ABSTRACT

This paper introduces the Multi-Band Excited WaveNet a neural vocoder for speaking and singing voices. It aims to advance the state of the art towards an universal neural vocoder, which is a model that can generate voice signals from arbitrary mel spectrograms extracted from voice signals. Following the success of the DDSP model and following the development of the recently proposed excitation vocoders we propose a vocoder structure consisting of multiple specialized DNN that are combined with dedicated signal processing components. All components are implemented as differentiable operators and therefore allow joined optimization of the model parameters. To prove the capacity of the model to reproduce high quality voice signals we evaluate the model on single and multi speaker/singer datasets. We conduct a subjective evaluation demonstrating that the models support a wide range of domain variations (unseen voices, languages, expressivity) achieving perceptive quality that compares with a state of the art universal neural vocoder, however using significantly smaller training datasets and significantly less parameters. We also demonstrate remaining limits of the universality of neural vocoders e.g. the creation of saturated singing voices.

Index Terms— neural vocoder, differentiable signal processing, singing synthesis, speech synthesis.

1. INTRODUCTION

The introduction of the WaveNet [5] has demonstrated that DNN can be trained to produce high quality speech signals when conditioned on a mel spectrogram. This result has triggered numerous research activities aiming to reduce the high computational demands of the original WaveNet or to reduce the size of the training data that is required [6, 7, 8, 10]. Recently research focus has been extended from single speaker models to multi speaker models or even universal neural vocoders [1, 2, 11] that is vocoders that support arbitrary speakers, languages and expressivity. An important motivation for constructing a universal neural vocoder is the simplification of the process to create new voices for TTS systems. An interesting line of research in this context are models that try to incorporate prior information about the speech signal into the generator [12, 13, 14]. These models, in the following denoted as excitation networks, simplify the task of the generator by means of splitting the vocal tract filter (VTF) into a dedicated unit. Instead of generating the speech signal the generator is then used only to produce the excitation signal. On the other hand, only one of these models [4] takes a mel spectrogram as input. The others use more classical vocoder parameters like F0, line spectral frequencies, and an voiced/unvoiced flag. The idea to introduce domain knowledge into the model seems particularly interesting. It is in line with the recent DDSP [4] framework for music synthesis that replaces a part of the generator by means of a sinusoidal model and uses the DNN only to control the parameters of the sinusoidal model. The main disadvantage of using the classical vocoder parameters for conditioning is the fact that these parameters are deeply entangled. Disentangling a set of heterogeneous vocoder parameters seems significantly more difficult than disentangling for example the speaker identity from the mel spectrogram. This is due to the fact that the mel spectrogram is a homogeneous representation similar to images and therefore techniques for attribute manipulation that have proven useful for image manipulation (notably disentanglement) can be applied with only minor changes. By consequence research on voice attribute manipulation like: Speaker Identity Conversion [15], rhythm and F0 conversion [16, 17], Gender Conversion [18], speaker normalization [19] generally starts with a (mel) spectral representation of the voice signal. In a companion paper that demonstrates high quality singing voice transpositions over multiple octaves [20], the manipulation of the mel spectrogram and the resynthesis with a neural vocoder has proven highly effective.

These experiences motivate our research into extending the voice signals that are supported by neural vocoders. The present paper discusses especially the case of speech and singing signals and will present a new neural vocoder with significantly better support for singing than existing models. To achieve this goal we will introduce 2 novelties that are the central contributions of the present research:

• To improve the signal quality as well as to ease the use of the vocoder in practical applications we will replace the approximate VTF estimation from the mel spectrogram proposed in [4] by means of a small separate model that predicts the cepstral coefficients of the VTF.

• To facilitate the generation of long and stable quasi periodic oscillations that are crucial for singing we simplify the task of the excitation generator by means of splitting the generator into a small DNN that predicts the F0 contour from the input mel spectrogram and a differentiable wavetable generator that produces the corresponding excitation. The subsequent WaveNet then operates without recursion and only has the task to shape the given periodic pulses in accordance with the conditioning mel spectrogram.

The rest of the paper is organized as follows. In section 2 we will introduce the various components of the model and put them into context of existing work. In section 3 we will describe the model topology, in section 4 we will describe the datasets and will discuss our experimental results.
2. MODEL COMPONENTS

The present section will discuss the structure of the proposed neural vocoder that we denote as multi band excited WaveNet. We will not

discuss relations with existing work. The fundamental idea of

the present work follows and extends the arguments in [12, 13, 3, 14] that the excitation networks with objective to simplify the task of the

WaveNet generator by means of removing the VTF from the gener-

ator output. Similar to [4] we use the mel spectrogram to represent

the acoustic features. The following section describes the proposed

contributions in more details.

2.1. VTF generation

[4] proposes to recover an approximate all-pole representation of

the VTF by means of first converting the log amplitudes in the mel spec-

trogram to linear amplitudes and then applying the pseudo-inverse of

the mel filter bank to recover an approximation of the linear am-

plitude spectrum from which an all-pole model of the envelope can

be obtained. It is well known known however that all-pole estima-

tion from harmonic spectra is subject to systematic errors [21]. To

counter these systematic errors the generation of the VTF by means

of an auxiliary DNN seems a preferable option. Here we propose to

use an auxiliary DNN that predicts a cepstral representation of the

VTF. This prediction is cheap because it is performed frame wise and

operates therefore with a small sampleree. We limit the model to

predict causal cepstral coefficients, so that the resulting VTF will

be minimum phase [22].

Whether we use all-pole VTF or cepstral representations, in

both cases when we predict the VTF from the Mel spectrogram we

encounter the question of the gain coefficients. If we do not constrain

the VTF we create a gain ambiguity because any gain in the VTF can

be compensated by a inverse gain in the excitation generator. We

therefore decide to force the cepstral model to have zero gain.

2.2. Wavetable based excitation generation

The existing excitation networks all use a WaveNet or more gen-

erally a DNN to create the quasi periodic excitation. In our experi-

ments notably for singing signals we noticed that the generation of a

stable quasi periodic excitation is a difficult problem for the genera-

tor. For our neural vocoder we therefore decided to create a quasi pe-

riodic excitation and pass this excitation together with a white noise

signal through the WaveNet. Given the F0 contour is already correct

the WaveNet now serves only create the appropriate pulse form and

operate therefore with a small samplerate. We limit the model to

predict causal cepstral coefficients, so that the resulting VTF will

be minimum phase [22].

The signal flow will be discussed in more detail below.

The overall schematic diagramm of the MBExWN generator is

shown in fig. 1. The diagram represents the flow of a single frame of

a mel spectrogram with 80 channels. Each block displays the

output dimension of the block in the format time x channels (batch dimension not shown).

The input Mel spectrogram enters three subnets: First the F0

subnet that produces an F0 sequence with upsampling factor 100. The

sequence of layers of the F0 predictor is specified in terms of

layer type (C:Conv1D, L:linear upsampling) followed by a short pa-

rameter specfication. The Conv1D layer parameters are given as ker-

nels x number of filters optionally followed by an upsampling-

parameter specfication. The Conv1D layer parameters are given as ker-

nel size x number of filters optionally followed by an upsampling-

factor. If given the upsampling performed by means of reshaping

channels into time dimension. As an example consider the layer specfication C:3x240x2. This would be implemented by means of a

Conv1D layer with kernel size 3 and 120 channels followed b a re-

shape operation that upsamples by factor 2 by means of folding every

other channel into time direction. The linear interpolation layer L is a

Conv1D layer with precomputed parameters that performs upsampling.

The only parameter here is the upsampling factor.

The F0 net specfication is then as follows: C:3x150, C:3x300x2,

C:5x150, C:3x600x5, C:1x120, C:3x500x5, C:1x100, C:3:50,L:2

The activation functions in the F0 predictor are all relu and are

situated after each convolutional layer. The only exception here is the

last layer that uses a soft sigmoid as activation function. The

output vector is then offset and scaled to the desired F0 range. In

the presnet model this range is 45Hz-1400Hz. After this operation the

F0 contour passes through the wavetable generator described in

section 2.2. It follows a reshape operation and a concatenation of a

white noise signal duplicating the size of the excitation signal. The

basic excitation signal then enters the pulse shaping WaveNet. This

WaveNet is following the classical configuration using gated tanh

activations and kernel size 3. It consists of 2 blocks of 5 layers,

having 240 or 320 channels for single or multi voice models.

Fig. 1. MBExWN schematic generator: Green boxes are DNN mod-

els, yellow boxes are differentiable operators, red ovals are losses.

The numbers below the boxes specify the output dimensions of the

box in the format time x channels (batch dimension not shown).

3. MODEL TOPOLOGY

where the $N$ is the size of the wavetable, $F_k$ the F0 contour in Hz

and $R$ the samplerate in Hz. Because $F_k$ is a continuous variable

the values to be taken from the wavetable will not fall onto the grid

of values stored in the tables. For the gradient to pass through the

wavetable into the F0 predictor it is important that the positions

$P_k$ are not quantized! Instead the values to be output from the wavetable

need to be linearly interpolated.

$$P_k = N \left( \sum_{i=0}^{k} (F_i / R) \right) \% 1, \quad (1)$$
The PostNet is a single Conv1D layer that reduces the channel size from 30 to 15 to adapt the WaveNet output for the subsequent a PQMF [10] synthesis filter with 15 bands. The VTF predictor is again a CNN with the specification: C:3x400, C:1x600, C:1x400, C:1x400, C:1x160. Activations functions are relu after all but the last convolutional layer. The final layer does not have any activation function and passes directly into a real valued FFT operator to produce a minimum phase spectral envelope [22].

VTF and excitation signal produced by the PostNet are multiplied in the spectral domain to produce the final speech signal. The STFT parameter are copied from the parameters used for creating the mel spectrogram.

4. EXPERIMENTS

For the following experiments we used 4 databases. The first is the LJSpeech single speaker dataset [23] denoted as LJ in the following. The second, denoted as SP, is a multi speaker dataset composed of VCTK [24], PTDB [25] and AttHack [26] datasets. The SP dataset contains approximately 45h of speech recorded from 150 speakers. For singing voice experiments we used a single singer dataset containing a greek byzantine singer [27] denoted as DI and for the multi singer model a database composed of the NUS [28], SVDB [29], PJS [30], JVS, [31] and Tohoku [32] datasets, as well as an internal datasets composed of 2 pop, 6 classical singers. This dataset contains about 27h of singing recordings from 136 singers. The last database will be denoted as SI.

All database recordings were resampled to 24kHz. All voice files were annotated automatically with F0 contours using the FCN estimator [33]. We employ the noise separation algorithm described in [34] to separate deterministic and noise components and calculate the noise/total energy balance over 4 periods of the F0. We annotate segments with more than 50% of the energy in the noise component as unvoiced.

For the optimization we use Adam optimizer [35] with learning rate $\beta_1 = 0.9, \beta_2 = 0.999$, for training without discriminator and $\beta_1 = 0.5, \beta_2 = 0.5$ for training with discriminator. Batch size is always 40, and the segment length is approximately 200ms.

As objective functions we use the following loss functions. The first loss is the F0 prediction loss given by

$$L_{F0} = \frac{\sum_k ||F_k - \hat{F}_k||}{\sum_k 1}. \quad (2)$$

$F_k$ is the target F0 and $\hat{F}_k$ are the predicted value at time sample position $k \in K$ and $K$ is the set of points that are annotated as voiced and further than 50ms away from a voiced/unvoiced boundary. For these unambiguously voiced sections the F0 predictor can be optimized using only the prediction error.

The second loss is a multi resolution spectral reconstruction loss similar to [2]. It is composed of two terms the first one calculated as normalized linear magnitude differences and the second as log magnitude differences.

$$L_A = \frac{||S - \hat{S}||_2}{||S||_2}; \quad \text{and}$$

$$L_L = \frac{1}{K \cdot M} \| \log(S) - \log(\hat{S}) \|_1. \quad (4)$$

Here $S$ and $\hat{S}$ are the magnitudes of the STFT of the target and generated signals and $K$ and $M$ are the number of frames and the number of bins in the STFT matrices.

The final reconstruction loss is then the mean of the reconstruction losses obtained for the different resolutions

$$L_R = \frac{\sum_j (L_{A,j} + L_{L,j})}{\sum_j 1}. \quad (5)$$

where $j$ runs over the resolutions. For the foillown gexperiemnts we used STFT with window size in seconds given by $M \in [0.02, 0.0375, 0.075]$, and hop size in seconds $H \in [0.00375, 0.0075, 0.015]$. The reconstruction loss is used as objective function for the pulse shaping WaveNet and for the F0 predictor around voiced unvoiced boundaries (more precisely within 50ms of these boundaries within voiced segments, and within 20ms of these boundaries in unvoiced segments). In these transition areas we expect the F0 annotation to be less reliable and not sufficient to create optimal resynthesis performance. Therefore here we optimize the F0 predictor as part of the generator.

Finally, when training with the discriminator loss $L_D$ we use exactly the same discriminator configuration and loss as [2]. The only difference is that we only use 2 discriminator rates. The first one working on the original samplerate and the second after average pooling of factor 4. We motivate the decision to drop the last discriminator with the fact that the stability of the periodic oscillations is already ensured by the excitation model and therefore the discriminator is only needed to evaluate the pulse form and the balance between deterministic and stochastic signal components.

For each model we first pretrain the F0 prediction model over 100k batches using only the eq. (2) as objective function. Pretraining the F0 predictor reliably achieves prediction errors below 3Hz. We wont further discuss these. As a next step we pretrain the full generator strating with the pretrained F0 model loaded. Pretraining of the generator runs for 200k batches. To create a generator without adversarial loss we continue training the generator for further 400k iterations. When training with adversarial loss we load the discriminator after the 200k training steps for the generator and train with discriminator for further 800k batches.

4.1. Perceptual Evaluation

In the following section will compare different models and configurations. We will denote these using a code structured like: TXC. Here T will be replaced by the model type using the following short-cuts: MW: multi band excited WaveNet introduced here, MMG: multi band melgan from [16], UMG: universal melgan vocoder from [2]. The further codes will be used only for the MW models, where X is either U for multi voice (universal) models or S for single voice models. Finally C is a sequence of letters representing specific components missing from the full model. Here only a single letter is used. The letter in the last position v indicates that the model does not use a dedicated module for VTF prediction. For the MW model we have trained two multi voice models. A singing model that is trained with the full pitch range available in the SI dataset and a speech model on the SP dataset. In the tables below when seeing data is treated the singing model is used. Equivalently the speech model will be used for speech. During the perceptual evaluation we used the speech model as well as those singing signals that do stay in a pitch range that was part of our speech databases. For that special cases we denote the model as MWU_{SP}.

We first summarize results about pretraining. Pretraining the F0 models on any of the datasets converges reliably to an F0 prediction error around 2Hz for singing and around 2.5Hz for speech. Pretraining the generator achieves spectral reconstruction errors in the order of 3dB for singing and 3.2dB for speech. Reconstruction error on
the mel spectrogram is even smaller and generally <2dB. Listening to the generated sounds reveals a constant buzz in many of the noise sections. The main problem here are residual pulses that are not sufficiently suppressed by the pulse forming wavenet. To solve this problem we will use the time domain discriminators proposed originally in 35.

4.2. Perceptual tests

We have conducted a perceptual test evaluating the perceived quality of the selected MWU and MWS models trained on multi and single user database. We will use seen and unseen speakers, languages, expressivities, as well as singing styles. For these tests we use three baselines. We used an open source multi-band melgan implementation 1 and trained it for 1M iterations on the DI and LJ datasets. Further we downloaded original samples together with resynthesized results of the Universal MelGan model 2 and used these as a baseline for the multi voice models. Each of the tests has been conducted by 42 participants, consisting of audio and music professionals working at or with IRCAM and native English speakers recruited via the prolific online platform 3.

In contrast to perceptual tests performed in other studies our main interest is the perceptually transparent resynthesis of the original speech signal. Therefore we chose to perform a MUSHRA test containing the reference signal and a group of resynthesized signal that the participants can play as they like. The task given was to concentrate on any differences that might be perceived between the original and the resynthesis and to rate the perceived differences on a scale from 0 to 100 with categories imperceptible (80-100), perceptible, not annoying (60-80), slightly annoying (40-60), annoying (20-40), very annoying (0-20). Results are listed in table table (1). The first column indicates the data source the data is taken from. The second column marked HREF represents a hidden reference (copy of the reference) for which we expect and observe an evaluation around 90 for all cases. In the second column we find the MBExWN models trained on a multi voice dataset. In the sub sequent columns we find various baselines.

In the upper part of the table we find the perceptual evaluation of singing data. In the first line the evaluation data of the SI dataset is used. The result of the MWExWN model trained on the singing voice dataset is equivalent to the result of the hidden reference. In the second line we compare the multi singer model with dedicated single singer models trained on the DI dataset as well as the multi speaker model. Note that the singer DI is neither part SI nor of SP. The best result here is obtained by the the single singer MBExWN model. This model is trained exclusively on that singer. Both multi voice models, whether trained on sining or trained on speech achieve 90 for all cases. In the second column we find the MBExWN models trained on a multi voice dataset. In the sub sequent columns we find various baselines.

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| Singing Models/Singing Data | Data | HREF | MWU | MWS | MMG | MWU_SP |
|-----------------------------|------|------|------|------|------|--------|
| SI                          | 90 (4.2) | 90 (3.8) | - | - | - |
| DI                          | 89 (4.6) | 83 (5.8) | 89 (3.8) | 66 (8.4) | 80 (6.5) |
| Pop-sing                    | 88 (4.7) | 71 (8.4) | - | - | 76 (7.8) |
| Met-sing                    | 91 (2.8) | 57 (9.9) | - | - | 55 (8.8) |
| Speech Data/Speech Models   | Data | HREF | MWU | MWS | MMG | MWUv |
| SP                          | 92 (2.8) | 85 (7.3) | -1 | - | - |
| LJ                          | 90 (3.6) | 84 (6.1) | 85 (5.1) | 83 (5.6) | 77 (6.9) |
| Data                        | HREF | MWU | UMG |
| UMG_V                       | 92 (5.1) | 84 (6.3) | 79 (8.7) |

Table 1. Perceptual evaluation of the perceived difference between original and resynthesis for different models and conditions.

4.3. Complexity

The multi speaker model with 320 WaveNet channels has about 10M parameters and achieves inference speed of 50kSamples/s when running on a single core of an Intel i7 laptop CPU. On a NVidia V100 GPU the inference rate of 2.4Msamples/s. These numbers compare favourably with the universal melgan 2 that has 90M parameters and achieves an inference speed of 860kHz on a V100 NVidia GPU.

5. CONCLUSIONS

In this paper we have presented MBExWN a new neural vocoder with an externally excited WaveNet as source. A perceptual test has shown that the proposed model supports achieves near transparent quality even for out of domain data. The signal degrades when confronted with rough and saturated voices. Further research will be conducted to solve these cases.

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