

## Acoustic-Based Articulatory Phenotypes of Amyotrophic Lateral Sclerosis and Parkinson's Disease: Towards an Interpretable, Hypothesis-Driven Framework of Motor Control

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## Abstract

The purpose of this study was to determine the articulatory phenotypes of amyotrophic lateral sclerosis (ALS) and Parkinson's disease (PD) using a novel acoustic-based framework that assesses five key components of motor performance: Coordination, Consistency, Speed, Precision, and *Rate.* The use of interpretable, hypothesis-driven features has the potential to inform impairment-based automatic speech recognition (ASR) models and improve classification algorithms for disorders with divergent articulatory profiles. Acoustic features were extracted from audio recordings of 18 healthy controls, 18 participants with ALS, and 18 participants with PD producing syllable sequences. Results revealed significantly different articulatory phenotypes for each disorder group. Upon stratification into Early Stage and Late Stage in disease progression, results from individual receiver operating characteristic (ROC) curves and decision tree analyses showed high diagnostic accuracy for impaired Coordination in the Early Stage and impaired Rate in the Late Stage. With additional research, articulatory phenotypes characterized using this framework may lead to advancements in ASR for dysarthric speech and diagnostic accuracy at different disease stages for individuals with distinct articulatory deficits.

**Index Terms**: differential diagnosis, dysarthric speech, interpretable features, automatic speech recognition, objective assessment

## 1. Introduction

Despite the negative impact of disordered articulation on speech intelligibility, there is currently no established set of metrics of articulatory impairment that reliably and accurately distinguish among divergent speech motor disorders<sup>1</sup>. The need for improved accuracy and efficiency in speech assessments has long been documented<sup>2</sup>. While disruptions in articulation have been found to be increasingly important for differential diagnosis<sup>3,4</sup>, there is little consensus about the core articulatory features that characterize distinct speech motor disorders. This gap in speech marker development reflects our limited understanding of how neurologic disease affects speech motor function and as a result, (1) slows the development of ASR systems and classification algorithms for differential diagnosis and (2) negatively impacts clinical confidence in assessment and treatment of speech motor disorders<sup>2</sup>. These deficiencies in objective, impairment-based articulatory features motivate our research on identifying speech motor phenotypes.

Current approaches for classifying speech motor impairments rely primarily on the detection of abnormal speech

characteristics by human labelers, specifically expert speechlanguage pathologists<sup>5-8</sup>. The most widely accepted set of atypical speech features was developed to classify dysarthria subtypes (i.e., flaccid, spastic, ataxic, hypokinetic, hyperkinetic, mixed)<sup>5,6</sup>. This feature set, known as the Darley, Aronson, and Brown (DAB) paradigm, was proposed over 50 years ago prior to the advent of modern speech analytic techniques. Despite the perceptual biases inherent to symptombased phenotyping<sup>7,9</sup>, research has been slow to validate the DAB features using quantitative analyses.

Data-driven approaches have attempted to address the limitations of perceptual assessments through the use of automatic feature extraction from open-source software programs such as OpenSMILE<sup>10,11,12</sup>. Although some of these feature sets have achieved high diagnostic accuracy rates for differential diagnosis, the opaque nature of the features - and the means by which they are derived - provides little insight into the underlying physiology of the motor disorder<sup>13</sup>. Recent work by Hlavnička et al.14 and software programs such as NeuroSpeech<sup>15</sup> have offered more interpretability by grouping features into speech subsystems (e.g., respiration, phonation, articulation, resonance). Nevertheless, despite previous research showing that articulatory features account for the majority of intelligibility loss in dysarthric speakers compared to features from the other subsystems<sup>3,4</sup>, the articulatory subsystem remains widely studied as a unidimensional system, with much of the focus on more global measures such as articulatory rate. Current studies have discussed a plethora of novel features, but there is little guidance regarding how these features map onto different components of articulation. The absence of a comprehensive view of articulation is problematic because specific pathophysiologies may have differential impacts on articulatory function<sup>16-19</sup>.

In Rowe & Green (2019), we proposed a framework comprised of four key components that comprehensively characterize speech motor control: *Coordination*<sup>20-22</sup>, *Consistency*<sup>20,23,24</sup>, *Speed*<sup>20,25</sup>, and *Precision*<sup>20,25</sup>. Using this framework, with the added component of  $Rate^{19}$ , we presented a subset of interpretable acoustic metrics that correspond to each of the articulatory components (see Figure 1). For the rationale behind our feature selection, see Rowe & Green (2019)<sup>26</sup>. Our primary goals in developing this framework are (1) to identify articulatory phenotypes of distinct speech motor disorders that can eventually guide individualized treatment and (2) to facilitate selection of hypothesis-driven, impairment-based features that will improve classification accuracy of distinct speech motor disorders.

In the current study, we tested the validity of our hypothesis-driven features by investigating the phenotypes of disorder groups known to differ on these articulatory dimensions: hypokinetic dysarthria secondary to Parkinson's disease (PD) and mixed flaccid-spastic dysarthria secondary to amyotrophic lateral sclerosis (ALS). We are also interested in the classification accuracy of our hypothesis-driven features both prior to perceptible changes in the patients' speech and after symptoms emerge. While severity stratification can introduce bias, running algorithms on the full continuum of severities obscures phenotype changes that might occur throughout the disease, which may be crucial for early diagnosis and treatment. Thus, to allow for the discovery of disease stage-based phenotypes as well as potential early biomarkers, we stratified the ALS and PD groups into Early Stage and Late Stage for our second research question.



Figure 1: Five key components of speech motor control and the corresponding acoustic features.

To investigate the underlying articulatory impairments and subsequently test their diagnostic accuracy in patients with ALS and PD, we asked the following research questions:

- 1. <u>Disorder-Based Phenotypes:</u> Are there differences in the articulatory components between the ALS group, the PD group, and healthy controls?
- <u>Disease Stage-Based Phenotypes:</u> What is the classification accuracy of the articulatory components for distinguishing between:
  - a. Early Stage ALS and Early Stage PD?
  - b. Late Stage ALS and Late Stage PD?

#### 2. Methods

### 2.1. Participants

Speech samples from 18 healthy controls, 18 participants with ALS, and 18 participants with PD were obtained from the XRMB dysarthria database and from an ongoing prospective study on speech deterioration due to ALS.

Prior to analysis, participants in the ALS and PD groups were stratified into Early Stage and Late Stage based on ratings by two speech-language pathologists. The clinicians blindly rated the participants as "Early Stage" if they perceived the speech of the participant as indistinguishable from that of a healthy control. If the clinicians detected abnormalities in the participant's speech, they were instructed to rate the participant as "Late Stage." The clinicians also rated sentence intelligibility on a visual analog scale (VAS) from 0 (normal) to 100 (very impaired). While the ALS group had a greater range of speech deficits compared to the PD group, there were no statistical differences in sentence intelligibility between the two groups prior to stratification, at the early stage, nor at the late stage.

Inter-rater reliability for sentence intelligibility ratings was calculated using ICC agreement (.90) and inter-rater reliability

for disease stage classification was calculated with Cohen's kappa (.89). All participants were native English speakers. Neither the control group nor the clinician raters had any history of speech, language, or hearing problems. Participant demographics and intelligibility ratings are reported in Table 1.

Table 1: Demographic and speech characteristics of the ALS group, PD group, and control group.

	Ν	Age	Sex	Sentence Intelligibility (100 = very impaired; 0 = normal)
Controls	18	58.7 (9.1)	9 M, 9 F	0 (0)
ALS				17.11 (31.79)
Early Stage	9	54.0 (12.4)	7 M, 2 F	.61 (1.83)
Late Stage	9	57.1 (10.1)	4 M, 5 F	33.61 (39.13)
PD				2.57 (6.37)
Early Stage	10	55.1 (11.4)	4 M, 6 F	.58 (1.32)
Late Stage	8	56.5 (11.0)	7 M, 1 F	5.06 (9.14)

#### 2.2. Procedures

Acoustic features were extracted from audio recordings of participants producing syllable sequences during the sequential motion rate (SMR) portion of the diadochokinetic (DDK) task<sup>27</sup>. To obtain the SMR, participants were instructed to produce the syllable sequence /pataka/ as many times as they could on one breath, as quickly and accurately as possible. We used this task because it is widely administered in clinical settings and because degraded performance on this task is strongly associated with bulbar motor involvement<sup>28</sup>. A headmounted microphone was positioned at approximately 5 cm from the mouth during the recordings. Recordings were sampled at a rate of 22 kHz. Acoustic analyses of the first three repetitions of /pataka/ for each participant were conducted offline using Praat<sup>29</sup>. Formant settings were adjusted based on the gender of the participants, with the maximum formant frequency set to 5500 Hz for women and 5000 Hz for men.

#### 2.3. Measurements

The five components of speech motor control were represented using novel and existing acoustic features. All acoustic measurements were completed in Praat<sup>29</sup>.

#### 2.3.1. Coordination (Ratio of VOT to Syllable Length)

For our measure of *Coordination*, we used the mean ratio of voice onset time (VOT) to syllable duration for each participant. VOT was segmented manually based on a wideband spectrogram and was defined by the time interval between the acoustic energy of the stop consonant and the periodic wave energy of the subsequent vowel. Inter-rater reliability was assessed using a second trained researcher who remeasured the VOTs of 10% of the samples (ICC = .94). Lower values indicate less aspiration and therefore reduced *Coordination*.

#### 2.3.2. Consistency (Between-Repetition Variability in VOT)

For our measure of Consistency, we used the mean coefficient of variation of VOT between repetitions for each participant. The standard deviation of VOT was computed on three repetitions of each syllable (i.e., /pa/, /ta/, /ka/). The coefficient of variation was then calculated to allow for interpretation of the relative magnitude of the standard deviation. Larger values indicate greater differentiation between the repetitions and therefore reduced Consistency.

#### 2.3.3. Speed (F2 Slope)

For our measure of Speed, we used the mean slope of the second formant (F2) in the consonant-vowel transition of /ka/ for each participant. The velar plosive /k/ was used to calculate this measure because its transition was the most robust of the three consonants, typically characterized by a decreasing trajectory. Linear predictive coding was used to identify the formants in the speech sample. Then, the entire vowel was manually segmented from the first glottal pulse to the last glottal pulse on a wideband spectrogram. A Praat<sup>27</sup> script was used to extract the continuous formant trajectories of the first and second formants. We then calculated the F2 slope of /ka/, with the onset and offset frequencies defined by the first time point of the formant and the midpoint of the formant, respectively. The midpoint was used to control for coarticulatory effects from the subsequent consonant. Inter-rater reliability was assessed using a second trained researcher who remeasured the F2 slopes of 10% of the samples (ICC = .91). Smaller negative values indicate slower tongue movement and therefore reduced Speed.

#### 2.3.4. Precision (Between-Consonant Variability in F2 Slope)

For our measure of Precision, we used the mean standard deviation of the F2 slope in the consonant-vowel transitions of the three distinct consonants (i.e., /p/, /t/, and /k/) within each repetition of /pataka/ for each participant. Lower values indicate less differentiation between the three consonants and therefore reduced Precision.

#### 2.3.5. Rate (Syllables per Second)

For our measure of Rate, we used the number of syllables produced per second by dividing the total time required to complete three repetitions of /pataka/ by nine (i.e., the number of syllables). Lower values indicate fewer syllables produced per second and therefore reduced Rate.

#### 2.4. Statistical Analysis

A linear mixed effects (LME) model was conducted for group comparisons on the five different features. Performance on each feature was assessed as a function of diagnosis group. A subject-dependent intercept was included in the model as a random effect to account for the inter-subject variability in articulatory features. Then, effect sizes for all group differences on each of the features were calculated using Cohen's d.

Individual ROC curves were completed to assess the diagnostic efficacy of each feature at varying discrimination thresholds to differentiate between Early Stage ALS and PD and between Late Stage ALS and PD. The sensitivity and specificity of each feature was calculated based on an optimal cutpoint that maximized the value of (*sensitivity*<sup>2</sup> + *specificity*<sup>2</sup>). The area under the curve (AUC) provides the rate of successful classification based on each feature.

Data classification was also performed using ensemble decision trees with leave-one-out cross-validation (subsampling). The relative importance of each feature was estimated using the mean decrease in impurity (MDI) method, in which the impurity decrease from each feature was averaged across trees. Because we are interested in specific hypothesisdriven features, we used bagging rather than random sampling of features at each node. While individual ROC curves provide critical information regarding the sensitivity and specificity of each feature, decision trees take into account more complex relationships between the features to build a prediction algorithm that provides a weighted composite score. Furthermore, in contrast to other machine learning methods, such as support vector machine (SVM) models, decision trees offer an advantage as they allow for more transparency in both data classification and feature weighting. This transparency is informative to software engineers in feature selection for future classification algorithms and clinicians in using these features to guide diagnosis and treatment.

#### 3. Results

#### 3.1. Research Question 1: Disorder-Based Phenotypes

Prior to stratification, the ALS group had significantly more impaired *Coordination* than the PD group. Compared to controls, the ALS group was significantly more impaired across all dimensions except *Consistency*, while the PD group was significantly more impaired in *Speed* only (see Figure 2).



Figure 2: Boxplots of comparisons (dotted line = mean, solid line = median) with Cohen's d's and significance levels. The yaxes of Speed and Consistency were reversed (absolute value and multiplied by -1, respectively) for ease of interpretation.

# 3.2. Research Question 2a: Disease Stage-Based Phenotypes (Early Stage)

In the Early Stage of the diseases, PD had significantly more impaired *Speed* than ALS, but ALS had significantly more impaired *Coordination* than PD (see Table 2 and Figure 3). According to our ROC curve analysis for each feature individually, *Coordination* revealed the highest AUC (.81), sensitivity (.80), specificity (.89), and accuracy (.84) for differentiating Early Stage ALS and Early Stage PD (see Table 3 and Figure 3). The decision tree analysis with nine folds revealed an overall AUC of .88 when accounting for the

relationships between all five features. An MDI of 4.0 indicated that *Coordination* had the highest importance level for estimating group membership.



Figure 3: Left panel: Barplots of z scores (horizontal line at 0 = control group) with Cohen's d's and significance levels. Right panel: Individual ROC curves for each acoustic feature and overall decision tree ROC curve (ALS = 0, PD = 1).

## 3.3. Research Question 2b: Disease Stage-Based Phenotypes (Late Stage)

In the Late Stage of the diseases, ALS was significantly more impaired in all components except *Consistency* (see Table 2 and Figure 3). According to the ROC analysis for each feature individually, *Rate* had the highest AUC (.90), sensitivity (.88), specificity (.89), and accuracy (.88) for differentiating patients with Late Stage ALS and Late Stage PD (see Table 3 and Figure 3). The decision tree analysis with eight folds revealed an overall AUC of .87 when accounting for the relationships between all five features. An MDI of 4.0 indicated that *Rate* had the highest importance level for estimating group membership.

Table 2: Means and standard deviations for each group.

	Early	Stage	Late S			
	ALS	PD	ALS	PD	Control	
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	
Coordination	.25 (.06)	.32 (.07)	.23 (.09)	.31 (.08)	.34 (.08)	
Consistency	24.33 (4.66)	19.42 (6.27)	31.26 (9.18)	27.18 (11.20)	24.30 (8.70)	
Speed	-8.76 (3.89)	-5.70 (4.25)	-2.98 (2.01)	-5.89 (4.21)	-8.16 (3.78)	
Precision	8.92 (2.69)	8.49 (3.02)	3.51 (1.77)	5.91 (3.02)	8.64 (2.97)	
Rate	7.03 (.91)	6.69 (1.08)	3.58 (1.05)	5.27 (1.04)	6.87 (1.10)	

Table 3: *Classification results of individual ROC curve analysis and decision tree analyses.* 

	Early Stage					Late Stage						
	AUC	Sens	Spec	Cut	Acc	Imp (DT)	AUC	Sens	Spec	Cut	Acc	Imp (DT)
Coordination	.81	.80	.89	.30	.84	.40	.79	.88	.89	.26	.88	.38
Consistency	.74	.70	.88	-21.83	.79	.20	.63	.50	.89	-22.69	.71	.06
Speed	.70	.70	.89	-6.31	.79	.25	.72	.75	.89	3.54	.82	.08
Precision	.54	.30	1.00	-6.16	.63	.06	.81	.75	.78	4.39	.77	.09
Rate	.60	.60	.67	-6.89	.63	.09	.90	.88	.89	4.56	.88	.40
DT	.88						.87					

Note: For all classifications, ALS was coded as 0 and PD was coded as 1. Features with highest importance based on decision tree analyses are bolded. DT = decision tree, *sens* = sensitivity, *spec* = specificity, *cut* = cutpoint, acc = accuracy, *imp* = importance level

#### 4. Discussion

This study represents the next step towards our goal of characterizing articulatory phenotypes using an interpretable framework of speech motor control (i.e., *Coordination, Consistency, Speed, Precision,* and *Rate*). As a whole, ALS and PD had distinct articulatory phenotypes, with the ALS group significantly more impaired than controls across all dimensions except *Consistency* and the PD group significantly more impaired than controls in *Speed*. Our individual ROC analyses revealed high classification accuracy for impaired *Coordination* in the Early Stage and impaired *Rate* in the Late Stage. The MDI metrics from our decision tree analyses confirmed the importance of *Rate* and *Coordination* in estimating the appropriate diagnosis, even when accounting for the complex relationships between the five features.

While the specific effects on articulatory function are not yet well understood, previous literature suggests distinct manifestations of pathophysiologies in movement in general<sup>16-</sup> <sup>18</sup>. ALS is characterized by gradual degeneration of upper and lower motor neurons<sup>30</sup>. This progressive weakness of speech musculature results in broad impairments across multiple articulatory domains such as dyscoordination between supraand subglottal gestures<sup>31</sup>, decreased capacity to generate speed<sup>32,33</sup>, and reduced phoneme distinctiveness<sup>30</sup>, which were all indicated by our findings. Also consistent with our results, the initial primary deficit in PD is slowed movement Speed due to a dopamine deficiency<sup>34</sup>. This finding, in conjunction with the preserved Rate noted in the PD group, confirms the speedrate dissociation characteristic of hypokinetic dysarthria seen in PD<sup>32</sup>, which may be related to "articulatory undershoot" or the inability to achieve full range of motion due to poor control over muscle contractions<sup>35</sup>. These results support the construct validity of our features as sensitive measures of distinct articulatory deficits (Research Question 1).

Furthermore, the individual ROC curves and subsequent decision tree analyses indicated that using features representative of Coordination and Speed may improve classification accuracy algorithms for ALS and PD prior to any perceptible changes in speech (Research Question 2a). Notably, the early stage classification performance we obtained from our features was greater than that found in previous studies investigating disorder group differences in the presymptomatic stage<sup>12,36</sup>. The articulatory phenotypes of ALS and PD diverged more upon onset of speech symptoms, with Rate having the highest diagnostic accuracy and importance level (Research Question 2b). This finding is consistent with literature that has shown syllables per second derived from the DDK task to be sensitive to differentiating disorder types<sup>19,30</sup>. However, our additional findings of high diagnostic accuracy and importance for Coordination indicate that this task could be used as a more comprehensive measure of motor performance.

Taken together, the findings suggest that our framework has potential as a valid diagnostic tool with which we can discriminate speech motor disorders based on their underlying articulatory impairments. These phenotypes—derived from interpretable, hypothesis-driven features—can inform classification algorithms for differential diagnosis and guide impairment-based feature selection for ASR models, ultimately increasing clinical confidence in assessing and treating speech motor disorders. Further research is needed to validate our acoustic features against corresponding biomechanical features.

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