Adversarial-Free Speaker Identity-Invariant Representation Learning for Automatic Dysarthric Speech Classification

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Outline

Automatic dysarthria speech classification

- Speech dysarthria due to Parkinson's disease (PD) $\rightarrow$ disturbances of muscular control on speech production system
  - Imprecise articulation, abnormal speech rhythm, reduced stress, breathiness

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Dysarthric speech classification using:

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

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

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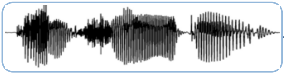
State-of-the-art automatic dysarthric speech classification systems

- Traditional machine learning approaches
- Deep learning approaches

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

» Traditional machine learning approaches (Hegde et al., 2019; Kodrasi and Bourlard, 2020; Hernandez et al., 2020)



Handcrafted feature computation

e.g., MFCCs, sparsity parameter

Classic classifiers

e.g., SVM

Decision: Dysarthric / Healthy

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

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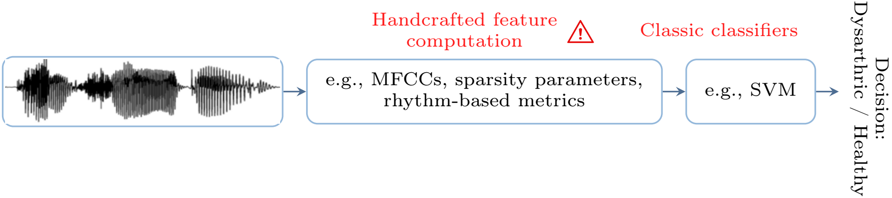


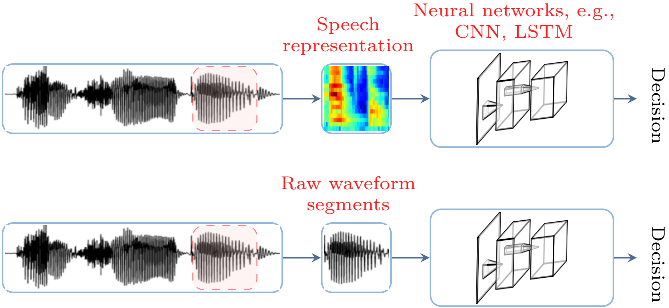
⚠ May fail to adequately capture pathological speech characteristics

⚠ May fail to characterize abstract but important acoustic cues

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)



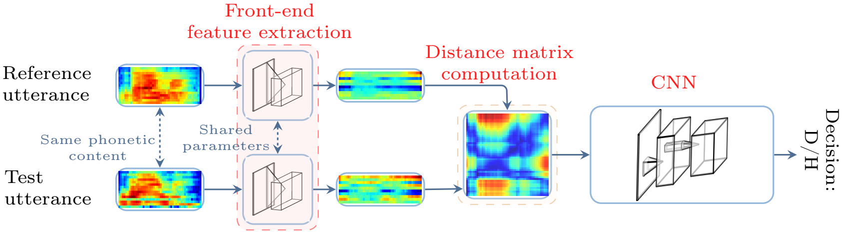
⚠ no explicit attempts to guide the networks to learn robust features

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

» Deep learning approaches

- Pairwise training using distance-based CNNs (Janbakhshi et al., 2021)

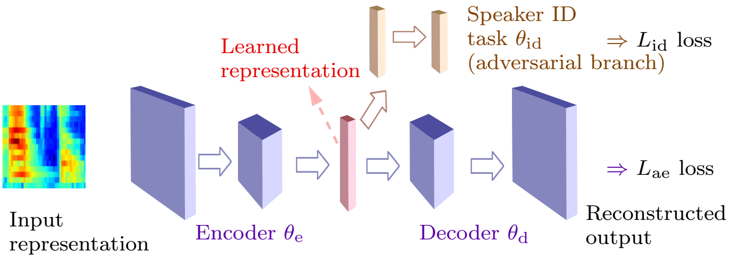
  ⚠ A single network for different but phonetically matched utterances



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

» Deep learning approaches

- Supervised speaker identity-invariant representation learning with adversarial training (Janbakhshi and Kodrasi, 2021)

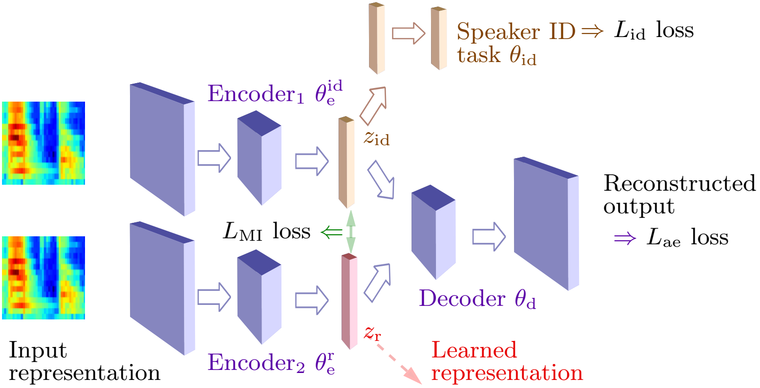


⚠ Difficulty of training the adversarial network for obtaining the speaker identity-invariant representation

Outline

Supervised representation learning via feature separation

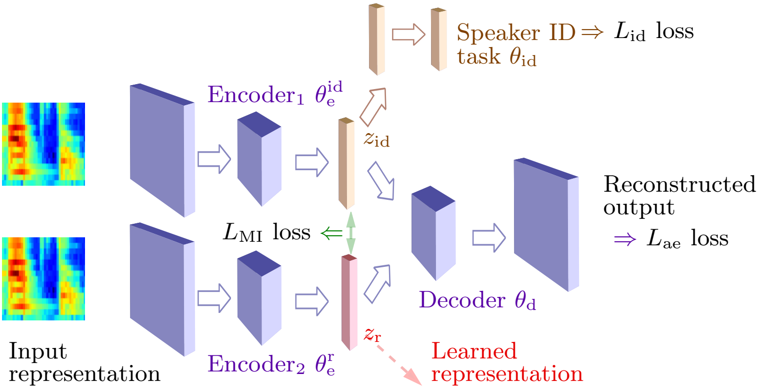
- Speaker identity-invariant representation via feature separation
  - Dual representation learning
  - Jointly <u>minimizing</u> the auto-encoder reconstruction loss and <u>minimizing</u> a speaker ID loss using one of the representations while <u>minimizing</u> a MI criterion between the two representations



Supervised representation learning via feature separation

Speaker identity-invariant representation training → feature separation

- Requires MI approximation, i.e., $I(z_{\mathrm{id}}, z_{\mathrm{r}})$
  - Challenging for high-dimensional variables with unknown probability distributions



Supervised representation learning via feature separation

Speaker identity-invariant representation training → feature separation

- Requires MI approximation, i.e., $I(z_{\mathrm{id}}, z_{\mathrm{r}})$
  - Challenging for high-dimensional variables with unknown probability distributions
  - Variational contrastive log-ratio upper bound (vCLUB) → an upper bound for MI (Cheng et al., 2020)

$$I_{\mathrm{vCLUB}}(z_{\mathrm{id}}, z_{\mathrm{r}}) = \mathbb{E}_{p(z_{\mathrm{id}}, z_{\mathrm{r}})}\left[\log q_{\phi}(z_{\mathrm{id}}|z_{\mathrm{r}})\right] - \mathbb{E}_{p(z_{\mathrm{id}})}\mathbb{E}_{p(z_{\mathrm{r}})}\left[\log q_{\phi}(z_{\mathrm{id}}|z_{\mathrm{r}})\right], \tag{1}$$

  - $q_{\phi}(z_{\mathrm{id}}|z_{\mathrm{r}})$ → variational approximation of $p(z_{\mathrm{id}}|z_{\mathrm{r}})$ → modelled by a neural network with overall parameters of ϕ

Supervised representation learning via feature separation

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  - $q_\phi(z_{\mathrm{id}}|z_{\mathrm{r}})$ $\rightarrow$ variational approximation of $p(z_{\mathrm{id}}|z_{\mathrm{r}})$ $\rightarrow$ modelled by a neural network with overall parameters of ϕ
  - Approximating ϕ by maximizing the log-likelihood loss, i.e., $L_{\mathrm{ll}}(\phi) = \log q_\phi(z_{\mathrm{id}}|z_{\mathrm{r}})$
  - $L_{\mathrm{MI}}(\theta_e^{\mathrm{id}}, \theta_e^{\mathrm{r}}) = I_{\mathrm{vCLUB}}(z_{\mathrm{id}}, z_{\mathrm{r}})$

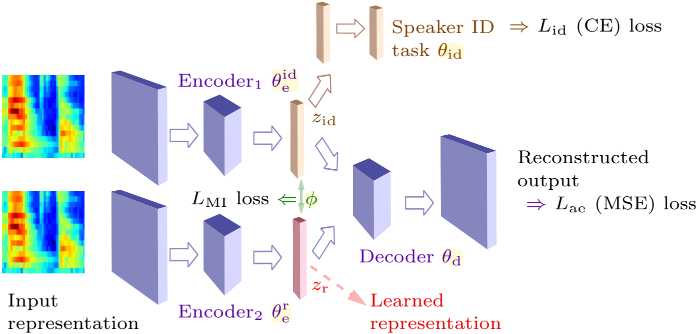
Supervised representation learning via feature separation

Speaker identity-invariant representation training → feature separation

$$(\hat{\theta}_e^{\mathrm{id}}, \hat{\theta}_e^{\mathrm{r}}, \hat{\theta}_{\mathrm{d}}, \hat{\theta}_{\mathrm{id}}) = \arg \min_{\theta_e^{\mathrm{id}}, \theta_e^{\mathrm{r}}, \theta_{\mathrm{d}}, \theta_{\mathrm{id}}} E(\theta_e^{\mathrm{id}}, \theta_e^{\mathrm{r}}, \theta_{\mathrm{d}}, \theta_{\mathrm{id}}, \hat{\phi}) \tag{3}$$

$$\hat{\phi} = \arg\min_{\phi} -L_{\mathrm{ll}}(\phi, \hat{\theta}_e^{\mathrm{id}}, \hat{\theta}_e^{\mathrm{r}}) \tag{4}$$

$$E(\theta_e^{\mathrm{id}}, \theta_e^{\mathrm{r}}, \theta_{\mathrm{d}}, \theta_{\mathrm{id}}, \hat{\phi}) = L_{\mathrm{ae}}(\theta_e^{\mathrm{id}}, \theta_e^{\mathrm{r}}, \theta_{\mathrm{d}}) + \lambda L_{\mathrm{id}}(\theta_e^{\mathrm{id}}, \theta_{\mathrm{id}}) + \beta L_{\mathrm{MI}}(\theta_e^{\mathrm{id}}, \theta_e^{\mathrm{r}}, \hat{\phi}), \tag{5}$$

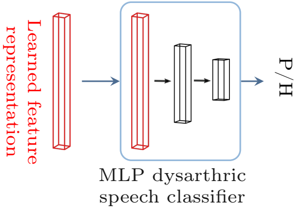


Supervised speech representation learning for pathological detection

» Final dysarthric speech classification
  - Training the final dysarthric speech classifier operating on the learned feature (bottleneck) representation

» Evaluating an unseen test speaker
  - Applying soft voting on the classifier prediction scores for all input Mel spectrograms belonging to that speaker

(Step 2)
final dysarthric speech classification



Outline

Experimental results

- Dataset: Spanish PC-GITA database (Orozco et al., 2014)
  - Discriminating PD patients from healthy speakers
  - Dysarthric speech classification task train/evaluation data → Speaker-independ 10-fold cross-validation framework
  - Speaker ID auxiliary task train/evaluation data → utterance splits of neurotypical speakers in the training set
- Evaluation metrics for dysarthric speech classification and speaker ID
  - Accuracy
  - AUC: area under ROC curve

Experimental results

» Proposed learned representation in the feature separation framework vs. the state-of-the-art representation learned by adversarial training

- Feature separation framework with and without auxiliary modules, i.e., speaker ID ($\lambda \neq 0$) and MI minimizer ($\beta \neq 0$)

λ	β	PD classification ↑		speaker ID ↓	
		Accuracy (%)	AUC	Accuracy (%)	AUC
✗	✗	57.2	0.72	58.3	0.98
✓	✗	61.4	0.75	49.6	0.98
Proposed adversarial-free feature separation framework					
✓	✓	75.2	0.82	5.0	0.67
Adversarial framework from Janbakhshi and Kodrasi (2021)					
–	–	77.0	0.85	5.2	0.67

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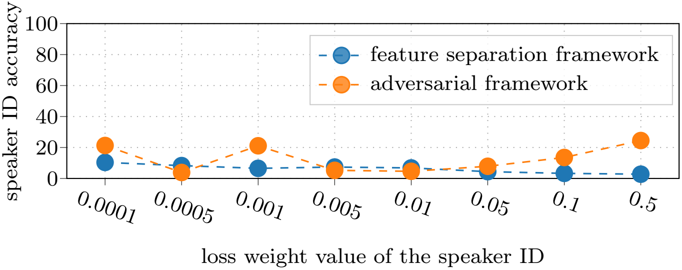
- Efficacy of the proposed feature separation framework in suppressing speaker identity cues → robust representation for the dysarthric speech classification
- No statistically significant difference in performance of the feature separation and adversarial framework

Experimental results

» Proposed learned representation in the feature separation framework vs. the state-of-the-art representation learned by adversarial training

- Sensitivity of speaker-invariant representation learning to the weight values of speaker ID loss (λ)



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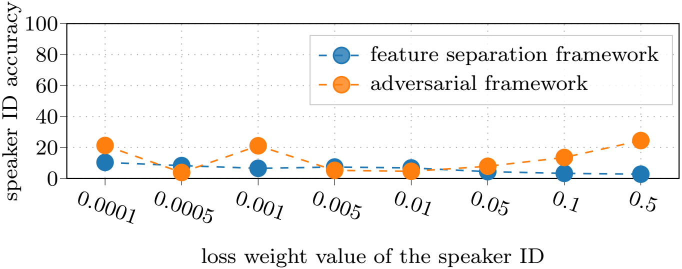

- The feature separation framework is less sensitive to the weight values of speaker ID loss compared to adversarial training

Outline

Summary

- Proposing a supervised representation learning framework for dysarthric speech classification

- An adversarial-free feature separation framework to suppress speaker identity cues unrelated to dysarthria in the learned representation
  - Training a dual encoder generating two representations and a single decoder
  - Supervising one of the representations with a speaker ID task while minimizing a MI criterion between the two representations

- Proposed framework is successful in obtaining a speaker identity-invariant representation $\rightarrow$ more informative representations for dysarthric speech classification
  - While is more robust to the choice of some of the training parameters compared to its adversarial counterpart framework

Thank You

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