Experimental Investigation on STFT Phase Representations for Deep Learning-based Dysarthric Speech Detection

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Virtual ICASSP 2022

May 2022

Outline

Automatic dysarthric speech detection

- Dysarthria of speech → disturbances of muscular control on speech production system
  - Imprecise articulation, abnormal speech rhythm, pitch variation, breathiness

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Dysarthric speech detection using:

- Subjective screening based on judgment of medical practitioners
  - Labor-intensive
  - Inconsistency
  - Difficulties with early diagnosis

- Automatic and objective method
  - Efficient and economical
  - Repeatable
  - Early diagnosis

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State-of-the-art automatic dysarthric speech detection

- Traditional machine learning approaches
- Deep learning approaches

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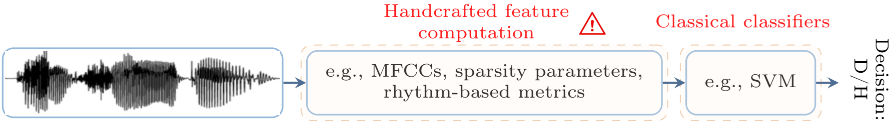


⚠ May fail to adequately capture dysarthric speech characteristics

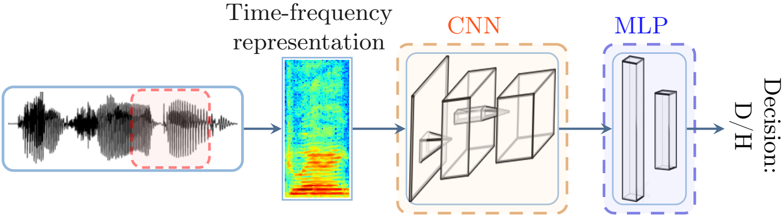
⚠ May fail to characterize abstract but important acoustic cues

State-of-the-art automatic dysarthric speech detection

- Deep learning approaches → data-driven approaches using no prior knowledge
  - Exploit high-level abstract features from low-level time-frequency speech representations or raw waveform using neural networks

State-of-the-art automatic dysarthric speech detection

- Mainstream deep learning approaches
  - Rely on processing magnitude spectrum (or features derived from the magnitude spectrum) (Vaiciukynas et al., 2017; Vasquez et al., 2017; An et al., 2018)



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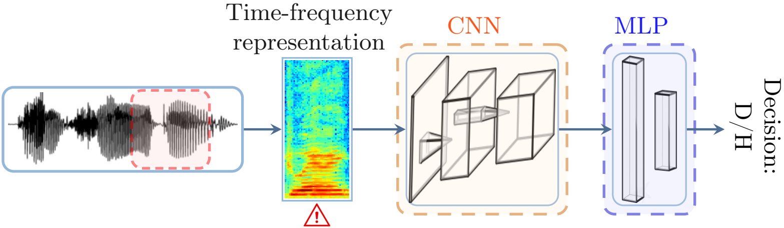
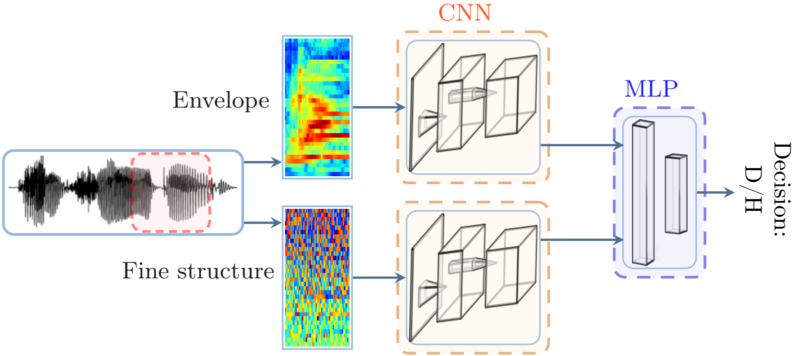
⚠ Ignoring complementary acoustic cues in phase spectrum



State-of-the-art automatic dysarthric speech detection

- Deep learning approaches
  - Dual CNN-based framework using temporal envelope and fine structures (Kodrasi, 2021)



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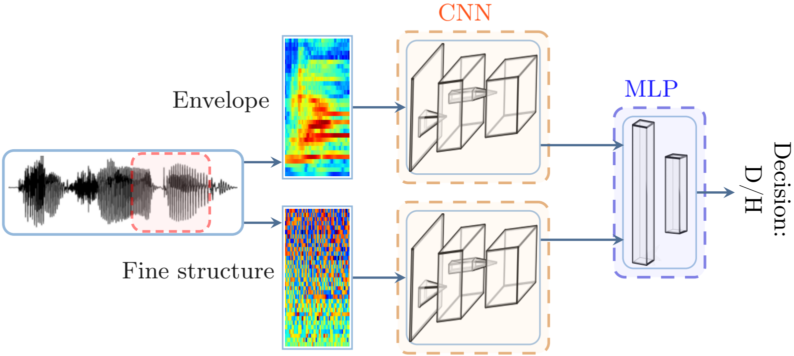
⚠ Not clear if the incorporation of the analytical phase was beneficial



Outline

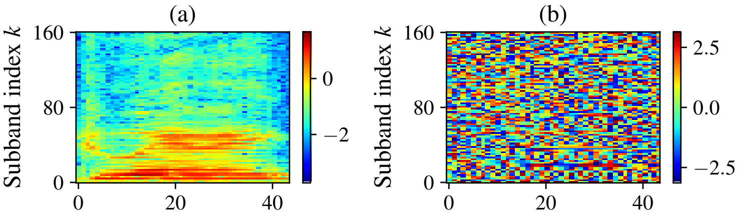
STFT phase representations for dysarthric speech detection

STFT magnitude and phase representations

$$S_{k,l} = |S_{k,l}|e^{j\theta_{k,l}},$$

(a) $|S_{k,l}| \rightarrow$ the magnitude of l-th segment at the k-th subband

(b) $\theta_{k,l} \rightarrow$ the phase of l-th segment at the k-th subband



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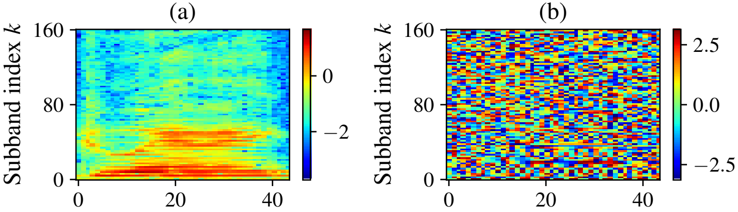


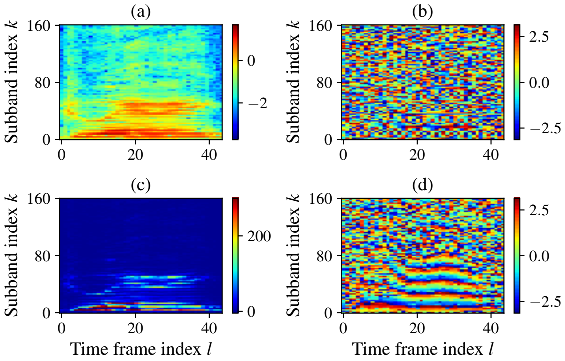
» Expected difficulty in processing the phase spectrum

- Discontinuous and irregular → lack of visible spectro-temporal patterns

STFT phase representations for dysarthric speech detection

» Proposing to use two alternative phase representations revealing spectro-temporal structures

- Modified group delay (MGD) spectrum→ reflecting the cepstrally smoothed derivative of phase along the **frequency** axis (Murthy and Gadde, 2003)
- Instantaneous frequency (IF) spectrum→ reflecting the derivative of phase along the **time axis** (Stark and Paliwal, 2008)



(a) Log of magnitude
(b) Unprocessed phase
(c) MGD
(d) IF

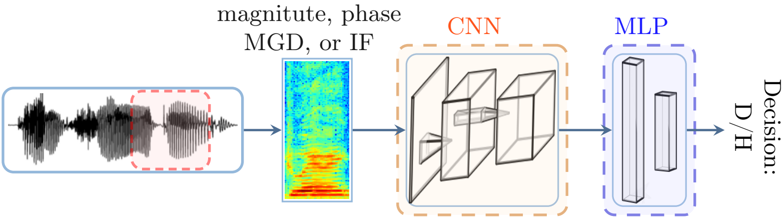
STFT phase representations for dysarthric speech detection

- Proposing to use two alternative phase representations revealing spectro-temporal structures
  - Modified group delay (MGD) spectrum (Murthy and Gadde, 2003)
    - Expected to capture articulation deficiencies and vowel quality changes in dysarthric speech
  - Instantaneous frequency (IF) spectrum (Stark and Paliwal, 2008)
    - Expected to capture pitch variation in dysarthric speech

Dysarthric speech detection experiments via phase representations

» Baseline networks and the proposed network

- Baseline single input CNNs
- Baseline dual input CNN using temporal envelope and fine structure
- Proposed dual input CNNs



Using either of STFT magnitude, unprocessed phase, MGD, IF spectra as input

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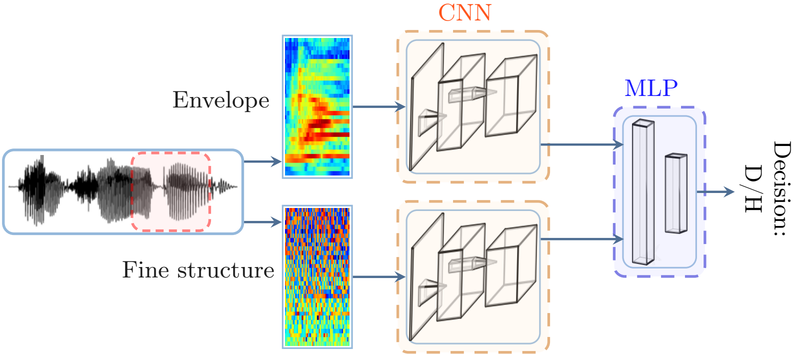

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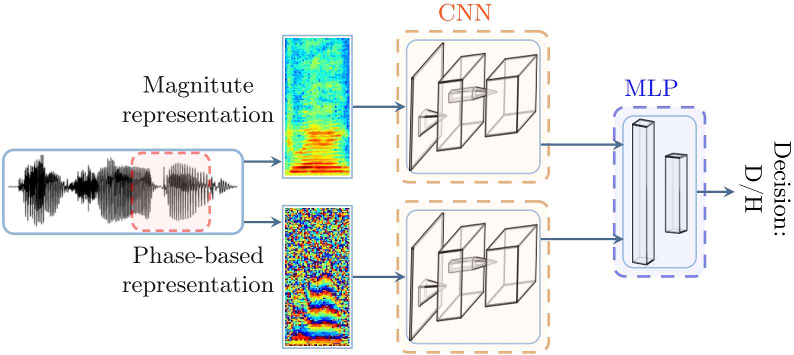

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Experimental results

» Dataset: Spanish PC-GITA database (Orozco et al., 2014)

- 50 PD patients vs. 50 healthy speakers
- Speaker-independent 10-fold cross-validation framework

» Evaluation metrics

- Dysarthric speech detection accuracy: percentage of correctly classified neurotypical and PD speakers
- AUC: area under ROC curve

Experimental results

- Dysarthric speech detection performance
  - Using the baseline single input CNNs operating on magnitude and phase representations

Representation	Accuracy [%]	AUC
Magnitude	69.72	0.77
Phase	62.76	0.70
MGD	70.78	**0.79**
IF	**72.64**	**0.79**

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  - Any of the phase representations similarly to the magnitude spectrum provide useful cues for dysarthric speech detection
  - IF gives the highest performance while the unprocessed phase gives the lowest performance

Experimental results

» Dysarthric speech detection performance

- Using the baseline dual input CNN and proposed dual input CNNs

Representation	Accuracy [%]	AUC
Magnitude-Phase	87.32	0.93
Magnitude-MGD	80.92	0.90
Magnitude-IF	**93.68**	**0.97**
Baseline Envelope-Fine structure	86.04	0.94

Experimental results

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- All dual input CNNs outperform their single input counterparts → all phase representations contain complementary cues to the magnitude spectrum
- Using the magnitude and IF spectra yields the highest performance, outperforming the baseline dual input CNN

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Summary

- » Investigating the applicability of STFT phase representations for dysarthric speech detection
  - Two alternative representations revealing hidden structures of the phase spectrum, i.e., the MGD and IF spectra
- » Using a single input CNN it has been shown that all considered phase representations contain dysarthric cues
- » Using a dual input CNN it has been shown that all phase representations serve as complementary features to the magnitude spectrum
  - Combination of magnitude and IF spectra yields a high performance

Thank You

Reference

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