



A Neural TTS System with Parallel Prosody Transfer from Unseen Speakers

Slava Shechtman, Raul Fernandez

IBM Research AI

slava@il.ibm.com, fernanra@us.ibm.com

Abstract

Modern neural TTS systems are capable of generating natural and expressive speech when provided with sufficient amounts of training data. Such systems can be equipped with prosody-control functionality, allowing for more direct shaping of the speech output at inference time. In some TTS applications, it may be desirable to have an option that guides the TTS system with an ad-hoc speech recording exemplar to impose an implicit fine-grained, user-preferred prosodic realization for certain input prompts. In this work we present a first-of-its-kind neural TTS system equipped with such functionality to transfer the prosody from a parallel text recording from an unseen speaker. We demonstrate that the proposed system can precisely transfer the speech prosody from novel speakers to various trained TTS voices with no quality degradation, while preserving the target TTS speakers' identity, as evaluated by a set of subjective listening experiments.

Index Terms: prosody transfer, expressive speech synthesis, hierarchical prosody controls,

1. Introduction

Over the past decade, Neural Text-to-Speech (TTS) methods have made significant strides in enhancing the naturalness of synthesized speech, utilizing sequence-to-sequence (S2S) architectures [1, 2, 3]. Originally, those architectures implicitly predicted speech prosody, and thus lacked prosody controllability. Later models were further extended with such functionality. Hierarchical prosodic representations from various temporal scales of speech waveform, either learnt [4, 5] or measured [6, 7, 8, 9], were recently proposed to manipulate the synthesized prosody at various levels of granularity. These representations can be directly obtained from the speech recording, and are designed to be used as inputs, along with phoneme sequences, to generate and control high-quality speech output, and then manipulated in an intuitive way at inference time to obtain a particular prosodic realization [6, 7, 8, 9].

In some TTS applications, such as customer-care chat bots, it is useful to have an option to impose a precise user-defined prosody rendering for certain input texts by directly providing an audio recording exemplar to a TTS system. In this setup one expects the system to generate a specific prompt while closely mimicking the user's prosody (assuming the same text is spoken by the user) and ignoring the user's identity. We refer to this functionality as *parallel prosody transfer from unseen speakers*, or in short, *Unseen Parallel Prosody Transfer (UPPT)*. In real applications, it is desirable to have not a dedicated system to solve this problem, but rather to have an UPPT-enabled architecture capable of prosody transfer when provided with a {text, prompt} pair, and of defaulting to regular inference otherwise

when only the text is available.

Prior work on prosody transfer within S2S models has evolved from architectures that transplant broader prosodic features [10] toward models operating at more fine-grained resolutions [4, 11, 12]. One common feature among these works is that they propose dedicated models that *always* require an exemplar input to generate output, a limitation that we wish to eschew in this work. The most similar example from prior art is the approach described in the CopyCat2 architecture [13]. This model is both a conventional TTS system and a prosody-transfer system, and is capable of mimicking the fine-grained prosody implicit in a recording. It differs from our work, notably, in that it is confined to speakers seen in training, and does not accommodate unseen speakers, as required by the UPPT application. To the best of our knowledge, the proposal of an architecture flexible enough to accommodate default synthesis and prosody transplanted from any arbitrary, unseen speakers while maintaining high-quality output and preserving the target speaker's identity is a novel contribution of this work.

2. Architecture

When prosodic features are learnt from the training data, special caution should be taken to disentangle the speaker's identity from this prosodic representation, in order to make it less data sensitive and more suitable to the prosody-transfer task from an unseen speaker [13]. We have addressed this constraint by adopting a set of Hierarchical Prosody Controls (HPCs) originally proposed in [7] as an alternative. HPCs are less data sensitive by construction, are extracted directly from the recordings (no training is involved), and are globally normalized, making them only weakly dependent on the training data (due to the normalization procedure [6]) and more suitable to the UPPS use case. It was previously shown that HPCs are speaker agnostic [8], are able to generate a wide variety of speaking styles [8, 14], and provide word-level emphasis control [7].

In this work we precisely follow the HPC-controllable [7] Non-Attentive-Tacotron2 (NAT2) [3] architecture proposed in [14] as the speech-generation module of our system (see Fig. 1). We hypothesize, though, that the prosody-transfer precision can benefit from HPCs with a finer resolution than those proposed in those works, and consequently experiment with various kinds of HPC hierarchies, as described in Section 2.1. As detailed in [14], an input phonetic sequence passes through a Phonetic Encoder, is combined with the embedded HPC feature sequence, undergoes upsampling based on the predicted phone durations, and generates a sequence of acoustic feature vectors by an autoregressive Spectral Decode that are finally fed to an independently trained LPCNet [15] neural vocoder (see Fig. 1).

During training, the acoustic decoder obtains the ground-

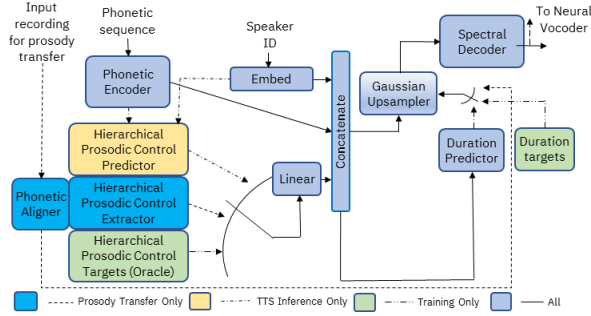


Figure 1: The proposed HPC-controllable neural TTS with a prosody transfer capability

truth HPCs and minimizes the acoustic regression loss, based on $L_1 + L_2$ loss operator [1], plus the duration prediction loss [3]. During inference, the system supports two modes of operation: a TTS mode and a prosody-transfer mode. To enable the TTS mode, an HPC predictor module is separately trained [14]. The HPC predictor is fed with the pretrained phonetic encoder (with all its trainable weights frozen) and predicts the HPC sequence by minimizing an MSE regression loss [8]. To enable the prosody-transfer mode, one has to provide a parallel audio recording in addition to the regular TTS input. The HPC parameter sequence is extracted directly from the recording (as detailed in section 2.2) and fed to the speech generation model, bypassing the HPC sequence prediction. While in prosody-transfer mode, the phone durations from the input recording can be either directly used or predicted by the duration predictor.

2.1. Hierarchical Prosody Controls (HPCs)

Hierarchical Prosody Controls (HPCs) comprise a low-dimensional set of temporal prosodic measurements (e.g. rhythm, pitch, energy), evaluated hierarchically over several linguistically-meaningful temporal intervals [8], e.g., sentence- and word-intervals [8] or utterance- and phone-intervals [9].

In this work we make use of a set of four prosodic measurements [8] at various temporal hierarchies, as summarized below. In addition to the sentence- and word-level HPCs [8], we investigate here how adding finer HPC granularity (i.e. syllable- and phone-level features) can facilitate the prosody-transfer precision. Therefore, we generalize the HPC formulation in [8] to support any amount of temporal hierarchy levels.

Let T be a desired HPC temporal hierarchy, e.g., $T = (\textit{sentence}, \textit{word}, \textit{syllable})$. Then, the absolute prosodic measurement set $H^{T_i} = \{h_{dur}^{T_i}, h_{\Delta f_0}^{T_i}, h_{f_0}^{T_i}, h_{\angle f_0}^{T_i}\}$ is evaluated (per intervals T_i), as follows:

- $h_{dur}^{T_i}$: The log of the average phone duration, along T_i .
- $h_{\Delta f_0}^{T_i}$: The f_0 dynamics (i.e., the difference between the 95- and 5-percentiles of $\log-f_0$), along T_i .
- $h_{f_0}^{T_i}$: The median $\log-f_0$, along T_i minus the median $\log-f_0$, along a corresponding single speaker data set. Note that the second term is required to make the absolute pitch measurement gender-agnostic.
- $h_{\angle f_0}^{T_i}$: The $\log-f_0$ linear regression slope along T_i .

The f_0 -based HPC measurements are performed based on a pitch trajectory obtained by the *RAPT* pitch detector [16] at 5ms time steps, and linearly interpolated through unvoiced regions.

The previous prosodic measurements also require phonetic alignment of the input waveform (at least for the fine-grained prosodic measurements). While offline forced alignment is not

usually a problem for high-quality TTS corpora, the precision of phonetic alignment can deteriorate in the UPPT use case, where just a single utterance of unknown audio quality from an unseen speaker must be phonetically aligned (see Section 2.2).

The H^{T_i} measurements are performed once per T_i interval and then propagated down to the temporal granularity of the phonetic encoder outputs (i.e., phones) to form piecewise functions that are constant within the corresponding T_i intervals. Based on the propagated absolute interval measurements \tilde{H}^{T_i} we construct the unnormalized *hierarchical* measurements by concatenating the corresponding *residual* interval measurements, according to (1).

$$P = [\tilde{H}^{T_0}, \tilde{H}^{T_1} - \tilde{H}^{T_0}, \dots, \tilde{H}^{T_i} - \tilde{H}^{T_{i-1}}, \dots] \quad (1)$$

Eventually, each input utterance is represented by a *normalized* HPC matrix \hat{P} of size $N_{\textit{phones}} \times N_{\textit{HPC}}$ (with the k -th column of \hat{P} denoted by \hat{p}_k), obtained by applying a global (corpus-wise) normalization on P (with p_k as its k -th column). Let the k -th component's global mean and standard deviation be μ_k and σ_k respectively. The normalization is then given by

$$\hat{p}_k = (p_k - \mu_k) / 3\sigma_k \quad (2)$$

In this work we explore the TTS and UPPT modes based on (*sentence, word*), (*sentence, word, syllable*) and (*sentence, word, phone*) hierarchies.

To support inference in TTS mode when observed HPC targets are unavailable, an HPC predictor is trained to generate the appropriate measurements. We empirically found that the original HPC predictor architecture (i.e., 3 stacked Bi-LSTM layers with 128 hidden nodes with output linear layer) [8] works well for the proposed HPC variants. Large-scale crowd-sourced MOS tests (up to 100 subjects, 40 samples per system, 25 votes per sample) revealed that an HPC-controlled *NAT2* architecture [14] generates speech with the same quality and naturalness for all the proposed variants.

2.2. Unseen Parallel Prosody Transfer (UPPT)

We consider two approaches for HPC-based prosody transfer within a *NAT2* TTS architecture [14] customized for UPPT:

- *HPC import*: the sequence of HPC features is extracted from the input audio, the duration predictor module is further applied to predict the phone durations. In that case the rhythm transfer may become less precise, but this setup is less vulnerable to alignment errors.
- *HPC and duration import*: the sequence of HPC features and phone durations are directly extracted from the input audio. Timing transfer may be more precise but also more sensitive to potential alignment errors.

Both approaches require automatic alignment of a single utterance of potentially noisy quality and uttered by unseen speakers. This can be a challenge, and certain alignment errors are inevitable, so there is a certain trade-off between the *average* prosody transfer precision (depending on the HPC granularity) and the amount of perceivable *local* quality issues due to occasional alignment errors. In our work we make use of the open-source Montreal Forced Aligner (MFA) package [17] with its pretrained US English triphone acoustic model *english_us_arpa* and default speaker adaptation [17] to obtain the temporal intervals for HPC calculations. Although rare alignment problems resulted in occasional local audible quality deterioration, we found it performs reasonably well on unseen data of various quality (see more details in Section 4).

When evaluating HPCs (see Section 2.1) for an utterance from a novel speaker, one needs to estimate their median $\log-f_0$ to evaluate the $h_{f_0}^{T_i}$ components. We do this based on the input utterance. Additionally, for the final normalization we use the pre-stored global (multi-speaker) statistics collected from the seen speakers (i.e., the TTS training data).

3. Experimental Setup

The training material for our speech synthesis system comprises proprietary wide-band (22.05 kHz) speech corpora, ranging from 16k to 23k sentences, from three professional native speakers of US English (2 females and 1 male) uttered in various speaking styles. One female and one male voice were selected as target synthesis voices to evaluate prosody transplantation in a *neutral* style. For UPPT evaluation we constructed a set of 40 source utterances containing versatile samples from various speakers, speaking styles and data sets, selected by listening to the reference recordings only, according to the following guidelines: Choose samples between 5 and 25 words that convey “interesting” (“non-average”) prosodic patterns, and try to avoid many long sentences, as that might make the subjective assessment task more difficult for the listeners. Based on this, we selected the following data for six speakers:

- 20 *out-of-domain*, unseen samples from the *test-clean* section of LibriTTS [18], uttered by four *unseen* unprofessional speakers (two females (set L-F) and two males (set L-M); five utterances from each). The selected speaker IDs are: *121_127105*, *1089_134686*, *2300_131720*, *3575_170457*.
- 10 *in-domain* unseen recordings from one *unseen* professional female speaker
- 10 *in-domain* unseen recordings from one *seen* (in training) professional male speaker

We trained the following multi-speaker TTS systems sharing the prosody-controlled NAT2 architecture of [14] with various prosody controls to assess different prosody transplantation techniques. (See Section 2.2 for more details on the HPC definitions and durations employed by Systems 2-8.)

1. *Ref*: a system that implements classic prosody transfer by means of *reference encoding* [10] instead of HPCs. Here the trainable *reference encoder* generates a fixed-sized utterance-level prosodic embedding from the input spectrogram. This embedding is broadcast-concatenated with the phonetic encoder outputs [10] (instead of HPCs in Fig. 1) and then fed into the spectral decoder. For the sake of consistency, the remaining encoder-decoder architecture is identical to the rest of the HPC-controlled systems.
2. *HPC0-TTS*: an HPC-controlled TTS system [14], that deploys the two-level HPCs [14, 8] (sentence- and word- level). On inference, the HPCs are predicted from the input phonetic sequence. This system does no prosody transfer.
3. *HPC0-D0*: an HPC-controlled prosody transfer system [14], that deploys the two-level HPCs [14, 8] (sentence- and word-level) and applies *HPC import* only.
4. *HPC0-D1*: Like *HPC0-D0* with additional *duration import*.
5. *HPC1-D0*: an HPC-controlled prosody transfer system [14], that deploys three-level HPCs (sentence-, word- and syllable-level) and applies *HPC import* only.
6. *HPC1-D1*: Like *HPC1-D0* with additional *duration import*.
7. *HPC2-D0*: an HPC-controlled prosody transfer system [14], that deploys three-level HPCs (sentence-, word- and phone-level) and applies *HPC import* only.

8. *HPC2-D1*: Like *HPC2-D0* with additional *duration import*.

Table 1: 4-scale prosody similarity after the prosody transfer to a male target speaker

		Dissim. ⁺	Dissim.	Sim.	Sim. ⁺	Score	Rank
Ref.	All	40.8%	31.5%	20.0%	7.8%	1.95	5
	L-F	28.5%	39.0%	23.0%	9.5%	2.14	
	L-M	47.0%	28.5%	17.5%	7.0%	1.85	
HPC0-TTS	All	38.1%	27.6%	23.6%	10.6%	2.07	4
	L-F	30.5%	29.5%	30.0%	10.0%	2.20	
	L-M	43.0%	24.5%	22.5%	10.0%	2.00	
HPC0-D0	All	9.1%	19.5%	38.1%	33.2%	2.95	3
	L-F	13.5%	21.5%	37.0%	28.0%	2.80	
	L-M	8.5%	22.5%	40.0%	29.0%	2.90	
HPC0-D1	All	7.2%	17.2%	34.4%	41.1%	3.09	3
	L-F	9.0%	28.0%	32.0%	31.0%	2.85	
	L-M	10.0%	16.0%	34.5%	39.5%	3.04	
HPC1-D0	All	8.5%	17.6%	37.5%	36.4%	3.02	3
	L-F	13.5%	20.0%	36.5%	30.0%	2.83	
	L-M	6.5%	19.5%	35.0%	39.0%	3.07	
HPC1-D1	All	5.2%	14.8%	38.4%	41.6%	3.16	2
	L-F	8.5%	17.0%	35.0%	39.5%	3.06	
	L-M	5.5%	11.5%	40.5%	42.5%	3.2	
HPC2-D0	All	4.1%	11.9%	38.2%	45.8%	3.257	1
	L-F	6.5%	14.5%	42.0%	37.0%	3.10	
	L-M	2.5%	11.0%	33.5%	53.0%	3.37	
HPC2-D1	All	5.4%	11.5%	36%	47.1%	3.248	1
	L-F	8.5%	17.0%	34.5%	40.0%	3.06	
	L-M	4.0%	10.0%	36.0%	50.0%	3.32	

4. Evaluation

We designed a set of subjective evaluations to assess how well the prosody is transferred from various input utterances to a male and a female target voices that are part of a multi-speaker TTS training corpus. We conducted several crowd-based subjective listening tests to evaluate : (i) prosody similarity, (ii) quality & naturalness, (iii) speaker similarity. All experiments were conducted on the AMT crowd-sourcing platform with votes collected from 30-45 subjects qualified as *masters* [19]. 40 parallel stimuli with identical texts per system were used in the *prosody similarity* and *quality naturalness* tests with each stimuli assessed by 20 distinct subjects on average (800 votes per system). *Speaker similarity* was tested with 10 stimuli per system, assessed by 20 distinct speakers each (200 votes per system). The outcomes for each target speaker (male and female) were evaluated in distinct experiments.

(i) *Prosody similarity* was assessed by a 4-level pairwise similarity test, as in [20], where subjects assessed unordered stimuli pairs with one stimulus containing an input recording with the source prosody, and the other a corresponding synthetic sample uttered by either of the prosody transfer systems (randomized). The subjects were asked to “ignore the speaker identity” and “judge how similar they find the samples in terms of *how the speakers are saying them*, i.e., their intonation, speaking pace, rhythm, pausing, etc.” The 4-level scale was labeled with “Very dissimilar” (Dissim⁺), “Somewhat Dissimilar” (Dissim), “Somewhat similar” (Sim), “Very similar” (Sim⁺). The results for this test are presented in Tables 1 and 2, showing the distribution over raw similarity values plus the average score (assuming values 1 to 4 in the 4-level categorical scale). A Barnard’s exact test [21] (two-sided, $p = 0.05$) was used to calculate significance between systems

Table 2: 4-scale prosody similarity after the prosody transfer to a female target speaker

		Dissim. ⁺	Dissim.	Sim.	Sim. ⁺	Score	Rank
Ref.	All	38.1%	31.9%	21.1%	8.9%	2.01	4
	L-F	33.5%	31.5%	24.5%	10.5%	2.12	
	L-M	34.5%	32.0%	21.0%	12.5%	2.12	
HPC0-TTS	All	38.1%	29.6%	23.8%	8.5%	2.03	4
	L-F	33.5%	27.0%	30.5%	9.0%	2.15	
	L-M	35.5%	29.5%	24.0%	11.0%	2.11	
HPC0-D0	All	8.5%	21.8%	38.1%	31.6%	2.93	3
	L-F	11.5%	24.5%	34.5%	29.5%	2.82	
	L-M	7.0%	21.0%	38.0%	34.0%	2.99	
HPC0-D1	All	6.2%	16.6%	40.1%	37.0%	3.08	2
	L-F	6.5%	20.0%	32.5%	41.0%	3.08	
	L-M	9.0%	15.5%	36.5%	39.0%	3.08	
HPC1-D0	All	5.8%	15.9%	40.1%	38.2%	3.11	2
	L-F	8.5%	20.0%	37.0%	34.5%	2.98	
	L-M	5.0%	17.5%	34.0%	43.5%	3.16	
HPC1-D1	All	5.1%	11.2%	37.6%	46%	3.24	1
	L-F	6.5%	11.5%	39.0%	43.0%	3.19	
	L-M	5.5%	10.5%	40.5%	43.5%	3.22	
HPC2-D0	All	3.8%	11.8%	36.2%	48.2%	3.288	1
	L-F	3.5%	14.0%	37.5%	45.0%	3.24	
	L-M	2.5%	13.0%	34.5%	50.0%	3.32	
HPC2-D1	All	3.8%	12.2%	35.6%	48.4%	3.286	1
	L-F	5.0%	15.5%	35.5%	44.0%	3.19	
	L-M	2.5%	10.5%	33.5%	53.5%	3.38	

on the binary similar/dissimilar votes to determine a ranking among the 8 systems (or among groupings thereof) that do not differ significantly from each other in terms of prosodic similarity. We are including in the rightmost column the rank received by the system from column 1 (smallest is best). In addition to the results for *all* the UPPT stimuli set (6 speakers), we also present the scores for the more challenging input subsets (i.e. unprofessional LibriTTS [18]), pooled by gender. These results demonstrate that the proposed HPC-based systems (of various HPC granularity) significantly outperform the reference system. The results also reveal that adding finer granularity to HPC features as well as importing phone durations gradually improve the prosody transfer precision. There is a high variance for the perceived prosody similarity when transferring prosody from various input voices. However, one can clearly notice that the same unseen voices perform similarly for both same-gender and cross-gender prosody transfer. One can also observe that prosody transfer from out-of-domain unprofessional recordings is not consistently worse than the overall performance (that includes professional recordings of the in-domain material).

(ii) *Quality & naturalness* assessment is presented in Table 3 (with distinct tests for male *M* and female *F* target speakers). In addition to MOS scores (with *PCM* recordings anchor) we provide the stimulus count (out of 40) with audible local problems that presumably have appeared as a result of forced-alignment errors (as tagged by a speech expert listening). We found the majority of such errors were too subtle to significantly reduce MOS, but may be indicative of potential sensitivity of a system to forced alignment during UPPT inference. The MOS results reveal that the quality of the proposed HPC-based prosody transfer systems is preserved as compared to the reference TTS operation (*HPC0-TTS*) and outperforms the *Ref* system. The MOS score differences between various HPC-based system configurations is found to be not statistically significant ($p = 0.05$). However, based on the alignment-error counts, the models based on the phone-level HPCs (*HPC2-D0*, *HPC2-*

Table 3: MOS scores and alignment error count after the prosody transfer

System	F		M	
	MOS	Aln.Err.	MOS	Aln.Err.
Ref.	3.62 ± 0.07	0	3.46 ± 0.07	0
HPC0-TTS	3.86 ± 0.06	0	3.71 ± 0.07	0
HPC0-D0	3.89 ± 0.06	0	3.75 ± 0.07	0
HPC0-D1	3.87 ± 0.07	0	3.71 ± 0.07	1
HPC1-D0	3.94 ± 0.06	0	3.74 ± 0.07	1
HPC1-D1	3.94 ± 0.06	3	3.77 ± 0.07	1
HPC2-D0	3.88 ± 0.07	5	3.74 ± 0.07	3
HPC2-D2	3.92 ± 0.06	7	3.74 ± 0.07	2
PCM	4.51 ± 0.05	0	4.51 ± 0.05	0

Table 4: 4-scale speaker similarity after the prosody transfer compared to the TTS inference

		Dissim. ⁺	Dissim.	Sim.	Sim. ⁺	Score	Rank
Ref	F	17.1%	22.1%	27.1%	33.7%	2.77	3
	M	12.0%	17.8%	41.4%	28.8%	2.87	3
HPC0-D0	F	5.0%	12.1%	31.7%	51.3%	3.30	2
	M	2.6%	12.6%	38.7%	46.1%	3.28	2
HPC0-D1	F	3.0%	14.1%	33.2%	49.7%	3.30	2
	M	3.1%	14.1%	38.2%	44.5%	3.24	2
HPC1-D0	F	9.6%	13.6%	29.8%	47.0%	3.14	2
	M	4.7%	18.8%	33.9%	42.7%	3.15	2
HPC1-D1	F	6.1%	10.1%	39.9%	43.9%	3.22	2
	M	6.2%	17.2%	40.1%	36.5%	3.07	2
HPC2-D0	F	4.0%	16.1%	37.7%	42.2%	3.18	2
	M	4.2%	16.7%	38.0%	41.1%	3.16	2
HPC2-D1	F	7.5%	14.6%	36.7%	41.2%	3.12	2
	M	3.7%	14.7%	38.7%	42.9%	3.21	2
HPC0-TTS	F	2.5%	9.0%	21.6%	66.8%	3.53	1
	M	1.8%	4.7%	37.1%	56.5%	3.49	1

DI) are not recommended, although they result in the highest prosody similarity scores (Tables 1, 2).

(iii) *Speaker similarity* evaluation results are finally presented in Table 4 (with distinct tests for male *M* and female *F* target speakers, and all the systems compared to the regular TTS system *HPC0-TTS*). The rightmost column identifies systems that do not differ significantly (in terms of Barnard’s exact test) with the same rank, demonstrating for all the HPC-based systems non-significantly different speaker similarity scores¹.

5. Summary

We presented a novel HPC-based neural TTS system with UPPT functionality, and demonstrated through extensive perceptual evaluations that the systems can transfer prosody from input exemplars uttered by novel speakers to various trained TTS voices with high precision while incurring no quality degradation and preserving the target speaker similarity. Extensions of this work will dive deeper into the robustness of the techniques under more extreme transfer conditions (e.g., unusually elongated sounds), and look into going beyond pitch and duration to transfer various timbral effects observed in an input recording, as might be the case with highly emotive speech.

¹Audio samples are available at <https://ibm.biz/IS23-TBE>

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