# WHAT DOES A NETWORK LAYER HEAR? ANALYZING HIDDEN REPRESENTATIONS OF END-TO-END ASR THROUGH SPEECH SYNTHESIS

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## ABSTRACT

End-to-end speech recognition systems have achieved competitive results compared to traditional systems. However, the complex transformations involved between layers given highly variable acoustic signals are hard to analyze. In this paper, we present our ASR probing model, which synthesizes speech from hidden representations of end-to-end ASR to examine the information maintain after each layer calculation. Listening to the synthesized speech, we observe gradual removal of speaker variability and noise as the layer goes deeper, which aligns with the previous studies on how deep network functions in speech recognition. This paper is the first study analyzing the end-to-end speech recognition model by demonstrating what each layer hears. Speaker verification and speech enhancement measurements on synthesized speech are also conducted to confirm our observation further.

***Index Terms*—** automatic speech recognition, end-to-end, analysis, interpretability

## 1. INTRODUCTION

Traditional ASR systems consist of multiple modules: an acoustic model, a language model, and a pronunciation lexicon. Each of them is trained separately and then composed together to perform speech recognition. Complex training procedures are required to obtain state-of-the-art results. End-to-end systems, on the other hand, enjoy several benefits over traditional hybrid systems. The training pipeline is often more straightforward, and each submodule can be optimized jointly to avoid error propagation. State-of-the-art results have also been reported given the vast amount of training data [1].

However, the black-box nature of end-to-end systems prohibits researchers from analyzing the functionality of every single module, e.g., in what layer does the network perform denoising, remove speaker information, or extract linguistic features? This has led the community to develop various techniques to dissect end-to-end systems, with the hope of

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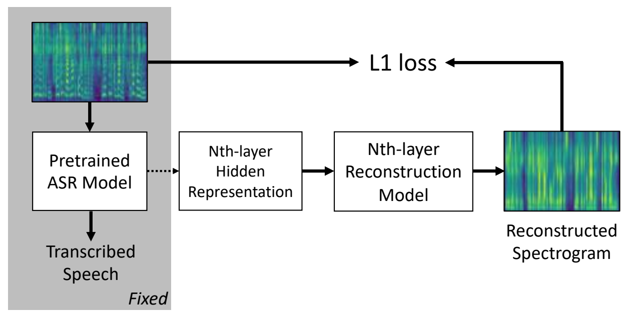



**Fig. 1**: Illustration of the proposed speech reconstruction method applied on hidden representations of the ASR model.

better comprehending the complex, highly nonlinear transformations inside the network. Previous research analyzing end-to-end ASR involves investigating the underlying phonetic representations learned in the course of training [2, 3, 4]. Interpretable filters with SincNet [5] is proposed and shown capable of removing noise after training.

Visualization of model internals is a widely considered way to analyze deep networks. Examples include visualizing filters in CNNs [6], plotting saliency maps [7], or drawing alignments learned by attention-based sequence-to-sequence models in end-to-end ASR [8]. Visualization of convolutional kernels is natural for image-related tasks, which led us to wonder whether we can ”audify” hidden layers in a similar way, namely, to hear what the layers hear. While the studies above provide fruitful insight regarding the working mechanism of end-to-end systems, approaches utilizing perception other than vision have yet to be discovered.

We propose an intuitive and interpretable method of studying what network layers in end-to-end ASR ”hear” when transcribing speech. This is done via reconstructing the input speech from hidden layers of a trained end-to-end ASR system, as shown in figure 1. The experimental results show that the information of speaker characteristics and noise is gradually discarded in each layer, and representations of the same linguistic content spoken by different speakers and under various recording conditions are normalized, which is in line with previous findings [2].

To the best of our knowledge, this is the first study to analyze the behavior inside end-to-end ASR models with speech reconstruction from the hidden representations of the network. We strongly recommend the readers to listen to the recovered samples on the demo page [1].

## 2. METHODOLOGY

### 2.1. End-to-end ASR Systems

To describe our proposed method, we first introduce an end-to-end automatic speech recognition paradigm to be analyzed and define notations in use.

With the goal of investigating different aspect of input signal preserved by the end-to-end ASR in mind, we denote the speech data $x$ to be composed of three different components: the linguistic content $z$, the identity of the speaker $s$ and any other information present in the audio signal $n$ such as recording conditions. Given the paired training data $x$ and $z$, an end-to-end ASR model can be treated as a function $z = ASR(x)$ which transcribes speech to text. Further more, for the $k$-th layer of our interest to synthesize speech, we denote the hidden representation $h_k = ASR_k(x)$.

### 2.2. Probing Model

In this section, we present our approach of probing model internals through reconstruction.

With hidden representations $h_k$ extracted from the $k$-th layer of ASR, our probing model is trained to recover the input speech using simple feed-forward networks. Formally, let the probing model be $D_k$ and $\tilde{x}$ being the synthesized speech, our synthesizer can be trained with the standard reconstruction loss:

$$\mathcal{L}_{\text{recon}} = \|\tilde{x} - x\|, \quad \tilde{x} = D_k(h_k). \tag{1}$$

Since ASR models extract only the linguistic content $z$ inside the input speech, speaker characteristics $s$ and noises $n$ are discarded in the hidden representations $h_k$. The reconstruction loss thus acts as a surrogate for measuring the loss of $s$ and $n$. Let $\tilde{s}_k$ and $\tilde{n}_k$ be the amount of information left in $h_k$. $\mathcal{L}_{recon}$ is therefore a proxy of the difference between $\{s, n\}$ and $\{\tilde{s}_k, \tilde{n}_k\}$.

Note that our probing model are made non-contextual, and observe simply the current frame representation. We avoid using attention-based models like Tacotron [9] where every output frame has access to the whole input signal. This ensures that our probing model faithfully convey information left in the intermediate representations learned by the speech-to-text model.

### 2.3. Measuring the voice of each layer

Once we are able to synthesize speech using probing model, we can directly adopt various metrics evaluated on the raw waveform to analyze the intermediate representations of end-to-end ASR. For instance, speaker verification can be conducted to measure the amount of speaker information present in the hidden layers; metrics evaluating performance of speech enhancement models such as perceptual evaluation of speech quality(PESQ)[10] and short-time objective intelligibility(STOI) [11] can also be employed to determine the denoising capability of noise-robust ASR.

## 3. EXPERIMENTS

### 3.1. Experimental Setup

**Data sets** We use the train-clean-100 subset of LibriSpeech [12] as our clean set for training and the dev-clean and test-clean subset is used for development and evaluation. We also augment the clean training set with MUSAN[13] corpus in the settings roughly following that of X-Vector[14] as our noisy set and mix the test-clean set with noises at fixed SNR ratio (20, 10, 0dB).

**E2E ASR Models** We explore two ASR architectures in the experiments. One is a **VGG-LSTM** model similar to [15], which is comprised of 4 convolutional layers and 5 bidirectional long short-term memory (LSTM) layers. Each convolutional layer is followed by a ReLU activation layer and max-pooing is applied every 2 convolutional layers. The other one is a **pure-LSTM** model, which has only 5 bidirectional LSTM layers, with downsampling performed after 2, 3 and 4-th layer. The input to the models is 80-dimensional mel-spectrograms. Deltas and accelerations are added and stacked along the channel dimension. Both models are trained with Connectionist Temporal Classification(CTC) loss. Table 1 shows the achieved WER(%) of the models. We take the models trained on clean set without augmentation data as our baseline ASR models, and the ones trained on noisy set are our noise-robust ASR models.

**Probing Model** A 4-layered Highway network is used for probing model of all hidden layers. Hidden states of downsampled layers are first up-sampled back by a linear projection then fed into the Highway network. The model is trained to minimize L1 loss between the synthesized and the original mel-spectrograms.

For post-processing, we obtain linear spectrograms by applying pseudo-inverse on generated mel-filterbanks, and

| **Model** | **Augmentation** | **WER** (%) | |
|---|---|---|---|
| | | dev-clean | test-clean |
| LSTM | No | 30.72 | 30.98 |
| LSTM | Yes | 25.23 | 25.45 |
| VGG-LSTM | No | 29.02 | 29.55 |
| VGG-LSTM | Yes | 22.64 | 22.51 |

**Table 1**: Speech recognition word error rates on LibriSpeech with 100 hours of training data.

[1] https://yuanpj.github.io/Voice-in-ASR/

|  | SNR | type | VGG-LSTM |  |  |  |  |  | pure-LSTM |  |  |  |  |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
|  |  |  | cnn1 | cnn2 | cnn4 | blstm1 | blstm3 | blstm5 | blstm1 | blstm2 | blstm3 | blstm4 | blstm5 |
| (a) | clean | robust | 4.38 | 4.68 | 7.18 | 16.48 | 30.03 | 48.07 | 6.92 | 12.63 | 23.92 | 33.55 | 46.85 |
| (b) |  | baseline | 4.47 | 4.72 | 6.76 | 16.20 | 32.87 | 48.12 | 7.03 | 13.97 | 23.26 | 34.55 | 47.49 |
| (c) | 20 dB | robust | 5.80 | 6.27 | 9.23 | 18.11 | 30.40 | 47.75 | 8.44 | 14.97 | 24.98 | 33.80 | 47.07 |
| (d) |  | baseline | 5.80 | 6.19 | 9.21 | 18.85 | 33.28 | 47.82 | 8.84 | 17.65 | 25.37 | 35.53 | 47.54 |
| (e) | 10 dB | robust | 9.81 | 10.75 | 13.87 | 20.87 | 30.49 | 47.37 | 13.89 | 19.66 | 25.93 | 33.79 | 46.85 |
| (f) |  | baseline | 9.89 | 10.92 | 15.00 | 24.00 | 36.75 | 47.48 | 14.64 | 24.31 | 30.06 | 37.83 | 47.03 |
| (g) | 0 dB | robust | 23.15 | 24.63 | 28.62 | 31.50 | 34.91 | 46.22 | 29.14 | 33.15 | 33.69 | 38.46 | 46.21 |
| (h) |  | baseline | 23.18 | 25.27 | 29.80 | 37.66 | 44.56 | 48.13 | 30.54 | 39.90 | 42.10 | 45.41 | 47.89 |

**Table 2**: EER results obtained by the ThinResNet[16] on the reconstructed speech utterances.

then use the Griffin-Lim reconstruction algorithm to generate speech waveform.

### 3.2. Speaker Information

**Objective evaluation.** Two speaker verification systems in the previous study are implemented to quantify the amount of speaker information of recovered speech. The first model, following [17], which is a LSTM-based neural architecture, maps a sequence of variable-length mel-spectrogram frames to a fixed-dimensional embedding and is trained using the generalized end-to-end(GE2E) loss function. The second model, ThinResNet[16] is composed of a modified ResNet architecture, which extracts the features from the spectrogram of a speech utterance, and a NetVLAD/GhostVLAD[18] layer to aggregate the features along the temporal axis to an embedding.

Both models are trained on the VoxCeleb2[19] dataset, which is comprised of 1 million utterances from 6000 different speakers, and can achieve 4.51%, 3.34% EER respectively on the test-clean split of LibriSpeech[12] dataset.

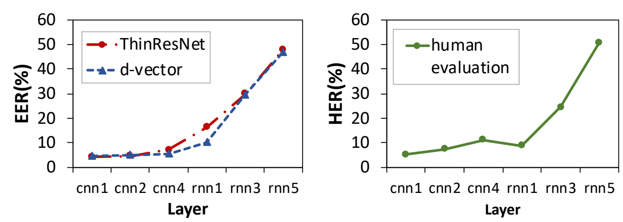
We reconstruct a bunch of speech utterances from every layer of the 4 kinds of ASR models. Then we randomly sample the same number of positive and negative pairs to test the above two speaker verification models to estimate the amount of speaker information. The results are shown in Table 2 (We only present the results from ThinResNet because the results from two speaker verification models are quite similar.) The two big columns represent the ASR network architectures, and from left to right is from the top layer to the deepest layer. Rows(a, c, e, g) mean that we take the speech at different SNR ratio as the robust VGG-LSTM or pure-LSTM inputs, while rows(b, d, f, h) are to feed the baseline ASR models. If we listen to the recovered speech, we can directly recognize that utterances of different speakers from the deeper layer become more indistinguishable from each other than shallower layer. Meanwhile, the EER values are increased along the layers of all models, meaning that the speaker characteristics are gradually removed out steps by steps.

In comparison between the EER of two network architecture, we found that the cnn part of VGG-LSTM slightly influences the speaker information of hidden representation, while the lstm parts of both architecture seriously wipe out the speaker information.

It's worth noting that although both the baseline and robust ASR models have similar EER when the inputs are clean, robust ASR can achieve better EER under noisy conditions. This could be attributed to the ability of robust models to remove the interference of other speakers in noisy speech.

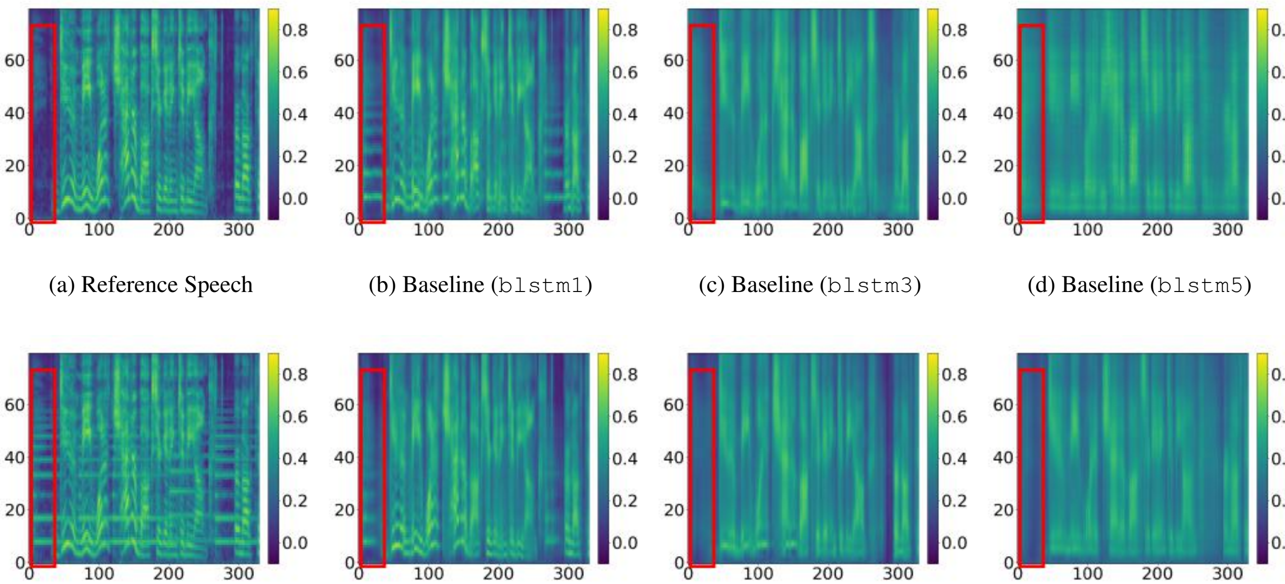
**Subjective evaluation.** We also perform a human evaluation test to ensure that the measurement of speaker verification models on the reconstructed speech is consistent with that performed by human beings. The recovered speech is reconstructed from the hidden representations of well-trained robust VGG-LSTM ASR model. For the speaker verification measurements, we sample the same number of positive and negative reconstructed speech utterance pairs out of 6 layers, to test the two speaker verification models which will be described in the section 3.2. For the human evaluation test, we randomly sample 10 recovered speech utterance triplets (two from the same speaker, one from another) of 6 layers. Subjects first listen to two speech utterances from different speakers, and then listen to the third one and answer which speaker is same as the third one. Human error rate(HER) calculates subjects' mean error rate of the triplets from same layers. Figure 2 shows the result of the robust VGG-LSTM ASR model. In Figure 2a, the EER of both the speaker verification measurement remain low before `blstm1`, but then the values are dramatically increased at `blstm3` and `blstm5`.

Results of subjective test Figure 2b are consistent with that of speaker verification models. Most people can verify the correct speaker before `blstm1`. However, the reconstruct utterances from deeper layers are also hard for people to verify, so the HER also greatly rises after `blstm1`.




(a) Speaker Verification (b) Human Test

**Fig. 2**: Evaluation on robust VGG-LSTM ASR



(a) Reference Speech (b) Baseline (`blstm1`) (c) Baseline (`blstm3`) (d) Baseline (`blstm5`)

(e) Corrupted Speech (f) Noise-Robust (`blstm1`) (g) Noise-Robust (`blstm3`) (h) Noise-Robust (`blstm5`)

**Fig. 3**: 80-dimensional mel-spectrograms generated by the probing model of (b)(c)(d) baseline VGG-LSTM and (f)(g)(h) noise-robust VGG-LSTM. Removal of noises (piano music) are most prominent in layer `blstm1`, highlighted by red bounding boxes. As observed in the figure, noises are still present in (b), but are mostly wiped out in (f).

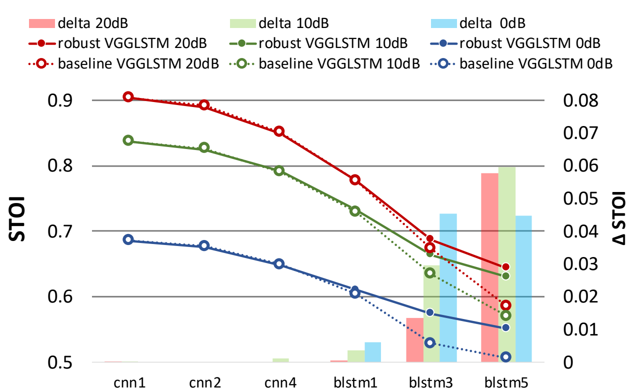



**Fig. 4**: Speech quality measurement of synthesized speech using STOI.

### 3.3. Noise Information

In this section, we compare intermediate representations learnt by baseline models and that of their noise-robust counterparts trained on noise-augmented samples. [20, 21] proposed learning noise-invariant representation for automatic speech recognition, which makes us curious about whether models trained with distorted audio samples automatically learns to draw noisy and clean inputs closer together in the hidden layers. In Figure 4 we report STOI on baseline and robust ASR. We observe an inevitable drop of STOI in both baseline and robust VGG-LSTM. This can be attributed to the loss of speaker information and subsequent degradation of intelligibility. However, the gap of STOI between baseline and robust ASR widens starting from `blstm1` all the way to `blstm5`. We suspect that in our models, first few layers of LSTM serves the purpose of removing the background noise information. Visualization of the mel-spectrograms generated by our probing model further supports the claim. In Figure 3, our probing model, taking the `blstm1` layer of noise-robust VGG-LSTM as input, which is asked to reconstruct both noisy and clean speech, failed to recover the corrupted speech in figure 3e, demonstrating that noise-robust ASR successfully eliminates added noise in its hidden representation.

## 4. CONCLUSION

In this paper, we seek to answer the question of what a neural network layer hear through directly recovering speech from hidden representations of end-to-end ASR model. We demonstrate that properties of hidden layers can be interpreted and synthesized into the form perceptible by human other than vision, thanks to the task nature of ASR. Various measures including subjective and objective test are conducted on synthesized speech, and evaluation of speaker variability and noise robustness show findings highly consistent with the literature, demonstrating the effectiveness of the proposed approach.

## 5. REFERENCES


[1] Daniel S. Park, William Chan, Yu Zhang, Chung-Cheng Chiu, Barret Zoph, Ekin D. Cubuk, and Quoc V. Le, "SpecAugment: A Simple Data Augmentation Method for Automatic Speech Recognition," in *Proc. Interspeech 2019*, 2019, pp. 2613–2617.

[2] Abdel rahman Mohamed, Geoffrey E. Hinton, and Gerald Penn, "Understanding how deep belief networks perform acoustic modelling," *2012 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 4273–4276, 2012.

[3] Tasha Nagamine, Michael L Seltzer, and Nima Mesgarani, "Exploring how deep neural networks form phonemic categories," in *Sixteenth Annual Conference of the International Speech Communication Association*, 2015.

[4] Yonatan Belinkov, Ahmed Ali, and James Glass, "Analyzing Phonetic and Graphemic Representations in End-to-End Automatic Speech Recognition," in *Proc. Interspeech 2019*, 2019, pp. 81–85.

[5] Mirco Ravanelli and Yoshua Bengio, "Interpretable convolutional filters with sincnet," *arXiv preprint arXiv:1811.09725*, 2018.

[6] Matthew D Zeiler and Rob Fergus, "Visualizing and understanding convolutional networks," in *European conference on computer vision*. Springer, 2014, pp. 818–833.

[7] Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman, "Deep inside convolutional networks: Visualising image classification models and saliency maps," *CoRR*, vol. abs/1312.6034, 2013.

[8] William Chan, Navdeep Jaitly, Quoc Le, and Oriol Vinyals, "Listen, attend and spell: A neural network for large vocabulary conversational speech recognition," in *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2016, pp. 4960–4964.

[9] Yuxuan Wang, R.J. Skerry-Ryan, Daisy Stanton, Yonghui Wu, Ron J. Weiss, Navdeep Jaitly, Zongheng Yang, Ying Xiao, Zhifeng Chen, Samy Bengio, Quoc Le, Yannis Agiomyrgiannakis, Rob Clark, and Rif A. Saurous, "Tacotron: Towards end-to-end speech synthesis," in *Proc. Interspeech 2017*, 2017, pp. 4006–4010.

[10] Antony W Rix, John G Beerends, Michael P Hollier, and Andries P Hekstra, "Perceptual evaluation of speech quality (pesq)-a new method for speech quality assessment of telephone networks and codecs," in *2001 IEEE International Conference on Acoustics, Speech, and Signal Processing*. IEEE, 2001, vol. 2, pp. 749–752.

[11] Cees H Taal, Richard C Hendriks, Richard Heusdens, and Jesper Jensen, "An algorithm for intelligibility prediction of time–frequency weighted noisy speech," *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 19, no. 7, pp. 2125–2136, 2011.

[12] Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur, "Librispeech: an asr corpus based on public domain audio books," in *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2015, pp. 5206–5210.

[13] David Snyder, Guoguo Chen, and Daniel Povey, "Musan: A music, speech, and noise corpus," *arXiv preprint arXiv:1510.08484*, 2015.

[14] David Snyder, Daniel Garcia-Romero, Gregory Sell, Daniel Povey, and Sanjeev Khudanpur, "X-vectors: Robust dnn embeddings for speaker recognition," in *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2018, pp. 5329–5333.

[15] Takaaki Hori, Shinji Watanabe, Yu Lin Zhang, and William Chan, "Advances in joint ctc-attention based end-to-end speech recognition with a deep cnn encoder and rnn-lm," in *INTERSPEECH*, 2017.

[16] J. S. Chung A. Zisserman W. Xie, A. Nagrani, "Utterance-level aggregation for speaker recognition in the wild.," in *ICASSP, 2019*, 2019.

[17] L. Wan, Q. Wang, A. Papir, and I. L. Moreno, "Generalized end-to-end loss for speaker verification," in *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, April 2018, pp. 4879–4883.

[18] Y. Zhong, R. Arandjelović, and A. Zisserman, "GhostVLAD for set-based face recognition," in *Asian Conference on Computer Vision*, 2018.

[19] A. Zisserman J. S. Chung*, A. Nagrani*, "Voxceleb2: Deep speaker recognition.," in *INTERSPEECH, 2018*, 2018.

[20] Dmitriy Serdyuk, Kartik Audhkhasi, Philémon Brakel, Bhuvana Ramabhadran, Samuel Thomas, and Yoshua Bengio, "Invariant representations for noisy speech recognition," *arXiv preprint arXiv:1612.01928*, 2016.

[21] Davis Liang, Zhiheng Huang, and Zachary C Lipton, "Learning noise-invariant representations for robust speech recognition," in *2018 IEEE Spoken Language Technology Workshop (SLT)*. IEEE, 2018, pp. 56–63.