

ANALYSIS AND TRANSFORMATION OF VOICE LEVEL IN SINGING VOICE

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ABSTRACT

We introduce a neural auto-encoder that transforms the musical dynamic in recordings of singing voice via changes in voice level. Since most recordings of singing voice are not annotated with voice level we propose a means to estimate the voice level from the signal's timbre using a neural voice level estimator. We introduce the *recording factor* that relates the voice level to the recorded signal power as a proportionality constant. This unknown constant depends on the recording conditions and the post-processing and may thus be different for each recording (but is constant across each recording). We provide two approaches to estimate the voice level without knowing the recording factor. The unknown recording factor can either be learned alongside the weights of the voice level estimator, or a special loss function based on the scalar product can be used to only match the contour of the recorded signal's power. The voice level models are used to condition a previously introduced bottleneck auto-encoder that disentangles its input, the mel-spectrogram, from the voice level. We evaluate the voice level models on recordings annotated with musical dynamic and by their ability to provide useful information to the auto-encoder. A perceptive test is carried out that evaluates the perceived change in voice level in transformed recordings and the synthesis quality. The perceptive test confirms that changing the conditional input changes the perceived voice level accordingly thus suggesting that the proposed voice level models encode information about the true voice level.

Index Terms— Voice transformation, voice conversion, auto-encoder, voice level

1. INTRODUCTION

Voice level is the power with which human voice is produced. For singing, the voice level 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. Singing voice as a musical instrument inherits this quality and professional singers can sing a continuous spectrum of dynamics by adjusting the voice level. Similarly in speech most speakers can adapt the voice level 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 [2].

For both, singing and speech, not only the signal's power changes with the change in voice level but a wide range of voice properties as well, such that most people can easily distinguish soft speech close to the ear from someone shouting from far away, even though the signal's power might be the same at the listeners ear [3]. In fact the perceived loudness of sounds does only marginally depend on the signal power at the listener as our brain compensates for attenuations due to distance to the source [3].

Voice level can be derived from the intensity measured using a calibrated *sound pressure level* (SPL) meter at a fixed distance to the singer [2] and the relationship between voice level and other voice parameters have been investigated in various studies. In [4] glottal inverse filtering [5] is used to analyse the difference between soft, normal and loud voice in the glottal waveform. The relationships between open quotient, f_0 , lung pressure and sound pressure level are investigated in [6]. In [2] the relationship between vocal effort and the articulation, f_0 , creaky voice and formant positions is studied and the distance between speaker and addressee is used to vary the vocal effort / voice intensity of the participants. Special attention to the open quotient is given by the study in [7].

These studies have paved the way for glottal pulse models [8] which can be used to modify pulse parameters as a function of the voice level [9, 10]. However, the practical application of these models is limited as robustly obtaining glottal pulse parameters from voice recordings remains challenging. In [11] voice level changes were done by shifting the formant positions in vowels according to the statistics computed on a singing database. Related to the voice level in voice is the roughness as rough voice generally tends to occur in voice with very high voice level. Rough voice is, however, a different singing style that can happen in quiet singing as well. Some work has been done to simulate the effect of rough voice in singing synthesis [12, 13].

In this paper we aim to use neural networks to transform the voice level of singing voice recordings. Based on the observations above the voice level manifests itself heavily in the timbre. Thus it does not suffice to simply rescale the original signal. Numerous datasets with singing voice exist, however only a small fraction contains voice level annotations. Therefore, in this paper we provide a method to train a neural network to extract voice level without the need for explicitly annotated voice level. The estimated voice level can be calibrated using any of the recording conditions present in the database of singing recordings as a reference condition.

Thus, the contributions of this work are the following. (1.) We present an unsupervised algorithm that allows training a deep neural network to predict the voice level without the need to create annotated data. (2.) We use this voice level measure to train a bottleneck auto-encoder [14, 15] to transform the voice level in recordings of singing voice. The remaining paper is structured as follows: In Section 2 we introduce two ways to estimate the voice level from voice recordings where no voice level annotation exists. In Section 3 we present our adaptations of [16] to include the voice level 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 a short summary and an outlook in Section 6.

2. EXTRACTING VOICE LEVEL 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

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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 power and the recorded signal’s power as microphones have different directivities and transfer functions and the signal gain is adjusted to minimise quantisation noise when digitalising the microphone signal.

Therefore, without explicit annotation it is impossible to infer the voice level from an audio recording’s power. Still, if we look at the speech production mechanism, we notice that humans cannot increase the voice level without changing other properties of their voice [2, 4, 6, 7]. Thus we can infer the voice level from the signal’s timbre.

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 level l :

$$p = a_r l \quad (1)$$

with p and l being time varying sequences here and with the proportionality factor a_r 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

$$p = a_r^s l \quad (2)$$

for all files generated by a speaker s with a different a_r^s for each speaker.

The speaker dependent recording factor a_r^s can be learned alongside the weights θ of a neural network N_θ . As we aim to learn the voice level contour l from the spectral properties of the signal we have to prevent the network from using the signal power. This can be done by frame-wise normalisation thus removing the power contour from the input.

Using an L_2 error, we get the following error function

$$\|p - a_r^s N_\theta(n(x))\|_2^2 \quad (3)$$

with frame-wise normalisation n .

The resulting neural network N_θ allows estimating the voice level from the normalised signal: During inference we use the same recording factor for all recordings, in which case we can compare the recordings as if they were made under the same recording conditions. To calibrate the estimations to a specific recording we use the recording factor of that recording.

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. Prior to calculating the loss we choose a such that the L_2 error

$$e_a = \|p - aq\|_2^2 = \sum_t (p_t - aq_t)^2 \quad (4)$$

is minimal for each training sample:

$$\hat{a} = \operatorname{argmin}_a e_a \quad (5)$$

For a fixed pair of target and estimate (p, q) there exists an analytic optimal solution for a :

$$\hat{a} = \frac{p \cdot q}{\|q\|_2^2} = \frac{\sum_t p_t q_t}{\sum_t q_t^2} \quad (6)$$

where \cdot denotes the scalar product. Combining (4) and (6) and normalising $e_{\hat{a}}$ by $\|p\|_2^2$ yields the scalar product loss:

$$e_{\text{sep}} := \frac{e_{\hat{a}}}{\|p\|_2^2} = 1 - \frac{(p \cdot q)^2}{\|p\|_2^2 \|q\|_2^2} = 1 - (\bar{p} \cdot \bar{q})^2 \quad (7)$$

with $\bar{x} := x/\|x\|$ 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.

To calibrate the estimation during inference to the recording environment of a specific recording, we can calculate the recording factor according to (6) and rescale the network output by that factor.

3. PROPOSED VOICE LEVEL TRANSFORMATIONS

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

We can use this auto-encoder to validate the proposed voice level estimator that was introduced in Section 2 and show that it really represents the (perceived) voice level. If the transformed recordings are perceived to have been sung with a voice level that is coherent with the intended transformation (louder, less loud), we can conclude that the proposed voice level estimators in fact encode the voice level.

4. EXPERIMENTS

4.1. Data

All experiments are trained on the same dataset as [16], which is a combined dataset of CREL Research Database (SVDB) [17], NUS sung and spoken lyrics corpus [18], from the i-Treasures Intangible Cultural Heritage dataset [19] PJS phoneme-balanced Japanese singing-voice corpus [20], JVS-MuSiC [21], Tohoku Kiritan and Itako singing database [22], VocalSet: A singing voice dataset [23], as well as singing recordings from our internal singing databases used for the IRCAM Singing Synthesizer [24] and other projects.

4.2. Architecture

We train two voice level 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 voice level estimators and to match the input data to the auto-encoders that will be conditioned on these voice level 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 [25].

Both networks, **Le** and **Ad**, 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 voice level estimator has thus a receptive field of 5 frames or 50 ms. The mel-spectrograms are normalised frame-wise when fed as input to the voice level estimators.

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 500k updates using the adam [26] optimiser ($\beta_1 = 0.9$, $\beta_2 = 0.999$) with an initial learning rate of 1×10^{-4} . The learning rate is reduced by a factor of $\sqrt[4]{0.1}$ if the validation loss does not decrease for a period of 16k updates, with a minimum learning rate of 1×10^{-6} .

4.3. Auto-encoders

We train two auto-encoder configurations, one for each voice level estimator. For the auto-encoder we use almost the same architecture as in [16] only with the conditional input changed, as we add the voice level to the list of conditional inputs. Thus the auto-encoders are conditioned on the voice level, the f_0 and the voiced-unvoiced mask. We use the f_0 model from [27] and the mel-inverter from [28].

4.4. Evaluation methods

Since the dataset that we used to train our models does not include annotations for the voice level, 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 level. Thus, it suffices to show that the information extracted by our voice level estimators reflects the perceived voice level.

We use recordings that are labelled into different dynamics to investigate the relationship between dynamic and the proposed voice level estimator. Labelled data was obtained in [24] by asking a singer to sing one note from all combinations of the dynamics pp, mp, mf, f and ff and all French vowels on the same pitch. Thus we can create histograms over the estimated voice level for different dynamics and vowels. If the proposed method reflects the true voice level, lower dynamics should correspond to lower values in voice level.

Furthermore, we claim that the proposed voice level estimate is useful for changing how loud a phrase has been sung. Thus, if the proposed auto-encoder indeed succeeds in changing the signals properties in a way that it is perceived as sung with the desired voice level, we can conclude that the proposed voice level estimators indeed encode the voice level. To this end we asked 40 participants in a perceptive online study to rate the perceived voice level 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 voice level was changed while for the other the voice level 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 [25]. 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 voice level changes of both models and the ground truth reference.

The auto-encoder’s precision is evaluated by measuring the average difference between requested voice level and voice level measured in the synthesised mel-spectrograms for various voice level changes. The results are given in Table 1. The samples used for the perceptive test are available on our website¹.

5. RESULTS

5.1. Classification of dynamic

Figure 1 visualises the relationship between estimated voice level of **Ad** and the symbolic dynamic annotation of the recordings used for this investigation. Similar histograms are produced by model **Le**. First, we observe that louder dynamics produce higher voice level values so we can conclude that the voice level does indeed include information about how loud a note has been sung. If we look at the individual phonemes, we see that the dynamics create different clusters with increasing mean though for some vowels some dynamics have rather large overlap, e. g. for /e/ the pp and mp are largely overlapping: This is because we see the histogram of the voice level for each frame which naturally varies over time for the same dynamic for instance as a side effect of vibrato. Thus while some selected frames from different dynamics may be equally loud, the overall notes still have different loudness and can be measured as averages over larger durations. Furthermore, dynamics are subjective and a matter of interpretation. It could be that this particular singer does not make such a big difference between pp and mp for an /e/ in terms of voice level.

Comparing the histograms from different vowels we observe that the voice level can be very different for different phonemes under the same dynamic. This is because not all vowels are in fact equally loud. The vowel /a/, being an open vowel, can be sung much louder than /u/, being a close vowel. Thus for the same dynamic we can expect the resulting voice level to be different and it is no surprise that the estimated voice level for /a/ is much higher than for /u/. This explains why, if we average over all vowels, adjacent dynamics overlap — because the variations in voice level due to the phoneme are on the same scale as the variations due to the dynamic. Nevertheless, we can still very clearly distinguish between loud dynamics (f, ff) and quiet dynamics (pp, mp).

5.2. Accuracies

From Table 1 we can see that the auto-encoders can use the information provided by the voice level estimator and successfully disentangle the voice level 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

¹recherche.ircam.fr/anasynt/bous/aeint2022

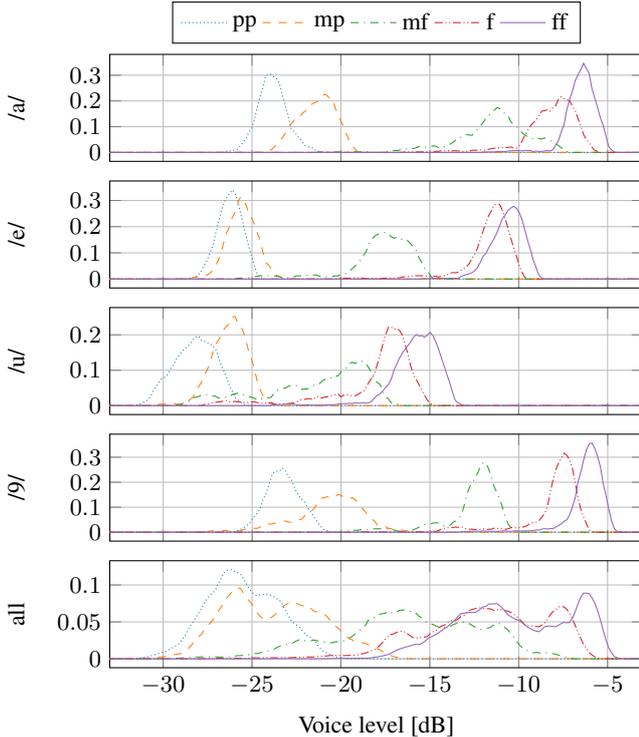


Fig. 1. Estimated voice level values for recordings in different dynamics plotted for the voice level model *Ad*. The graphs show smoothed relative histograms using a Gaussian kernel with $\sigma = 0.31$ dB. Only frames inside stable phonation are used, unvoiced frames and frames close (50 ms) to a voiced / unvoiced boundary are ignored. We show histograms for four selected vowels (out of a total of 15 vowels in the French language) and the average over all vowels (bottom). All graphs share the same horizontal axis. Phoneme annotations are in X-SAMPA.

made in Section 2.1 might in fact be violated in the training dataset which caused the voice level estimator *L θ* to provide inconsistent information.

5.3. Perceptive test

Table 2 summarises the results from the perceptive test. From the upper table we can see, that both models are able to create a noticeable change in voice level for small changes in the target voice level. For the auto-encoder with adaptive recording factor (*AdA*) we observe that it has trouble creating convincing results for high increases in voice level. 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

	-10 dB	-6 dB	0 dB	6 dB	10 dB
<i>AdA</i>	2.42	1.50	0.86	1.94	2.50
<i>LeA</i>	2.71	1.75	0.81	2.99	4.68

Table 1. Transformation precision [dB] of the auto-encoders. Errors are calculated between target voice level (as given to the auto-encoder) and voice level of the output (the voice level estimator applied to the transformed mel-spectrogram) for various voice level changes. The error is calculated on a logarithmic scale to provide meaningful values.

Voice level	-10 dB	-6 dB	6 dB	10 dB
<i>AdA</i>	-1.57 ± 0.32	-0.84 ± 0.20	0.55 ± 0.20	0.08 ± 0.32
<i>LeA</i>	-1.29 ± 0.33	-0.74 ± 0.22	0.69 ± 0.18	0.83 ± 0.22

Quality	-10 dB	-6 dB	0 dB	6 dB	10 dB
GT			4.64 ± 0.12		
<i>AdA</i>	2.12 ± 0.49	3.32 ± 0.37	3.82 ± 0.25	3.55 ± 0.31	2.78 ± 0.37
<i>LeA</i>	2.61 ± 0.44	3.40 ± 0.39	3.80 ± 0.26	3.55 ± 0.30	3.55 ± 0.39

Table 2. Results of the perceptive test for relative voice level (subjective scale from -2 to 2) and audio quality (subjective scale from 1 to 5) with 95% confidence intervals.

opposite of the desired effect. The perceptive test suggests that the auto-encoders have a more noticeable impact when decreasing the voice level, 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 voice level than the auto-encoder with learned recording factor, *LeA*. For increasing the voice level *LeA* seems to be better suited than *AdA*.

The quality ratings are given in the lower table of Table 2 For self-reconstruction and small amounts of voice level change both models, *AdA* and *LeA*, seem to work equally well. For large changes in voice level the auto-encoder with learned recording factor (*LeA*) outperforms the auto-encoder with adaptive recording factor (*AdA*) by a margin. For increases in voice level *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 1. For decrease in voice level 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 voice level. 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 voice level in singing voice, and therefore the voice level estimators capture the information about the true voice level.

6. CONCLUSIONS

We have introduced a method to estimate the voice level 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 (*L θ*) 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 voice level estimators have been used to condition a bottleneck auto-encoder to disentangle the voice level from mel-spectrograms. We have shown that both models produce consistent values and can produce the effect of changed voice level on singing recordings in most cases and with acceptable quality.

While the proposed auto-encoders produce a noticeable change in voice level, the audio quality is still significantly lower than real recordings especially when increasing the voice level. Consequently this first publication on neural voice level 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 voice level opens new ways of voice classification, analysis and transformation.

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