

#### Introduction

Automatic speaker recognition algorithms typically characterize speech audio using short-term spectral features that encode the physiological and anatomical aspects of speech production. Such algorithms do not fully capitalize on speaker-dependent characteristics present in behavioral speech features.

In this work, we:

- 1) Develop a vocal-style encoder called DeepTalk for capturing speaker-dependent behavioral speech characteristics
- 2) Combine DeepTalk with physiological speech feature-based speaker recognition methods to improve speaker recognition performance in challenging audio conditions
- Integrate DeepTalk into a Text-To-Speech (TTS) synthesizer to generate synthetic speech audios 3) for evaluating the fidelity of DeepTalk-based vocal style features

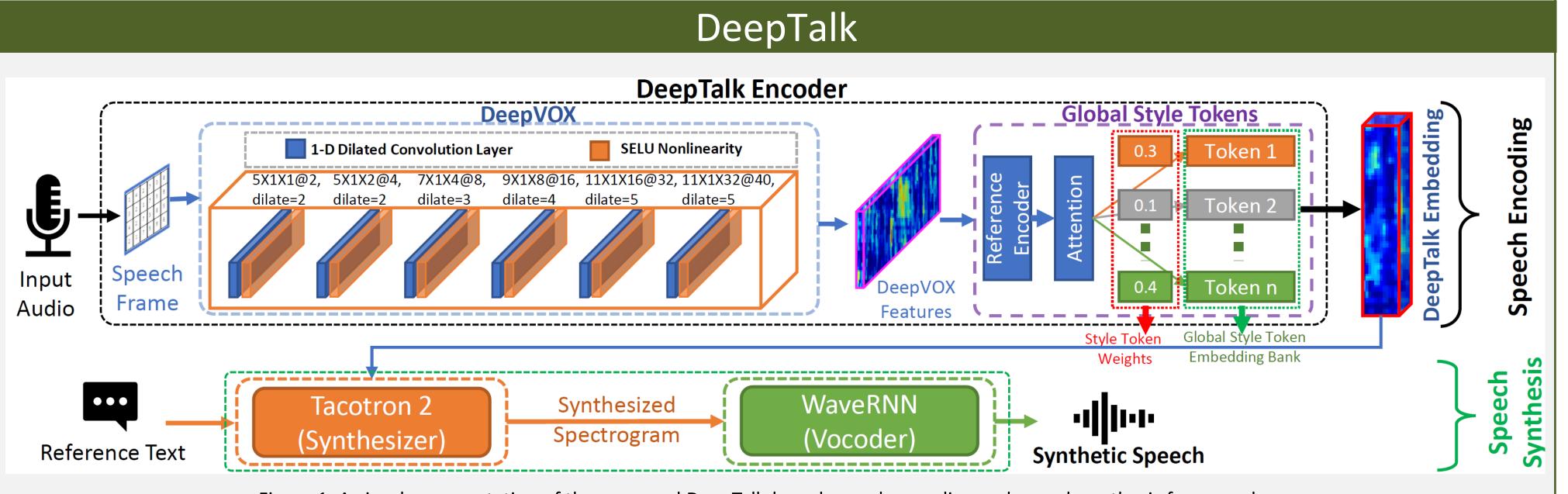


Figure 1: A visual representation of the proposed DeepTalk-based speech encoding and speech synthesis framework

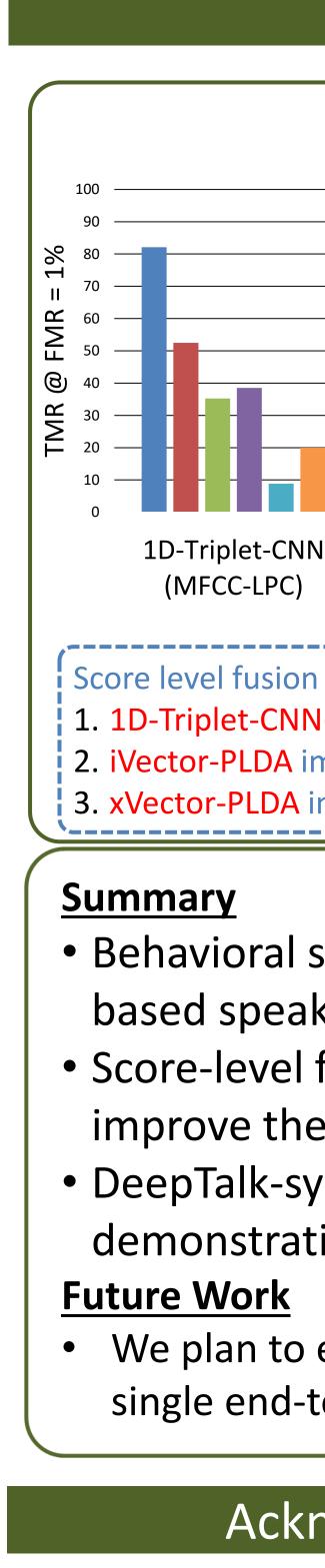
In this work, we develop a speech encoder called DeepTalk, to capture behavioral speech characteristics directly from raw speech audio without any word- or frame-level annotations. The DeepTalk architecture (Fig. 1) consists of separate speech encoding and speech synthesis branches.

- Speech Encoding: The speech encoding branch feeds a raw input audio into a DeepVOX[1] network to extract short-term speech features, called DeepVOX features. DeepVOX is a 1D-CNN based speech filterbank that extracts speaker-dependent speech features directly from raw speech audio. DeepVOX features are then fed to a Global Style Token (GST)-based[2] prosody embedding network to extract the DeepTalk embedding.
- Speech Synthesis: The speech synthesis branch feeds the DeepTalk embedding and a reference text into a Tacotron2-based synthesizer[3] to generate a Mel spectrogram, which is then converted to the synthetic speech waveform using a WaveRNN-based neural vocoder[4]

Experimental results show the efficacy of the DeepTalk embedding for performing both speaker recognition and speech synthesis, as compared to baseline methods.

# MICHIGAN STATE DeepTalk: Vocal Style Encoding for Speaker Recognition and Speech Synthesis Anurag Chowdhury<sup>1</sup>, Arun Ross<sup>1</sup>, Prabu David<sup>2</sup>

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## Datasets and Experiments

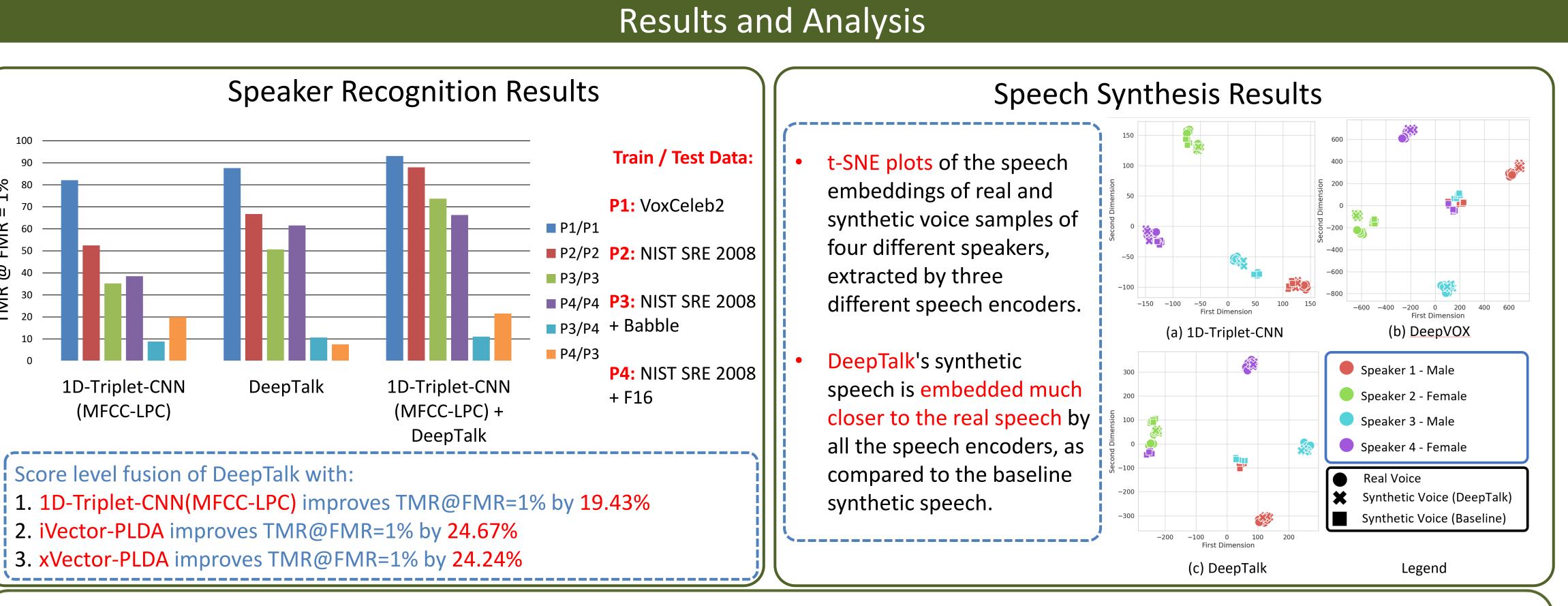
Following experiments are performed in this work:

xVector-PLDA[8], i-vector-PLDA [9], and 1D-Triplet-CNN [10] methods were used to establish baseline physiological speaker verification performance.

**DeepTalk** is used to perform **vocal-style feature-based** speaker verification experiments

The DeepTalk and baseline methods are **combined** at a weighted score level to evaluate the speaker recognition benefits of combining behavioral and physiological speech features.

Figure 2: The above datasets were used for performing the experiments in this work



• Behavioral speech features extracted by DeepTalk method outperform majority of physiological speech featurebased speaker verification methods

• Score-level fusion of DeepTalk with physiological speech feature-based speaker recognition methods further improve the speaker verification performance in majority of the experiments across all the methods • DeepTalk-synthesized speech is judged near-identical to real speech by SOTA speaker recognition methods, demonstrating DeepTalk's efficacy at vocal style modeling

• We plan to extend our work towards combining physiological and behavioral speech characteristics at feature-level in a single end-to-end network architecture for further improving the speaker recognition performance.

### Acknowledgement

# preprint arXiv:2008.11668 (2020).

[2] Wang, Yuxuan et al. "Style Tokens: Unsupervised Style Modeling, Control and Transfer in End-to-End Speech Synthesis." In International Conference on Machine Learning, 2018

- [3] Shen et al. "Natural TTS Synthesis by Conditioning WaveNet on Mel Spectrogram Predictions." In IEEE ICASSP, 2018. [4] Kalchbrenner, et al. "Efficient Neural Audio Synthesis." In International Conference on Machine Learning, 2018
- [5] Chung, Joon Son et al. "Voxceleb2: Deep speaker recognition." In INTERSPEECH 2018.
- effect of additive noise on speech recognition systems," Speech communication, 1993.

#### VoxCeleb2 [5]

Number of Speakers: 5,994 in training set 118 in test set

**Type of Speech Data:** Interview Speech

#### NIST SRE 2008 [6]

Number of Speakers: 1336 in training set 200 in test set

**Type of Speech Data:** Phone call and Interview Speech

#### **NOISEX-92** [7]

Noise dataset: Airplane (F16) Noise Babble Noise

#### References

[1] Chowdhury, Anurag, and Arun Ross. "DeepVOX: Discovering Features from Raw Audio for Speaker Recognition in Degraded Audio Signals." arXiv

[6] "2008 NIST speaker recognition evaluation trainingset part 2 ldc2011s07," https://catalog.ldc.upenn.edu/LDC2011S05, Accessed: 2018-03-06. [7] Andrew Varga and Herman JM Steeneken. "Assessmentfor automatic speech recognition: II. NOISEX-92: adatabase and an experiment to study the