Vásquez-Correa, J. F. Vargas Bonilla, R. Arora, N. Dehak, P. S. Nidadavolu, H. Christensen, F. Rudzicz, M. Yancheva, H. Chinaei, A. Vann, N. Vogler, T. Bocklet, M. Cernak, J. Hannink, and E. Nöth, "NeuroSpeech: An open-source software for Parkinson's speech analysis," *Digital Signal Processing*, vol. 1, pp. 1–17, 2018.

[23] A. Rueda and S. Krishnan, "Clustering Parkinson's and age-related voice impairment signal features for unsupervised learning," *Advances in Data Science and Adaptive Analysis*, vol. 10, no. 2, 2018. [Online]. Available: https://www.worldscientific.com/doi/abs/10.1142/S2424922X18400077

[24] M. B. Kursa, "Feature selection with the Boruta package," *Journal of Statistics*, vol. 36, no. 11, pp. 1–13, 2010.

[25] J. I. Godino-Llorente, S. Shattuck-Hufnagel, J. Y. Choi, L. Moro-Velázquez, and J. A. Gómez-García, "Towards the identification of idiopathic Parkinson's Disease from the speech. New articulatory kinetic biomarkers," *PLoS ONE*, vol. 12, no. 12, pp. 1–35, 2017.