DEEP SPEECH INPAINTING OF TIME-FREQUENCY MASKS

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ABSTRACT

In particular, recent approaches outperform traditional statistical SE systems, especially for high-variance noises [2]. SE algorithms based on deep neural networks typically belong to one of the following groups: (i) causal systems that maintain the conventional approach of speech and noise estimation using regression methods [3, 4, 5] and (ii) end-to-end systems, including generative approaches, that are usually non-causal and require longer temporal integration windows [6]. While the latter tend to have higher latency, they are capable of suppressing highly non-stationary noise maskers, including brief, loud intrusions. Specifically, an application of such non-causal approach to the source separation problem yielded almost 20 dB of signal-to-distortion ratio improvement [7].

The task of generative, context-based, information retrieval has been traditionally investigated in the field of computer vision, whereby it’s referred to as the image completion or inpainting [8, 9, 10]. A similar problem was recently considered in the context of audio processing and was coined the name of audio inpainting [11, 12, 13]. While recent studies reported promising results in the retrieval of missing audio information, they typically consider relatively simple signals, unlike natural speech. This work extends the existing audio inpainting framework to speech processing and proposes how it could be incorporated into general-purpose SE systems.

In this paper, we introduce the task of speech inpainting focused on the context-based recovery of missing or degraded information in time-frequency representations of natural speech. Specifically, we considered a broad range of distortions including (i) time gaps, similar to packet loss [14], but with non-uniformly distributed holes up to 400 ms in duration, (ii) frequency gaps, similar to the bandwidth extension problem [15] but with missing frequency bins cumulatively up to 3200 Hz in bandwidth and (iii) irregular, random gaps disrupting up to 40% of the overall time-frequency representation of speech. According to the authors’ knowledge, this problem and at such scale hasn’t been investigated to date.

To tackle the problem of speech inpainting we propose an end-to-end framework based on the U-Net architecture [16] trained via deep feature losses [17, 18, 19]. According to recent studies, the use of deep feature losses for training SE systems can improve their overall performance, depending on the deep feature extraction approach [17, 18]. We hypothesize that a specialized deep feature extractor, tailored specifically for speech processing, will lead to the best performance of our system. Thus, we introduce speechVGG, a deep speech features extractor, based on the classic VGG-16 architecture [20], trained on the word classification task. We explore different configurations of the extractor for the training of the framework and compare it with the conventional training based on $L_1$ loss and other control conditions.

We introduce two configurations of the framework for informed or blind inpainting, depending on the availability of the masks indicating missing or degraded parts of speech signal. In the case of blind speech inpainting, we evaluated the system using different types of masking, such as the replacement or addition of high amplitude noise to the masked time-frequency representation of speech.

The paper is structured as follows: section 2 introduces our framework, section 3 describes the evaluation of the proposed system, and section 4 includes critical discussion, proposes the direction of future work and concludes the paper.

1. INTRODUCTION

Tremendous developments in the field of speech enhancement (SE) in the past years have been mainly attributed to deep learning [1]. In particular, recent approaches outperform traditional statistical SE systems, especially for high-variance noises [2]. SE algorithms based on deep neural networks typically belong to one of the following groups: (i) causal systems that maintain the conventional approach of speech and noise estimation using regression methods [3, 4, 5] and (ii) end-to-end systems, including generative approaches, that are usually non-causal and require longer temporal integration windows [6]. While the latter tend to have higher latency, they are capable of suppressing highly non-stationary noise maskers, including brief, loud intrusions. Specifically, an application of such non-causal approach to the source separation problem yielded almost 20 dB of signal-to-distortion ratio improvement [7].

The task of generative, context-based, information retrieval has been traditionally investigated in the field of computer vision, whereby it’s referred to as the image completion or inpainting [8, 9, 10]. A similar problem was recently considered in the context of audio processing and was coined the name of audio inpainting [11, 12, 13]. While recent studies reported promising results in the retrieval of missing audio information, they typically consider relatively simple signals, unlike natural speech. This work extends the existing audio inpainting framework to speech processing and proposes how it could be incorporated into general-purpose SE systems.

In this paper, we introduce the task of speech inpainting focused on the context-based recovery of missing or degraded information in time-frequency representations of natural speech. Specifically, we considered a broad range of distortions including (i) time gaps, similar to packet loss [14], but with non-uniformly distributed holes up to 400 ms in duration, (ii) frequency gaps, similar to the bandwidth extension problem [15] but with missing frequency bins cumulatively up to 3200 Hz in bandwidth and (iii) irregular, random gaps disrupting up to 40% of the overall time-frequency representation of speech. According to the authors’ knowledge, this problem and at such scale hasn’t been investigated to date.

To tackle the problem of speech inpainting we propose an end-to-end framework based on the U-Net architecture [16] trained via deep feature losses [17, 18, 19]. According to recent studies, the use of deep feature losses for training SE systems can improve their overall performance, depending on the deep feature extraction approach [17, 18]. We hypothesize that a specialized deep feature extractor, tailored specifically for speech processing, will lead to the best performance of our system. Thus, we introduce speechVGG, a deep speech features extractor, based on the classic VGG-16 architecture [20], trained on the word classification task. We explore different configurations of the extractor for the training of the framework and compare it with the conventional training based on $L_1$ loss and other control conditions.

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2. MATERIALS & METHODS

2.1. Data & preprocessing

We performed all of our experiments using the LibriSpeech corpus, an open read speech dataset sampled at 16 kHz [21]. We used the (train-clean-100) subset to train, test-clean subset to validate training performance and dev-clean, as a held-off data to evaluate all the models explored in this work. All available speech recordings were divided into 1024 ms long segments. The magnitude of each segment was obtained by taking absolute values of a complex short-
2.2. U-Net for speech inpainting

The main part of the proposed framework is a deep neural network with the U-Net architecture, originally applied to the problem of biomedical image segmentation [16]. Here, the U-Net was trained to recover, missing or degraded parts of log magnitude STFT of short segments of speech, obtained as specified in Section 2.1. The complete framework is illustrated in Fig. 1.

The U-Net for speech inpainting is composed of six encoding (blue, Fig. 1) and seven decoding blocks (green, Fig. 1). Each encoding block consists of a 2D convolution layer with ReLu activation. The encoding block firstly upsamples its input, using maximal pooling layers, at the end of each block in the feature extractor (see Section 2.3 for details). The output from the corresponding encoding block is subsequently concatenated with the output from the corresponding decoding block. Such concatenated set of features is then processed through a 2D convolution with leaky ReLu activation ($\alpha = 0.2$). Batch normalization [22] is applied after each 2D convolution layer across the network. The final decoding block is a 1D convolution with a linear activation function outputting the recovered version of the distorted input. Parameters of convolution layers in subsequent blocks of the U-Net are listed in Table 1.

We considered two versions of the U-Net: performing informed and blind speech inpainting. In the informed case, the mask is available at the U-Net input and all 2D convolutions in the network are replaced with partial convolutions (PC) [10], that only process valid (not masked) parts of their input and ignore the rest. Here, we wanted to explore whether our framework can both identify and restore missing or degraded parts of the input. We refer to such setup as the blind speech inpainting and all convolution layers in the U-Net perform standard, full, 2D convolutions ($c$). Otherwise, the two configurations of the U-Net are identical in terms of their architecture, training and evaluation.

As phase information is discarded in our framework, we apply the local weighted sums algorithm [23, 24] to reconstruct speech waveforms directly from the recovered STFT magnitudes. None of several attempts of incorporating STFT phase as an input feature for the framework was successful.

2.3. Deep feature losses in training

The deep feature losses $L_{DF}$ for training the U-Net are obtained by computing the $L_2$ distance between representations of the recovered and actual STFT magnitudes at pooling layers, at the end of each block in the feature extractor (see Section 2.4 for details).

We hypothesize that, analogically, similar architecture could be applied for extracting high-dimensional representations of distinct speech-specific features, such as harmonics, formats or phonemes.

Maintaining the same architecture that consisted of five main blocks with max-pooling layers (yellow, Fig. 1), we adapted the classic VGG-16 network [20] to become a deep speech feature extractor. The network was re-trained to classify words from LibriSpeech corpus, instead of images from ImageNet dataset, thus speechVGG (sVGG). In particular, we extracted speech segments corresponding to 1000 most frequent words, that were at least 4 letters long, from the training data (train-clean-100). The speech segments were pre-processed in the same way as specified in Section 2.1 to obtain their log magnitude STFT. We then applied SpecAugment [26] to improve the performance of the classifier, by randomly replacing blocks of time and frequency bins in the training data with mean values. To accommodate the varying length of different words, the spectrograms were randomly padded with zeros to match the U-Net’s output shape of 128 x 128.

2.4. Deep feature losses in training

The sVGG was employed to train our U-Net for speech inpainting with deep feature losses [17, 18, 19]. Instead of per-pixel $L_1$ loss, we employed a deep feature extractor. Insights from computer vision suggest that outputs from pooling layers in subsequent blocks of convolutional neural networks represent different features of the input image [25]. We hypothesize that, analogically, similar architecture could be applied for extracting high-dimensional representations of distinct speech-specific features, such as harmonics, formats or phonemes.

Table 1. Model parameters. The table contains parameters used in convolution layers of the U-Net network for speech inpainting. Block 0 corresponds to the final 1D convolution ($conv1d$, Fig. 1).

| Block | Encoding - $conv$ | Decoding - $dconv$ |
|-------|-------------------|-------------------|
| 0     | -                 | (1, 1)            |
| 1     | (7, 16)           | (3, 1)            |
| 2     | (5, 32)           | (3, 16)           |
| 3     | (5, 64)           | (3, 32)           |
| 4     | (3, 128)          | (3, 64)           |
| 5     | (3, 128)          | (3, 128)          |
| 6     | (3, 128)          | (3, 128)          |

To train the U-Net for speech inpainting via deep feature losses [17, 18, 19], instead of per-pixel $L_1$ loss, we employed a deep feature extractor. Insights from computer vision suggest that outputs from pooling layers in subsequent blocks of convolutional neural networks represent different features of the input image [25]. We hypothesize that, analogically, similar architecture could be applied for extracting high-dimensional representations of distinct speech-specific features, such as harmonics, formats or phonemes.

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2.4. Deep feature losses in training

The sVGG was employed to train our U-Net for speech inpainting with deep feature losses (Fig. 1). For each training batch of time-frequency masked speech segments, the U-Net was applied to recover missing or degraded information. Here, instead of computing, per-pixel, $L_1$ loss between the original ($Y$) and the reconstructed ($\hat{Y}$) STFTs to train the network, they were both processed through a
To investigate the influence of the depth of our framework in the informed speech inpainting task when the exact mask is available at the input (see Fig. 2 for details). Here, we replaced masked parts of the input STFT representation with zeros. We considered three shapes of masks covering: time segments, time segments & frequency bins, or random parts of the spectrogram of elliptical shapes, resembling brush strokes (Fig. 2 top-right, left, middle, respectively). Each mask was designed to cover a specific portion of information in time and/or frequency domain distributed between one to four intrusions, none shorter than 3 bins (24 ms or 187.5 Hz bandwidth).

We considered different configurations of the framework trained with deep feature losses, obtained using either the sVGG (low-, high-, full-sVGG) or VGG-16 pre-trained on the ImageNet data (imgVGG). We compared them with the case, where the U-Net was trained using $L_1$, per-pixel loss (noVGG). In each configuration, the U-Net was trained using input STFT magnitudes with time & frequency or random masks, chosen randomly with equal probability for each training sample. Coverage of the mask was each time drawn from the normal distribution $N(\mu = 29.4\%, \sigma = 9.9\%)$.

Each time, we evaluated the system performance on the held-off dev-clean data. We considered different sizes of masks ranging from 10% up to 40% information missing. For time and time & frequency masks, the proportion corresponds to the number of time and/or frequency bins removed and for the random case, to the overall area of the input STFT covered by the mask.

We assessed the performance of different configurations of the framework using the short term objective intelligibility (STOI) and perceptual evaluation of speech quality (PESQ), measured between the original and recovered speech segments. For each setup, the results were compared to the baseline of the masked (unprocessed) case. We used an additional control condition, where missing parts of the input STFT were filled with speech-shaped noise derived from the original voice sample.

Results of the evaluation are presented in Table 2. Each configuration of the proposed framework improved both STOI and PESQ for all the considered shapes and sizes of intrusions (by up to 0.2 and 1.35, respectively), as compared to both masked and control cases. The use of deep feature losses in training yielded better results, as compared to the case when the U-Net was trained with the $L_1$ loss (noVGG). However, only the speechVGG (sVGG), not the VGG-16 pre-trained on the ImageNet data (imgVGG), was used as a feature extractor in training, led to notable improvements in STOI & PESQ. In particular, speechVGG utilizing all five blocks (full-sVGG) to obtain $L_{DF}$ provided the best overall performance (Table 2 in bold).

### 3. RESULTS

The whole framework was implemented in Python using TensorFlow. All of the explored models were trained using ADAM optimizer [27]. Data were fed to each model in mini-batches of size 32. Each considered configuration of the U-Net for speech inpainting was trained for 30 full epochs using either per-pixel ($L_1$) or deep feature losses ($L_{DF}$). The sVGG classifier for deep feature extraction was trained using a cross-entropy loss for 50 full epochs.

#### 3.1. Informed speech inpainting

The first set of experiments was performed to assess the performance of our framework in the informed speech inpainting task when the deep feature extractor $E$. Then, the $L_1$ distance, between activations from a set of extractor’s pooling layers, at the end of each block, ($N$) was computed to obtain the deep feature loss $L_{DF}$:

$$L_{DF} = L_1(E_N(Y), E_N(\hat{Y}))$$

To investigate the influence of the depth of the sVGG on the U-Net performance we compared several configurations of blocks used to compute $L_{DF}$ in training. Specifically, we set $N$ to be only the first three, presumably corresponding to lower-level speech features, such as harmonics (low-sVGG), and the last two, possibly related to higher-level features, like phonemes (high-sVGG), or all five available blocks (full-sVGG). To determine whether the sVGG is capable of extracting speech-specific features, we compared it to the original VGG-16 network pre-trained on the ImageNet data (imgVGG). U-Nets trained with deep feature losses were each time compared to their counterpart optimized using $L_1$, per-pixel loss, between the original and reconstructed speech representations (noVGG).

### 3.2. Blind speech inpainting

Blind speech inpainting refers to the case when the mask is not available at the input and reflects a more generalized application of our framework. Since partial convolutions are not used, the U-Net needs to both identify and recover the masked parts of the input speech. Therefore, we hypothesized that the type of distortion may influence framework performance.

To address this issue, we considered three different cases by setting the masked values in the input STFT magnitude to either zero (-gaps), the same as in the informed case, white noise (-noise) or a mixture of the original information and the noise (-additive). The noise was added directly to input frequency bins and its amplitude was set to produce transient mixtures at very low SNR, below -10 dB (i.e. very disruptive noise level).

In this experiment, we selected the best configuration of the framework from the previous experiment, namely the (full-sVGG) using all five blocks to compute $L_{DF}$. The network setup was the
Table 2. Informed speech inpainting (partial convolutions). See [31] for details on the framework configurations. The table contains averaged STOI & PESQ measured between the recovered and actual speech segments. The best score for each metric was denoted in bold.

| Hole  | Size | Masked STOI | Masked PESQ | noVGG STOI | noVGG PESQ | imgVGG STOI | imgVGG PESQ | low_sVGG STOI | low_sVGG PESQ | high_sVGG STOI | high_sVGG PESQ | full_sVGG STOI | full_sVGG PESQ |
|-------|------|-------------|-------------|-----------|-----------|-----------|-----------|-------------|-------------|--------------|--------------|--------------|--------------|
| Time  | 10%  | 0.893       | 2.561       | 0.901     | 2.802     | 0.926     | 3.118     | 0.917       | 3.117       | 0.931        | 3.211        | 0.927        | 3.171        | 0.938        | 3.240        |
|       | 20%  | 0.772       | 1.872       | 0.800     | 2.260     | 0.879     | 2.755     | 0.860       | 2.713       | 0.881        | 2.780        | 0.870        | 2.720        | 0.887        | 2.809        |
|       | 30%  | 0.641       | 1.476       | 0.688     | 1.919     | 0.805     | 2.428     | 0.779       | 2.382       | 0.806        | 2.431        | 0.783        | 2.340        | 0.811        | 2.450        |
|       | 40%  | 0.536       | 1.154       | 0.598     | 1.665     | 0.724     | 2.171     | 0.695       | 2.109       | 0.726        | 2.166        | 0.693        | 2.042        | 0.730        | 2.179        |
| Rand. | 10%  | 0.880       | 2.842       | 0.892     | 3.063     | 0.941     | 3.477     | 0.927       | 3.399       | 0.943        | 3.476        | 0.935        | 3.387        | 0.944        | 3.496        |
|       | 20%  | 0.809       | 2.233       | 0.830     | 2.543     | 0.912     | 3.079     | 0.897       | 3.040       | 0.914        | 3.075        | 0.905        | 2.993        | 0.918        | 3.114        |
|       | 30%  | 0.713       | 1.690       | 0.745     | 2.085     | 0.872     | 2.702     | 0.856       | 2.680       | 0.873        | 2.698        | 0.862        | 2.602        | 0.878        | 2.735        |
|       | 40%  | 0.644       | 1.355       | 0.682     | 1.802     | 0.837     | 2.443     | 0.823       | 2.422       | 0.841        | 2.437        | 0.824        | 2.333        | 0.846        | 2.479        |

Table 3. Blind speech inpainting (full convolutions). See [32] for details on the framework configurations. This table is analogous to table 2.

| Hole  | Size | Masked-gaps STOI | Masked-gaps PESQ | PC-gaps STOI | PC-gaps PESQ | FC-gaps STOI | FC-gaps PESQ | FC-noise STOI | FC-noise PESQ | FC-additive STOI | FC-additive PESQ |
|-------|------|------------------|------------------|-------------|-------------|-------------|-------------|--------------|--------------|----------------|-----------------|
| Time  | 10%  | 0.893            | 2.561            | 0.938       | 3.240       | 0.930       | 3.191       | 0.919        | 3.066        | 0.933          | 3.216           |
|       | 20%  | 0.772            | 1.872            | 0.857       | 2.809       | 0.875       | 2.725       | 0.863        | 2.677        | 0.906          | 2.971           |
|       | 30%  | 0.641            | 1.476            | 0.811       | 2.450       | 0.798       | 2.384       | 0.792        | 2.374        | 0.882          | 2.788           |
|       | 40%  | 0.536            | 1.154            | 0.730       | 2.179       | 0.714       | 2.086       | 0.707        | 2.072        | 0.854          | 2.617           |
| Rand. | 10%  | 0.869            | 2.423            | 0.920       | 3.034       | 0.911       | 3.000       | 0.896        | 2.859        | 0.912          | 3.023           |
|       | 20%  | 0.729            | 1.790            | 0.853       | 2.566       | 0.840       | 2.490       | 0.828        | 2.411        | 0.885          | 2.759           |
|       | 30%  | 0.598            | 1.391            | 0.772       | 2.178       | 0.757       | 2.108       | 0.743        | 2.041        | 0.854          | 2.562           |
|       | 40%  | 0.484            | 1.053            | 0.680       | 1.845       | 0.665       | 1.772       | 0.659        | 1.787        | 0.828          | 2.413           |

same, expect all partial convolutions (PC) were replaced with regular, full 2D convolutions (FC). The framework was re-trained and evaluated separately for each type of intrusion (gaps, noise, additive noise). The evaluation framework was kept the same as in the case of informed speech inpainting (see [31] for details).

Averaged evaluation results are presented in table 2 for different configurations of the framework trained to perform both informed and blind speech inpainting. All of the considered framework configurations successfully recovered missing or degraded parts of the input speech that was confirmed by the increased STOI and PESQ scores, as compared when the masked information was missing (Masked-gaps). While the improvements were notable, the framework for informed inpainting (PC-gaps) outperformed its blind counterparts when parts of the input STFT were set to zeros or noise (FC -gaps, -noise, respectively). Interestingly, when the masked values were mixed with, not replaced by, the noise, the framework in the blind setup (FC-additive) yielded the best overall results for larger intrusions of all the considered shapes. These results suggest that the framework for blind speech inpainting takes advantage of the access to the original information underlying the noisy disruptions, even when the transient SNR is very low.

4. DISCUSSION

In this work, we introduced a novel framework for the retrieval of missing or degraded part in time-frequency representation of speech, based on the U-Net network trained via deep speech feature losses. In particular, the proposed framework allowed to recover missing or degraded information, leading to substantial improvements in STOI and PESQ scores, for intrusions as big as 400 ms or 3.2 kHz bandwidth. We showed that the use of deep speech feature extractor employed to train the framework improves the system’s performance, as compared to the typical L1, per-pixel loss. We confirmed our initial hypothesis that sVGG, but not imgVGG, applied to obtain deep feature losses led to the best outcomes.

Our results suggest that the proposed framework is capable of both identifying degraded information in speech STFTs and recovering it. In particular, the framework for blind speech inpainting yielded substantial improvements in both STOI and PESQ objective evaluation when the information was missing or when it was distorted by the additive noise. It’s important to note that in our experiments employing noisy intrusions, the noise was applied directly to the input speech STFT. To address this, a broader range of ecological noises should be considered in future experiments applying the framework to joint speech denoising and inpainting.

Although our experiments considering additive noise were simplified, our findings provide a promising outlook for applying the proposed blind speech inpainting as an extension of the current SE framework. We believe that the integration of non-causal, end-to-end approaches, such as this one, with the existing causal methods can bridge the current methodological gap and lead to the next generation of general-purpose speech enhancement systems.
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