RECURRENT NEURAL NETWORK POSTFILTERS FOR STATISTICAL PARAMETRIC SPEECH SYNTHESIS

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ABSTRACT

In the last two years, there have been numerous papers that have looked into using Deep Neural Networks to replace the acoustic model in traditional statistical parametric speech synthesis. However, far less attention has been paid to approaches like DNN-based postfiltering where DNNs work in conjunction with traditional acoustic models. In this paper, we investigate the use of Recurrent Neural Networks as a potential postfilter for synthesis. We explore the possibility of replacing existing postfilters, as well as highlight the ease with which arbitrary new features can be added as input to the postfilter. We also tried a novel approach of jointly training the Classification And Regression Tree and the postfilter, rather than the traditional approach of training them independently.

Index Terms — Recurrent Neural network, Postfilter, Statistical Parametric Speech synthesis

1. INTRODUCTION

Deep Neural Networks have had a tremendous influence on Automatic Speech Recognition in the last few years. Statistical Parametric Speech Synthesis[1] has a tradition of borrowing ideas from the speech recognition community[2], and so there has been a flurry of papers in the last two years on using deep neural networks for speech synthesis[3][4][5]. Despite this, it would be difficult to argue as of now that deep neural networks have had the same success in synthesis that they have had in ASR. DNN-influenced improvements in synthesis have mostly been fairly moderate. This becomes fairly evident when looking at the submissions to the Blizzard Challenge[6] in the last 3 years. Few of the submitted systems use deep neural networks in any part of the pipeline, and those that do use DNNs, do not seem to have any advantage over traditional well-trained systems.

Even in cases where the improvements look promising, the techniques have had to rely on the use of much larger datasets than is typically used. The end result of this is that Statistical Parametric Synthesis ends up having to lose the advantage it has over traditional unit-selection systems[2] in terms of the amount of data needed to build a reasonable system.

That being said, it is still be unwise to rule out the possibility of DNNs playing an important role in speech synthesis research in the future. DNNs are extremely powerful models, and like many algorithms at the forefront of machine learning research, it might be the case we haven’t yet found the best possible way to use them. With this in mind, in this paper we explore the idea of using DNNs to supplement existing systems rather than as a replacement for any part of the system. More specifically, we will explore the possibility of using DNNs as a postfilter to try to correct the errors made by the Classification And Regression Trees (CARTs).

2. RELATION TO PRIOR WORK

The idea of using a postfilter to fix flaws in the output of the CARTs is not very new. Techniques such as Maximum Likelihood Parameter Generation (MLPG)[8] and Global variance[9] have become standard, and even the newer ideas like the use of Modulation Spectrum[10] have started moving into the mainstream. These techniques provide a significant improvement in quality, but suffer from the drawback that the post-filter has to be derived analytically for each feature that is used. MLPG for instance exclusively deals with the means, the deltas, and the delta-deltas for every state. Integrating non-linear combinations of the means across frames or arbitrary new features like wavelets into MLPG will be somewhat non-trivial, and requires revisiting the equations behind MLPG as well as a rewrite of the code.

Using a Deep Neural Network to perform this postfiltering can overcome many of these issues. Neural networks are fairly agnostic to the type of features provided as input. The input features can also easily be added or removed without having to do an extensive code rewrite.

There has been prior work in using DNN based postfilters for parametric synthesis in [11] and [12]. However, we differ from these in several ways. One major difference is in the use of Recurrent Neural Networks (RNNs) as opposed to standard feedforward networks or generative models like Deep Belief Nets. We believe that inherent structure of RNNs is particularly suited to the time sensitive nature of the speech signal. RNNs have been used before for synthesis in [3], but as a replacement for the existing acoustic model and not as a
In addition to this, we also explore the use of lexical features as input to the postfilter. To our knowledge, this is the first attempt at building a postfilter (neural network based or otherwise) that can make use of text based features like phone and state information in addition to spectral features like the MCEP means and standard deviations. We also describe our efforts in making use of a novel algorithm called Method of Auxiliary Coordinates (MAC) to jointly train the CARTs and the postfilter, rather than the traditional approach of training the postfilter independent of the CART.

3. RECURRENT NEURAL NETWORKS

The standard feedforward neural network processes data one sample at a time. While this may be perfectly appropriate for handling images, data such as speech or video has an inherent time element that is often ignored by these kind of networks. Each frame of a speech sample is heavily influenced by the frames that were produced before it. Both CARTs and feedforward networks generally tend to ignore these interdependencies between consecutive frames. Crude approximations like stacking of frames are typically used to attempt to overcome these problems.

A more theoretically sound approach to handle the interdependencies between consecutive frames is to use a Recurrent Neural Network\[13\]. RNNs differ from basic feedforward neural networks in their hidden layers. Each RNN hidden layer receives inputs not only from its previous layer but also from activations of itself for previous inputs. A simplified version of this structure is shown in figure 1. In the actual RNN that we used, every node in the hidden layer is connected to the previous activation of every node in that layer. However, most of these links have been omitted in the figure for clarity. The structure we use for this paper is more or less identical to the one described in section 2.5 of \[14\].

![Fig. 1. Basic RNN](image)

To train an RNN to act as a postfilter, we start off by building a traditional Statistical Parametric Speech Synthesis system. The particular synthesizer we use is the Clustergen system\[15\]. Once Clustergen has been trained on a corpus in the standard way, we make Clustergen re-predict the entire training data. As a result, we will now have Clustergen’s predictions of Mel Cepstral Coefficients (MCEPs) which is time aligned with the original MCEPs extracted from speech. We then train an RNN to learn to predict the original MCEP statistics based on Clustergen’s predictions of the MCEP statics and deltas. This trained RNN can then be applied to the CART’s predictions of test data to remove some of the noise in prediction. We use 25 dimensional MCEPs in our experiments. So the RNN takes 50 inputs (25 MCEP statics + 25 deltas) and predicts 25 features (MCEP statics). The results of doing this on four different corpora are shown in table 1. Each voice had its own RNN. Mel Cepstral Distortion\[16\] is used as the objective metric.

| Voice     | Baseline | With RNN |
|-----------|----------|----------|
| RMS (1 hr)| 4.98     | 4.91     |
| SLT (1 hr)| 4.95     | 4.89     |
| CXB (2 hrs)| 5.41   | 5.36     |
| AXB (2 hrs)| 5.23   | 5.12     |

| Voice     | Baseline | With RNN |
|-----------|----------|----------|
| RMS (1 hr)| 4.75     | 4.79     |
| SLT (1 hr)| 4.70     | 4.75     |
| CXB (2 hrs)| 5.16   | 5.23     |
| AXB (2 hrs)| 4.98   | 5.01     |

RMS and SLT are voices from the CMU Arctic speech databases\[17\], about an hour of speech each. CXB is an American female, and the corpus consists of various recordings from audiobooks. A 2-hour subset of this corpus was used for the experiments described in this paper. AXB is a 2-hour corpus of Hindi speech recorded by an Indian female. RMS, SLT, and AXB were designed to be phonetically balanced. CXB is not phonetically balanced, and is an audiobook unlike the others which are corpora designed for building synthetic voices.

The RNN was implemented using the Torch7 toolkit\[18\]. The hyper-parameters were tuned on the RMS voice for the experiment described in table 1. The result of this was an RNN with 500 nodes in a single recurrent hidden layer, with sigmoids as non-linearities, and a linear output layer. To train the RNN, we used the ADAGRAD\[19\] algorithm along with a two-step BackPropagation Through Time\[20\]. A batch size of 10, and a learning rate of 0.01 were used. Early stopping was used for regularization. L1, L2 regularization, and momentum did not improve performance when used in addition to early stopping. No normalization was done on either the output or the input MCEPs. The hyperparameters were not tuned for any other voice, and even the learning rate was left unchanged.

The results reported in table 1 are with the MLPG option in Clustergen turned off. The reason for this is that MLPG requires the existence of standard deviations, in addition to the means of the parameters that the CART predicts. There is no
true set of standard deviations that can be provided as training data for the RNN to learn to predict; it only has access to the true means in the training data. That being said, we did however apply MLPG by taking the MCEP means from the RNN, and standard deviations from the original CART predictions. We found that it did not matter whether the means for the deltas were predicted by the RNN or if they were taken from the CART predictions themselves. The magnitudes of the deltas were typically so small that it did not influence the RNN training as much as the statics did. So, the deltas were omitted from the RNN predictions in favor of using the deltas predicted by the CARTs directly. This also made the training a lot faster as the size of the output layer was effectively halved. The results of applying MLPG on the results from the previous set of experiments are shown in Table 3. As can be seen in the tables, the RNN always improves the system or is no worse. The decrease in MCD is much smaller though. With MLPG turned on, the decrease in MCD with the RNN system is not large enough for humans to be able to do reasonable listening tests. With MLPG turned off though, the RNN system was shown to be vastly better in informal listening tests. But our goal was to build a system much better than the baseline system with MLPG, and so no formal listening tests were done.

### 4. ADDING LEXICAL FEATURES

In all of the previous experiments, the RNN was only using the same input features that MLPG typically uses. This however does not leverage the full power of the RNN. Any arbitrary feature can be fed as input for the RNN to learn from. This is the advantage that an RNN has over traditional post-filtering methods such as MLPG or Modulation Spectrum.

We added all of Festival’s lexical features as additional input features for the RNN, in addition to CART’s predictions of f0, MCEP statics and deltas, and voicing. The standard deviations as well as the means of the CART predictions were used. This resulted in 776 input features for the English language voices and 1076 features for the Hindi one (the Hindi phoneset for synthesis is slightly larger). The output features were the same 25-dimensional MCEPs from the previous set of experiments. The results of applying this kind of RNN on various corpora are shown in the following tables. As for the previous set of experiments, each voice had its own RNN. Table 3 and Table 4 show results without and with MLPG respectively. In addition to the voices tested in previous experiments, we also tested this approach on three additional voices: KSP (Indian male, 1 hour of Arctic), GKA (Indian male, 30 mins of Arctic), and AUP (Indian male, 30 mins of Arctic).

| Voice       | Baseline | With RNN |
|-------------|----------|----------|
| RMS (1 hr)  | 4.98     | 4.77     |
| SLT (1 hr)  | 4.95     | 4.71     |
| CXB (2 hrs) | 5.41     | 5.27     |
| AXB (2 hrs) | 5.23     | 5.07     |
| KSP (1 hr)  | 5.13     | 4.88     |
| GKA (30 mins) | 5.55  | 5.26     |
| AUP (30 mins) | 5.37  | 5.09     |

As can be seen in the tables, the RNN always gives an improvement when MLPG is turned off. [21] reports that an MCD decrease of 0.12 is equivalent to doubling the amount of training data. The MCD decrease in Table 3 is far beyond that in all of the voices that are tested. It is especially heartening to see that the MCD decreases significantly even in the case where the corpus is only 30 minutes. With MLPG turned on, the RNN always improves the system or is no worse. The decrease in MCD is much smaller though.

With MLPG turned on, the decrease in MCD with the RNN system is not large enough for humans to be able to do reasonable listening tests. With MLPG turned off though, the RNN system was shown to be vastly better in informal listening tests. But our goal was to build a system much better than the baseline system with MLPG, and so no formal listening tests were done.

### 5. JOINT TRAINING OF THE CART AND THE POSTFILTER

The traditional way to build any postfilter for Statistical Parametric Speech Synthesis is to start off by building the Classification And Regression Trees that predict the parameters of the speech signal, and then train or apply the postfilter on the output of the CART. The drawback of this is that the CART is unnecessarily agnostic to the existence of the postfilter. CARTs and postfilters need not necessarily work well together, given that each has its own set of idiosyncrasies when dealing with data. MCEPs might not be the best representation that connects these two. In an ideal system, the CART and the postfilter should jointly agree upon a representation of the data. This representation should be easy for the CART to learn, as well as reasonable for the postfilter to correct.

One way of achieving this goal is to use a fairly new technique called Method of Auxiliary Coordinates (MAC) [22]. To understand how this technique works, we need to mathematically formalize our problem.

Let $X$ represent the linguistic features that are input to the CART. Let $Y$ be the correct MCEPs that need to be predicted at the end of synthesis. Let $f_1(X)$ be the function that the CART represents, and $f_2$ the function that the RNN represents. The CART and the RNN both have parameters that are learned as part of training. These can be concatenated into one set of parameters $W$. The objective function we will want to minimize can therefore be written as:

$$E(W) = ||f_2(f_1(X; W); W) − Y||^2$$

Table 4. RNN with all lexical features. MLPG on

| Voice     | Baseline | With RNN |
|-----------|----------|----------|
| RMS (1 hr) | 4.75     | 4.69     |
| SLT (1 hr) | 4.70     | 4.64     |
| CXB (2 hrs) | 5.16     | 5.15     |
| AXB (2 hrs) | 4.98     | 4.98     |
| KSP (1 hr) | 4.89     | 4.80     |
| GKA (30 mins) | 5.27     | 5.17     |
| AUP (30 mins) | 5.10     | 5.02     |
The MAC algorithm basically rewrites the above equation to make it easier to solve. This is done by explicitly defining an intermediate representation \( Z \) that acts as the target for the CARTs and as input to the RNN. The previous equation can now be rewritten as:

\[
E(W, Z) = \| f_2(Z; W) - Y \|^2 \\
t.s. Z = f_1(X; W)
\]

The hard constraint in the above equation is then converted to a quadratic penalty term:

\[
E(W, Z; \mu) = \| f_2(Z; W) - Y \|^2 + \mu \| f_1(X; W) - Z \|^2
\]

where \( \mu \) is slowly increased towards \( \infty \).

The original objective function in the first equation only had the parameters of the CART and the RNN as variables to be used for the minimization. The rewritten objective function adds the intermediate representation \( Z \) as an auxiliary variable that will also be used in the minimization. We minimize the objective function by alternatingly optimizing the parameters \( W \) and the intermediate variables \( Z \). Minimizing with respect to \( W \) is more or less equivalent to training the CARTs and RNNs independently using a standard RMSE criterion. Minimization with respect to \( Z \) is done through Stochastic Gradient Descent. Intuitively, this alternating minimization has the effect of alternating between optimizing the CART and RNN, and optimizing for an intermediate representation that works well with both.

We applied this algorithm to the RNN and CARTs built for the SLT and RMS voices built for table 1. The results of this are shown in table 5. Starting from the second iteration, any further optimization of either the \( W \) or the \( Z \) variables only results in a very small decrease in the value of the objective function. So, we did not run the code past the second iteration.

We did not try MAC for the RNNs which use lexical features. This is because running the \( Z \) optimization on those RNNs would have given us a new set of lexical features for which we would have no way of extracting from text.

| Method          | SLT | RMS |
|-----------------|-----|-----|
| RNN from table 1| 4.89| 4.91|
| 1st MAC iteration | 4.86| 4.92|
| 2nd MAC iteration | 4.89| 4.92|

On our experiments on the RMS and SLT voices, there was no significant improvement in MCD. There are marginal MCD improvements in the 1st iteration for the SLT voice but these are not significant. Preliminary experiments suggest that one reason for the suboptimal performance is the overfitting towards the training data. It is difficult to say why the MAC algorithm does not perform very well in this framework. The search space for the parameters and the number of possible experiments that can be run is extremely large though, and so it is likely that a more thorough investigation will provide positive results.

6. DISCUSSION

In this paper, we have looked at the effect of using RNN based postfilters. The massive improvements we get in the absence of other postfilters such as MLPG indicate that the RNNs are definitely a viable option in the future, especially because of the ease with which random new features can be added. However the combination of MLPG and RNNs are slightly less convincing. This could mean that the RNNs have learned to do approximately the same thing as MLPG does. Or it could mean that MLPG is not really appropriate to be used on RNN outputs. We believe that the answer might actually be a combination of both. The right solution might ultimately be to find an algorithm akin to MAC which can tie various postfilters together for joint training. Future investigations in these directions might lead to insightful new results.

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