On using the UA-Speech and TORGO databases to validate automatic dysarthric speech classification approaches

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Outline

Automatic dysarthric speech classification

- Dysarthria of speech → disturbances of muscular control on speech production system
  - Cerebral Palsy (CP), Amyotrophic Lateral Sclerosis (ALS)
  - Imprecise articulation, abnormal speech rhythm, pitch variation, breathiness

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Dysarthric speech classification 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 classification systems

- Traditional machine learning approaches
- Deep learning approaches

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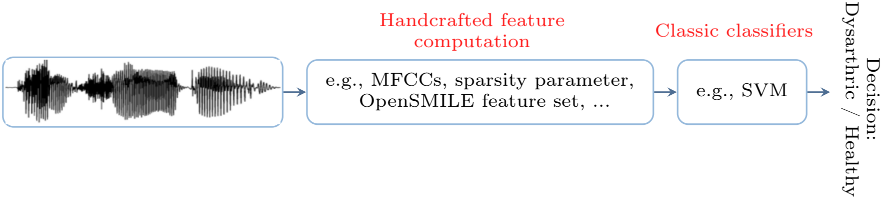
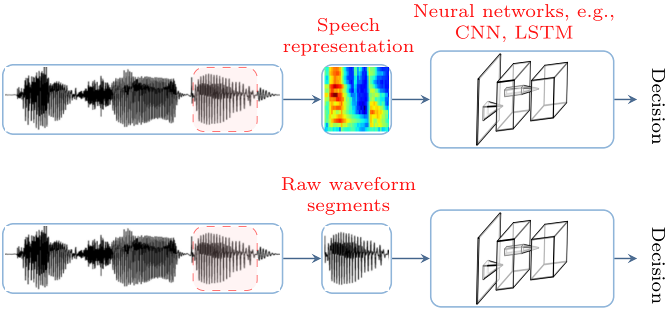


State-of-the-art automatic dysarthric speech classification systems

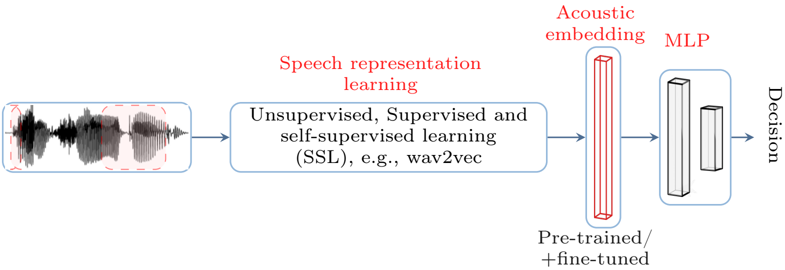
» Deep learning approaches → data-driven approaches using no prior knowledge

- Exploit high-level abstract features from low-level speech representations or raw waveforms using neural networks (Vaiciukynas et al., 2017; Mallela et al., 2020; Narendra et al., 2021)



State-of-the-art automatic dysarthric speech classification systems

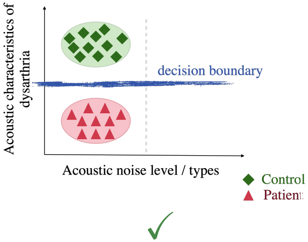
- Deep learning approaches → data-driven approaches using no prior knowledge
  - Speech representation (embedding) learning + downstream task, i.e., dysarthric speech classification (Janbakhshi and Kodrasi, 2021; Yang et al., 2021; Janbakhshi and Kodrasi, 2022)

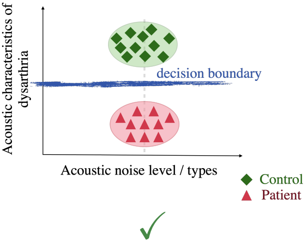


Underlying assumption

» Assumptions in state-of-the-art automatic dysarthria classification systems

- Control and dysarthric speakers are recorded in the same (ideally noiseless) environment using the same recording setup. ✓





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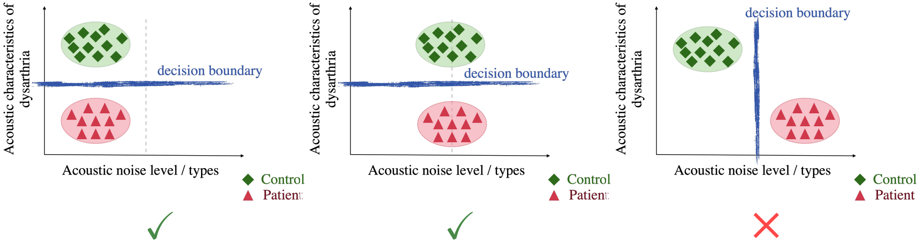
  - Control and dysarthric speakers are recorded in the same (ideally noiseless) environment using the same recording setup. ✓
- Consistent violation of the assumptions across the speaker groups
  - Trained classifiers would learn characteristics of the recording environment instead of dysarthric speech characteristic. ✗



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- Some of publicly available datasets, validated in many state-of-the-art automatic dysarthria classification approaches, might not fulfill such assumptions!
  - UA-Speech (Rudzicz et al., 2012) and TORGO (Kim et al., 2008) ✗

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Investigating the recording environment bias on dysarthric speech classification

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Investigating if the dysarthria classification results using the UA-Speech and TORGO databases reflect the characteristics of the recording environment rather than characteristics of dysarthric speech.

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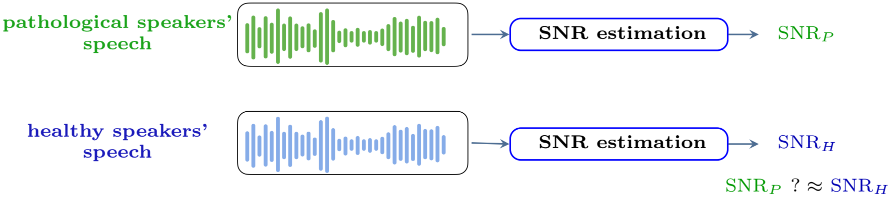
(1) assessing variability in recording conditions using signal-to-noise ratio (SNR) estimation



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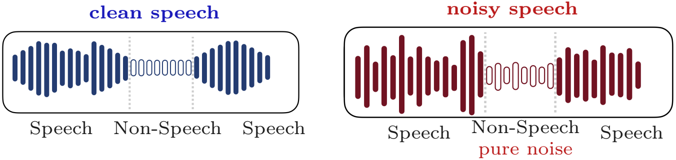
(2) assessing state-of-the-art dysarthria classification approaches on speech-only and non-speech-only segments



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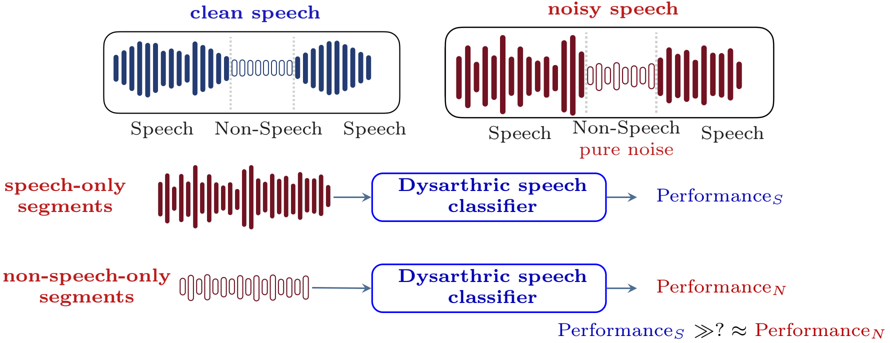

Outline

Evaluation

- Dataset 1: English UA-Speech (Rudzicz et al., 2012)
  - Discriminating 15 dysarthric (CP) patients from 13 healthy speakers
  - Considering recordings of 721 phonetically-matched utterances per speaker
  - Leave-one-speaker-out validation framework
- Dataset 2: English TORGO (Kim et al., 2008)
  - Discriminating 7 dysarthric (CP or ALS) patients from 7 healthy speakers
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- Applied VAD: forced alignment from a ASR system (Hermann and Magimai-Doss, 2021) to extract speech and non-speech segments
- Evaluation metric for dysarthric speech classification
  - Speaker-level classification accuracy

SNR of control and dysarthric recordings

- SNR estimation
  - Using a data-driven recurrent neural network to estimate utterance-level SNR (Li et al., 2021)

Mean and standard deviation of the estimated SNRs [dB] across all utterances of control and dysarthric speakers in the UA-Speech and TORGO databases.

Speakers	UA-Speech	TORGO
Control	3.7 ± 11.5	2.1 ± 13.2
Dysarthric	-7.6 ± 16.1	-4.0 ± 14.7

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- Large variation in the acoustic conditions of the recorded utterances for both databases
- Large difference in the average SNRs of control and dysarthric utterances in both databases
- No guarantee that automatic dysarthria classification approaches validated on these databases learn speech characteristics or recording conditions changes for the two groups of speakers.

Dysarthria classification approaches

- SVM classifier trained on hand crafted features
  - OpenSMILE feature set + PCA dimensionality reduction
  - MFCCs functionals (48-dimensional feature vectors)
  - Sparsity-based features (129-dimensional feature vectors)

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- Wav2vec2 learned representation + MLP classifier
  - MLP trained on wav2vec2 embeddings with or without fine-tuning (Yang et al., 2021)

Dysarthria classification [mean and standard deviation of the accuracy]

Approach validated on **UA-Speech**	Speech	Non-speech	Speech&Non-speech
SVM+openSMILE	81.0 ± 19.8	84.5 ± 21.9	83.3 ± 21.1
SVM+MFCCs	81.0 ± 1.7	100.0 ± 0.0	100.0 ± 0.0
SVM+sparsity-based features	94.0 ± 1.7	96.4 ± 0.0	96.4 ± 0.0
CNN+Mel spectrograms	95.2 ± 1.7	97.6 ± 1.7	98.8 ± 1.7
SRL+Mel spectrograms	98.8 ± 1.7	100.0 ± 0.0	100.0 ± 0.0
MLP+ft-wav2vec2	95.2 ± 1.7	97.6 ± 1.7	95.2 ± 1.7
MLP+wav2vec2	54.8 ± 1.7	58.3 ± 1.7	54.8 ± 1.7

Approach validated on **TORGO**	Speech	Non-speech	Speech&Non-speech
SVM+openSMILE	60.0 ± 5.4	82.2 ± 6.3	71.1 ± 12.6
SVM+MFCCs	60.0 ± 0.0	88.9 ± 3.1	57.8 ± 3.1
SVM+sparsity-based features	73.3 ± 0.0	93.3 ± 0.0	73.3 ± 5.4
CNN+Mel spectrograms	53.3 ± 11.5	77.8 ± 10.2	68.9 ± 10.2
SRL+Mel spectrograms	71.1 ± 3.1	100.0 ± 0.0	91.1 ± 3.1
MLP+ft-wav2vec2	60.0 ± 5.4	57.8 ± 3.1	60.0 ± 5.4
MLP+wav2vec2	55.6 ± 3.1	57.8 ± 3.1	57.8 ± 6.3

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- Performance of majority of approaches using non-speech segments is the same or even better than when using speech segments or complete utterances from the UA-Speech and TORGO databases
- Classification results obtained on the UA-Speech and TORGO databases can be greatly affected by characteristics of the recording environment and setup

Outline

Summary

- Investigating the use of the UA-Speech and TORGO databases to validate automatic dysarthria classification approaches

- Hypothesizing that classification results could be biased towards capturing characteristics of the recording environment rather than characteristics of dysarthric speech
  - Estimating the utterance-level SNRs on these databases
  - Validating state-of-the-art dysarthria classification approaches on the speech and non-speech segments of these database

- Experimental results have shown that:
  - Utterance-level SNRs in control and dysarthric recordings are considerably different in both databases
  - State-of-the-art approaches achieve the same or a better dysarthria classification performance when using only the non-speech segments than when using only the speech segments.

- Awareness on the bias of recordings quality in validating classification approaches

Thank You

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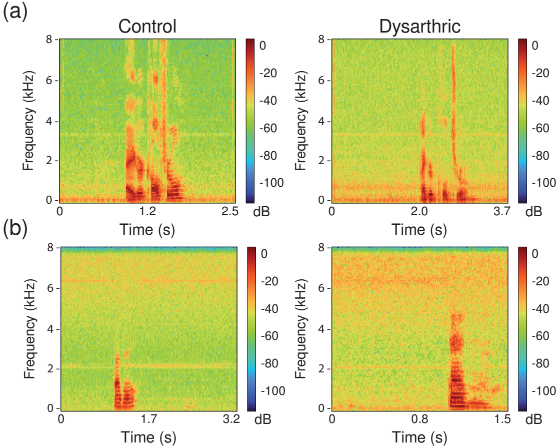
UA-Speech and TORGO databases



Spectrograms of an exemplary utterance from a control and dysarthric speaker from the a) UA-Speech and b) TORGO databases.