A Curriculum Learning Method for Improved Noise Robustness in Automatic Speech Recognition

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Abstract

The performance of automatic speech recognition systems under noisy environments still leaves room for improvement. Speech enhancement or feature enhancement techniques for increasing noise robustness of these systems usually add components to the recognition system that need careful optimization. In this work, we propose the use of a relatively simple training method called accordion annealing which is inspired by curriculum learning. It uses a multi-stage training schedule where samples at SNR values as low as -15 dB are first added and subsequently samples at increasing higher SNR values are gradually added up to an SNR value of 50 dB. Because of the necessity of providing many different SNR valued samples, we additionally use a method called per-epoch noise mixing (PEM) to generate the noisy training samples online during training. Both the accordion annealing and the PEM methods are used during training of a recurrent neural network which is then evaluated on three databases. Accordance annealing improves the relative average accuracy of this network by 2 % when tested in a high SNR range (50 dB to 0 dB) and by 42 % in a low SNR range (-20 dB to 0 dB) on the Grid Corpus database.

1. Introduction

The performance of automatic speech recognition (ASR) systems has increased significantly with the use of deep neural networks (DNNs) [1]. However, their performance in noisy environments still leaves room for improvement. Over the past decades, a multitude of methods to improve noise robustness of ASR systems has been proposed [2], with many methods being applicable to DNNs. These methods enhance noise robustness at various levels and are applied prior to feature extraction, at the feature level, and during training.

Some example enhancement methods applied prior to feature extraction include denoising methods [3] and source separation methods [4] [5]. Methods applied at the feature level include methods that produce auditory-level features [6] and feature space adaptation methods [7]. Some methods use deep neural networks (DNNs), e.g. feature denoising with deep autoencoders [8] [9] and feature extraction from the raw waveform via convolutional neural networks (CNNs) [10] [11]. Many of these approaches add components to the speech recognition system that need careful optimization.

The training method itself can have a major influence on the performance of a neural network under different noise conditions. Training on noisy data is an established method of increasing the noise robustness of a network. Noisy training sets with a range of signal-to-noise ratio (SNR) values e.g. 10 dB - 20 dB [12] or 0 dB - 30 dB [10] are used during training. Other training methods such as dropout [13] which is intended to improve regularisation, have been shown to also improve noise robustness [12]. The same is true for model adaptation/noise aware training techniques [12].

This paper presents general training methods for improving noise robustness in recurrent neural network (RNN)-based recognizers. RNNs are used here because they have demonstrated state-of-the-art performance in tasks such as the common sequence labelling task in speech recognition [14], [15] and in clean speech recognition [16]. In particular, we introduce a new training strategy called accordion annealing (ACCAN) which exploits the benefits of curriculum-based training methods. By first training the network on low SNR levels down to −15 dB and gradually increasing the SNR range to encompass higher SNR levels, the trained network shows better noise robustness when tested under a wide range of SNR levels.

This work also investigates the usefulness of adding noise both at the acoustic waveform level and at the feature representation level during training. In particular, we exploit a method called per-epoch noise mixing (PEM), which is a waveform-level data augmentation method. It enables us to generate a new training set for every epoch of training, i.e. each training sample is mixed with a newly sampled noise segment at a randomly chosen SNR in every epoch. This form of augmentation prevents networks from relying on constant noise segments for classification and helps in creating the necessary training samples over a wide SNR range. These steps lead to improved generalization and noise robustness of the trained network. Our results are evaluated on an isolated word recognition task using three different databases, namely TIDIGITS, TIMIT and Grid. Every database is tested on a large SNR range going from clean conditions (> 50 dB) down to −20 dB.

The paper is organized as follows: Section 2 presents our training methods for improved noise robustness. The evaluation setup is detailed in Section 3, with results given in Section 4 followed by discussions in Section 5 and concluding remarks in Section 6.

2. Training methods for increased noise robustness

2.1. Baseline method

Our baseline method takes advantage of multi-condition training in order to increase the noise robustness [17] of the network. Pink noise is added to a clean dataset to create samples with the desired SNR. Each training sample is randomly chosen to be of
an SNR level in the range 0 to 50 dB with 5 dB steps. This wide range is larger than the SNR ranges used in previous work (e.g. 0 to 30 dB as in [10]). Our exhaustive simulations show that using such a large range resulted in the best performance on the test datasets. The noise mixing is done once at the waveform-level before Mel-frequency cepstral coefficient (MFCC) audio features are computed. This one set of training data is presented to the network over all training epochs.

### 2.2. Gaussian noise injection

Gaussian noise injection is a well-known method for improving generalisation in neural networks [18]. It is used here to improve the noise robustness of the network.

During training, artificial Gaussian noise is added to the MFCC features created from the different SNR samples. The amount of additive noise is drawn from a zero-centered Gaussian distribution. Using a Gaussian with a standard deviation of $\sigma = 0.6$ yielded the highest accuracy gains. This method is referred to as the “Gauss-method” in the rest of the paper.

### 2.3. Per-epoch noise mixing (PEM)

PEM is a method for adding noise to the waveform level during training. In every training epoch, each training sample is mixed with a randomly sampled noise segment at a randomly sampled SNR. The training procedure consists of the following steps:

1. Mix every training sample with a randomly selected noise segment from a large pink noise file to create a resulting sample at a randomly chosen SNR level between 0 to 50 dB.
2. Extract audio features (e.g. MFCCs) for the noise-corrupted audio to obtain the training data for the current epoch.
3. Optional: add Gaussian noise to the audio features.
4. Train on newly generated training data for one epoch.
5. Discard this training data after the epoch.
6. Repeat from step 1 until training terminates.

This method has several key advantages over conventional pre-training preprocessing methods. First, it enables the full potential of data augmentation in this speech recognition task. With conventional methods, augmenting training data at the waveform level with real-world noise at various SNR values is prohibitively expensive in terms of processing time and training data size. Augmenting every sample of a dataset with $m$ noise samples mixed at $n$ different SNRs would increase the training data size by $m \times n$ and accordingly, the amount of time needed to pre-process the data. With PEM, training is done on the GPU while the CPU pre-processes the next epoch training data.

PEM shows the network every training sample at a selection of SNRs and with as many noise samples as can be extracted from the noise file and as needed by the number of epochs to reach a steady-state accuracy level. As the training data can be easily augmented online, other noise types, different SNR training ranges, and even different audio features can be quickly tested. In order to compare against the baseline and Gaussian methods, the same 60 min pink noise file and SNR range is used as in the baseline method.

In contrast to the Gauss-method, PEM permits more control over the training data. Real-world noise is added to the acoustic waveform at controlled SNRs, ensuring that the training data corresponds to realistic noise corruption with results that can be evaluated. Of course, PEM can be combined with Gaussian noise addition (optional step three in Section 2.3). We refer to PEM without Gaussian noise injection as “Vanilla-PEM” and to PEM with Gaussian noise injection as “Gauss-PEM”.

### 2.4. Accordion Annealing

Our novel ACCAN training paradigm is designed to achieve high accuracy under both high and low SNR ranges. It is inspired by curriculum learning strategies [19] such as SortaGrad [16], a curriculum method for higher-accuracy convergence. Here, the novel ACCAN algorithm is used to obtain improved noise robustness.

The training has a multi-stage schedule. In the first stage, the neural network is trained on the lowest SNR samples. In the following stages, the SNR training range is expanded in 5 dB steps towards higher SNR values. A typical schedule is shown in Table 1. In every stage, training repeats until the validation loss no longer improves. At the end of each stage, the weights of the best network are stored and used as the starting point for the next stage. Both training and validation sets share the same SNR range.

The best results were achieved by starting the training at $\text{SNR} = -15 \text{dB}$ and terminating when the network is successfully trained at $50 \text{dB}$ SNR, resulting in 14 training stages.

ACCAN uses both PEM and Gaussian noise injection methods. The PEM method is especially helpful because it allowed us to dynamically expand the training SNR range during training. Other approaches, e.g. starting from high SNR levels and going to low SNR levels were also explored, but resulted in networks with worse noise robustness than ACCAN and are therefore not included in this work.

### 3. Setup

#### 3.1. Audio databases

All methods were evaluated on an isolated word recognition task using three different databases. These databases allowed coverage of many different speakers and different vocabularies as well as vocabulary sizes.

1. **TIDIGITS** [20]. We used a subset consisting of only single digit utterances and only adult speakers. This consists of 2464 training samples and 2486 testing samples for ten classes (digits 0 to 9).

2. **TIMIT** [21]. The two most common sentences (“she had your dark suit in greasy wash water all year” and “don’t ask me to carry an oily rag like that”) were taken from each speaker, chopped into words and labelled accordingly. This resulted in 924 training samples and 336 testing samples covering 21 classes.

3. **Grid** [22]. This corpus is intended for perceptual studies of speech processing, but can also be used for our isolated word recognition task. There are 1000 sentences spoken by each of 34 speakers. The grid word vocabulary contains four commands (bin, lay, place, set), four colors (blue, green, red, white), 25 letters (A-Z except W), ten digits (0-9) and four adverbs (again, now, please, soon), resulting in 47 classes. The training and test sets were determined by a random 90%/10% shuffle, resulting in 153,000 training samples and 17,000 test samples.

For evaluation, we used both the clean and noise corrupted test sets of the above databases. The noise corrupted test sets

| Stage | SNR range [dB] |
|-------|----------------|
| 1     | [-15]          |
| 2     | [-15,-10]      |
| ...   | ...            |
| 14    | [-15:5:50]     |

Table 1: The ACCAN training strategy
were created by mixing the clean samples with either babble noise from the NOISEX database [23] or pink noise generated by the Audacity [24] software, with each noise type added at 15 different SNR values from 50 dB to -20 dB in 5 dB steps.

3.2. Audio features

We used a close-to-HTK implementation [25] for extracting MFCC features from the audio samples. The default procedure and the parameters of this toolbox were left unchanged. The implementation included a pre-emphasis step with a pre-emphasis coefficient of $\alpha = 0.97$. The analysis frame duration was 25 ms and the frame shift was 10 ms. The 12 cepstral coefficients were augmented by the 0th order log energy coefficient. Additionally, both delta and delta-delta features were computed, resulting in the final 39-dimensional MFCC vector per frame. The features were zero-mean and unit variance normalized across each dimension over the whole training set.

3.3. Neural network configuration

A three-layer RNN architecture was used for the isolated word recognition task. The first layer consisted of 200 gated recurrent unit (GRU) [26]. GRUs are a faster-to-compute alternative to long short-term memory (LSTM) units for sequence modelling. Both show similar advantages compared to vanilla RNNs [27], i.e. their memory-like architecture helps to overcome the vanishing gradient problem in training [28]. The second layer used 200 fully-connected neurons with ReLU activation functions [29]. The third layer served as the output layer, consisting of either 10 (TIDIGITS), 21 (TIMIT) or 47 (Grid) output neurons with a softmax activation function. For all layers, Glorot uniform initialization [30] was used to initialize weights and biases.

During training, the Adam stochastic optimization method [31] was used. The last 10% of each training set was kept for the validation set. The network capacity was high enough to handle the isolated word recognition task on all chosen databases. To prevent overfitting, dropout [13] (dropout probability=0.5) was used. Early-stopped training was also employed when the validation loss did not improve for 50 epochs (for the smaller databases TIDIGITS and TIMIT) or 10 epochs (for the larger Grid database). The network with the lowest validation loss was kept for evaluation. The training process was repeated for five different random seeds of network weight initialization.

4. Results

The reported results were averaged over the five weight initializations for the network parameters. Every database was tested in its clean condition and with added pink noise or babble noise at 15 SNR levels from 50 dB to -20 dB in 5 dB steps. We focus on comparing average accuracy over three SNR ranges:

- **Full SNR range**: [clean signal, 50 dB to -20 dB]
- **High SNR range**: [50 dB to 0 dB]
- **Low SNR range**: [0 dB to -20 dB]

The test results of the described training methods in Section 4 are given in Tables 2 and 3 and are further analyzed in the following subsections.

4.1. Noise addition methods

This section summarizes results from the baseline, Gauss, vanilla-PEM and Gauss-PEM methods, all trained on the SNR range from 0 dB to 50 dB.

**Baseline**: All methods outperform the baseline method across the whole SNR range.

**Vanilla-PEM vs. Gauss**: On the low SNR range, Vanilla-PEM improves accuracy on TIDIGITS and TIMIT by 4.7 to 6.9 % over the baseline, outperforming the 1.0 to 5.3 % increase seen by the Gauss method. Vanilla-PEM did especially well on TIMIT, achieving greater than 10% increase over the baseline.

However on the Grid database, Gauss achieved a higher 3.7 % increase compared to the 2.7 % increase by Vanilla-PEM. On the high SNR range, both methods lead to comparable improved accuracy.

**Gauss-PEM**: The combined Gauss-PEM method achieves the highest accuracy on both high and low SNR ranges. The absolute accuracy gains over the baseline method are between 4.2 to 12.8 % on the low SNR range and between 2.0 to 14.5 % on the high SNR range.

Table 2: Average test accuracy (%) on full SNR range, high SNR range and low SNR range for databases TIDIGITS, TIMIT and Grid. Highest accuracy values are printed in bold.

| Database | Test on full SNR range | Test on high SNR range | Test on low SNR range |
|----------|------------------------|------------------------|-----------------------|
| TIDIGITS | Method | Full | High | Low | Full | High | Low | Full | High | Low | Full | High | Low | Full | High | Low |
| Baseline | Vanilla-PEM | Gauss-PEM | ACCAN | Baseline | Gauss-PEM | ACCAN | Baseline | Gauss-PEM | ACCAN | Baseline | Gauss-PEM | ACCAN |
| TIMIT | Method | Full | High | Low | Full | High | Low | Full | High | Low | Full | High | Low | Full | High | Low |
| Baseline | Vanilla-PEM | Gauss-PEM | ACCAN | Baseline | Gauss-PEM | ACCAN | Baseline | Gauss-PEM | ACCAN | Baseline | Gauss-PEM | ACCAN |
| Grid | Method | Full | High | Low | Full | High | Low | Full | High | Low | Full | High | Low | Full | High | Low |
| Baseline | Vanilla-PEM | Gauss-PEM | ACCAN | Baseline | Gauss-PEM | ACCAN | Baseline | Gauss-PEM | ACCAN | Baseline | Gauss-PEM | ACCAN |

4.2. Accordion Annealing

To further increase noise robustness, we combined the ACCAN method with the Gauss-PEM method. Test results showed that ACCAN improves noise robustness considerably when compared to the case where only Gauss-PEM is used. In addition, the ACCAN network showed a further increase in accuracy in the high SNR range for two out of three databases.

**Expert networks**: We also trained networks on a single SNR level noise, in this case, three such “expert” networks were trained using the Gauss-PEM method for levels of -5 dB,

\[1\] Trained on 0 dB to 50 dB
\[2\] Trained on -15 dB to 50 dB
-10 dB and -15 dB. The test results from the TIDIGITS database in Table 3 show that the networks perform especially well at the single trained SNR value but degrade quickly in performance for higher and lower SNR values. In comparison, the ACCAN network outperforms the expert networks for the lowest SNR level of -15 dB, though the performance is comparable to the optimally-trained expert networks at a given SNR level in general.

Comparison to Gauss-PEM: The different training methods in Table 2 used a training set with a SNR range of [0 dB to 50 dB]. To match the training range of the ACCAN network, a new Gauss-PEM network was trained on this wider SNR range [-15 dB to 50 dB]. The test results for detailed SNR values are given in the last 2 rows of Table 3 for the TIDIGIT database and test results for all three databases and the two different noise types are given in the bottom two rows of each database section in Table 2. The results in Table 2 show that ACCAN outperforms Gauss-PEM for low SNRs ranges across all databases, and with improved accuracy in the high SNR range on two out of three databases, namely TIDIGITS and Grid.

5. Discussion

All proposed training methods lead to networks with increased noise robustness in the low SNR range in comparison with the baseline method. The results generalize across both tested noise types, with the performance ranking of training methods preserved across these noise types.

The best noise robustness performance is obtained using the ACCAN training strategy. The multi-stage training starts at low SNRs, where annealed networks achieve accuracy comparable to networks optimized for a single low SNR level. During gradual exposure to higher SNRs in the training process, accordanance networks maintain their excellent noise robustness with even better high SNR level accuracy than networks trained using Gauss-PEM on both TIDIGITS and Grid databases. A part of the improved noise robustness can be attributed to the expanded training SNR range that goes down to -15 dB. This is confirmed as Gauss-PEM did also benefit from an increased SNR range during training. However, the improvement due to the increased training range is much smaller than the increase from using ACCAN.

From the results, we can determine if the waveform-level noise addition (Vanilla-PEM) or the feature level noise injection (Gauss) is a better training method for noise robustness. One way to contrast these methods is that Vanilla-PEM is a data augmentation method, while the Gauss method improves network regularization by directly adding noise to input features. Indeed, the results reflect this characterization: the smaller TIDIGITS and TIMIT databases improved more from the use of Vanilla-PEM than Gauss, as PEM expanded the number of data samples. However, because the Grid corpus is a larger database, it did not benefit as much from Vanilla-PEM’s extra samples and instead benefited from the noise regularization of the Gauss method. Combining both methods led to better results than using either method alone.

When compared to the baseline method, all training methods improved not only the noise robustness of the trained networks but also, perhaps surprisingly, their accuracy on the high SNR range. The use of both Vanilla-PEM and Gaussian noise injection methods ensured that the network did not see the same data in every epoch and thus improved its generalisation capabilities.

Advantageously, the PEM method avoids the unnecessary creation of a large training database for network training. Because the method is used to create the dataset samples during training epochs, these simulations do not require that a large database to be created before commencing training. Instead, mixed samples are only created online when needed. This results in saved time and computation, for example, when a particular training method like ACCAN requires many samples in a wide and changing SNR range, and cases in which training only terminates when a stopping criteria is reached.

6. Conclusion

This work proposes new training methods to improve the noise robustness of RNNs for an isolated word recognition task. The networks are trained for a wide SNR range with the use of the Vanilla-PEM training method which adds noise at the waveform level and the Gauss method which injects Gaussian noise at the feature level. The use of the novel multi-stage ACCAN training method further increases the noise robustness of the network. This method is a training strategy inspired by curriculum learning. The network is first trained on the lowest SNR value and is then gradually exposed to samples for an increasing SNR range towards higher SNR values. The results on the three databases show that the accordanance-annealed network shows a relative increase in accuracy over the baseline trained network in the low SNR range (0 dB to -20 dB), i.e., between 27 to 88%. At the same time, the accuracy did not drop in the high SNR range (50 dB to 0 dB) and even improves by 2.0 to 18 % over the baseline network.

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