Concatenative Resynthesis with Improved Training Signals for Speech Enhancement

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1. Concatenative Resynthesis

What is it? Methods that replace short units of noisy speech with matching units of clean speech, thus producing a noiseless signal while improving the quality of the speech (Mandel 2014).

Core component. Use a DNN to learn a *non-linear similarity metric* between short units of noisy and clean speech.

Current limitation. *Exact match* criterion is required to train the DNN.

Given:

- chunks of clean speech $\{z\}_{j=1}^{J}$
- chunks of noisy speech $\{x\}_{i=1}^{I}$
  - where $x_i = z_i \oplus \text{noise}$

Exact match criterion uses paired examples for training:

- positive examples: (z_i, x_i)
- negative examples: (z_j, x_i) with $i \neq j$

What's the problem? This restrictive criterion limits the training signal available for learning to the DNN.

Goal

Improve the training signal available to the DNN to learn a more useful and generalizable similarity function.

Proposed approach: Rather than exactly matching clean and noisy examples, select pairs that are *sufficiently similar using* acoustic, phonetic and prosodic characteristics of the signal. Thus, make more efficient use of the available data by allowing substitution of a clean signal with another *similar* clean signal.

2. Technical Overview

Data

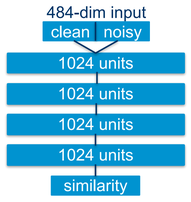
- CHiME2-GRID small vocabulary dataset with utterances using fixed grammar: "*command color preposition letter digit adverb.*"
- Household noises at different SNR
- Single speaker
- Train set: 460 utterances
- Validation set: 40 utterances
- Test set: 24 utterances

Feature extraction

- Compute log mel spectrograms
- Extract 11-frame *chunks* of duration 192 ms
- Each chucks overlaps with its neighbors by 10 frames
- Training set: 113,896 paired examples

Paired-input network (DNN)

- input: concatenated clean & noisy vectors
- 4 hidden layers
- output: 2-unit softmax layer
- cross-entropy loss
- Adam SGD



Baseline

- DNN with exact match criterion from Mandel et al., 2014 [1]

3. Methods

3a. Phonetic Similarity

Find pairs of chunks $(z_i, x_j), i \neq j$ that are sufficiently similar phonetically to be substitutes and thus serve as positive examples for the DNN.

Frame-wise phonetic similarity:

$$s_{Ph}(z_i, z_j) = \frac{1}{F}\sum_{k=1}^{F}\delta(p_k^{(z_i)}, p_k^{(z_j)})$$

where δ is the Kronecker *delta* function such that $\delta(u, v) = 1$ when $u = v$ and $\delta(u, v) = 0$ otherwise.

In our case:

- $F = 11$ frames per chunk
- A chunk is labeled as $z_i = p_1^{(z_i)} \cdots p_F^{(z_i)}$ with phonetic labels $p_k \in [1, 38]$
- threshold for positive examples: $s_{Ph} \geq \frac{8}{11}$
- threshold for negative examples: $s_{Ph} \leq \frac{3}{11}$
- resulted in a training set: ~1,500,000 paired examples (tenfold increase from previous work [2])

3b. Perceptual Similarity

Improve the discriminative power of the DNN for distinguishing commonly confused phones in speech.

- Use perceptual confusion to categorize the phonetic labels into 10 groups: *stressed vowels, unstressed vowels, voiced plosives, unvoiced plosives, affricates, voiced fricatives, unvoiced fricatives, approximants, nasals, and silence*.
- Represent a chunk by a vector $q^{(z_i)} = \{q_1^{(z_i)}, \ldots, q_F^{(z_i)}\}$ where $q_k \in \{1 \ldots 10\}$ represents one the ten groups.

Frame-wise perceptual similarity:

$$s_Q(z_i, z_j) = \frac{1}{F}\sum_{k=1}^{F}\delta(q_k^{(z_i)}, q_k^{(z_j)})$$

In our case:

- threshold for negative examples: $s_q \geq \frac{8}{11}$ while phonetically dissimilar with $s_{Ph} \leq \frac{8}{11}$

3c. Acoustic and Prosodic Similarity

Use per-frame acoustic intensity, fundamental frequency, and periodicity to evaluate the similarity between chunks.

Frame-wise intensity similarity:

$$s_I(I_i, I_j) = e^{-\alpha_I \|I_i - I_j\|}$$

Use similar approach for fundamental frequency (with α_F) and periodicity (with α_{Pe}).

Overall frame-wise acoustic and prosodic similarity:

$$s(z_i, z_j) = \lambda_{Ph} s_{Ph}(z_i, z_j) + \lambda_I s_I(z_i, z_j) + \lambda_F s_F(z_i, z_j) + \lambda_{Pe} s_{Pe}(z_i, z_j)$$

In our case:

- values for hyperparameters $\lambda_{Ph}, \lambda_I, \lambda_F, \lambda_{Pe}, \alpha_I, \alpha_F, \alpha_{Pe}$: Bayesian optimization minimizing the frame-wise error rate on the development set

4. Evaluation

4a. Objective

To evaluate the quality of the mapping, $x \to z$, we can compare the frame-level phonetic transcriptions of x and z.

Frame-wise error rate:

$$e_f(z, x) = 1 - \frac{1}{F}\sum_{k=1}^{F}\delta(p_k^{(z)}, p_k^{(x)}), (2)$$

Phone error rate: score with SCTK after collapsing repeated phones and aligning the phonetic sequences of the clean and denoised signals. Reconstructed chunks overlap by 5 frames; overlapping frames with differing labels are annotated with composite phones.

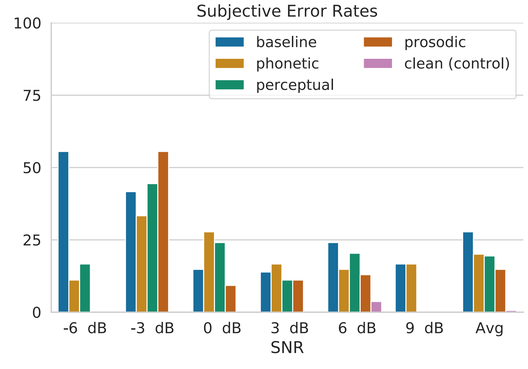
4b. Subjective

Intelligibility listening test: within-subject design with 3 participants.

Stimuli: 60 utterances based on 12 randomly selected noisy utterances from the test set

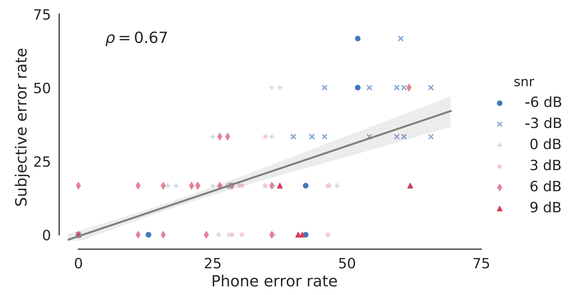
- 12 resynthesized using baseline
- 12 resynthesized using phonetic similarity
- 12 resynthesized using perceptual similarity
- 12 resynthesized using acoustic and prosodic similarity
- 12 clean counterparts serving as control

Subjective intelligibility error rate: proportion of words incorrectly transcribed by the participants.



5. Objective versus Subjective Metrics

Subjective intelligibility error rates were found to be strongly correlated with the objective frame-wise and phone error rates.



6. Summary

- Combining similarity based on phonetic content and periodicity of the signals yields noiseless speech that is more intelligible to humans.
- Computed error metrics can be effectively used for tuning and evaluating such systems.
- It is possible to perform this in an efficient and scalable manner by using approximate nearest neighbors for aiding in the selection of training data.
- There is a correlation of computed error metrics with subjective human evaluations based on intelligibility listening tests.

Future work: Investigate performance and scalability on large vocabulary and speaker independent speech.

7. Acknowledgments

This material is based upon work supported by the National Science Foundation under Grant No. IIS-1618061. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

References

[1] M. I. Mandel, Y. S. Cho, and Y. Wang, "Learning a concatenative resynthesis system for noise suppression," in 2014 IEEE Global Conference on Signal and Information Processing (GlobalSIP), Dec 2014, pp. 582–586.

[2] M. I. Mandel and Y. S. Cho, "Audio super-resolution using concatenative resynthesis," in Applications of Signal Processing to Audio and Acoustics (WASPAA), 2015 IEEE Workshop on, 2015, pp. 1–5.