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Synchronous analysis of abnormal acoustic and linguistic production in Parkinson's speech

Daniel Escobar-Grisales[1], *Cristian David Ríos-Urrego*[1], *Marco Sabato Siniscalchi*[2] *Adolfo M. García*[3], *Yamile Bocanegra*[4] , *Leonardo Moreno*[5],*Elmar Nöth* [6], *Juan Rafael Orozco-Arroyave*[1,6]

[1] GITA Lab, University of Antioquia UdeA; [2]Faculty of Engineering, Università degli Studi di Palermo; [3]CNC, Universidad de San Andrés; [4]GNA Lab, Universidad de Antioquia; [5]Hospital Pablo Tobón Uribe; [6]LME Lab, Friedrich-Alexander Universität.

daniel.esobar@udea.edu.co

Abstract

Parkinson's disease is a neurodegenerative disorder involving speech and language deficits. Often, these are separately studied as proxies of motor and non-motor (e.g., cognitive) symptoms, respectively. Conversely, links between both dimensions remain virtually uncharted. This paper introduces a methodology that enables the synchronous study of acoustic and linguistic patterns in Parkinson's speech. Our findings show that verbs and nouns provided relevant acoustic and linguistic information not only to model motor impairments but also to understand non-motor symptoms like those that appear when Parkinson's disease patients develop mild cognitive impairment.

Index Terms: Speech analysis, linguistic analysis, Parkinson's disease, cognitive decline, linguistic units, acoustic modeling.

1. Introduction

Parkinson's disease (PD) is a neurodegenerative condition that involves the loss of dopaminergic neurons in the basal ganglia of the midbrain. Reduction of such neurons interferes with the transmission of signals necessary to coordinate and regulate movements, resulting in motor impairments including rigidity, resting tremor, and postural instability. Although motor disorders are more evident, alterations in the basal ganglia and other brain regions could also produce non-motor symptoms namely sleep disorders, cognitive decline, depression, and others.

Continuous monitoring of PD progression is essential for properly treating and managing the symptoms. While different approaches have been proposed to detect and track PD, automatic speech and language analyses have become a promising, non-invasive, and low-cost alternative. Different speech abnormalities may appear in PD patients including reduced voice quality, monotonicity, and difficulty in articulation to produce phonemes, words, and other sounds [1]. Additionally, alterations in brain regions like the prefrontal, temporal, and motor cortices lead to lexico-semantic abnormalities, including reduced verbal fluency and alterations in the usage and production of specific linguistic units mainly verbs and nouns [2, 3].

Automatic analysis of PD using speech signals has increased over the years. Acoustic features such as pitch, jitter, shimmer, formant frequencies, and Mel Frequency Cepstral Coefficients (MFCCs) have been employed to distinguish between PD patients and healthy controls (HC) or to assess the severity of speech impairments [4]. Although these features have been used in several speech processing applications [5], researchers have also developed specific feature sets to model particular speech dimensions including prosody, articulation, phonation, and intelligibility [6]. For instance, articulation features model the patient's ability to control the movement of different articulators to produce speech [7]. These approaches have achieved accuracies of up to 86% classifying between PD patients and HC using connected speech tasks such as monologues [8].

Deep Learning (DL) approaches have also been employed in different studies about Parkinson's speech signals. Typically, time-frequency representations are used to feed Convolutional Neural Networks (CNNs) which can be trained from scratch or using pre-trained models such as those based on ResNet arquitectures [9, 10]. In [11], the authors reported accuracies of up to 84% classifying between PD patients vs. HC subjects using Mel-spectrograms to feed a CNN architecture based on a ResNet topology. Recent works implemented a model combining unidimensional-CNN (1D-CNN) and bidimensional-CNN (2D-CNN) to capture frequency and time information [12]. Other works combine CNNs with recurrent architectures to take advantage of the temporal nature of speech signals. In [13] a 1D-CNN followed by a Long Short-Term Memory (LSTM) was used to classify PD patients vs. HC subjects. The authors reported accuracies of 77% on an independent test set recorded under non-controlled acoustic conditions, indicating a good generalization capability. Another interesting and clinically useful characterization based on DL models is the phonemic identifiability [3, 14], where a pre-trained model allows measuring the precision of specific pronounced phonemes. Although other DL approaches tend to perform better, this characterization offers the advantage of a better interpretation, which makes it more useful and reliable in clinical applications. In [15], the authors used phonemic identifiability features and achieved accuracies of up to 78% in the PC-GITA database, outperforming previous results obtained with other speech dimensions such as articulation or prosody, and achieving similar results when considering characterizations based on foundation models such as Wav2vec 2.0.

Speech production also involves cognitive processes during word selection, grammatical organization, and other processes that are affected due to the progressive death of neurons in brain regions [16]. In [17], the authors used the Wav2vec 2.0 model to generate frame-wise representations and predictions. This fine-granularity approach allowed the identification of segments with better discriminatory power. The results indicated that the segments with better discrimination capability tend to occur when motor verbs are pronounced. However, the frame-wise representation proposed in that study could contain information from other speech segments because the Wav2vec 2.0 model is based on a transformer architecture, i.e., the model has access to the entire recording during inference, making it difficult to guarantee that representations linked to verb pronunciation only contain information from those specific segments. In the present paper, we consider feature sets such as phonemic identifiably to obtain a characterization that only uses the information of the specific speech segment. Contrary to what was presented

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by the authors in [17], we can ensure that the characterization of a segment depends only on the segment information and it is not altered by its context. In addition, to ensure that the lexical content of the recordings is not biased by the speech task, in this work we asked the patients to retell a previously read story, namely *retelling task*. We analyzed the frame-wise classification performance between PD patients and HC subjects. This fine granularity approach enabled the analysis of those linguistic units where the model has high classification. This analysis suggests that discriminative speech segments are mainly composed of verbs and nouns. To validate these findings, we performed subject-wise classification using only frame predictions corresponding to segments where either a noun or a verb was pronounced. With this approach, subject-wise classification improved by 7% compared to the methods that considered all frame predictions. Finally, we developed the same analysis considering PD patients with and without Mild Cognitive Impairment (MCI) to further analyze which are the distinctive lexical units when PD patients develop MCI.

2. Material and methods

Figure 1 summarizes the general approach addressed in this paper. First, the recording is split into 80 ms frames with an overlap of 40 ms. Then, the representation of each frame is obtained using phonological features and MFCCs. These frame-wise representations are used to feed a neural network with a sigmoid function in its last layer. Frame-wise classification enables the identification of those speech segments that yield high scores, which are indicative of PD patients and also low scores that are indicative of HCs. Each recording is aligned with its manual transcription, allowing associating discriminatory segments with their corresponding linguistic units. Once we identify relevant linguistic units, we performed a subject-wise classification using the frame-wise prediction linked to the initial part of each linguistic unit. A similar analysis was conducted to compare possible linguistic impairments in PD patients with MCI (namely wMCI) vs. without MCI (namely woMCI).

2.1. Data

The corpus considered for this study is the same as the one used in [3] and [18]. It consists of 80 speakers, 40 with PD and 40 HC. All patients were diagnosed by an expert neurologist following the UK PD Society Brain Bank criteria. Motor symptoms were assessed following the third section of the Unified Parkinson's Disease Rating Scale (UPDRS-III) [19] and the Montreal Cognitive Assessment (MoCA) scale. The first one evaluates motor symptoms; whereas the second one is administered to evaluate possible cognitive decline reflected in patients as MCI. The participants were asked to read a text rich in action verbs, and later they were asked to retell the story in their own words. Therefore, lexico-semantic content to be reproduced was held constant across participants., i.e., all participants had similar lexical conditions, therefore the words chosen by the speakers are expected to belong to similar lexical spaces.

Participants were matched regarding age, gender, and education level. Demographic and clinical information are presented in Table 1. All participants signed an informed consent pursuant to the Declaration of Helsinki. The study was approved by the Institutional Ethics Committee at University of Antioquia, Medellín, Colombia.

Table 1: *Clinical and demographic information. [F/M]: Female/Male. UPDRS-III: Unified Parkinson's Disease Rating Scale, section III, H&Y: Hoehn & Yahr scale, MoCA: Montreal Cognitive Assessment, wMCI/woMCI: with MCI/without MCI. MCI screening followed level-1 criteria of the Movement Disorder Society Task Force [20].*
**p-values calculated using Mann–Whitney U tests*

	PD patients	**HC subjects**	**PD vs HC**
Sociodemographic variables			
Sex [F/M]	15/25	15/25	–
Age	61.9±7.3	62.3±9.3	0.84*
Years of education	12.8±4.6	12.2±5.0	0.63*
Clinical variables			
UPDRS-III	31.0±12.5	–	–
H&Y	2.1± 0.3	–	–
MoCA	24.8± 3.0	26.7±1.6	>0.01*
wMCI/woMCI	16/24	–	–

2.2. Acoustic modeling

Each recording was segmented into 80 ms frames with a step of 40 ms. Within each segment, posterior values corresponding to the 18 phonological classes are extracted in segments with 25 ms length and steps of 20 ms using the Phonet toolkit [14]. With the extracted phonological posteriors, statistical functionals (mean, standard deviation, maximum, minimum, kurtosis, and skewness) are estimated per speech frame (80 ms). Besides, twelve MFCC coefficients are calculated per speech frame and concatenated with the resulting 108 (18×6) statistical functionals, forming a 120-dimensional feature vector per speech segment.

2.3. Linguistic analysis on PD

To analyze the behavior of frame prediction in specific linguistic units such as verbs, adverbs, nouns, and others, we performed forced alignment between the transcriptions and their corresponding recordings. This alignment was conducted using WebMAUS[1] [21]. Then, we performed a Part-Of-Speech (POS) tagging using the "es_core_news_sm" model from the *spaCy* library to obtain all the linguistic units produced in the recordings with their corresponding timestamps.
The motivation behind having a detailed look at specific lexical units in PD patients comes from the fact that they often show abnormal production patterns of specific linguistic units, particularly verbs [18]. Studies utilizing functional Magnetic Resonance Imaging (fMRI) scans have shown no significant differences in brain connectivity when comparing PD and HC subjects during noun processing. Conversely, significant differences have been observed in the brain activity of these groups during verb processing [22, 23].

3. Experiments and results

Acoustic features were extracted from all recordings following the method described in Section 2.2. The classification was performed with three fully connected layers with a Sigmoid activation function in the final layer to make a frame-wise prediction. Values of the Sigmoid function close to 1 indicate that the model is confident regarding detecting a PD patient. Similarly, values close to 0 indicate the model has detected a healthy

[1]https://clarin.phonetik.uni-muenchen.de/BASWebServices/interface/WebMAUSBasic

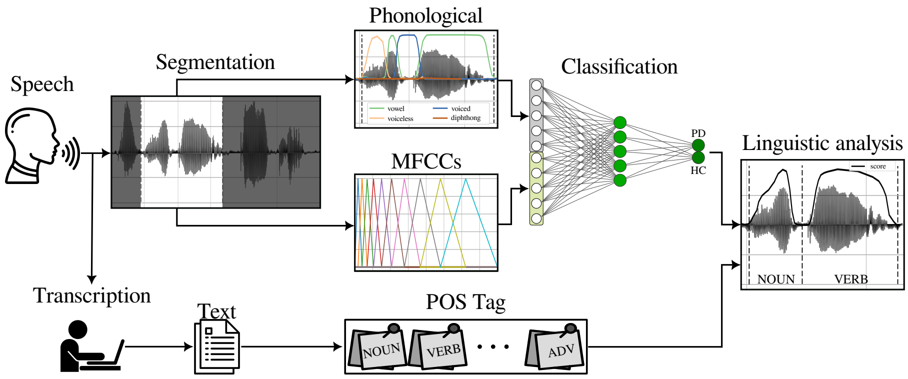

Figure 1: *General approach addressed in this study*

speaker. Parameters' optimization was done following a nested cross-validation strategy with five folds in the external loop that define an equal number of test sets, while four folds in the internal loop define the training and validation sets. Early stopping, dropout, and l_2 regularization were considered to mitigate possible overfitting. In all experiments, the subject class was determined by the mode across all predictions. The analysis of frames with better discrimination capability and specific linguistic units was performed using predictions from the test set, therefore no bias is guaranteed in the process.

3.1. Baseline: frame-wise classification

Table 2 shows the results obtained when all frames are considered. This constitutes the baseline result because there is no lexical-semantic analysis behind the method. Reported values correspond to the average performance in the five test sets of the external cross-validation.

Table 2: *Baseline classification performance of PD vs. HC using all frames in the recordings.*

	Accuracy	Sensitivity	Specificity	F1-score
Frame-wise	62.16	56.41	65.90	57.15
Subject-wise	67.72	62.50	70.56	66.61

To analyze the discriminatory segments in the frame-wise classification, we considered the correctly classified subjects and examined the distribution of their scores. Based on such a distribution, we selected frames with scores above the 85th percentile for PD patients and below the 15th percentile for HC subjects. Only those frames that formed segments of at least 240 ms were considered. This value approximately corresponds to the average length of a syllable in Spanish, and syllables typically consist of three phonemes (approx. 80 ms each) [24, 25]. The percentile thresholds were selected to ensure high-confident scores, and to make sure that all subjects correctly classified had at least one reliable segment. Figure 2 shows the percentage of different linguistic units in the "high-confident" segments. According to the upper part of the figure, the discriminatory segments are primarily composed of verbs and nouns. A similar pattern is observed when analyzing PD and HC groups separately (bottom part of Figure 2).

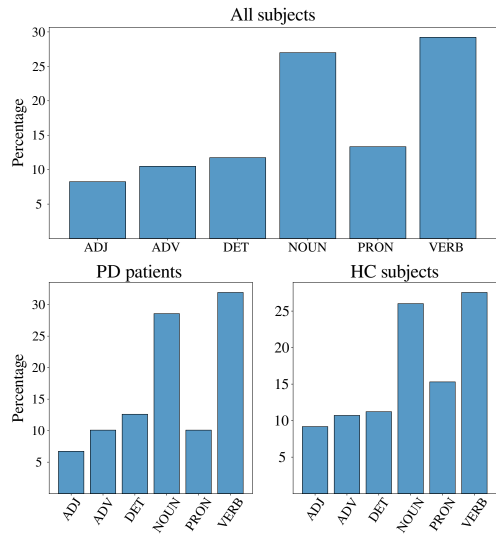

Figure 2: *Percentage of linguistic units with discriminatory segments. All POS tags were considered, but the graph displays only six: ADJ (Adjectives), ADV (Adverbs), DET (Determinant), NOUN (Nouns), PRON (Pronouns), VERB (Verbs).*

3.2. Classification using specific linguistic segments

Results of the previous experiment suggest that segments where a noun or verb was pronounced are highly reliable for classifying PD patients and HC subjects. Additionally, given the fact that the starting part of movements (including speech production) are highly informative for discriminating between PD and HC subjects [7, 8], we wanted to extend the concept to the production of specific linguistic units. In this experiment, we focused only on frames that correspond to the first 240 ms, where a verb or noun was pronounced, thereby modeling the process of planning and finding the corresponding word during message production [26]. Table 3 presents the subject-wise results of discriminating of PD vs. HC. Notice that both linguistic units yield an improvement of 7% accuracy compared to the scenario showed in Table 2, where all frames in the recordings regardless of their corresponding linguistic unit were considered.

Notice that the accuracy of verbs and nouns is similar, indicating that in principle, both linguistic units provide similar information. However, the research community in neuroscience is aware of the existence of different "additional" patterns that

Table 3: *PD vs. HC subject-wise classification performance using frames of specific linguistic units.*

	Accuracy	Sensitivity	Specificity	F1-score
Verbs	74.22	70.93	77.32	74.13
Nouns	74.28	65.55	82.36	73.92

may emerge with disease progression. One of the most studied is related to cognitive decline and is known as MCI. It is known that MCI patients exhibit abnormal speech and language production [27, 28]; however, little is known about PD patients who also suffer/develop from MCI. The next experiment intends to contribute to a better understanding of this phenomenon.

3.3. Analysis of linguistic units in wMCI and woMCI PD patients

This experiment aims to analyze whether the MCI condition influences the previous findings. Figure 3 shows the spectrum of linguistic units that composed discriminatory segments. These segments were found by following the same strategy as in the first experiment. Notice that discriminatory segments in the woMCI group are mainly composed of verbs, which was expected because PD patients without MCI constitute a regular cohort, i.e., they exhibit motor symptoms linked to abnormal verb production [2, 29]. Besides, discriminatory segments in the wMCI group are predominantly composed of nouns. This finding confirms previous observations indicating that when motoric (as opposed to cognitive) functions are selectively compromised, verb processing becomes distinctly impaired, given that this category is grounded in motor brain networks. Conversely, when motoric and cognitive deficits coexist, lexico-semantic deficits extend to nouns and other categories, arguably reflecting more generalized word retrieval anomalies [30].

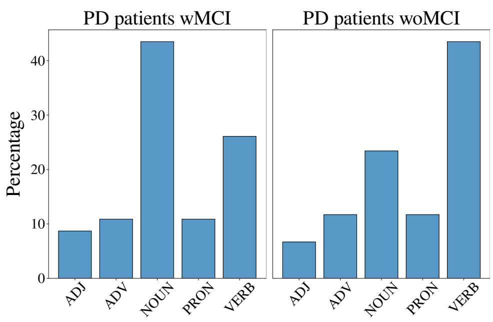

Figure 3: *Percentage of linguistic units in the discriminatory segments for patients with and without MCI. All POS tags in the retellings were considered. The graph displays the most prevalent: ADJ (Adjectives), ADV (Adverbs), DET (Determinant), NOUN (Nouns), PRON (Pronouns), VERB (Verbs).*

To assess the impact of this finding on the woMCI and wMCI groups, we analyzed the classification results for both groups following the same pipeline as in the previous experiment. We used two different subsets of HC to keep age and gender balance along the comparisons with the wMCI and woMCI patient groups. Table 4 summarizes the results. Notice that for woMCI we improved the accuracy obtained with nouns by 4%. In contrast, the wMCI group yielded better results with the noun frames, outperforming verb frames by about 5%.

Figure 4 compares modeling verbs vs. nouns in wMCI and

Table 4: *Layer-wise PD vs. HC classification performance.*

	Accuracy	Sensitivity	Specificity	F1-score
wMCI				
Verbs	71.96	67.51	76.17	71.86
Nouns	76.08	68.62	83.14	75. 9
woMCI				
Verbs	76.16	74.39	78.15	76.08
Nouns	72.85	63.46	81.19	72.24

woMCI PD patients. Notice that the AUC value obtained with verbs is larger than the one with nouns in patients woMCI, which confirms findings previously reported in the literature. Regarding the scores obtained with the wMCI group, in this case the pattern switches, i.e., the AUC of nouns is larger than the one of verbs, which is also a pattern already reported in neuroscience studies.

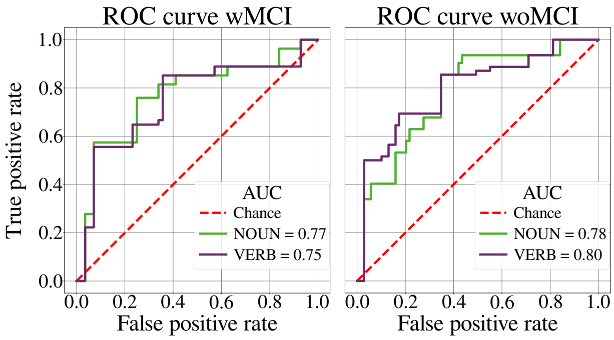

Figure 4: *ROC curves for wMCI and woMCI PD patients vs. their corresponding HC groups.*

4. Discussion and conclusions

This study shows that there exist links between distinctive patterns in speech segments and specific linguistic units produced by PD patients. Our results suggest that alterations in speech production may not be solely influenced by motor disorders, but also by an altered retrieval and production of specific linguistic units, such as verbs and nouns. Subject-wise classification with only frames of verbs or nouns outperformed classification results when no specific lexical units are considered. Besides objectively showing that verb production is abnormal in PD patients, the paper goes beyond and shows that, within the group of PD patients, those who develop MCI show impaired production of verbs and nouns, while the woMCI group only shows the abnormal verb production pattern, confirming what has been reported in neuroscience literature but not considering objective and automatic speech processing methods [30]. The results reported in this paper align with previous hypotheses where noun production is associated with brain areas in charge of visual and conceptual knowledge, i.e., temporal lobe, while verb processing is associated with areas in charge of action and motor processing, i.e., frontal lobe [31]. Finally, there are subtypes of MCI patients where temporal lobes are more affected, therefore accounting for impaired noun production [32]. This could partially explain the findings reported for the case of the wMCI patients group.

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