Detecting Voice Modes for Vocal Hyperfunction Prevention

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Abstract

Background/Motivation:

- Estimated that 6.6% of US working population affected by voice disorders; most commonly associated with chronic vocal abuse/misuse (vocal hyperfunction)
- Precise role of vocal hyperfunction in the etiology of voice disorders not well understood making diagnosis and treatment less precise
- Need the capability to do long-term ambulatory monitoring of voice use and to extract features that differentiate hyperfunctional from normal/healthy voice production

Procedures:

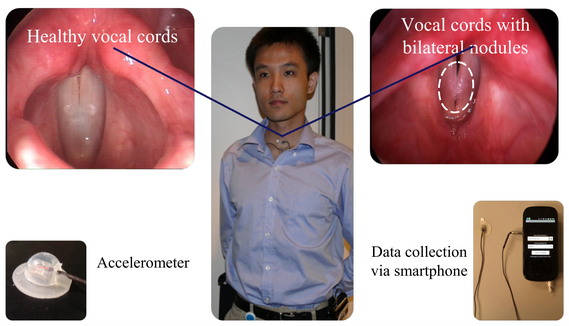
- We explored techniques to recognize vocal hyperfunction by inferring vocal cord (fold) movement based on non-invasive neck-skin acceleration signal
- Non-acoustic voice features derived from acceleration signal used to classify voice qualities in healthy speaker who mimicked vocal hyperfunction
- Applied 79 traditional features of dysphonia that included variants of HRN, signal jitter, shimmer, and spectral shape
- SVMs were trained using soft margin radial basis functions with parameters chosen based on the best mean AUC

Results:

- Using single-class SVM, we found a best crossvalidated F-score of 0.843 for modal phonation detection
- Further investigating unsupervised clustering of segmented data based on most significant chosen features to characterize underlying mechanisms associated with vocal hyperfunction

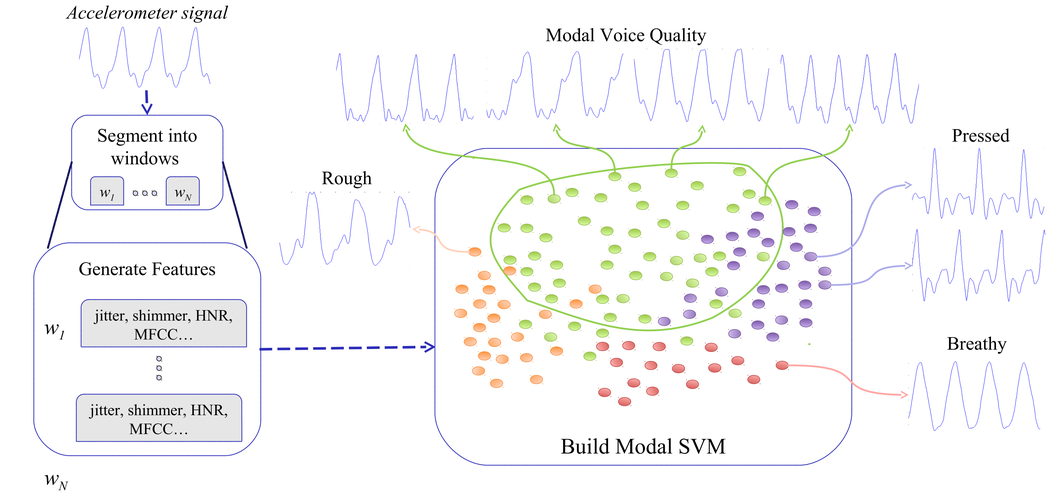
Ambulatory Voice Monitor

Noninvasive measurement of vocal cord vibration using a neck-mounted accelerometer connected to a smartphone.

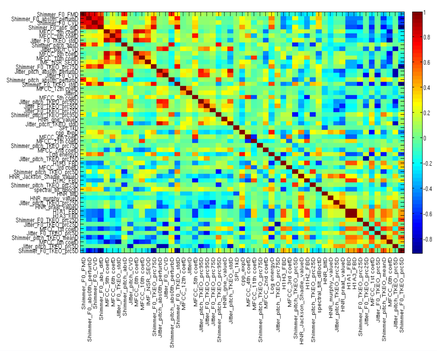


Experimental Setup

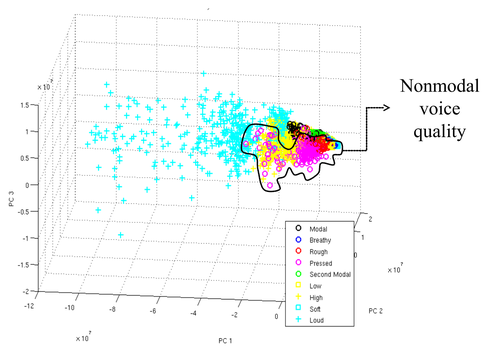
A healthy adult female speaker was instructed to produce sustained vowel sounds (a, e, i, o , u) mimicking modal (normal), breathy, rough, and pressed voice qualities. Features were calculated over non-overlapping 100-msec windows, generating a total of 1,836 data points (64% modal, 13% breathy, 13% rough and 10% pressed). We removed all features with a cross-correlation coefficient of more than 0.9 with any other feature, leaving a total of 55 features.



Heat map of correlation for 55 least correlated features



Visualization of exemplar data in 3 PCA dimensions



Results

Classifying modal in a vocally-normal subject mimicking disordered voice qualities

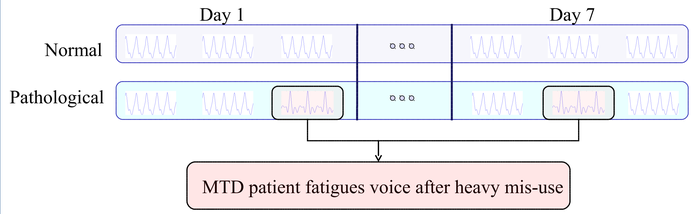
- Single class (using modal only)
- Two-class (using modal versus breathy/rough/pressed)

Window Size	SVM Type	F-score	Sens.	Spec.	PPV	NPV
100 ms	Single Class	0.843	0.848	0.421	0.838	0.440
	Two Class	0.835	0.832	0.498	0.838	0.486
1 sec	Single Class	0.827	0.821	0.476	0.833	0.455
	Two Class	0.827	0.821	0.500	0.833	0.478

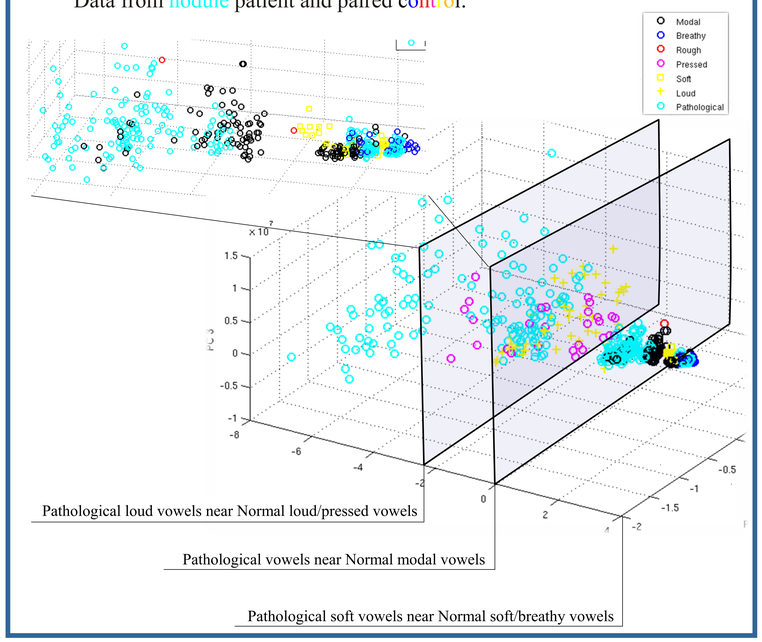
From Lab to Field

- Working with real patients on the examination of continuous speech over 7 days (over 15 GB per patient!)
- Many types of hyperfunction; monitor patients pre-therapy/post-therapy and pair with a vocally-normal control
- Near term goal is prediction of vocal hyperfunction episodes

Data from MTD patient and paired control:



Data from nodule patient and paired control:



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