INTO-TTS: INTONATION TEMPLATE BASED PROSODY CONTROL SYSTEM

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ABSTRACT
Intonations play an important role in delivering the intention of a speaker. However, current end-to-end TTS systems often fail to model proper intonations. To alleviate this problem, we propose a novel, intuitive method to synthesize speech in different intonations using predefined intonation templates. Prior to TTS model training, speech data are grouped into intonation templates in an unsupervised manner. Two proposed modules are added to the end-to-end TTS framework: an intonation predictor and an intonation encoder. The intonation predictor recommends a suitable intonation template to the given text. The intonation encoder, attached to the text encoder output, synthesizes speech abiding the requested intonation template. Main contributions of our paper are: (a) an easy-to-use intonation control system covering a wide range of users; (b) better performance in wrapping speech in a requested intonation with improved objective and subjective evaluation; and (c) incorporating a pre-trained language model for intonation modelling. Audio samples are available at [https://srtts.github.io/IntoTTS](https://srtts.github.io/IntoTTS).

Index Terms— Speech synthesis, Intonation, Prosody, Text-to-speech, End-to-end TTS

1. INTRODUCTION

In oral conversations, it is crucial to deliver speech in an appropriate intonation to ensure the speaker’s correct intention. Despite its identical syntactic structure, a single sentence can convey various intentions with different intonations. For example, in English, if a speaker asks a yes/no question in a falling intonation, then it is more probable that the speaker is demanding for confirmation or a gentle request rather than an actual answer, while the same interrogative sentence in a rising manner functions as a genuine question [1][2]. Utterances wrapped in a poorly chosen intonation often lead to miscommunication.

The same holds true for speech synthesis. TTS systems should be able to synthesize speech in an appropriate intonation to the context, or at least allow users to choose one, in case they have a specific preference. However, many of the existing TTS systems fail to do so, degrading its naturalness. They usually take text as the only input. With no additional cues being provided, they lack ability to synthesize a single sentence in various intonations. To mitigate this issue, some approaches propose to control prosody by feeding auxiliary information along with the text. One approach is utilizing a prosody embedding extracted from a reference encoder [3], followed by many other variations [4][7]. Their methods allow users to control some prosody factors in detail. However, to our best knowledge, they all require a reference audio for synthesis, leaving it a user’s burden to explore.

The Global Style Tokens (GST) [8] method utilizes tokens as soft labels to control speech styles. Users can either feed a reference audio or adjust the tokens to synthesize speech in various styles. However, the exact roles of each token are still ambiguous. This does not guarantee that a specific style factor, such as intonation, can be properly reflected to the model. Moreover, additional works should be preceded to investigate appropriate weights and tokens to map their numerical values to the corresponding style labels. These reference encoder-based methods mainly aim to imitate the general style of the reference speech. Hence, controlling a specific factor, such as intonation, is not a suitable task for these approaches.

In this work, we propose Into-TTS, a novel, intuitive method to synthesize speech in different intonations using predefined Intonation Templates (IT). We extend the template-based approaches [9][10] to the intonation level, introducing intonation templates that are created using an unsupervised clustering method. These predefined intonation templates provide users a simple solution to synthesize speech in an intonation pattern they demand, offering only a limited number of options to the users. Moreover, the unsupervised clustering approach requires no additional annotation, therefore most of currently available speech corpora can be directly utilized.

In the proposed method, two modules are added to a Tacotron [11][12] variant [13]: an intonation predictor and an intonation encoder. The intonation predictor learns to recommend an intonation template suitable to the given text. The intonation encoder takes an intonation template index as input, yielding the corresponding intonation embedding to the decoder. This enables the TTS model to synthesize speech in the given intonation accordingly.

Inference works in two different modes: AUTO and MANUAL. In the AUTO mode, where no specific preference to an intonation pattern type is provided, the intonation predictor automatically recommends a suitable intonation to
the text, then it’s synthesized accordingly. In the MANUAL mode, when a specific preference to an intonation is explicitly requested, the TTS model synthesizes speech in that specific intonation template. In either mode, it is no longer necessary to control numerous factors individually, which allows users to easily utilize the system, even if they have little background knowledge.

Main contributions of this paper include but are not limited to:

- A convenient intonation control system that can cover various types of users, even those without professional knowledge on TTS frameworks.
- Improved performance to synthesize speech in a desired intonation.
- Feasibility to incorporating pre-trained language model to intonation modelling in TTS frameworks.

2. PROPOSED METHOD

The proposed method consists of two parts: (a) creating intonation templates by unsupervised clustering; and (b) jointly training the TTS model with the intonation predictor and the intonation encoder, utilizing a predefined set of intonation templates.

2.1. Intonation Templates

Linguists typically classify English intonation into the following four patterns: declarative, yes/no question, incredulity, and obviousness [14]. However, manually annotating these intonation patterns is not an easy task. As many researchers have pointed out, it requires high cost and often yields unreliable annotated results, partly due to the complexity of the ToBI [15] system [4,16].

In this paper, we propose a method to automatically classify intonations without any annotated audio data, creating intonation templates in an unsupervised manner. First, all audio files are de-noised and trimmed with a very tight margin. The trimming process minimizes false detection of F0 after the end of utterances, and eases sentence-final alignment among the recordings. F0 is then extracted from speech by the RAPT [17] algorithm. The F0 values of unvoiced segments are linearly interpolated according to the F0 values of the nearby voiced segments. Next, to eliminate the speaker variation effect on F0, the F0 values in each utterance are \( L_2 \)-normalized, i.e. dividing the F0 values by the square root of the sum of the squared F0 values. After the normalization, the last 0.5 seconds of the F0 values from each recording are selected for clustering, since the mean length of sentence-final intonation segments in English is 0.37 seconds with the standard deviation of 0.15 [18]. These sentence-final frames of F0 are automatically classified into \( N \) types of intonations via k-means clustering.

![Figure 1](image1.png)

**Figure 1:** A set of intonation templates that roughly corresponds to the Liberman’s classification of English intonation patterns [14]. Each F0 contour represents the centroid of each cluster after k-means clustering.

Figure 1 illustrates the F0 contours of the centroids of each intonation cluster after k-means clustering. We empirically observed that choosing \( N = 4 \) yields a set of intonation templates closest to the Liberman’s classification of English intonation [14]. This also has an advantage of providing users with an appropriate number of intuitive options. When \( N \) is greater than 4, it creates a couple of intonation templates that are similar enough for users without any linguistic background to properly differentiate.

2.2. Model Architecture

Into-TTS is built upon a Tacotron variant [13]. This Tacotron variant is mainly based on Tacotron 2 [12], with some modifications to utilize the acoustic features from the LPCNet vocoder [19]. We add two modules to this Tacotron variant model: an intonation predictor and an intonation encoder.

As illustrated in Figure 2, the intonation predictor learns to recommend a suitable intonation template to the context of text. The intonation encoder handles the intonation information and passes it to the decoder.

2.2.1. Intonation Predictor

The intonation predictor takes the text encoder output \( e_{1:l} \) as input, where \( l \) is the length of the input text. The intonation predictor yields a predicted intonation template index, \( \hat{p} \). The intonation predictor consists of two linear layers. The first layer has 128 dimensions with ReLU as an activation function. The second layer has a size of \( N \) dimensions, where \( N \)
is the number of intonation templates. In this paper, we use $N = 4$, as mentioned in Section 2.1. The second layer has Softmax as an activation function. Finally, an average pooling layer follows, computing the most probable intonation template. Stop gradient is applied to the input of the intonation predictor to prevent the intonation predictor from affecting any other modules during training. We add a cross-entropy loss of weight 0.1 to the intonation predictor $L_{IP}$ along with the loss from [13] $L_{Tacotron}$.

2.2.2. Intonation Encoder

The intonation encoder takes a pre-annotated intonation template index as input. It yields the corresponding intonation embedding from the lookup table. Feeding a pre-annotated intonation template index to the intonation encoder helps train the model more efficiently, preventing any errors from the intonation predictor in earlier training steps. The output from the intonation encoder, $i$, is replicated to $i_{1:N}$ to match the text length, then is concatenated to the output of the text encoder, providing the intonation information to the decoder.

2.3. Inference Modes: AUTO and MANUAL

During inference, two modes are available: AUTO and MANUAL, as shown in Figure 3. In the AUTO mode, when no specific preference to intonation exists, Into-TTS determines an intonation template automatically. As illustrated in the blue dotted lines in Figure 3, the intonation predictor automatically recommends a compatible intonation template for the context of the input text. This AUTO mode has a great advantage of making the inference process straightforward by eliminating a mandatory step of determining an intonation pattern, even when no specific preference is given. Hence, it can cover a wide range of users, even those who are reluctant to choose an intonation pattern for every single sentence.

On the other hand, the MANUAL mode is utilized when an explicit preference to a specific intonation type is given. In this mode, the intonation predictor is ignored. Instead, the intonation encoder takes the manually chosen intonation template index as input. The red dotted line in Figure 3 represents the inference process in the MANUAL mode. Even in the MANUAL mode, there is no need to control numerous parameters to control prosody as in the previous reference encoder-based methods. In users’ perspective, they are offered only $N + 1$ options: the AUTO mode or one of the $N$ intonation templates. This simplicity in the inference process lowers the barrier for non-professional users.

3. EXPERIMENTAL SETUP

An internal database of total 21.2 hours of English speech recordings from 13,000 sentences was utilized for the experiments. All of the recordings are from two professional voice actors, a male and a female. 300 utterances from each speaker were selected as a test set and excluded from training. The VCTK dataset [20] was included along with the internal database to create a set of intonation templates. We empirically observed that including the VCTK dataset helps generalize intonation patterns among different speakers, yielding a better set of intonation templates.

The Tacotron variant model [13] was tested as a very baseline. Baseline-GST model was compared to investigate if the GST-based approach [8] can synthesize speech in a specifically requested intonation. In the baseline-GST model, the reference encoder with the GST is utilized instead of the intonation encoder. In the inference phase, to generate speech in an intended intonation template, we select one representative speech from the training set for each intonation template and feed it to the reference encoder. The intonation predictor
Table 1: Pitch distance and Mean Opinion Score (MOS) with 95% confidence intervals.

| Model Configuration | Intonation Predictor | Intonation Encoder | Metrics         |
|---------------------|---------------------|--------------------|-----------------|
| Ground Truth        | X                   | X                  | X (4.46 ± 0.06) |
| Baseline [13]       | X                   | X                  | X (4.08 ± 0.10) |
| Baseline-GST        | O                   | X (Reference Encoder) | 0.327            | 4.11 (±0.09) |
| Into-TTS (proposed) | O                   | O                  | 0.278           | 4.18 (±0.09) |
| Into-TTS + BERT     | O (BERT)            | O                  | 4.18 (±0.08)    |

is also added to the baseline-GST model to utilize the AUTO mode as in Into-TTS. All of the TTS models were trained for 350k steps. The bunched LPCNet [21] was utilized as a neural vocoder to convert the acoustic features into actual waveforms.

With recent developments in incorporating pre-trained language model to TTS systems [22–24], a stand-alone intonation predictor finetuned from a pre-trained BERT BASE model [25] was tested for comparison, in addition to the proposed intonation predictor. This BERT predictor is finetuned for three epochs and takes normalized text as input.

4. RESULTS AND DISCUSSION

4.1. Objective Evaluation

We use the mean pitch distance as the objective evaluation measurement. The pitch distance is calculated as a Euclidean distance of the F0 values of the sentence-final 0.5 seconds between speech samples synthesized by a specific intonation template and the centroid of the corresponding intonation template. The speech samples from Into-TTS were synthesized in the MANUAL mode, producing four different types of intonations for each sentence. The corresponding speech samples from the baseline-GST model were synthesized by feeding the speech with smallest pitch distance to the centroid of the corresponding intonation template, to the reference encoder. The proposed method shows the smallest mean pitch distance for both sets, compared to the baseline GST model as shown in Table 1. The smaller mean pitch distance observed in Into-TTS proves that the proposed intonation encoder synthesizes speech samples in the desired F0 contour more properly, closer to the requested intonation template.

4.2. Subjective Evaluation

For subjective evaluation, 195 testers were recruited via Amazon Mechanical Turk[1] for mean opinion score evaluation. Each tester was provided with randomly chosen 72 speech samples. The testers were instructed to evaluate the speech samples in the following scale: Excellent(5), Good(4), Fair(3), Poor(2), and Bad(1) with an interval of 0.5.

The speech samples from Into-TTS and the baseline-GST model were synthesized in the AUTO mode, the intonation predictor automatically choosing an intonation type for each sentence. As shown in Table 1, Into-TTS achieves the highest mean opinion score, outperforming all of the baselines. The improved mean opinion score of the baseline-GST model suggests that the intonation predictor combined with the reference encoder helps enhance overall naturalness of synthesized speech. The enhancement in naturalness is even more apparent in the proposed Into-TTS, where the proposed intonation predictor is incorporated with the proposed intonation encoder, as shown in the highest mean opinion score of Into-TTS. This result proves that our proposed model realizes improved naturalness compared to the previous approaches, even offering an easy-to-use TTS system to users at the same time. Additionally, similar performance was observed when the intonation predictor had been replaced by the BERT predictor. This suggests that our proposed intonation predictor’s performance is comparable to that of the pre-trained language model.

5. CONCLUSION AND FUTURE WORK

In this work, we propose Into-TTS, an intuitive TTS system to synthesize speech in a desired intonation. After creating intonation templates in an unsupervised clustering method, we introduce the following two modules to the end-to-end TTS model: the intonation predictor and the intonation encoder. The template-based approach along with the intonation predictor can cover a wide range of users, from those without any specific preference to those with a specific request. This method can even allow users with shallow expertise to utilize the TTS system conveniently. The proposed method outperforms the baseline models in two metrics: pitch distance and mean opinion score. These results prove that Into-TTS can synthesize speech that follows the desired pitch contour better than the previous approaches, even enhancing naturalness at the same time.
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