Analysis and transformations of intensity in singing voice

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Abstract

In this paper we introduce a neural auto-encoder that transforms the voice intensity in recordings of singing voice. Since most recordings of singing voice are not annotated with voice intensity we propose a means to estimate the relative voice intensity from the signal’s timbre using a neural intensity estimator. Two methods to overcome the unknown recording factor that relates voice intensity to recorded signal power are given: The unknown recording factor can either be learned alongside the weights of the intensity estimator, or a special loss function based on the scalar product can be used to only match the intensity contour of the recorded signal’s power. The intensity models are used to condition a previously introduced bottleneck auto-encoder that disentangles its input, the mel-spectrogram, from the intensity. We evaluate the intensity models by their consistency and by their fitness to provide useful information to the auto-encoder. A perceptive test is carried out that evaluates the perceived intensity change in transformed recordings and the synthesis quality. The perceptive test confirms that changing the conditional input changes the perceived intensity accordingly thus suggesting that the proposed intensity models encode information about the voice intensity.

Index Terms: Voice conversion, voice intensity, auto-encoder

1. Introduction

Voice intensity is the power with which human voice is produced. For singing, the intensity is strongly related to the musical dynamic and therefore an important medium to carry musical expression [1]. In music the dynamic refers to how loud an instrument is played and is often divided (with various degrees) in forte (strong, loud) and piano (weak, quiet). Singing voice as a musical instrument inherits this quality and professional singers can sing a continuous spectrum of dynamics by adjusting the intensity of their voice. Similarly in speech most speakers can adapt the intensity of their voice to various situations between speaking to a crowd of hundreds of people in an open field and exchanging information with their neighbour in a quiet library.

However for both, singing and speech, not only the signal’s power changes with the change in intensity but a wide range of voice properties as well, such that most people can easily distinguish whether someone whispers something in their ear or someone shouting at them from far away, even though the signal’s power might be the same at the listeners ear [2].

Voice intensity can be measured using a calibrated sound pressure level (SPL) meter [3] and the relationship between voice intensity and other voice parameters have been investigated in various studies. In [3] glottal inverse filtering [4] is used to analyse the difference between soft, normal and loud voice in the glottal waveform. The relationships between open quotient, $f_o$, lung pressure and sound pressure level are investigated in [5]. Special attention to the open quotient is given by the study in [6]. These studies have paved the way for glottal pulse models [7] which can be used to modify pulse parameters as a function of the intensity [8, 9]. However, the practical application of these models is limited as robustly obtaining glottal pulse parameters from voice recordings remains challenging.

In [10] intensity changes were done by shifting the formant positions in vowels according to the statistics computed on a singing database. Related to the intensity in voice is the roughness as rough voice generally tent to occur in voice with higher intensity. It is, however, a different singing style that can happen as a side effect of increased intensity. Some work has been done to simulate the effect or rough voice in singing synthesis [11, 12]. The intensity in relationship to different vowels has been studied by [13] to improve naturalness of speech synthesis. A discussion on intensity vs. distance of sounds in general can be found in [2].

In this paper we approach intensity transformation as an attribute transformation problem. We train a neural network to disentangle the intensity from the signal’s mel-spectrogram. Neural disentanglement has received large attention in recent years and has been applied for example to speaker identity [14, 15] and fundamental frequency [16].

The contributions of this work are the following. (1.) We present a method that allows training a deep neural network to predict the voice intensity without the need to create annotated data. (2.) We use this intensity measure to train an auto-encoder to transformation the intensity in recordings of singing voice. The remaining paper is structured as follows: In Section 2 we introduce two ways to estimate the relative voice intensity from voice recordings where no intensity annotation exists. In Section 3 we present our adaptions of [16] to include the voice intensity as a controllable parameter. We will explain our experimental validation in Section 4 and present and discuss the results in Section 5. Finally we will see an short summary and an outlook in Section 6.

2. Extracting voice intensity from audio recordings

Audio recordings are not calibrated measurements. The goal of a recording is to produce a signal that when played on a speaker will create sound waves that sound like the original source. The scaling of these signals is irrelevant as it is expected to be adjusted by the consumer or the sound engineer that further processes the sound. Thus, each recording has a different relationship between the source’s intensity and the recorded signal’s power as microphones have different directivities and transfer functions, which cause some signals to be recorded stronger than others, and the signal gain is adjusted to minimise quantisation noise when digitalising the microphone signal.

Therefore, without explicit intensity annotation it is impossible to infer the voice intensity from an audio recording’s signal power. Still, if we look at the speech production mechanism,
we notice that humans cannot increase the voice intensity without changing other properties of their voice [3, 5, 6]. Therefore spectral properties of voice signals change with changing voice intensity. This leads to the hypothesis of this paper that we can infer the voice intensity contour from a recording’s spectral properties.

2.1. Learned recording factor

Assuming all audio files of a dataset have been recorded under the same conditions, (same microphone, pre-gain, spatial positioning of speaker and microphone, etc.) with the same post-processing applied to them (in particular with same normalisation factor) we can assume that the power contour of the recorded signal $p$ is proportional to the voice intensity $i$:

$$p = a_i i$$

with $p$ and $i$ being time varying sequences here and with the proportionality factor $a_i$ which we shall call recording factor as it captures the effect of the recording conditions. For multi-speaker databases it is highly likely that some of these assumptions are violated; however, it is not unlikely that these assumptions still hold for all files of a fixed speaker $s$. Therefore we get the relationship

$$p = a_s^i i$$

for all files generated by a speaker $s$ with a different $a_s^i$ for each speaker.

The speaker dependent recording factor $a_s^i$ can be learned alongside the weights $\theta$ of a neural network $N_\theta$. As we aim to learn the intensity contour $i$ from the spectral properties of the signal we have to prevent the network from using the signal power by normalising the signal appropriately.

Using an $L_2$ error, we get the following error function

$$\|p - a_s^i N_\theta (n(x))\|_2^2$$

with some signal normalisation $n$.

The resulting neural network $N_\theta$ allows estimating the intensity from the normalised signal: To compare the intensity of two arbitrary recordings we use the same recording factor, e.g. $a_s = 1$. This puts the predicted intensity in relation to an imaginary reference point, i.e. as if measured at a specific but unknown point.

2.2. Adaptive recording factor

The assumptions from Section 2.1 require the files from the training dataset to be grouped by same recording conditions. This works well if the number of speakers is small and we can be sure that the files have not been normalised separately. However, for many databases we don’t know what kind of post-processing has been performed or whether the samples for a fixed speaker have been created over multiple recording sessions with slightly different conditions. In this case we would have to assign a different recording factor to each file. With the previous approach this causes problems as a gradient exists for a specific recording factor only if a sample associated with this recording factor is present in the training batch. Thus recording factors with a small percentage of associated files in the dataset are learned very slowly as they are updated rarely.

For the case where we cannot group the files into a reasonable amount of classes we propose an adaptive recording factor: Let $q := N_\theta(n(x))$ be the output of the neural network and $p$ the power curve associated with the input sample. Again, we assume (1), this time with a different recording factor $a$ for each training sample. We choose $a$ such that the $L_2$ error

$$e_a = \|p - a q\|_2^2 = \sum_i (p_i - a q_i)^2$$

is minimal for each training sample:

$$\hat{a} = \arg\min_a e_a$$

For a fixed pair of samples $(p, q)$ there exists an analytic optimal solution for $a$:

$$\hat{a} = \frac{p \cdot q}{\|q\|_2^2} = \frac{\sum_i p_i q_i}{\sum_i q_i^2}$$

where $\cdot$ denotes the scalar product. Combining (4) and (6) and normalising $e_a$ by $\|p\|_2^2$ yields the scalar product error:

$$e_{ap} := \frac{e_x}{\|p\|_2^2} = 1 - \frac{(p \cdot q)^2}{\|p\|_2^2 \|q\|_2^2} = 1 - (\hat{x} \cdot \hat{q})^2$$

with $\hat{x} := x/\|x\|$ denoting the unit vector in direction of $x$.

With the same reasoning as before the input signal has to be normalised to remove information of the signal energy.

3. Proposed intensity transformations

Having a method to infer the intensity from audio recordings could be useful for many applications and in different disciplines. In this publication we focus our attention to singing voice transformations. We can use a bottleneck auto-encoder [14] to disentangle the voice intensity from the mel-spectrogram of singing voice recordings. We extend the architecture of [16] to additionally include the voice intensity as conditional input.

A detailed description of this bottleneck auto-encoder is given in [16] so we only give a brief outline here: The autoencoder consists of a pair of networks, an encoder and a decoder which are cascaded (the input of the decoder is the output of the encoder). Additionally the decoder receives a conditional input, which in this case consists of the $f_v$, voiced-unvoiced mask and the intensity from Section 2. The auto-encoder is trained to reproduce its own input. The trick is that the encoder’s output has only few dimensions – here we reduce the 80 dimensional mel-spectrogram to latent code with only 2 dimensions. This creates an information bottleneck: The channel from encoder to decoder has only limited capacity and is insufficient to describe the whole mel-spectrogram. Therefore, the encoder has to prioritise which information it provides to the decoder. As the decoder already receives the $f_v$, voiced-unvoiced mask and the intensity from the conditional input, there is no benefit in also providing them in the latent code as well. Thus the encoder will remove these parameters to be able to use the precious bandwidth for more urgent information.

To change the intensity in singing voice recordings we can feed its mel-spectrogram to the auto-encoder and provide the desired intensity contour to the decoder. If the disentanglement has been successful, the decoder will use the new intensity contour to synthesise a mel-spectrogram with the original properties but with the desired intensity. The mel-spectrograms are inverted with the mel-inverter from [17].

We can use this auto-encoder to validate the proposed intensity estimator that was introduced in Section 2 and show that it really represents the (perceived) intensity. If the transformed
recording factor from Section 2.1 (Le) and the other with the adaptive recording factor strategy from Section 2.2 (Ad). As input to the estimators we choose the signal’s mel-spectrograms to provide a concise representation of the spectral properties to the intensity estimators and to match the input data to the auto-encoders that will be conditioned on these intensity estimators. Thus we use the same analysis parameters as in [16] to generate the mel-spectrograms. We experimented with different ways to estimate the signal power including the short-term-energy and perceptive loudness measures and found that we achieve the best results using the loudness measure from [26].

Both networks have the same architecture. The networks are simple convolutional feed-forward networks with 10 layers. Convolutions are 1d, treating the frequency bins as features. The number of filters is 100 in most of the layers, except the first, which has 80, the second to last, which has 50, and the last which has 1. The filter size is 3 in the first two layers and 1 elsewhere. With a step size of 12.5 ms per mel-frame the intensity estimator has thus a receptive field of 5 frames or 1 s.

We train the models with a batch size of 256 training samples of 80 mel-frames (or 1 s) each. The models are trained for 500 k updates using the adam [27] optimiser ($\beta_1 = 0.9$, $\beta_2 = 0.999$) with an initial learning rate of $1 \times 10^{-4}$. The learning rate is reduced by a factor of $\sqrt{0.7}$ if the validation loss does not decrease for a period of 16 k updates, with a minimum learning rate of $1 \times 10^{-6}$.

We train a baseline model BL with the same architecture but with constant input to obtain a reference as to how precise a model can be if it has no information available at all.

### 4.2. Architecture

We train two intensity estimators, one with the learned recording factor from Section 2.1 (Le) and the other with the adaptive recording factor strategy from Section 2.2 (Ad). As input to the estimators we choose the signal’s mel-spectrograms to provide a concise representation of the spectral properties to the intensity estimators and to match the input data to the auto-encoders that will be conditioned on these intensity estimators. Thus we use the same analysis parameters as in [16] to generate the mel-spectrograms. We experimented with different ways to estimate the signal power including the short-term-energy and perceptive loudness measures and found that we achieve the best results using the loudness measure from [26].

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We train the models with a batch size of 256 training samples of 80 mel-frames (or 1 s) each. The models are trained for 500 k updates using the adam [27] optimiser ($\beta_1 = 0.9$, $\beta_2 = 0.999$) with an initial learning rate of $1 \times 10^{-4}$. The learning rate is reduced by a factor of $\sqrt{0.7}$ if the validation loss does not decrease for a period of 16 k updates, with a minimum learning rate of $1 \times 10^{-6}$.

We train a baseline model BL with the same architecture but with constant input to obtain a reference as to how precise a model can be if it has no information available at all.

### 4.3. Auto-encoders

We train two auto-encoder configurations, one for each intensity estimator. For the auto-encoder we use almost the same architecture as in [16] only with the conditional input changed, as we add the intensity to the list of conditional inputs. Thus the auto-encoders are conditioned on the intensity, the $f_0$ and the voiced-voiced mask. We use the $f_0$ model from [28].

### 4.4. Evaluation methods

Since the dataset that we used to train our models does not include annotations for the voice intensity, we cannot evaluate the models directly with a ground truth. The hypothesis of this paper is that we can extract meaningful information from the spectral properties of the mel-spectrogram about the perceived voice intensity. Thus, it suffices to show that the information extracted by our intensity estimators reflects the perceived speech intensity. If the proposed auto-encoder indeed succeeds in changing the signals properties in a way that it is perceived as sung with the desired intensity, we can conclude that the proposed intensity estimators indeed encode the voice intensity.

To this end we asked 40 participants in a perceptive online study to rate the perceived intensity change of the transformed audio. Participants were presented pairs of audio where for each pair both files were generated using one of the auto-encoders and where in one file the intensity was changed while for the other the intensity was kept the same. Participants were asked to rate which recording sounded as if it was sung with a stronger / louder voice and could give an answer of -2, -1, 0, 1 or 2. The order within each pair and the overall order of the pairs were randomised and the volume of each of the files was normalised to the same average loudness according to the loudness model of [26]. In a second test, we asked 26 participants to rate the audio samples for their audio quality and computed a mean-opinion-score for each of the intensity changes of both models and the ground truth reference.

Furthermore, we analyse the consistency of the intensity estimators and the auto-encoders. The intensity estimators are evaluated by their ability to match the power contour of the given recordings by averaging the difference between the normalised contours in the logarithmic domain. Results are given in Table 1. The auto-encoder’s precision is evaluated by measuring the average difference between requested intensity and intensity measured in the synthesised mel-spectrograms for various intensity changes. The results are given in Table 2. The samples used for the perceptive test are available on our website.

### 5. Results

#### 5.1. Accuracies

Table 1 shows that both models, Ad and Le, can predict the intensity contours with an accuracy of 1 dB on average. This value is far lower than what we would obtain if no information about the voice intensity was available to the model as we can see for the baseline model BL.

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1. recherche.ircam.fr/anasyu/bous/acint2022
The values in this figure are averaged over all answers. Error bars represent the 95% confidence interval.

**Table 3**: Results of the perceptive test for relative intensity (subjective scale from −2 to 2) and audio quality (subjective scale from 1 to 5) with 95% confidence intervals.

| Intensity   | −10 dB | −6 dB  | 6 dB   | −10 dB |
|-------------|--------|--------|--------|--------|
| AdA         | −1.57 ± 0.32 | −0.84 ± 0.20 | 0.55 ± 0.20 | 0.08 ± 0.32 |
| LeA         | −1.29 ± 0.33 | −0.74 ± 0.22 | 0.09 ± 0.18 | 0.83 ± 0.22 |
| GT          | 1.64 ± 0.12 | 3.32 ± 0.37 | 3.82 ± 0.25 | 3.55 ± 0.31 |

From Table 2 we can see that the auto-encoders can use the information provided by the intensity estimator and successfully disentangle the intensity from the mel-spectrograms. The auto-encoder with adapted recording factor (AdA) performs with higher precision than the auto-encoder with learned recording factor (LeA). This indicates that the adapted recording factor model (Ad) is more robust than the learned recording factor model (Le) as some of the assumptions we made in Section 2.1 might in fact violated in the training dataset and which caused the intensity estimator Le to contain inconsistent information.

**5.2. Perceptive test**

Table 3 and Figures 1 and 2 summarise the results from the perceptive test. From Figure 1 we can see that both models are able to create a noticeable change in intensity for small changes in the target intensity. For the auto-encoder with adaptive recording factor (AdA) we observe that it has trouble creating convincing results for high increases in intensity. Investigating the files that were rated in the opposite direction we noticed that for those files the auto-encoder introduced significant amounts of artefacts which seemed to have created the opposite of the desired effect. The perceptive test suggests that the auto-encoders have a more noticeable impact when decreasing the intensity, which can be seen for both models and for all amounts of change. The auto-encoder with adaptive recording factor, AdA, seems to create a stronger effect when decreasing the intensity than the auto-encoder with learned recording factor, LeA. For increasing the intensity LeA seems to be better suited than AdA.

The quality ratings are given in Table 3 and in Figure 2. For self-reconstruction and small amounts of intensity change both models, AdA and LeA, seem to work equally well. For large changes in intensity the auto-encoder with learned recording factor (LeA) outperforms the auto-encoder with adaptive recording factor (AdA) by a margin. For increases in intensity LeA is able to hold its level of quality even for an increase of 10 dB. On the other hand LeA does make a larger error in Table 2. For decrease in intensity both auto-encoder models suffer strong degradation in quality although both models were successfully able to convince the participants that the recordings had much less intensity. Listening to these samples reveals that the auto-encoders increase the background noise significantly. Since our mel-inverter does not handle synthetic noise well, the overall audio quality is poor in these cases although the conversion itself is realistic.

From the test results we can conclude that the given auto-encoders were able to change the perceived intensity in singing voice, and therefore the intensity estimators capture the information about the voice intensity.

**6. Conclusions**

We have introduced a method to estimate the voice intensity from recordings with unknown amplification factors (recording factor). Two variants to overcome the missing the recording factor have been proposed: either by learning the unknown recording factor alongside the weights of the neural network (Le) or by adjusting the loss function to remove scaling and only compare the contours of the network’s output and the associated signal power (Ad). These intensity estimators have been used to condition a bottleneck auto-encoder to disentangle the voice intensity from mel-spectrograms. We have shown that both models produce consistent values and can produce the effect of changed voice intensity on singing recordings in most cases and with acceptable quality.

While the proposed auto-encoders produce a noticeable change in intensity, the audio quality is still significantly lower than real recordings especially when increasing the intensity. Consequently this first publication on neural intensity transformation has to be seen as a proof-of-concept rather than a well-polished system. Improvements to the audio quality are required for this method to be used in actual musical production. Nevertheless, the estimation method for the intensity opens new ways of voice classification, analysis and transformation.

![Figure 1: Perceived intensity change caused by changing the intensity with the proposed auto-encoders for various amounts. The values in this figure are averaged over all answers. Error bars represent the 95% confidence interval.](image)

![Figure 2: Subjective quality as reported by the participants on a scale from 1 to 5. The values in this figure are averaged over all answers. Error bars represent the 95% confidence interval.](image)
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8. References

[1] M. Umbert, J. Bonada, M. Goto, T. Nakano, and J. Sundberg, “Expression control in singing voice synthesis: Features, approaches, evaluation, and challenges,” IEEE Signal Processing Magazine, vol. 32, no. 6, pp. 55–73, 2015.

[2] J. M. Chowning, “Digital sound synthesis, acoustics and perception: A rich intersection,” in COST G-6 Conference on Digital Audio Effects (DAFX-00), 2000.

[3] E. B. Holmberg, R. E. Hillman, and J. S. Perkell, “Glottal airflow and transglottal air pressure measurements for male and female speakers in soft, normal, and loud voice,” The Journal of the Acoustical Society of America, vol. 84, no. 2, pp. 511–529, 1988.

[4] P. Alku, “Glottal inverse filtering analysis of human voice production—a review of estimation and parameterization methods of the glottal excitation and their applications,” Sadhana, vol. 36, no. 5, pp. 623–650, 2011.

[5] I. R. Titze and J. Sundberg, “Vocal intensity in speakers and singers,” The Journal of the Acoustical Society of America, vol. 91, no. 5, pp. 2936–2946, 1992.

[6] N. Henrich, C. d’Alessandro, B. Doval, and M. Castellengo, “Glottal open quotient in singing: Measurements and correlation with laryngeal mechanisms, vocal intensity, and fundamental frequency,” The Journal of the Acoustical Society of America, vol. 117, no. 3, pp. 1417–1430, 2005.

[7] B. Doval, C. d’Alessandro, and N. Henrich, “The spectrum of glottal flow models,” Acta acustica united with acustica, vol. 92, no. 6, pp. 1026–1046, 2006.

[8] A. Roebel, S. Huber, X. Rodet, and G. Degottex, “Analysis and modification of excitation source characteristics for singing voice synthesis,” in 2012 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2012, pp. 5381–5384.

[9] S. Huber and A. Roebel, “On glottal source shape parameter transformation using a novel deterministic and stochastic speech analysis and synthesis system,” in 16th Annual Conference of the International Speech Communication Association (INTERSPEECH), ISCA, 2015.

[10] E. Molina, I. Barbanchon, A. M. Barbanchon, and L. J. Tardón, “Parametric model of spectral envelope to synthesize realistic intensity variations in singing voice,” in 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2014, pp. 634–638.

[11] M. Gentilucci, L. Ardaillon, and M. Liumi, “Vocal distortion and real-time processing of roughness,” in International Computer Music Conference (ICMC), 2018.

[12] ———, “Composing vocal distortion: A tool for real-time generation of roughness,” Computer Music Journal, vol. 42, no. 4, pp. 26–40, 2019.

[13] K. Barkova, P. Haffner, and D. Larreur, “Intensity prediction for speech synthesis in french,” in ESCA Workshop on Prosody, 1993.

[14] K. Qian, Y. Zhang, S. Chang, X. Yang, and M. Hasegawa-Johnson, “Autovc: Zero-shot voice style transfer with only autoencoder loss,” in International Conference on Machine Learning (ICML). PMLR, 2019.

[15] K. Qian, Z. Jin, M. Hasegawa-Johnson, and G. J. Mysore, “F0-consistent many-to-many non-parallel voice conversion via conditional autoencoder,” in International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020.

[16] F. Bous and A. Roebel, “A bottleneck auto-encoder for f0 transformations on speech and singing voice,” Information, vol. 13, no. 3, p. 102, 2022.

[17] A. Roebel and F. Bous, “Neural vocoding for singing and speaking voices with the multi-band excited wavelet,” Information, vol. 13, no. 3, p. 103, 2022.

[18] L. Tsurulnik and S. Dubnov, “Singing voice database,” in International Conference on Speech and Computer (ICSC). Springer, 2019.

[19] Z. Duan, H. Fang, B. Li, K. C. Sim, and Y. Wang, “The nus sung and spoken lyrics corpus: A quantitative comparison of singing and speech,” in 6th Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC). IEEE, 2013.

[20] N. Grammalidis, K. Dimitropoulos, F. Tsalakianoud, A. Kikikides, P. Roussel, B. Denby, P. Chawah, L. Buchanan, S. Dupont, S. Laranja et al., “The i-treasures intangible cultural heritage dataset,” in 3rd International Symposium on Movement and Computing (MOCO), 2016.

[21] J. Koguchi, S. Takamichi, and M. Morise, “Psj: phoneme-balanced japanese singing-voice corpus,” in Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC). IEEE, 2020.

[22] H. Tamaru, S. Takamichi, N. Tanji, and H. Saruwatari, “Jvs-music: Japanese multispeaker singing-voice corpus,” arXiv preprint arXiv:2001.07044, 2020.

[23] I. Ogawa and M. Morise, “Tohoku kiritan singing database: A singing database for statistical parametric singing synthesis using japanese pop songs,” Acoustical Science and Technology, vol. 42, no. 3, pp. 140–145, 2021.

[24] J. Wilkins, P. Seetharaman, A. Wahl, and B. Parody, “Vocalset: A singing voice dataset,” in International Society for Music Information Retrieval Conference (ISMIR). ISMIR, 2018.

[25] L. Ardaillon, “Synthesis and expressive transformation of singing voice,” Ph.D. dissertation, Université Pierre et Marie Curie, 2017, https://hal.archives-ouvertes.fr/tel-01710926/document.

[26] B. R. Glasberg and B. C. Moore, “A model of loudness applicable to time-varying sounds,” Journal of the Audio Engineering Society, vol. 50, no. 5, pp. 331–342, 2002.

[27] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” in 3rd International Conference on Learning Representations (ICLR), 2014.

[28] L. Ardaillon and A. Roebel, “Fully-convolutional network for pitch estimation of speech signals,” in 20th Annual Conference of the International Speech Communication Association (INTERSPEECH). ISCA, 2019.