Source and Vocal Tract Cues for Speech-based Classification of Patients with Parkinson's Disease and Healthy Subjects

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Overview

1 Introduction

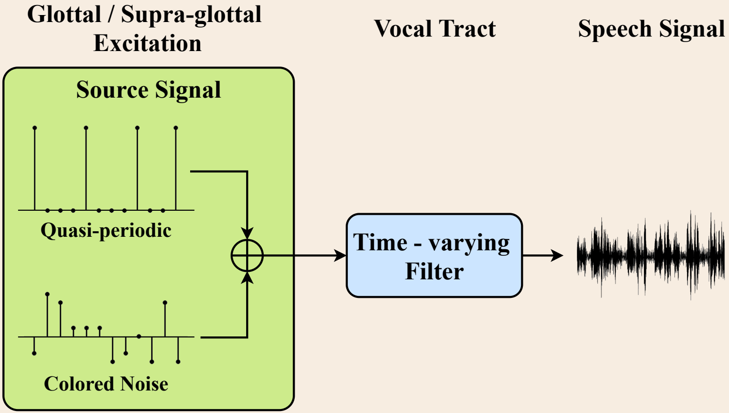
2 Dataset

3 PD vs. HC Classification

4 Experiments and Results

5 Conclusions

Source - Filter Model



G. Fant, Acoustic theory of speech production. Walter de Gruyter, no. 2, 1970.

Parkinson's Disease (PD)

- **Incurable** and **progressive neuro-degenerative** disorder affecting **muscle movements**[1]
  - Dopaminergic neurons degenerate
  - Deficit of neurotransmitter *dopamine* hampers coordinated and smooth muscular control
- Muscles responsible for speech production get affected leading to **dysarthria**[2]
  - Experienced by $\sim 90\%$ of the patients from the early stages of PD[3]

[1] https://www.mayoclinic.org/diseases-conditions/parkinsons-disease/

[2] P. Gómez et al., "Characterization of Parkinson's disease dysarthria in terms of speech articulation kinematics," Biomedical Signal Processing and Control, vol. 52, pp. 312–320, 2019.

[3] G. Moya-Galé and E. S. Levy, "Parkinson's disease-associated dysarthria: prevalence, impact and management strategies," Research and Reviews in Parkinsonism, vol. 9, pp. 9–16, 2019.

Effect of PD on Source and Vocal Tract

- PD impairs both **source** and **vocal tract** attributes of speech
  - **Source Impairment** - monopitch, monoloudness, low voice intensity, and reduced fundamental frequency range[1,2]
  - **Vocal Tract Impairment** - imprecise articulation, voice nasality, and increased acoustic noise[2]

[1] G. Moya-Galé and E. S. Levy, "Parkinson's disease-associated dysarthria: prevalence, impact and management strategies," Research and Reviews in Parkinsonism, vol. 9, pp. 9–16, 2019.

[2] L. Brabenec et al., "Speech disorders in Parkinson's disease: early diagnostics and effects of medication and brain stimulation," Journal of neural transmission, vol. 124, no. 3, pp. 303–334, 2017.

Our Objective

- To compare the source and vocal tract characteristics in PD patients and healthy subjects
- To analyze how the cues related to these components contribute individually and in combination toward automatic classification of individuals with PD and healthy controls (HC)

Literature Review

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Objective	Speech Features	Classifier
PD vs. HC classification	MFCC[1]	CNN-LSTM
	1D-CNN based features from raw speech[2]	BLSTM
	Auto-encoder based features from spectrogram, scalogram[3]	SVM, Softmax classifier
Classification & severity prediction of PD	MFCC, CSD, spectral dynamics, fundamental frequency variation[4]	Random Forest

[1] J. Mallela et al., "Voice based classification of patients with Amyotrophic Lateral Sclerosis, Parkinson's Disease and healthy controls with CNN-LSTM using transfer learning," in ICASSP, IEEE, pp. 6784–6788, 2020.

[2] J. Mallela et al., "Raw speech waveform based classification of patients with ALS, Parkinson's disease and healthy controls using CNN-BLSTM," in INTERSPEECH, pp. 4586–4590, 2020.

[3] B. Karan et al., "Stacked auto-encoder based time-frequency features of speech signal for Parkinson's disease prediction," in AISP, IEEE, pp. 1–4, 2020.

[4] T. Khan et al., "Assessing Parkinson's disease severity using speech analysis in non-native speakers," Computer Speech Language, vol. 61, p. 101047, 2020.

Overview

1 Introduction

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Dataset Description

- All speech data were collected at **National Institute of Mental Health and Neurosciences (NIMHANS)**, Bangalore, India

Condition	#Male	#Female	#Subjects	Age range (years)
PD	45	14	59	35 - 79
HC	44	16	60	22 - 53
Total	**89**	**30**	**119**	**22 - 79**

- Subjects had **six** different **native languages** - Bengali, Hindi, Kannada, Odiya, Tamil, and Telugu
- PD subjects had dysarthria severity in the range of 0 - 2 as per the UPDRS-III scale[1]

[1] D. J. Gelb et al., "Diagnostic criteria for Parkinson's disease," Archives of Neurology, vol. 56, no. 1, pp. 33–39, 1999.

Dataset Description

Speech Task	Duration (hours)
Image description (IMAG)	~ 12.83
Diadochokinetic Rate (DIDK)	~ 4.65
Spontaneous speech (SPON)	~ 5.62

- IMAG and SPON tasks were performed in the subjects' native language
- **Audio Recorder:** Zoom H6 with XYH-6 stereo microphone capsule
- **Sampling frequency:** 44.1 kHz (downsampled to 16 kHz)

Overview

1 Introduction

2 Dataset

3 PD vs. HC Classification

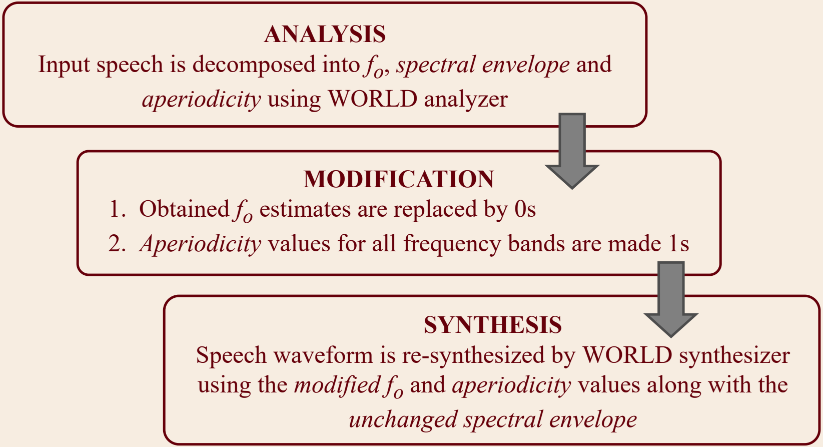
4 Experiments and Results

5 Conclusions

Source and Vocal Tract Features

Speech Component	Feature
Source	Fundamental frequency (f_o)
Vocal Tract	Voicing-removed MFCC (vrMFCC) [MFCC computed after voicing removal]
Source + Vocal Tract	MFCC

Voicing Removal Procedure



ANALYSIS

Input speech is decomposed into f_o, *spectral envelope* and *aperiodicity* using WORLD analyzer

MODIFICATION

1. Obtained f_o estimates are replaced by 0s
2. *Aperiodicity* values for all frequency bands are made 1s

SYNTHESIS

Speech waveform is re-synthesized by WORLD synthesizer using the *modified* f_o and *aperiodicity* values along with the *unchanged spectral envelope*

M. Morise et al., "WORLD: a vocoder-based high-quality speech synthesis system for real-time applications," IEICE Transactions on Information and Systems, vol. 99, no. 7, pp. 1877–1884, 2016.

Feature Extraction

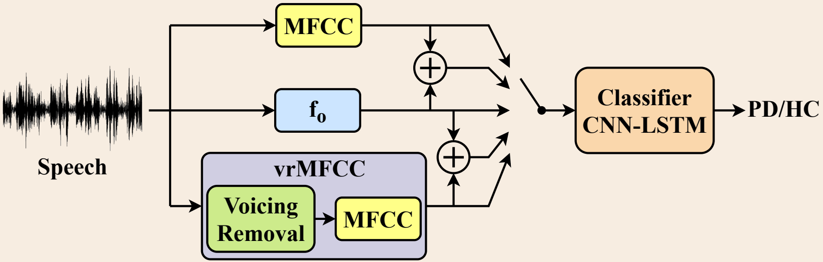
	$\mathbf{f_o}$	**MFCC**
Algorithm/Toolkit	SWIPE[1]	KALDI[2]
Dimension	3 ($1\ f_o + 1\ \Delta f_o + 1\ \Delta^2 f_o$)	39 (13 MFCC $+ 13\ \Delta$MFCC $+ 13\ \Delta^2$MFCC)
Temporal Setting	extracted every 10 ms	20 ms frame length, 10 ms overlap

- The f_o estimates for unvoiced/silence regions are replaced by 0s
- Utterance-level Z-score normalization is applied to each feature dimension independently

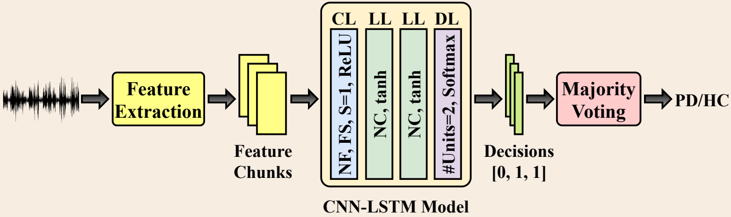
[1] A. Camacho and J. G. Harris, “A sawtooth waveform inspired pitch estimator for speech and music,” The Journal of the Acoustical Society of America, vol. 124, no. 3, pp. 1638–1652, 2008.

[2] D. Povey et al., “The Kaldi speech recognition toolkit,” in Workshop on automatic speech recognition and understanding, IEEE Signal Processing Society, 2011.

Classification Scheme



Classifier Configuration



CL: 1D-CNN layer
LL: LSTM layer
DL: Dense layer
NF: #filters
FS: Filter size
S: Stride
NC: #cells in LL

Feature Set	NF	FS	NC	#param	FLOPs
$\mathbf{f_o}$	18	20	64	55500	175.48k
MFCC / vrMFCC	5	20	64	54979	174.46k
$\mathbf{f_o}$**+MFCC / **$\mathbf{f_o}$**+vrMFCC**	5	20	64	55279	175.06k

J. Mallela et al., "Voice based classification of patients with Amyotrophic Lateral Sclerosis, Parkinson's Disease and healthy controls with CNN-LSTM using transfer learning," in ICASSP, IEEE, pp. 6784–6788, 2020.

Noise Conditions

- **Noise:**
  - Additive White Gaussian Noise (AWGN)
  - High-Frequency Channel Noise (HF)[1]
  - Pink Noise[1]
  - Babble Noise[1]
- **SNR:**
  - 0, 5, 10 and 20 dB
- **Train-Test Settings:**
  - **Matched:** Noise and SNR of the data used in training and testing the classifier are matched
  - **Mismatched:** Classifier trained with clean data is used to test both clean and noisy test samples

[1] A. Varga and H. J. Steeneken, "Assessment for automatic speech recognition: II. NOISEX-92: A database and an experiment to study the effect of additive noise on speech recognition systems," Speech communication, vol. 12, no. 3, pp. 247–251, 1993.

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2 Dataset

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Evaluation Protocol

- **Validation Scheme:**
  - 5-fold cross-validation
    - Each fold contains almost equal number of subjects from PD and HC classes
    - Similar distributions of age, gender, language and dysarthria severity are maintained across folds
- **Evaluation Metrics:**
  - Classification accuracy
  - Wilcoxon signed rank test[1] at 10% significance level

[1] RF Woolson, "Wilcoxon signed-rank test," Wiley encyclopedia of clinical trials, pp. 1–3, 2007.

Source (f_o) or Vocal Tract (vrMFCC)?

Table: Mean classification accuracies in % (SD in bracket); here blue colour indicates superiority at 10% significance level

Feature Set	Speech Task			
	IMAG	DIDK	SPON	Overall
f_o	74.19 (4.67)	75.33 (2.86)	88.12 (4.44)	79.21
vrMFCC	83.17 (3.56)	76.45 (4.31)	83.26 (3.41)	80.96

- Relative contributions of source and vocal tract cues toward PD vs. HC classification vary with the speech tasks at hand

Are They Complementary?

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Table: Mean classification accuracies in % (SD in bracket); # indicates that MFCC outperforms vrMFCC at 10% significance level; * and △ indicate that f_o+vrMFCC outperforms f_o & vrMFCC, respectively, at 10% significance level

Feature Set	Speech Task			
	IMAG	DIDK	SPON	Overall
f_o	74.19 (4.67)	75.33 (2.86)	88.12 (4.44)	79.21
MFCC	85.30 (4.92)	81.23 (2.40)#	88.04 (2.84)#	84.86
vrMFCC	83.17 (3.56)	76.45 (4.31)	83.26 (3.41)	80.96
f_o+vrMFCC	84.74 (3.69)*	83.42 (1.29)*△	90.36 (4.03)△	86.17

- Source and vocal tract cues complement each other in all tasks

Does Fusion of f_o and MFCC Help?

Table: Mean classification accuracies in % (SD in bracket); * and △ indicate that f_o+MFCC/vrMFCC outperforms f_o & MFCC/vrMFCC, respectively, at 10% significance level

Feature	Speech Task			
Set	IMAG	DIDK	SPON	Overall
f_o	74.19 (4.67)	75.33 (2.86)	88.12 (4.44)	79.21
MFCC	85.30 (4.92)	81.23 (2.40)	88.04 (2.84)	84.86
f_o+MFCC	88.65 (4.21)*	83.28 (4.09)*	91.91 (1.31)*$^{\triangle}$	87.95
f_o+vrMFCC	84.74 (3.69)*	83.42 (1.29)*$^{\triangle}$	90.36 (4.03)$^{\triangle}$	86.17

- Source information encoded in MFCC and f_o are different and complementary
- PD vs. HC classification accuracy benefits from f_o+MFCC fusion
- f_o+MFCC outperforms f_o+vrMFCC

Effect of Noise: Matched Train - Test

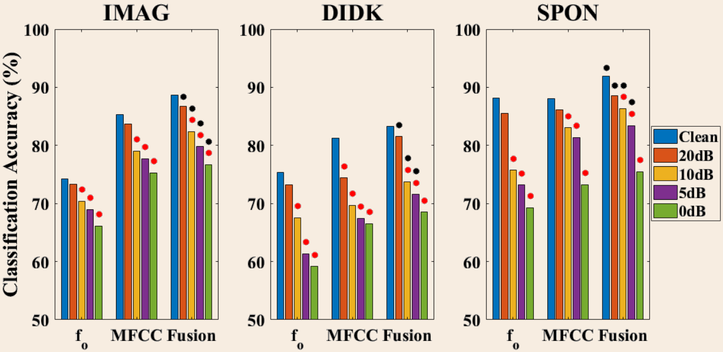

Figure: Mean classification accuracy over AWGN, HF, pink, and babble noise; here ● indicates drop in accuracy w.r.t. clean case at 10% significance level and ● marks the feature set which outperforms the other two at 10% significance level for a particular SNR

- Source and vocal tract features are complementary in the matched train-test noisy conditions

Effect of Noise: Mismatched Train - Test

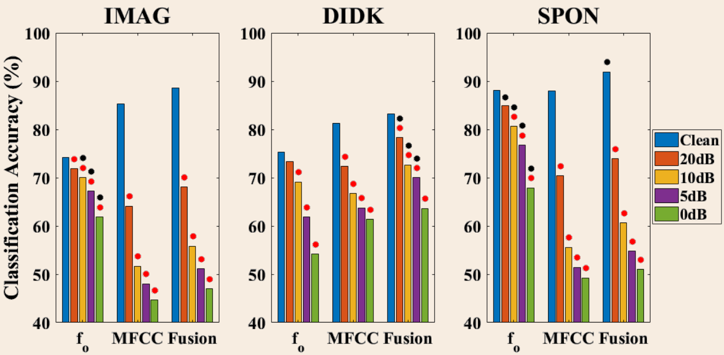

Figure: Mean classification accuracy over AWGN, HF, pink, and babble noise; here ● indicates drop in accuracy w.r.t. clean case at 10% significance level and ● marks the feature set which outperforms the other two at 10% significance level for a particular SNR

- f_o is highly robust against unseen noise and SNR conditions

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SPIRE LAB

1 Introduction

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Key Takeaways

- Relative merits of source and vocal tract cues vary in different speech tasks
- However, the two components complement each other consistently
- Among all the feature sets considered, f_o+MFCC is found to attain the highest classification accuracy under both clean and matched train-test conditions
- Robustness against unseen noise is predominantly observed in the case of source features encoded in f_o

Future Work

- To perform similar analysis using other source cues like glottal flow
- To assess the dysarthria severity using source and vocal tract cues

Acknowledgement

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THANK YOU

Have Questions/Suggestions?
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