Estimating "Good" Variability in Speech Production using Invertible Neural Networks

Poster No. 163

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International Seminar on Speech Production (Dec 14 – 18, 2020)

Work supported by NIH grant DC-002717 to Haskins Laboratories.

Introduction

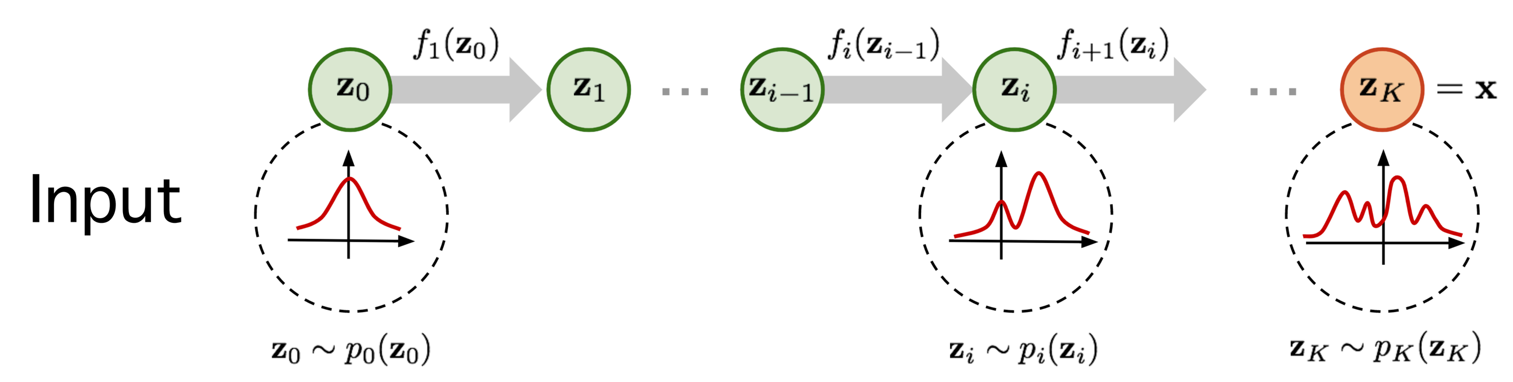
- Variability is widespread in speech, but not all of it is random. It can be decomposed into "good" and "bad" part w.r.t. speech tasks (uncontrolled manifold hypothesis [1,2], principle of motor abundance [3]).
- We examined a novel method of identifying "good" variability (flexibility) from speech data using flow-based invertible neural networks (**INN**)[6].

Data & Preprocessing

- **Data:** The Haskins IEEE electromagnetic articulography database (8 native English speakers; sentence reading; normal vs. fast speaking rate).
- **Samples:** 4 front vowels (/i, ɪ, ɛ, æ/).
- **Procedure:**
  - Normalization: Speaker-wise data normalization.
  - Feature extraction: 3 principal components (articulation) and 2 formant frequencies (F1, F2) ⇨ *3D to 2D mapping*.

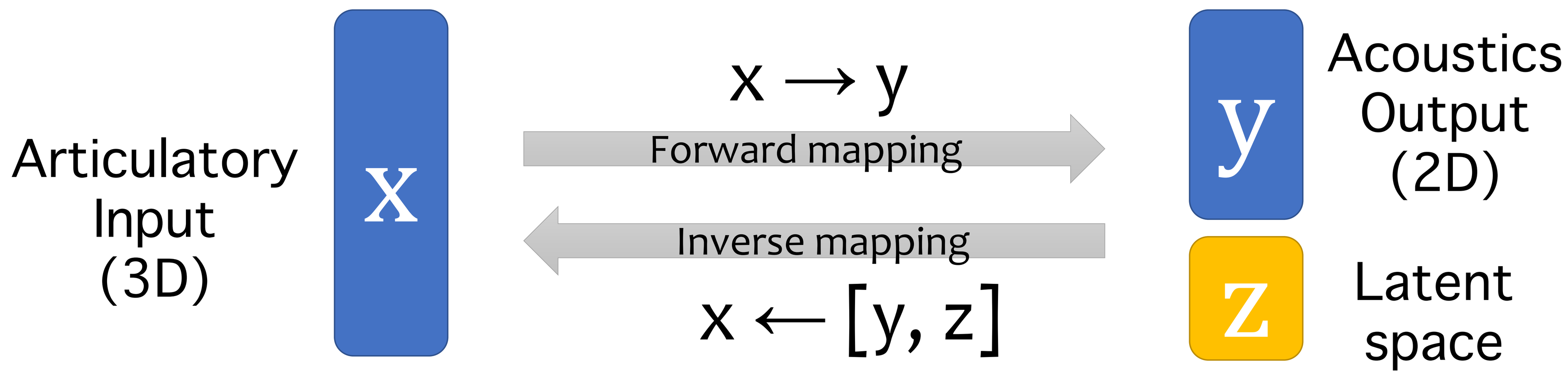
Flow-based Invertible Neural Networks

- **Normalizing-flow Technique** [4]



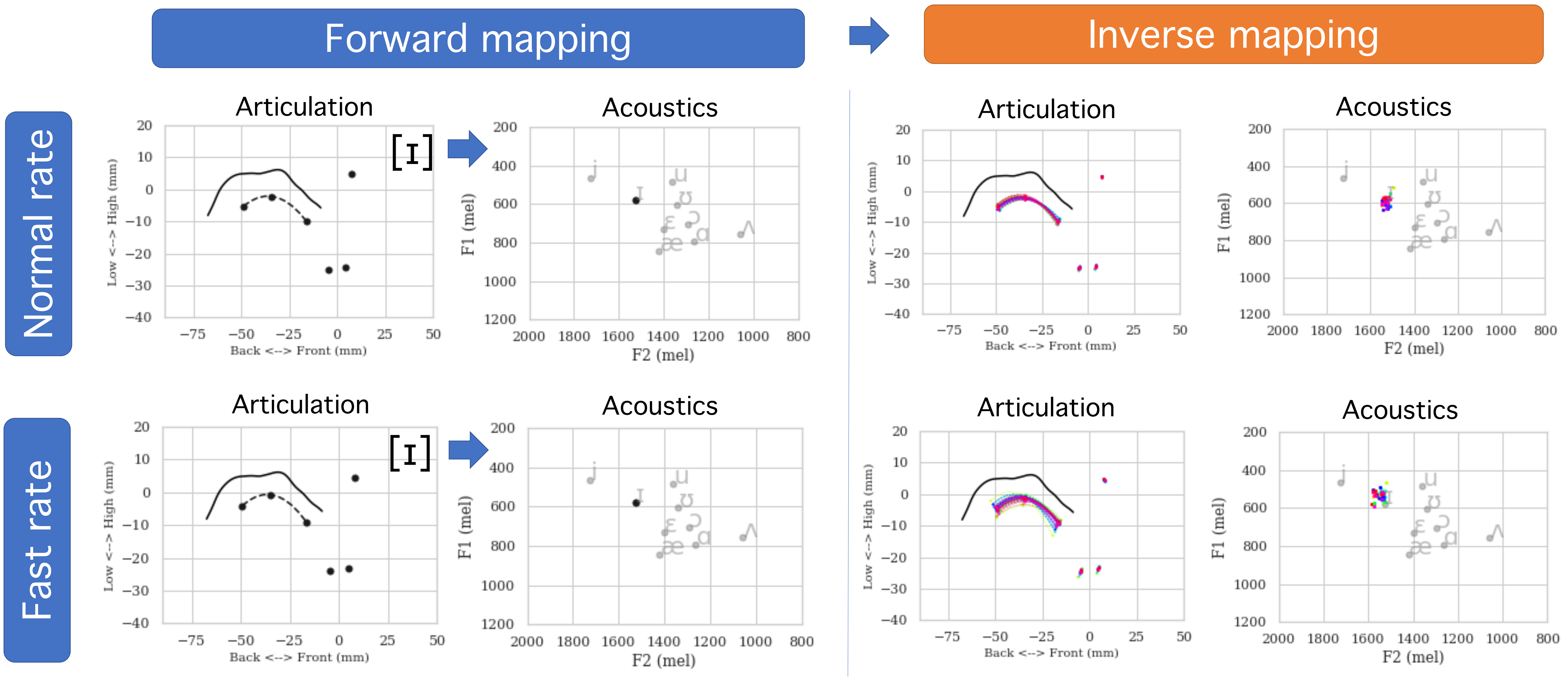
"Volume-preserving" transformations

- **Invertible Neural Networks** [6]



- **Training & Validation**
  - Model: Two INN models were trained per speaker ("normal" vs "fast" rate).
  - 3 Loss functions: forward/inverse loss with latent loss.
  - Validation: 20% of the data per speaker.

Results



Visualization from a single speaker's data (F01)

2D Gaussian latent samples were added

Why INNs?

- The learned latent space reveals "good" variability.
- There is no need for the dimensional mismatch.
- The computation of Jacobian is easy and tractable.

Conclusion

- The flow-based invertible neural networks can effectively estimate "good" variability (range of flexibility).
- More tests are required (phonetic context; neural ordinary differential equations; mixture density networks).

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For more, please check out
https://jaekookang.github.io/issp2020/