Abstract

Nearly all Statistical Parametric Speech Synthesizers today use Mel Cepstral coefficients as the vocal tract parameterization of the speech signal. Mel Cepstral coefficients were never intended to work in a parametric speech synthesis framework, but as yet, there has been little success in creating a better parameterization that is more suited to synthesis. In this paper, we use deep learning algorithms to investigate a data-driven parameterization technique that is designed for the specific requirements of synthesis. We create an invertible, low-dimensional, noise-robust encoding of the Mel Log Spectrum by training a tapered Stacked Denoising Autoencoder (SDA). This SDA is then unwrapped and used as the initialization for a Multi-Layer Perceptron (MLP). The MLP is fine-tuned by training it to reconstruct the input at the output layer. This MLP is then split down the middle to form encoding and decoding networks. These networks produce a parameterization of the Mel Log Spectrum that is intended to better fulfill the requirements of synthesis. Results are reported for experiments conducted using this resulting parameterization with the ClusterGen speech synthesizer.

Index Terms: Statistical Parametric Speech Synthesis, Deep Learning, Parameterization

1. Introduction

The speech coder used in modern Statistical Parametric Speech Synthesis has remained largely unchanged for a number of years. The standard coding technique is usually a variant of Mel Cepstral analysis. While many different parameterizations of the spectrum have been developed for synthesis, few have yet managed to survive in the long run. The most obvious indications of this are the systems that are submitted to the annual Blizzard Challenge. Very few statistical parametric systems submitted to the challenge since its inception use vocoders that do not use Mel Cepstral coefficients. Even highly successful techniques like the various flavors of STRAIGHT are rarely used by the synthesizer directly. These are usually converted into Mel Cepstral coefficients (MCEPs) before being used by statistical parametric systems.

This lack of new parameterizations that perform better than MCEPs is especially intriguing considering the amount of research effort that has gone into finding a replacement. An ideal parameterization for statistical parametric synthesis will have to fulfill all of the following requirements:

- It must be invertible
- It must be robust to corruption by noise
- It must be of sufficiently low dimension
- It must be in an interpolable space

Even if a parameterization technique were invented that could comply with three of the above four requirements, the technique would be useless if it did not at least partially satisfy the remaining one. Therein lies the difficulty of inventing a new parameterization. Mel Cepstral coefficients satisfy all of these requirements to a reasonable extent. However, this representation is not perfect and places a major bottleneck on the naturalness of modern parametric speech synthesizers. Techniques such as and rectify some of the problems that occur with this representation but the Mel Cepstral representation still leaves plenty of room for improvement.

In this age of big data and deep learning, it behooves us to try to construct a parameterization purely from data which might be more adept at dealing with all these constraints.

2. Stacked Denoising Autoencoder

Neural networks themselves have existed for many years but the training algorithms that had been used were incapable of effectively training networks that had a large number of hidden layers. This is because the standard technique used for training a neural network is the backpropagation algorithm. The algorithm works by propagating the errors made by the neural network at the output layer back to hidden layers and then adjusting the weights of the hidden layers using gradient descent or other techniques to minimize this error. When the network is very deep, the propagated error to the first few hidden layers becomes very small. As a result, the parameters of the first few layers change very little in training. One strategy that was developed in recent years was to start off by training the neural network one pair of layers at a time and then building the next pair on top of previous ones. This step is called pretraining because the weights that are obtained through this process are used as the initialization for the backpropagation algorithm. Pretraining techniques are believed to provide an initialization much closer to the global optimum compared to the random initializations that were originally used.

Our search for a technique to create a purely data-driven parameterization led us to the Stacked Denoising Autoencoder (SDA) which was developed for pretraining deep neural networks. The SDA is trained in a manner more or less identical to the layer-wise pretraining procedure described in and . As the name suggests, the Stacked Denoising Autoencoder is constructed by stacking several Denoising Autoencoders together to form a deep neural network. Each Denoising Autoencoder is a neural network that is trained such that it reconstructs the correct input sequence from an artificially corrupted version of the input provided to it. This process is shown in Figure. The network is fully connected between...
3. **Building Encoding and Decoding networks**

The ‘pretraining’ process for our approach is identical to the one for speech recognition. We build an SDA on our features by stacking multiple Denoising Autoencoders that were built by learning to reconstruct corrupted versions of the input. Once the SDA is trained, we then *unwrap* the SDA as shown in figure 1.

The SDA is actually rarely used in a task where the input needs to be reconstructed from the representation that the SDA transforms the input into. It is nearly always used to provide a lower dimensional representation on top of which a classifier such as logistic regression, or Support Vector Machines are used. An example of this is the Deep Bottleneck Features that are used in Speech Recognition [17][18]. However, such approaches are less relevant to parametric synthesis since it is not a classification problem.

The SDA is of particular interest to parametric speech synthesis because this network learns to reconstruct a noisy version of the input from a lower dimensional set of features. It is therefore apparent that the very definition of this network fits the first three of the four requirements of an ideal parameterization. We will discuss the fourth requirement in a later section.

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signal i.e. it learns a mapping between the phonemes of text and the values of this encoding. At synthesis time, the synthesizer predicts values of this encoding based on the input text. The decoding network converts this code back into a representation of the speech signal. This approach is similar to the one proposed for efficient speech coding in [19]. Apart from the fact that [19] proposes the use of the code for other applications, it is also different in that it specifically looks for a binary encoding. Such binary encodings are not very useful in a statistical synthesis framework because binary representations are not interpolable while synthesis is an inherently generative task.

### 3.1. Input features

In previous sections, we have discussed how a deep neural network will build a low-dimensional noise-robust representation of the speech signal, but what should our deep neural network actually encode? To put it more explicitly, what should be the input to our deep neural network that it can learn to reconstruct? Should it be the actual speech signal itself, the magnitude spectrum, the complex spectrum, or any of the other representations that signal processing research has provided us? In theory, the input representation should not matter since it has been proven that multilayer feedforward networks are universal approximators [20]. However, this proof places no constraints on the size or structure of the network. Nor does it provide a training algorithm that reaches the global optimum. Therefore, it is sensible to train the network on a representation that is known to be highly correlated with speech perception. Human hearing is known to be logarithmic both in amplitude [21], and frequency [22]. So, we propose that the Mel Spectrum and Mel Log spectrum are the most suitable representations that the network can be trained on. Despite using input and output layers that were linear, the network had difficulty working with the wide range of values in the Mel spectrum. Therefore, for the rest of this paper, we will only describe our attempts at using a deep neural network to get an invertible, low-dimensional, noise-robust representation of the Mel Log Spectrum.

### 4. Experiments and Results

We built the SDAs and the MLPs using the Theano [23] python library, and the parametric Speech Synthesizer using ClusterGen [24]. The input to the neural network was a 257-dimensional Mel Log Spectral vector which was obtained from a 512-point FFT of a 25ms speech frame. The encoding obtained using the network is 50-dimensional. This encoding size was chosen to make it easier for us to compare the quality with the 50-dimensional MCEP representation used in our baseline system. The Stacked Denoising Autoencoder was built in a 257 x 125 x 75 x 50 configuration i.e. 257 nodes in the input layer, 125 in the first hidden layer, 75 in the second, and 50 in the output layer. This results in an MLP with a 257 x 125 x 75 x 50 x 75 x 125 x 257 configuration for fine-tuning. The encoding network will therefore have a configuration of 257 x 125 x 75 x 50 and the decoding network, 50 x 75 x 125 x 257. In all of these networks, the layer that is contact with the Mel Log Spectra is a linear layer with no non-linear function involved. This is so the layer can deal with the range of values that the Mel Log Spectra can take. In all other layers, the neurons have sigmoid activations.

We ran experiments on 3 different voices: the RMS, and SLT voices from the CMU Arctic databases [25] and the Hindi corpus released as part of the 2014 Blizzard challenge [26]. The intention was to test the setup across gender as well as across language.

Evaluating the quality of the systems that we built poses an interesting problem. The standard objective metric used in nearly all evaluations of parametric speech synthesis is Mel Cepstral Distortion [27]. However, this metric is likely inherently unfair to our technique. This is because the default system that we compare against, like most statistical parametric synthesizers, works directly with the MCEPs. These systems optimize for the root-mean-squared error of MCEP prediction. In other words, they directly optimize for the metric. The technique that we are proposing gives us an encoding which is optimized for parametric synthesis. But optimizing for the prediction of this encoding need not necessarily optimize the Mel Cepstral Distortion directly. Therefore, any MCD-based results presented in this paper must be taken with a pinch of salt.

While our synthesizer might not directly optimize for MCD, the MCD is nevertheless a good indicator of listener perception; the argument here being that natural-sounding speech should have natural-appearing Mel Cepstral parameters. So, we will measure the quality of synthesis using the Mel Cepstra obtained from the Mel Log Spectra of the decoding network.

The first test is a simple analysis-resynthesis test. We measure how well our learned encoding is able to reconstruct the Mel Log Spectra of held-out test data. The results are shown in table 1.

| Voice             | MCD Scores |
|-------------------|------------|
| ARCTIC RMS        | 4.354      |
| ARCTIC SLT        | 4.315      |
| Hindi corpus      | 3.916      |

In all of the cases, the deep neural network trained for the voice is able to reconstruct the test set with relatively low error. It is however not obvious what these numbers should be compared against.

One major hinderance in the use of deep neural networks is the amount of effort that needs to go into the tuning of hyperparameters (batch size, learning rate, number of epochs, etc...). We did not want to use a technique that would require a lot of tuning for each new speaker. So, all neural network settings were tuned for one speaker (RMS) and identical configurations were used for the others. All the SDAs were pretrained with a batch size of 20 for 50 epochs, and the MLPs were trained with a batch size of 100 for 100 epochs. Based on the results shown in table [1], it appears that identical hyperparameter settings work well for multiple speakers.

As a test, we also tried using the RMS encoding and decoding networks for Analysis-Resynthesis of SLT held out data. This resulted in an MCD of 6.473, implying that the encoding that is learned by the deep neural network is speaker specific.

### 4.1. Synthesis tests

The next set of tests were on using the deep neural network’s 50-dimensional encoding as a parameterization for the ClusterGen statistical parametric synthesizer. MCD scores for the three above described voices are shown in table [2].

The Mel Cepstral Distortion is higher for the deep neural network encoding compared to the default system. In addition to this, the baseline system was preferred in informal subjective tests. As we had mentioned earlier in this section, we believe
Table 2: ClusterGen synthesis voice build

| Voice          | DNN Params | MCEP params |
|----------------|------------|-------------|
| ARCTIC RMS     | 5.851      | 5.161       |
| ARCTIC SLT     | 5.466      | 4.858       |
| Hindi corpus   | 4.680      | 4.134       |

that the MCD of the DNN systems were affected by the fact that the Deep Neural Network was not directly optimizing for the score like the default system was doing. The lack of a good objective metric that would work with the DNN approach to parameterization exacerbated the problem by making it difficult to make design decisions. This in turn prevented us from making use of the full capability of the deep neural network; this is probably the reason for the lower subjective quality. We believe that the use of a better objective metric would reflect a more positive light on our results. It would also help us make better decisions which would contribute towards better parameterizations and improved subjective results.

These results are actually quite promising because the relatively good MCD scores we get with the DNN encoding strongly indicate that the encoding exists in an interpolable space. This is important because synthesizers like ClusterGen form clusters of the data vectors at the leaves of the trees and represent the cluster by its mean[1]. Therefore, only representations like MCEPs or Line Spectral Pairs[28] have been found to be suitable. The interpolable space constraint is probably the most difficult to achieve of the four earlier stated constraints. Even if our data-driven parameterization currently does slightly worse compared to MCEPs, it is extremely encouraging to be able to find that this parameterization manages to satisfy all of the four requirements. Considering how close the difference is between the performance of the data-driven parameterization and that of the MCEPs, we expect that a more judicious design of the neural network coupled with better learning strategies will lead to great results in the future.

4.2. Network optimization

An investigation of a deep neural network parameterization would be incomplete without exploring the various possible structures of the neural network. We tested the neural network both by varying its width, as well as its depth. Table 3 summarizes the results of these experiments.

| SDA Structure                   | Analysis-Resynthesis | Voice Build |
|---------------------------------|-----------------------|-------------|
| 257 x 125 x 75 x 50             | 4.315                 | 5.466       |
| 257 x 750 x 50                  | 4.477                 | 5.543       |
| 257 x 1000 x 250 x 50           | 4.156                 | 5.454       |
| 257 x 175 x 125 x 75 x 50       | 4.003                 | 5.386       |
| 257 x 200 x 175 x 125 x 75 x 50 | 3.827                 | 5.374       |

All of these tests were on the SLT voice. The first column describes the structure of the Stacked Denoising Autoencoder. The unwrapped Multi Layer Perceptron that corresponds to each SDA would be twice as deep. The network described in the first row of the table is the same network as the one in the SLT row in table 2. As can be seen in the table, for a constant depth, increasing the width of the layers of the neural network improves the performance of the network. Increasing the depth, however, makes a much bigger impact on performance. This is in line with deep learning theory[29]. A deep narrow network also takes substantially less time to train compared to a shallow wide network. These trends are encouraging, and we expect further investigation in these directions to improve the performance further.

In an earlier section, when we described the training process of a Denoising Autoencoder, we had mentioned that it is trained to reconstruct the original input from a noisy version of the input. Traditionally, this ‘noise’ that is added involves arbitrarily setting some of the input parameters to zero. We also investigated using Gaussian noise since this is closer to the noise introduced by statistical parametric synthesizers. Unfortunately, this only had the effect of making synthesis quality worse compared to the traditional ‘noising’ strategy.

5. Discussion

All experiments described in this paper were run on one of the following Nvidia GPUs: Tesla M2050, GRID GK104, GTX670, GTX660, and the GTX580. Finding the right stable hardware combination that offers the most efficient training platform is also an investigatory task.

Although we have tried to build on work in related fields (particularly speech recognition and speech coding) in order to find reasonable topologies for our networks, the generative nature of speech synthesis does have inherently different requirements, thus we feel there is likely significant improvements possible within this core technology.

As it stands, this work concentrates on finding an encoding for modeling the vocal tract of the speaker, as that allows the most direct comparison with MCEP parameterization. However this technology is in no way constrained by that restriction and adding excitation, and prosodic information to the networks still fits within our method.
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