Free-classification of perceptually-similar speakers with dysarthria

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Free-classification of perceptually-similar speakers with dysarthria

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Abstract

Purpose: In this investigation, the construct of perceptual similarity was explored in the dysarthrias. Specifically, we employed an auditory free-classification task to determine whether listeners could cluster speakers by perceptual similarity; whether the clusters mapped to acoustic metrics; and whether the clusters were constrained by dysarthria subtype diagnosis.

Methods: Twenty-three listeners blinded to speakers' medical and dysarthria subtype diagnoses participated. The task was to group together (drag and drop) the icons corresponding to 33 speakers with dysarthria based on how similar they sounded. Cluster analysis and multidimensional scaling (MDS) modeled the perceptual dimensions underlying similarity. Acoustic metrics and perceptual judgments were used in correlation analyses to facilitate interpretation of the derived dimensions.

Results: Six clusters of similar-sounding speakers and three perceptual dimensions underlying similarity were revealed. The clusters of similar-sounding speakers were not constrained by dysarthria subtype diagnosis. The three perceptual dimensions revealed by MDS were correlated with metrics for articulation rate, intelligibility and vocal quality, respectively.

Conclusions: This study shows i) feasibility of a free-classification approach for studying perceptual similarity in dysarthria, ii) correspondence between acoustic and perceptual metrics to clusters of similar-sounding speakers; and iii) similarity judgments transcended dysarthria subtype diagnosis.

Introduction

The gold standard for classification of motor speech disorders, known as the Mayo Clinic approach, was set forth by Darley, Aronson and Brown (1969a, b; 1975) and developed further by Duffy (2005). In their seminal work, Darley and his colleagues rated 38 dimensions of speech and voice observed in 212 patients with dysarthria arising from seven different neurological conditions (1969a). Seven subtypes of dysarthria (flaccid, spastic, ataxic, hypokinetic, hyperkinetic dystonia, hyperkinetic chorea, and mixed), each possessing unique but overlapping clusters of perceptual features, were delineated. Key to the classification system is that the underlying pathophysiology of each type of dysarthria is presumed responsible for the resulting clusters of perceptual features. For example, cerebellar lesions affect the timing, force, range and direction of limb movements and result in dysrhythmic, irregular, slow and inaccurate actions. According to the Mayo Clinic approach, the speech features associated with ataxic speech (e.g., imprecise consonants, equal and even stress, and irregular articulatory breakdown) can be explained by the effects of cerebellar lesions on neuromuscular activity (as seen in the limbs). Thus, the explanatory relationship between locus of damage and the perceptual features associated with a dysarthria provides a valid and useful framework for clinical practice as well as research on motor speech disorders.

This expert, analytic evaluation of dysarthric speech is designed specifically to extract information relevant to differential diagnosis of dysarthria, which then serves as a source of corroborating information in the broader diagnosis of neurological disease or injury. But such a level of analysis is unlikely to uncover unique, etiology-based *communication disorders* because, as Darley and colleagues' work revealed, 1) not all speakers with a similar etiology exhibit similar speech symptoms, 2) speech symptoms within a given classification may differ along the severity dimension, and 3) there is considerable overlap in speech symptoms among the classification categories (e.g., imprecise consonants, slow rate). This gives rise to a gap in our ability to effectively leverage a dysarthria subtype diagnosis to identify appropriate treatment targets in order to address the resulting communication disorder. In the present report, we attempt to bridge this gap by exploring a paradigm that exploits a relatively simple level of analysis, namely perceptual-similarity. The hypothesis is that if listeners are able to identify clusters of similar sounding dysarthric speakers, listeners must be using perceptually-salient features to accomplish the task. By extension, the features that underlie the perceptual clusters may be suitable candidates for treatment targets, to the extent they contribute to the associated communication disorder. This line of reasoning is supported by work that demonstrates dysarthric speech with similar acoustic-perceptual profiles challenge listener perceptual strategies (and outcomes) in specific ways (e.g., Borrie et al., 2012; Liss et al., 2002; Liss, Utianski and Lansford, 2013).

The purpose of the present study was to investigate the construct of perceptual similarity in a heterogeneous cohort of speakers with dysarthria (i.e., speakers with varying dysarthria subtype diagnoses and severities). The speakers included in this study were recruited because the perceptual characteristics of their dysarthrias were consistent with the cardinal perceptual characteristics identified by Darley, Aronson and Brown (1969a, b). Three research questions were addressed, 1) can listeners cluster dysarthric speech samples without specific reference to speech features in an unconstrained free-classification task (see Clopper, 2008); 2) do the resulting clusters scale to meaningful or interpretable dimensions in the perceptual and acoustic domains; and 3) to what extent do the freely classified clusters contain speakers with similar dysarthria subtype diagnoses?

Method

Speakers and stimuli

Productions from 33 speakers were collected from a larger corpus of research in the Arizona State University Motor Speech Disorders lab (ASU MSD lab). Speakers were diagnosed with one of the following dysarthria subtypes by neurologists at the Mayo Clinic: ataxic dysarthria secondary to cerebellar degeneration (n = 11), mixed flaccid-spastic dysarthria secondary to amyotrophic lateral sclerosis (n = 10), hyperkinetic dysarthria secondary to Huntington's disease (n = 4), and hypokinetic dysarthria secondary to Parkinson's disease (n = 8). In order to be representative of previous research (Darley et al., 1969a, b), speakers were selected based on the presence of hallmark characteristics found within the Mayo Clinic classification system. Two speech-language pathologists (SLPs; including the second author J. Liss) concurred that the dysarthria type was consistent with the underlying medical diagnosis and severity was rated to be moderate to severe (Table 1).

All speaker stimuli were previously recorded and edited for use in a larger study conducted in the ASU MSD lab (e.g., Liss et al., 2009, 2010, 2013). Each speaker read stimuli from visual prompts presented on a computer screen. All recordings utilized a head-mounted microphone (Plantronics DSP-100), and participants were seated in a sound-attenuating booth. Recordings were made using a custom script in TF32 (Milenkovic, 2004; 16-bit, 44kHz), and saved directly to disc for subsequent editing using commercially available software (SoundForge; Sony Corporation, Palo Alto, CA) to remove any noise or extraneous articulations before or after target utterances. For the purposes of this study, the sentence "*The standards committee met this afternoon in an open meeting"* was selected from the corpus of speech stimuli, due to its diverse representation of speech sounds. Sentence durations across speakers were between 2.60 seconds and 13.544 seconds with a mean duration of 6.486 seconds.

Listeners

Twenty-three graduate students in Communication Disorders at ASU were recruited for this project. Participants were enrolled in a Motor Speech Disorders class and had received basic instruction in both dysarthria and differential diagnosis. Listeners were native English speakers, passed a threshold hearing screening, and self-reported normal cognitive skills.

Procedure

An auditory free-classification task, as detailed by Clopper (2008), was used to collect the similarity data. Free-classification is a perceptual sorting task, in which listeners are asked to group stimuli according to similarity. It was developed by cognitive psychologists interested in categorization of stimuli based on perceptual dimensions undefined by the experimenter (Imai, 1966; Imai and Garner, 1965). Free-classification permits examination of perceptual similarity while avoiding experimenter-imposed categories, and without naming distinctive perceptual characteristics. An attractive benefit of the free-classification method is that it is less time consuming than paired-comparison methods traditionally used to investigate perceptual similarity (Clopper, 2008). In the present study, the use of free-classification offered a faster and unconstrained listener task.

The stimulus materials (i.e., recordings of the sentence "*The standards committee met this afternoon in an open meeting"*) produced by each of the speakers were embedded into a single PowerPoint slide and presented to listeners. Each speaker's recording was randomly assigned a two-letter identifier (i.e., de-identified initials) to be used by listeners to keep track of the speakers during the free classification task. The individual sound files and static images of the identifiers were merged in PowerPoint, such that when listeners double-clicked the image the sound file played automatically. The merged files were placed neatly and randomly in 3 columns adjacent to a 16x16 cell grid in a single PowerPoint slide (see Figure 1). Each image was sized to fit precisely into one cell of the grid.

For the experimental task, listeners were seated in front of computers located in quiet listening cubicles. All computers were equipped with Sennheiser HD 280 sound attenuating headphones and were calibrated using a digital sound level meter and a flat plate coupler. Volume was set individually on each computer and participants did not adjust the volume. Listeners were informed that all of the speakers have *dysarthria*. However, the listeners did not know the underlying medical etiologies or dysarthria subtypes. Participants were instructed to listen to all of the merged sound files, via headphones, and to group the files in the grid (click, drag, drop) depending on how *similar* they sound. Listeners were not provided any other instruction regarding how to make their judgments of similarity. They did not know the purpose of the study until they were debriefed. They were told that icons of the speakers perceived as sounding similar should be placed next to (touching) one another. Listeners were free to make as many groups as they deemed appropriate, with as many speakers in each group as needed (see Figure 2). There was no time limit imposed on the task and listeners were permitted to listen to and re-arrange the speaker files as many times as necessary. Listeners recruited to participate in pilot testing indicated that the processing demands associated with the free-classification task taxed their working memory. Thus, listeners recruited for the present study were permitted, but not required, to make notations as they made their similarity judgments in the notes space below the PowerPoint slide. These notes were saved for subsequent examination.

Acoustic and perceptual measurements

Three sets of acoustic measures and one set of perceptual ratings were used in the correlation analyses (see Table 2 for detailed descriptions of the metrics). The sentence used in this study was one of five sentences produced by all speakers, whose classification results have been reported in previous work (Liss et al., 2009; Liss et al., 2010). Therefore, the first set of measures included previously published acoustic rhythm metrics (Liss et al., 2009) and envelope modulation metrics (Liss et al., 2010). The second set of metrics was designed to capture vowel space area and distinctiveness, and these data are reported in Lansford and Liss (in press a, b)[1]. The third new set of measures involved capturing the long-term average spectra (LTAS) of the sentences. Analysis of LTAS permits comprehensive exploration of the frequency distribution of a continuous speech sample, and has been used in previous investigations of vocal quality (Leino, 2009, Shoji, Regenbogen, Yu & Blaugrund, 1992), rhythmic disturbance in dysarthria (Utianski et al., 2012) and perceived speech severity in dysarthria (Tjaden, Sussman, Liu & Wilding, 2010).

Perceptual measures included scaled estimates of each speaker's overall severity, vocal quality, articulatory imprecision, nasal resonance and prosodic[2] disturbance. The ratings of these dimensions were obtained via a visual analog task (Alvin, Hillenbrand & Gayvert, 2005) completed by five speech-language pathologists (unaffiliated with the ASU MSD lab). The speakers' productions of the stimulus item used in the free-classification perceptual task were randomly presented, and the listeners were instructed to place a marker along a scale (ranging from normal to severely abnormal) that corresponded to their assessment of the speaker's level

[1] These vowel space metrics require inclusion of formant measures from vowels not present in the stimulus item used in the current experiment. Thus, formant measurements of vowels embedded in the phrases used in Lansford and Liss (in press, a, b) were used in the present analysis to facilitate calculation of the vowel space metrics.
[2] Listeners were instructed to judge prosodic disturbance without consideration of the speaker's overall speaking rate.

of impairment. Interrater reliability (Cronbach's alpha) for the ratings of severity, nasality, vocal quality, articulatory impression and prosody were .936, .873, .898, .946 and .812 respectively. The ratings were normalized (z-score) and averaged across speakers. Finally, intelligibility data (% words correct on a transcription task) collected for these speakers (as reported in Liss, Utianski & Lansford, 2013) were included as a perceptual measure.

Data analysis

The PowerPoint slide with each listener's final speaker groupings was coded alphanumerically and the final groupings were transferred into Microsoft Excel for subsequent analysis. Descriptive statistics were obtained to determine the mean, median and range of numbers of listener-derived groups and speakers included in each group.

The similarity data obtained from each listener were arranged into a 33 x 33 speaker-similarity matrix in Excel (See Appendix). A one was entered into cells corresponding to two speakers grouped together by a listener. Likewise, a zero was entered into the cells corresponding to speakers not grouped together. The individual listener's speaker-similarity matrices were summed and converted into a dissimilarity matrix for the subsequent analyses. First, the similarity data were subjected to an additive similarity tree cluster analysis described by Corter (1998) and used by Clopper (2008) to determine the number and composition of clusters of perceptually-similar speakers. Multidimensional scaling (MDS) of the similarity data was completed to examine the salient perceptual dimensions underlying speaker similarity in this group of speakers with dysarthria. Correlation analysis was conducted to facilitate interpretation of the perceptual dimensions underlying similarity as revealed by the MDS. In addition, noncompulsory notes made by listeners as they completed the perceptual task were examined to determine if the results of the quantitative analyses described above tracked to the acoustic and perceptual characteristics reported by the listeners to underlie speaker similarity in dysarthria.

Results

Descriptive analysis

Listeners derived an average of 7.7 clusters (*SD* = 2.85) of similar-sounding speakers, with a median of 7 and a range of 3-14 groups. The individual clusters of similar-sounding speakers included an average of 4.96 speakers (*SD* = 2.1), with a median of 4 and a range of 1-13 speakers. See Figure 3 for the 33 x 33 speaker-similarity matrix.

Cluster analysis

Additive similarity tree cluster analysis (Corter, 1998) was used to identify clusters of similar sounding speakers. The results of the cluster analysis are best visualized via dendogram representation of the similarity data, in which speakers were linked together one at a time at varying steps of the analysis (see Figure 3). Speakers that were most frequently grouped together by the listeners were linked first by the cluster analysis. Speakers joined existing clusters during subsequent steps of the analysis until all of the clusters joined to form a single group (see the top of the figure). The number of clusters revealed is experimenter-defined. For the purposes of this initial foray into similarity in the dysarthrias, a six-cluster solution was selected. This solution was analyzed primarily because it most closely resembled the descriptive data (i.e., average number of groups derived by the listeners). Unfortunately, this solution left speaker AM3 without a cluster. He was, therefore, excluded from subsequent cluster-based analyses. It is important to note that the composition of each of the six clusters was not limited to a single dysarthria subtype (see Table 3 for cluster member distribution); however, one cluster contained all of the speakers diagnosed with PD and one speaker with HD. Thus, these results support the notion that speaker-similarity in dysarthria may transcend dysarthria diagnosis.

Multidimensional scaling

The similarity data were subjected to PROXSCAL multidimensional scaling analysis (SPSS) and the normalized raw stress values obtained for models that included one to five dimensions were evaluated to determine the best fit of the data. Briefly, the stress of an MDS model refers to its overall stability. The normalized raw stress values of the one through five dimensional models were included in a scree plot to identify the point with which the addition of another dimension no longer substantially lowers stress (i.e., the “elbow” of the plot). The three-dimensional model (dispersion accounted for (DAF) = .9907; normalized raw stress = .0096; and stress 1 = .09621) was selected to facilitate visualization of the dimensions and to simplify subsequent interpretation. The clusters of similar-sounding speakers were plotted in the common space revealed by the MDS in Figures 5a, b, and c. In Figure 4a, the clusters were plotted in the two-dimensional space created by the first two dimensions derived by the MDS. Along the first dimension, cluster 1 (comprised mainly of speakers with PD) was clearly differentiated from the remaining five clusters. Further, clusters 2, 3 and 6 were well delineated by in this space. Some overlap, though, is noted between clusters 4 and 5. In figure 4b, the clusters were plotted in the two-dimension space created by the first and third dimensions revealed by the MDS. While substantial overlap of the clusters is evident in this representation of the common space, it is important to note that clusters 4 and 5, indistinguishable in the space created by the first two dimensions, were well delineated by the third dimension.

Correlation analysis

A series of correlation analyses was conducted in order to interpret the abstract dimensions revealed by the MDS. Due to the large number of acoustic and perceptual measures considered in this analysis, the dependent variables that correlated most meaningfully with the dimensions are presented below.

Dimension 1 (D1). Across all acoustic and perceptual variables, there were strong correlations with those measures related to rate and rhythm (see Tables 4-7 for a full account of results). Most notably, D1 correlated strongly with the acoustic measure of articulation rate (r = -.888). It also demonstrated a strong relationship with a measure of standard deviation of the durations of vocalic intervals (ΔV, r = .739). In addition, a number of moderate relationships with the other segmental rhythm metrics were revealed. As reported in Liss et al., 2009, many of the rhythm metrics (ΔV included) demonstrated strong relationships with articulation rate; therefore, it is not surprising that the D1 correlated with the majority of these temporally-based measures of rhythm.

As seen in Table 5, strong correlations also were found for EMS measures that can be interpreted relative to articulation rate (Below4 at 8000 Hz: r = .809; and strong correlations with Below4, Above4 and Ratio4 variables derived for most of the frequency bands). As reported by Liss et al., 2010, of all the EMS variables, Below4 at 8000 Hz correlated most strongly with articulation rate (r = -.862), but rate was also highly correlated with other 4 Hz variables in most of the frequency bands.

D1 did not correlate significantly with any of the vowel space metrics.

Conclusive support for D1 capturing articulation rate was not revealed for the LTAS measures (Table 6). The strongest relationships between the LTAS measures and D1 occurred for the pairwise variability (PV) measures in the 125, 250 and 500 Hz frequency bands. D1 was also weakly correlated with a few of the measures in the 1000 Hz band. Unlike EMS, very few of the LTAS measures were correlated with articulation rate, as would be expected. However, the LTAS variables that correlated significantly with D1 were also correlated with articulation rate, providing indirect support for the articulation rate hypothesis.

D1 was moderately to strongly correlated with all of the perceptual rating measures obtained from speech-language pathologists (SLPs) who scaled perceptual features of the sentences. Despite the strong relationships with the other perceptual ratings, D1 was not correlated with the intelligibility data collected for these speakers (see Table 7). Interestingly, articulation rate was moderately to strongly correlated with all of the perceptual rating measures (r's ranging from -.57 to -.78), but was not correlated with intelligibility (r = .243). Thus, it is possible that the relationship between D1 and articulation rate was responsible for the significant relationships between D1 and the perceptual ratings measures.

Dimension 2 (D2). Of all of the acoustic and perceptual variables, D2 was most strongly related to intelligibility (r = -.646). D2 was also correlated with the perceptual ratings measures of severity, nasality vocal quality, articulatory imprecision and prosody. The perceptual rating measures were significantly inter-correlated and were also significantly correlated with both articulation rate and intelligibility in this cohort of speakers. Intelligibility and articulation rate, however, were not correlated.

Like D1, D2 exhibited a few correlations with duration-based measures related to rate and rhythm, but less robustly. The strongest correlations from the rhythm metrics included a pair of intercorrelated measures of standard deviation of vocalic intervals that have been rate-normalized (nPVI-V and VarcoV; r = -.583 and -.447, respectively), and a measure of the proportion of the signal that is comprised of vocalic intervals (%V; r = .536). These measures were all significantly correlated with intelligibility (absolute r ranging from .395 to .512)

With regard to EMS metrics, D2 correlated significantly with many of the same variables that were correlated with the D1, albeit less strongly. A notable deviation from this pattern of results, however, was the moderate relationships between the D2 and the E3-6 variables in most of the frequency bands. Interestingly, the E3-6 variables were not correlated with D1. Liss et al. derived these variables largely because the energy in this region of the spectrum has been shown to be correlated with intelligibility (Houtgast & Steeneken, 1985). Indeed, the E3-6 variables, particularly in the higher frequency bands (e.g., 4000 and 8000 Hz bands), were significantly correlated with the intelligibility data collected for these speakers (e.g., r = .561 and .597, respectively). It should also be noted that many significant correlations were found between the EMS variables (particularly Below4, After4 and Ratio4) and the perceptual measures including intelligibility and the ratings of severity, vocal quality, nasality, articulatory imprecision and prosody.

D2 did not correlate significantly with any of the vowel space metrics.

For the LTAS metrics, D2 correlated significantly with all of the variables in the 4000 Hz band (r ranging from -.559 and -.623). In addition, slightly less significant relationships were revealed for the LTAS variables in the 8000 Hz band and D2. All of these LTAS variables were moderately related to the perceptual measures, including intelligibility and severity.

Dimension 3 (D3). Overall, D3 generally had weaker correlations with all acoustic and perceptual measures than did D1 and D2. None of the duration-based measures of rate and rhythm correlated significantly with D3. Modest relationships between D3 and an EMS measure of the dominant modulation rate were revealed for the 1000 and 2000 Hz bands (PeakAmp; r = -

.449 and -.469, respectively). While these metrics are thought to reflect, in part, speech rhythm, there is no straightforward interpretation in this context. None of the vowel space measures correlated significantly with D3. However, D3 was significantly correlated with all of the LTAS measures in the 8000 Hz band. While no direct interpretation for the metrics derived in this octave band exists, it has been demonstrated that the spectral peaks of most English fricatives are found in the higher frequency bands of the spectrum (voiceless > voiced; Hughes and Halle, 1956; Jongman, Waylung and Wong, 2000; Maniwa, Jongman and Wade, 2009). In addition, increased energy in high frequency LTAS (>5000Hz) has been found for speakers with breathy vocal quality (Shoji, Regenbogen, Yu & Blaugrund, 1992). This finding was corroborated by the results of a recent study that found the energy in high frequency LTAS for softly produced speech was relatively greater than that of loudly produced speech when LTAS for the conditions was normalized for overall sound pressure level (SPL; Monson, Lotto and Story, 2012).

Of all of the perceptual measures, D3 correlated only with the rating of vocal quality (r = -.414). Recall, the combined results of the cluster and MDS analyses demonstrated that clusters 4 and 5 were not well delineated by the first two dimensions (see Figure 4a); however, with inclusion of the third dimension, they were separated. A post hoc analysis (i.e., one-way analysis of variance with multiple comparisons) was conducted in order to determine if the clusters of speakers, particularly clusters 4 and 5, possessed significantly different ratings of vocal quality. Indeed, a main effect [$F(5, 31) = 20.838$, $p < .0001$] of cluster group on vocal quality rating was revealed. Inspection of the cluster means (see Table 8) revealed speakers belonging to cluster 5 had the highest vocal quality ratings (M = 1.17, SD = .4) and cluster 4 speakers had the lowest (M = .03; SD = .21). Bonferroni-corrected multiple comparisons demonstrated that the vocal quality ratings of the cluster 5 speakers were significantly higher (meaning more impaired) than those of the other clusters, with the exception of cluster 6. Thus, the results of this post hoc analysis provide some evidence to support interpretation of D3 as one that may capture some aspects of vocal quality.

Examination of listener notes

To assuage the processing and working memory demands placed on the listeners by the free classification task, listeners were permitted to take notes as they grouped together similar-sounding speakers. This afforded an opportunity to qualitatively evaluate the perceptual relevance of the dimensions revealed by the MDS analysis. In total, 21 of the 23 listeners elected to make notations as they completed the task. We found that 100% of these listeners mentioned rate and rhythm of speech in their notations. This finding corresponds with the quantitative results that demonstrated metrics capturing rate and rhythm were significantly correlated with a primary dimension underlying similarity in dysarthria. In addition, approximately 66% of listeners mentioned intelligibility in their notes. Again, this finding tracks to the results of our quantitative approach that revealed intelligibility was salient to similarity judgments. The third dimension revealed by MDS was correlated with the perceptual rating measure of vocal quality. Indeed, 85.7% of the listeners mentioned vocal quality characteristics in their notes. Other perceptual features mentioned by the listeners included: articulatory imprecision (62%), severity (23.8%), resonance (23.8%), prosody (23.8%), respiratory differences (19%), variable loudness (14.3%), pitch breaks (9%), word boundary errors (4.7%), and overall "bizarreness" (4.7%).

Discussion

The contributions of the present study are threefold. First, results demonstrate proof-of-concept for the use of an auditory free-classification task in the study of perceptual similarity in the dysarthrias. Because the paradigm does not rely on a predetermined set of clustering variables, listeners cluster by whatever similarities are salient to them. Until now it was not known whether dysarthria was amenable to free-classification by judges with minimal experience with dysarthria. The second contribution is the demonstration that the clusters were made along three dimensions and that these dimensions corresponded with independent acoustic and perceptual measures. The third contribution is that the results of this perceptual similarity task transcended dysarthria subtype diagnoses, providing support for the notion that the paradigm may provide clusters more closely linked with the nature of the communication disorder. These contributions and some of their limitations are detailed below.

Proof-of-Concept

Free classification methods have been used to investigate perceptual similarity of environmental sounds (Guastavino, 2007; and Gygi, Kidd and Watson, 2007), musical themes (McAdams, Viellard, Houix, and Reyonds, 2004), and American-English regional dialects (Clopper and Bradlow, 2009; and Clopper and Pisoni, 2007). To our knowledge, perceptual similarity has not been previously directly assessed in the dysarthrias. Therefore, it was necessary to determine the appropriateness of free classification techniques in the investigation of perceptual similarity in dysarthria. A feature of free classification that made it appealing for the current study is that it liberates participants from experimenter-defined categories. For example, Clopper and Pisoni (2007) found that in using a free classification task to investigate regional American-English dialects, listeners were able to make finer distinctions between dialectal speech patterns when specific labels were not experimenter-imposed. The ability of the statistical analyses to adequately model the similarity data in concert with the finding that the perceptual dimensions underlying similarity correlated meaningfully with acoustic and perceptual metrics supports the use of free classification methodology as a viable tool for the study of perceptual similarity in dysarthria.

In this initial assessment of perceptual similarity in dysarthria, it was necessary to make a variety of methodological decisions that were undoubtedly contributors to the cluster outcomes. Our targeted listeners were graduate students in communication disorders with basic familiarity with dysarthrias and the Mayo classification scheme, but with limited clinical exposure. We selected this group of listeners because they were expected to have more finely honed perceptual judgment skills than truly naïve participants, but less honed skills than those of clinicians experienced in the Mayo Clinic approach to differential diagnosis of dysarthria. While supported by intuition, this assumption must be verified in the context of experimental design. To identify ecologically valid parameters contributing to similarity, it will be important to explore how listener variables--such as clinical sophistication, experience/exposure, perceptual astuteness/awareness, or even listening strategies—influence judgments of perceptual similarity. Toward this end, clustering data elicited from practicing speech-language pathologists on these same stimuli are presently being analyzed, the results of which will partially inform this question.

A second methodological decision was to use speech samples, specifically a single sentence, from speakers who ranged in speech impairment from moderate to severe, and who were selected in a larger investigation because their speech exhibited perceptual characteristics associated with their dysarthria subtype diagnosis. There is every reason to believe that clustering decisions were influenced by both the speech sample used in the task and the constellation of speakers to be clustered, as this is a comparative task. Thus it will be critical in future studies to assess the stability of perceptual decisions for a given speaker across a variety of speech samples and across groups that vary in speaker composition. Optimally, a free-classification paradigm will reveal the most perceptually salient parameters for any given group of speakers, irrespective of speech sample material, and that individual members of the clusters will be similar on these parameters. Computational modeling methods conducted on sets of clustering data will be important for establishing characteristics that influence judgment stability.

Interpretability of the Dimensions Underlying Similarity

Multidimensional scaling of the similarity data uncovered a minimum of three salient perceptual dimensions underlying similarity in this cohort of speakers. In addition, the similarity-based clusters of speakers were well delineated in these dimensions (see Figure 4). The results of the correlation analyses, which compared the abstract MDS dimensions to a host of acoustic and perceptual measures, provided important information that facilitated their interpretation. The interpretations of the first two dimensions were fairly straightforward: D1 correlated strongly with measures capturing articulation rate and D2 correlated with measures capturing overall intelligibility. Interpretation of D3 was less clear; however, results of a post hoc analysis demonstrated it is probably related to vocal quality characteristics. A number of features included in the listeners' notations (e.g., pitch breaks and resonance) were not revealed as contributing to similarity by the quantitative approaches used in the present analysis. It is important to note that the statistical techniques used in this investigation were largely linear and it is likely that listeners' judgments of similarity are not always amenable to such approaches (e.g., potential binary decisions made by listeners regarding the absence or presence of a perceptual feature in a speaker or cluster of speakers). Thus, alternative techniques (e.g., logistic regression) should be considered as this line of research progresses. In addition, while a large number of acoustic and perceptual features were considered in this preliminary step, it was in no way exhaustive. The perceptual ratings of severity, vocal quality, nasality, articulatory imprecision and prosody were useful in this analysis, but are subjective and vulnerable to poor intra- and interrater reliability (e.g., Kreiman & Gerratt, 1988). Bunton and her colleagues (2007) investigated intrarater and interrater agreement for the Mayo Clinic system's perceptual indicators (i.e., the 38 dimensions of speech and voice originally outlined by the Mayo Clinic) and found listener agreement to be highest when ratings of each dimension were at the endpoints of a 7-point scale (e.g., *normal* or *very severe deviation from normal*). In other words, there was greater variability in listener agreement in the middle of the scale. Thus, a rating scale that denotes the absence or presence of a perceptual feature may prove useful in subsequent investigations of similarity in dysarthria.

Relationship Between Dysarthria Diagnosis and Similarity-Based Clusters

Given that the speakers used in this investigation were recruited because their speech exhibited the hallmark characteristics of their dysarthria diagnosis, one might expect that perceptual clustering would mirror dysarthria subtype more often than not. With the exception of cluster 1, which was comprised primarily of speakers with hypokinetic dysarthria with intact or fast speaking rate, this generally did not occur. Thus, the results of this analysis suggest that if we had sampled a random group of speakers with dysarthria (i.e., without selection of speakers based on perceptual features or dysarthria diagnosis), a similarity-clustering paradigm would be successful in identifying speakers with common acoustic speech features. However, it is important to note that while the clusters were not constrained by dysarthria subtype, influence of disease process on perceived acoustic similarity was evident. For example, clusters 2-6, each composed of a mixture of speakers with hyperkinetic, ataxic or mixed flaccid-spastic dysarthria, were well distinguished along the intelligibility dimension (D2). Examination of the speakers' severity ratings revealed that all speakers belonging to clusters 2 and 3, represented at one end of the D2/intelligibility continuum, were diagnosed with moderate dysarthria and at the other end of the continuum was cluster 6, composed of four speakers with severe dysarthria. Further evidence of disease process on listeners' judgments of similarity can be found for clusters 4 and 5. Recall, clusters 4 and 5 blurred along the first two dimensions, but were differentiated by the third/vocal quality dimension and the results of the post-hoc analysis discussed in the results section suggested that cluster 5 speakers had more abnormal vocal quality than cluster 4 speakers. Cluster 5 was composed of one speaker with ataxic and four speakers with mixed dysarthria (secondary to ALS) and cluster 4 was composed of a single speaker with ataxic and two speakers with hyperkinetic dysarthria. Given that strained-strangled vocal quality is a hallmark of mixed flaccid-spastic dysarthria and that these speakers were recruited because of the presence of such characteristics, it follows that vocal quality abnormalities would be greater for cluster 5 than for cluster 4.

The results of the present analysis are consistent with a taxonomical approach to dysarthria diagnosis, which has been offered as an alternative to classification (Weismer & Kim, 2010). Weismer and Kim (2010) proposed a taxonomical approach to studying dysarthria subtypes, in which the goal is to identify a core set of deficits (i.e., similarities) common to most, if not all, speakers with dysarthria. With respect to the present report, identification of perceptual similarities among dysarthric speech would facilitate 1) the detection of differences that reliably distinguish different types of motor speech disorders irrespective of damaged component of motor control; and 2) systematic investigation of the perceptual challenges associated with the defining features of dysarthria. Indeed, the acoustic and perceptual dimensions underlying similarity in this cohort of speakers – speaking rate, intelligibility and vocal quality – are speech features that generally unite speakers with dysarthria. Thus, the present investigation represents the first phase of research that explores the use of a taxonomical approach to understanding and defining dysarthria. The results of the cluster analysis, which identified six clusters of similar-sounding speaker, were experimenter-defined. This solution was selected largely because it reflected the mean number of speaker groups identified by the listeners. However, before all six clusters were united into a single group, clusters 2 and 3 merged, as did clusters 4, 5 and 6, forming three discrete groups (see Figure 3). Uncovering the acoustic and perceptual features that unite a more parsimonious clustering of speakers is the goal in developing a taxonomical approach. Thus, as this line of research advances, realization of this goal will become requisite.

Conclusion.

Results of the present investigation revealed 1) feasibility of a free-classification approach for studying perceptual similarity in dysarthria; 2) correspondence between acoustic and perceptual metrics to clusters of similar-sounding speakers; and 3) impressions of perceptual similarity transcended dysarthria subtype subtype. Together, these findings support future investigation of the link between perceptual similarities and the resulting communication disorders and targets for interventions.

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Appendix

Pooled speaker similarity matrix. The frequency with which each pair of speakers was judged to be similar by listeners is shown in each cell. This matrix was used to conduct the cluster and MDS analyses.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
AF1	0	0	14	8	0	2	4	6	0	6	9	1	1	1	4	2	3	3	3	1	2	0	6	10	3	8	0	1	1	2	0	0	0
AF2	0	0	2	4	8	7	6	3	5	2	4	3	4	5	4	5	3	3	7	4	5	11	0	1	7	1	1	0	0	1	1	0	0
AF7	14	2	0	6	1	3	5	8	2	8	7	0	1	0	3	4	1	1	2	1	7	0	9	12	1	4	0	1	1	2	0	0	0
AF8	8	4	6	0	0	7	6	7	10	6	12	2	1	5	9	8	6	7	9	1	8	3	2	11	4	4	0	1	0	2	0	0	0
AF9	0	8	1	0	0	3	1	2	2	2	0	9	11	5	3	3	3	1	3	10	2	7	2	1	2	2	1	2	2	1	0	2	2
AM1	2	7	3	7	3	0	8	1	7	4	3	6	3	13	8	5	11	10	5	2	6	3	1	0	4	3	0	1	0	0	0	1	1
AM3	4	6	5	6	1	8	0	3	4	2	5	3	1	5	4	3	3	6	3	1	2	3	2	2	5	0	2	2	2	3	1	1	2
AM4	6	3	8	7	2	1	3	0	6	12	6	1	1	2	4	3	1	2	3	1	5	4	5	13	4	4	1	0	1	0	2	1	1
AM5	0	5	2	10	2	7	4	6	0	8	7	1	4	2	4	15	6	4	8	2	15	6	0	7	4	0	1	0	0	2	0	0	0
AM6	6	2	8	6	2	4	2	12	8	0	6	0	2	1	7	6	2	3	5	1	12	3	4	9	4	3	0	1	1	2	0	0	0
AM8	9	4	7	12	0	3	5	6	7	6	0	1	0	3	5	6	4	4	11	1	6	4	3	10	6	5	0	1	1	3	0	0	0
ALSF2	1	3	0	2	9	6	3	1	1	0	1	0	15	10	1	1	6	5	1	19	0	1	0	0	2	1	0	0	0	0	0	0	0
ALSF5	1	4	1	1	11	3	1	1	4	2	0	15	0	5	4	3	6	3	2	19	4	3	0	1	2	0	0	0	0	0	1	0	0
ALSF6	1	5	0	5	5	13	5	2	2	1	3	10	5	0	7	1	10	11	4	6	0	2	0	0	2	3	0	0	0	0	0	0	0
ALSF7	4	4	3	9	3	8	4	4	4	7	5	1	4	7	0	7	10	11	9	3	7	2	0	2	5	3	0	1	0	1	1	0	0
ALSF8	2	5	4	8	3	5	3	3	15	6	6	1	3	1	7	0	5	2	7	3	14	4	1	8	4	0	1	0	0	1	0	0	0
ALSF9	3	3	1	6	3	11	3	1	6	2	4	6	6	10	10	5	0	10	5	6	3	5	0	1	3	2	0	0	0	1	0	0	0
ALSM1	3	3	1	7	1	10	6	2	4	3	4	5	3	11	11	2	10	0	6	2	4	3	0	3	4	5	0	1	0	1	0	0	0
ALSM4	3	7	2	9	3	5	3	3	8	5	11	1	2	4	9	7	5	6	0	1	9	4	5	4	4	5	1	1	1	1	1	2	2
ALSM7	1	4	1	1	10	2	1	1	2	1	1	19	19	6	3	3	6	2	1	0	1	2	0	1	2	0	0	0	0	0	0	0	0
ALSM8	2	5	7	8	2	6	2	5	15	12	6	0	4	0	7	14	3	4	9	1	0	5	1	5	6	0	0	1	0	2	1	0	0
HDM10	0	11	0	3	7	3	3	4	6	3	4	1	3	2	2	4	5	3	4	2	5	0	1	2	11	0	0	0	1	2	1	0	0
HDM11	6	0	9	2	2	1	2	5	0	4	3	0	0	0	0	1	0	0	5	0	1	1	0	7	2	9	5	3	3	3	3	6	6
HDM12	10	1	12	11	1	0	2	13	7	9	10	0	1	0	2	8	1	3	4	1	5	2	7	0	2	5	1	2	1	1	1	1	0
HDM8	3	7	1	4	2	4	5	4	4	4	6	2	2	2	5	4	3	4	4	2	6	11	2	2	0	0	0	1	1	3	2	0	0
PDF5	8	1	4	4	2	3	0	4	0	3	5	1	0	3	3	0	2	5	5	0	0	0	9	5	0	0	6	6	6	5	5	7	7
PDF7	0	1	0	0	1	0	2	1	1	0	0	0	0	0	0	1	0	0	1	0	0	0	5	1	0	6	0	19	16	13	20	22	19
PDM10	1	0	1	1	2	1	2	0	0	1	1	0	0	0	1	0	0	1	1	0	1	0	3	2	1	6	19	0	17	16	18	19	18
PDM12	1	0	1	0	2	0	2	1	0	1	1	0	0	0	0	0	0	0	1	0	0	1	3	1	1	6	16	17	0	16	16	16	18

PDM13	2	1	2	2	1	0	3	0	2	2	3	0	0	0	1	1	1	1	1	0	2	2	3	1	3	5	13	16	16	0	12	13	15
PDM15	0	1	0	0	0	0	1	2	0	0	0	0	1	0	1	0	0	0	1	0	1	1	3	1	2	5	20	18	16	12	0	21	19
PDM8	0	0	0	0	2	1	1	1	0	0	0	0	0	0	0	0	0	0	2	0	0	0	6	1	0	7	22	19	16	13	21	0	20
PDM9	0	0	0	0	2	1	2	1	0	0	0	0	0	0	0	0	0	0	2	0	0	0	6	0	0	7	19	18	18	15	19	20	0

Table 1

Dysarthric speaker demographic information

Speaker	Gender	Age	Dysarthria Diagnosis	Etiology	Severity
AF1	F	72	Ataxic	Cerebellar ataxia	Moderate
AF2	F	57	Ataxic	Multiple sclerosis / ataxia	Severe
AF7	F	48	Ataxic	Cerebellar ataxia	Moderate
AF8	F	65	Ataxic	Cerebellar ataxia	Moderate
AF9	F	86	Ataxic	Cerebellar ataxia	Severe
AM1	M	73	Ataxic	Cerebellar ataxia	Severe
AM3	M	79	Ataxic	Cerebellar ataxia	Moderate - severe
AM4	M	46	Ataxic	Cerebellar ataxia	Moderate
AM5	M	84	Ataxic	Cerebellar ataxia	Moderate
AM6	M	46	Ataxic	Cerebellar ataxia	Moderate
AM8	M	63	Ataxic	Cerebellar ataxia	Moderate
ALSF2	F	75	Mixed	ALS	Severe
ALSF5	F	73	Mixed	ALS	Severe
ALSF6	F	63	Mixed	ALS	Severe
ALSF7	F	54	Mixed	ALS	Moderate
ALSF8	F	63	Mixed	ALS	Moderate
ALSF9	F	86	Mixed	ALS	Severe
ALSM1	M	56	Mixed	ALS	Moderate
ALSM4	M	64	Mixed	ALS	Moderate
ALSM7	M	60	Mixed	ALS	Severe
ALSM8	M	46	Mixed	ALS	Moderate
HDM8	M	43	Hyperkinetic	Huntington's disease	Severe
HDM10	M	50	Hyperkinetic	Huntington's disease	Severe
HDM11	M	56	Hyperkinetic	Huntington's disease	Moderate
HDM12	M	76	Hyperkinetic	Huntington's disease	Moderate
PDF5	F	54	Hypokinetic	Parkinson disease	Moderate
PDF7	F	58	Hypokinetic	Parkinson disease	Moderate
PDM8	M	77	Hypokinetic	Parkinson disease	Moderate
PDM9	M	76	Hypokinetic	Parkinson disease	Moderate
PDM10	M	80	Hypokinetic	Parkinson disease	Moderate
PDM12	M	66	Hypokinetic	Parkinson disease	Severe
PDM13	M	81	Hypokinetic	Parkinson disease	Moderate
PDM15	M	57	Hypokinetic	Parkinson disease	Moderate

Note. M = Male; F = Female; ALS = amyotrophic lateral sclerosis

Table 2

Descriptions of the acoustic and perceptual metrics

Metrics	Description
Perceptual Measures	
Intelligibility	Percent words correct from a transcriptional task. Data originally reported in Liss, Utianski and Lansford (2013)
Severity	Perceptual rating of global, integrated impression of dysarthria severity obtained from five SLPs
Vocal quality	Perceptual rating of global, integrated impression of overall vocal quality obtained from five SLPs
Nasality	Perceptual rating of global, integrated impression of nasal resonance obtained from five SLPs
Articulatory imprecision	Perceptual rating of global, integrated impression of precision of articulatory gestures obtained from five SLPs
Prosody	Perceptual rating of global, integrated impression of speaker's rhythm, stress and intonation obtained from five SLPs
Rhythm Metrics	*(Liss et al., 2009)*
ΔV	Standard deviation of vocalic intervals
ΔC	Standard deviation of consonantal intervals
Proportion Vocalic	Percent of utterance duration composed of vocalic intervals
nPVI- V	Normalized pairwise variability index for vocalic intervals. Mean of the differences between successive vocalic intervals divided by their sum.
rPVI- C	Pairwise variability index for consonantal intervals. Mean of the differences between successive consonantal intervals.
Speaking Rate (sp. rate)	Number of (orthographic) syllables produced per second, excluding pauses.
rPVI- VC	Pairwise variability index for vocalic and consonantal intervals. Mean of the differences between successive vocalic and consonantal intervals.
nPVI VC	Normalized pairwise variability index for vocalic + consonantal intervals. Mean of differences between successive vocalic + consonantal intervals divided by their sum.
SD VC	Standard deviation of successive vocalic and consonantal segments
EMS Metrics	*The variables were obtained for each of the octave bands and the full signal. (Liss, Legendre and Lotto, 2010)*
Peak frequency	The frequency of the peak in the spectrum with the greatest amplitude.

	The period of this frequency is the duration of the predominant repeating amplitude pattern.
Peak amplitude	The amplitude of the peak described above (divided by overall amplitude of the spectrum).
E 3-6	Energy in the region of 3-6 Hz (divided by overall amplitude of the spectrum). This is roughly the region of the spectrum (around 4 Hz) that has been correlated with intelligibility (Houtgast & Steeneken) and inversely correlated with segmental deletions (Tilson & Johnson, 2008).
Below 4	Energy in the spectrum from 0-4 Hz (divided by overall amplitude of the spectrum).
Above 4	Energy in the spectrum from 4-10 Hz (divided by overall amplitude of the spectrum).
Ratio 4	Below 4/Above 4
LTAS Metrics	*Normalized to Root Mean Square (RMS) energy of entire signal and derived for 7 octave bands with center frequencies ranging from 125 - 8000 Hz (Utianski et al., 2012)*
RMS energy	RMS Energy
St. Dev. RMS energy	Standard deviation RMS energy (for 20ms windows)
Range RMS energy	Range RMS energy (for 20ms windows)
PVI RMS energy	Pairwise variability of RMS energy: mean difference between successive 20ms windows Range RMS energy
Vowel Metrics	*(Lansford and Liss, 2014 a, b)*
Quadrilateral VSA	Vowel space area. Heron's formula was used to calculate the area of the irregular quadrilateral formed by the corner vowels (i, æ, a, u) in F1 X F2 space. Towards this end, the area (as calculated by Heron's formula) of the two triangles formed by the sets of vowels, /i/, /æ/, /u/ and /u/, /æ/, /a/, are summed. Heron's formula is as follows: $\sqrt{s(s-a)(s-b)(s-c)}$, where s is the semiperimeter of each triangle, expressed as s = ½ (a + b + c), and a, b, and c each represent the Euclidean distance in F1 X F2 space between each vowel pair (e.g., /i/ to /æ/).
FCR	Formant centralization ratio. This ratio, expressed as $(F2_u + F2_a + F1_i + F1_u)/(F2_i + F1_a)$, is thought to capture centralization when the numerator increases and the denominator decreases. Ratios greater than 1 are interpreted to indicate vowel centralization.
Mean dispersion	This metric captures the overall dispersion (or distance) of each pair of

	the ten vowels, as indexed by the Euclidean distance between each pair in the F1 X F2 space.
Front dispersion	This metric captures the overall dispersion of each pair of the front vowels (i, ɪ, e, ɛ, æ). Indexed by the average Euclidean distance between each pair of front vowels in F1 X F2 space.
Back dispersion	This metric captures the overall dispersion of each pair of the back vowels (u, ʊ, o, a). Indexed by the average Euclidean distance between each pair of back vowels in F1 X F2 space.
Corner dispersion	This metric is expressed by the average Euclidean distance of each of the corner vowels, (i, æ, a, u), to the center vowel /^/.
Global dispersion	Mean dispersion of all vowels to the global formant means (Euclidian distance in F1 X F2 space).

Table 3

Listener derived clusters with members

Cluster	Speakers
1	PDF5, PDF7, PDM8, PDM9, PDM10, PDM12, PDM13, PDM15, HDM11
2	AF8, AM5, AM8, ALSF8, ALSM4, ALSM8,
3	AF1, AF7, AM4, AM6, HDM12
4	AF2, HDM8, HDM10
5	ALSF6, ALSF7, ALSF9, ALSM1, AM1
6	AF9, ALSF2, ALSF5, ALSM7

Note. A = Ataxia; ALS = amyotrophic lateral sclerosis; PD = Parkinson's disease; HD = Huntington's disease; M = Male; F = Female

Table 4

Significant correlations between MDS dimensions and temporal-based measures of rate and rhythm.

Dimension 1		Dimension 2	
Variable	*r*	Variable	*r*
Rate	-.888	nPVI-V	-.583
ΔV	.739	%V	.536
rPVI-VC	.55	VarcoV	-.447
VarcoV	-.547		
rPVI-C	.543		
nPVI-V	-.392		
VarcoVC	-.368		
%V	.346		

Note. See Table 2 for metric descriptions. Above metrics are rank ordered by level of significance (all $p < .05$). Insignificant correlations were not included.

Table 5

Significant correlations between MDS dimensions and measures of envelope modulation spectra.

Dimension 1		Dimension 2		Dimension 3	
Variables	*r* range	Variables	*r* range	Variable	*r*
Below4	.391 to .809	E3-6	-.433 to -.623	PeakAmp 2000	-.469
Above4	-.529 to -.731	PeakFreq[b]	.346 to .568	PeakAmp1000	-.449
Ratio4	.539 to .692	Above4[c]	-.436 to -.568		
PeakFreq	.41 to .605	Ratio4	.361 to .602		
PeakAmp[a]	.383 to -.695				

Note: Due to the large number of correlated variables, the results for dimensions 1 and 2 have been summarized and the range of correlation coefficients are reported. See Table 2 for metric descriptions. Above metrics are rank ordered by level of significance (all $p < .05$). Insignificant correlations were not included. [a] significant correlations found for the 125, 250, 1000, and 8000 Hz bands and for the full spectrum; [b] not significant for 250 Hz band or for the full spectrum; [c] significant correlations found for 250, 2000, 4000 and 8000 Hz bands.

Table 6

Significant correlations between MDS dimensions and measures of long-term average spectra.

Dimension 1		Dimension 2		Dimension 3	
Variable	*r*	Variable	*r*	Variable	*r*
PV125	-.583	nsd4000	-.623	N1RMS8000	-.493
PV250	-.52	N1RMS4000	-.599	nsd8000	-.474
PV500	-.517	PV4000	-.582	PV8000	-.447
N1RMS1000	.383	nRng4000	-.559	nRng8000	-.446
nRng1000	.377	PV8000	-.496		
nsd1000	.367	nsd8000	-.462		
		N1RMS8000	-.451		
		nRng8000	-.419		

Note. See Table 2 for metric descriptions. Above metrics are rank ordered by level of significance (all $p < .05$). Insignificant correlations were not included.

Table 7

Significant correlations between MDS dimensions and perceptual measures of intelligibility, severity, vocal quality, nasality, articulatory imprecision, and prosody.

Dimension 1		Dimension 2		Dimension 3	
Variable	*r*	Variable	*r*	Variable	*r*
Vocal quality	.716	Intelligibility	-.646	Vocal quality	-.414
Severity	.702	Severity	.632		
Nasality	.632	Prosody	.624		
Articulatory Precision	.544	Articulatory Precision	.622		
Prosody	.544	Nasality	.55		
		Vocal quality	.434		

See Table 2 for metric descriptions. Above metrics are rank ordered by level of significance (all $p < .05$). Insignificant correlations were not included.

Table 8

Mean vocal quality ratings (z-score normalized) for each similarity-based cluster

Cluster	*N*	*M*	*SD*
1	9	-.7463	.4015
2	6	.0413	.3566
3	5	-.5418	.2325
4	3	.0292	.2114
5	5	1.1699	.4013
6	4	.7066	.786

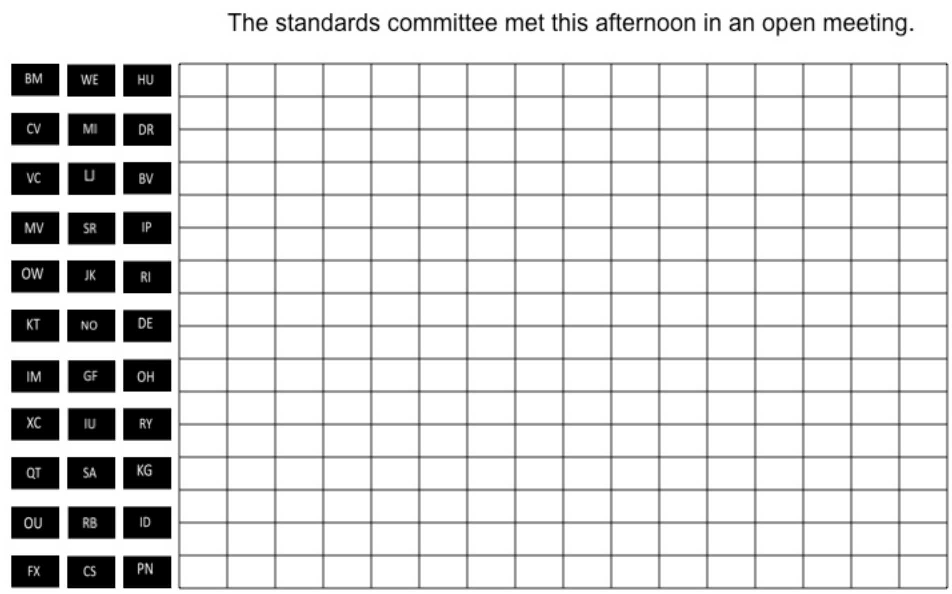


Figure 1. Screen shot of the PowerPoint slide used for the free-classification task in its beginning position. Each of the initialed black icons located on the left side of the slide was paired with a specific speaker's sound file. When the icons were double-clicked the sound file would play.

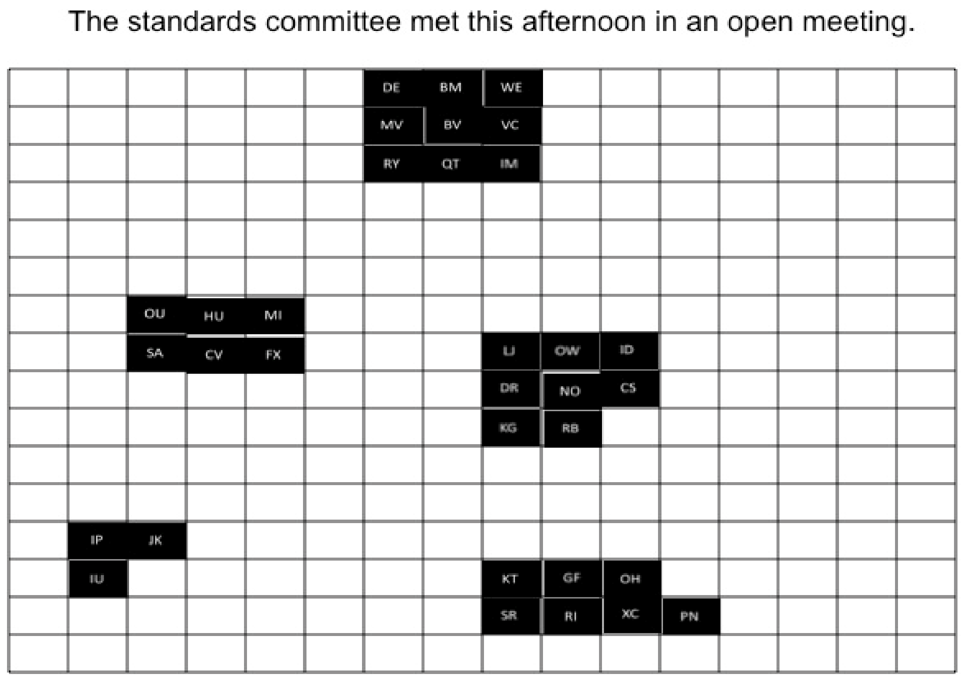


Figure 2. Screen shot of an example free-classification PowerPoint slide in its completed state, wherein, icons touching one another in the grid were considered to be similar-sounding.

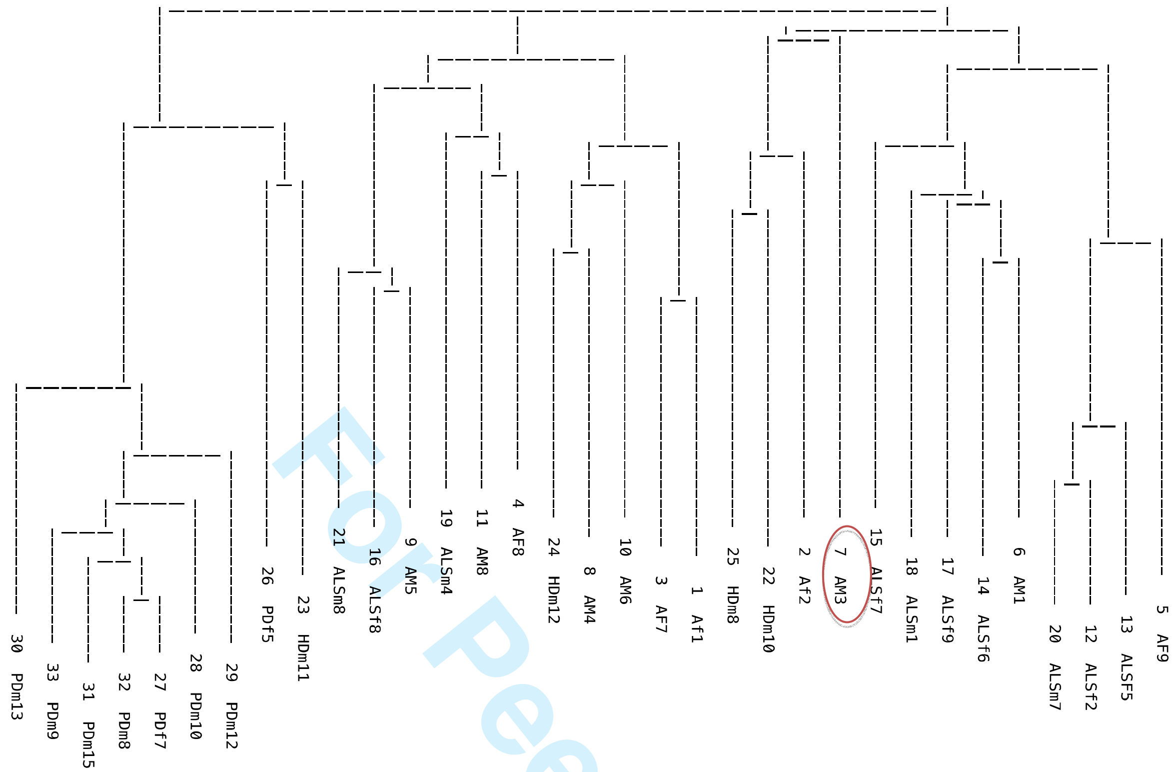
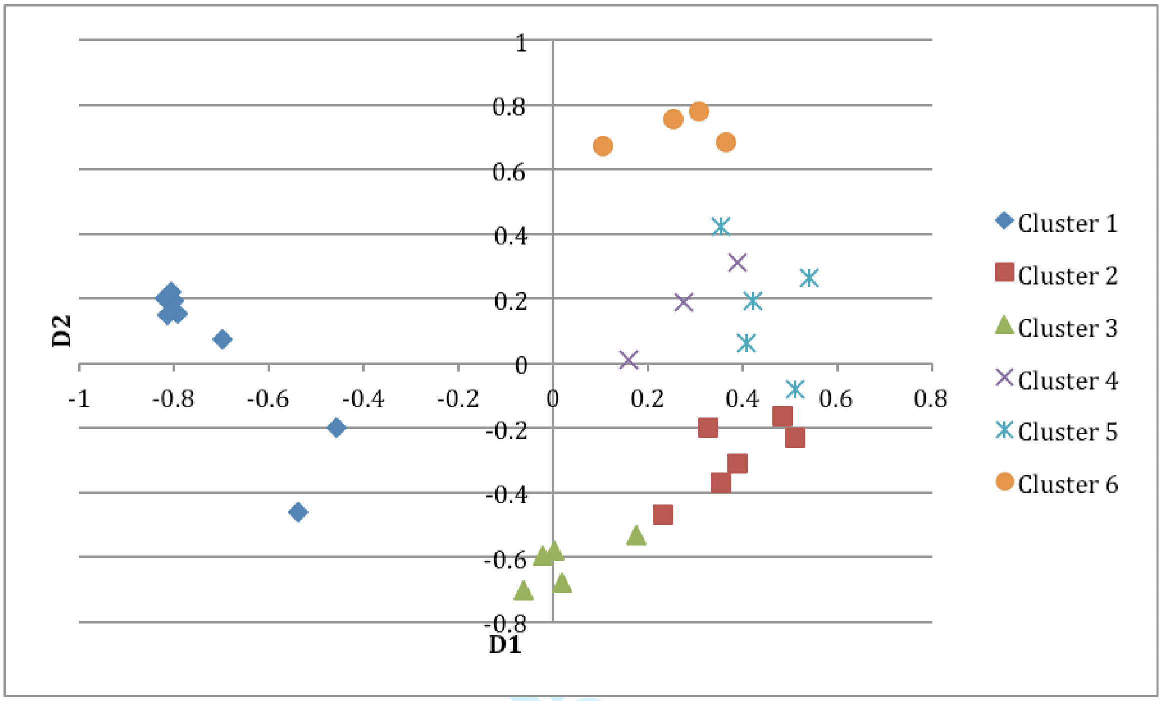
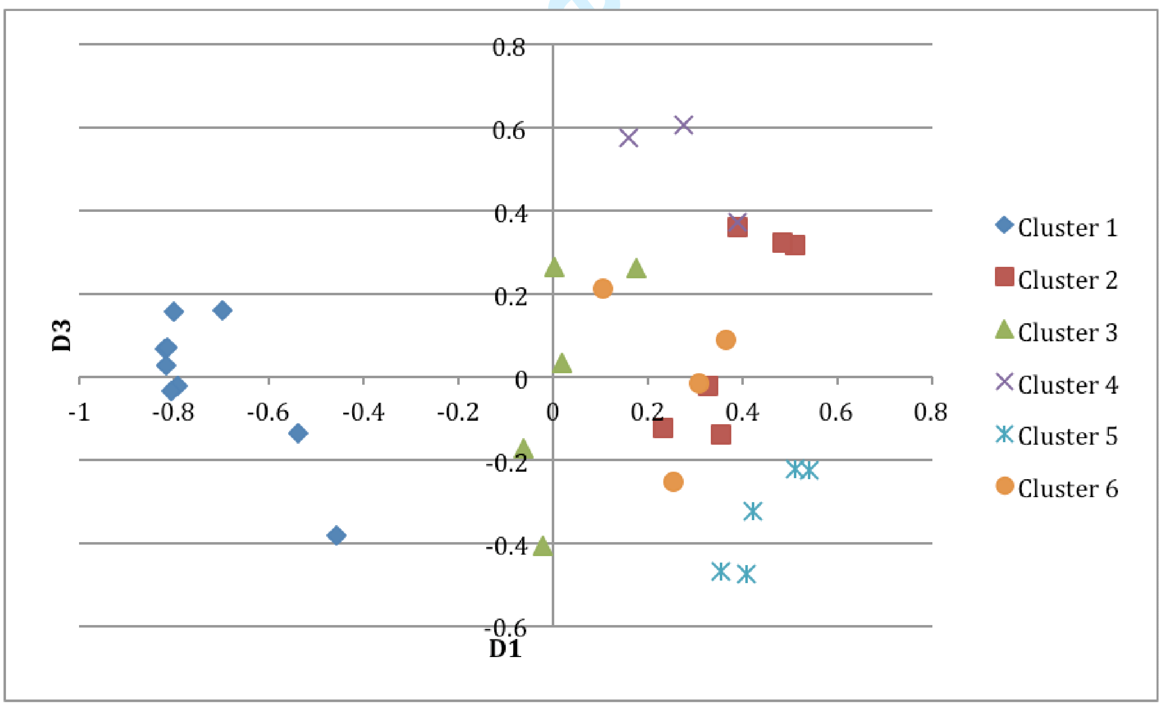


Figure 3. Dendogram derived from the cluster analysis. The dotted line corresponds to the solution selected for the present analysis. The solid lines demarcate cluster boundaries. One speaker, AM3, circled above, was not included in subsequent cluster-based analyses due to his late cluster linking.


D2
D1
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
Cluster 6


D3
D1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-1
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
Cluster 6

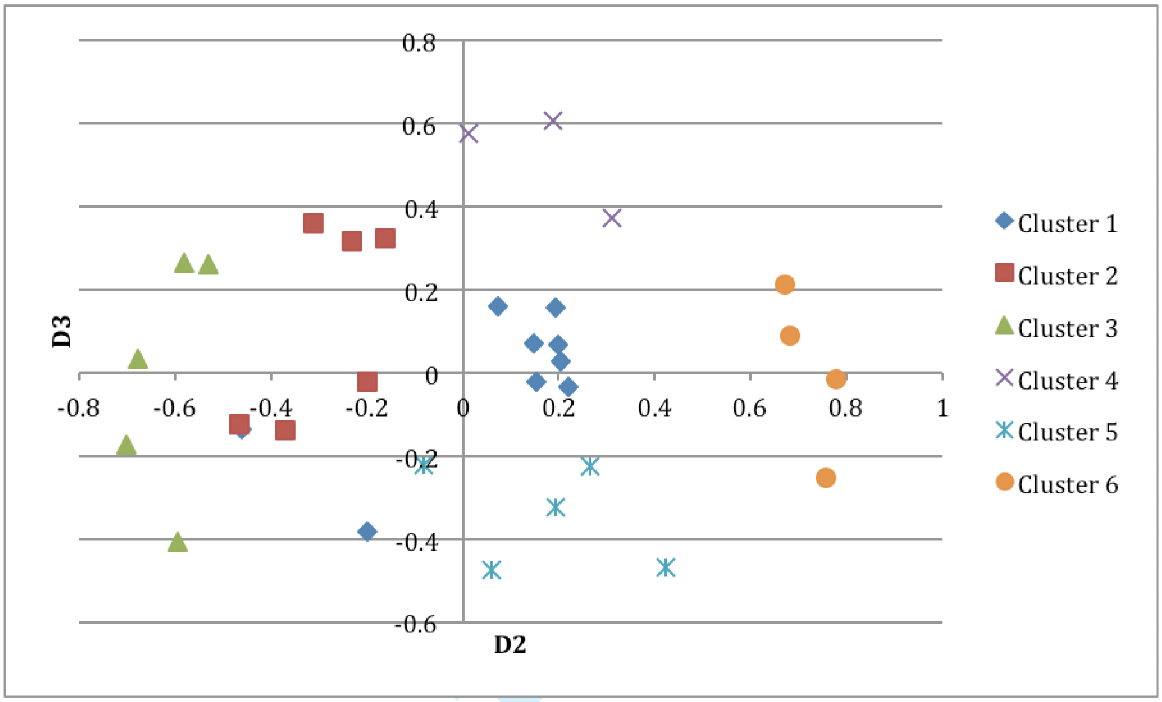


Figure 4a. Listener-derived clusters plotted in the perceptual space created by the first two dimensions derived by MDS (D1 and D2). *Figure 4b.* Listener-derived clusters plotted in the perceptual space created by D1 and D3. *Figure 4c.* Listener-derived clusters plotted in the perceptual space created by D2 and D3.