Foot-based Intonation for Text-to-Speech Synthesis using Neural Networks

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Abstract

We propose a method ("FONN") for F0 contour generation for text-to-speech synthesis. Training speech is automatically segmented into left-headed feet, annotated with syllable start/end times, foot position in the sentence, and the number of syllables in the foot. During training, we fit a superpositional intonation model comprising accent curves associated with feet and phrase curves. We propose to use a neural network for model parameter estimation. We tested the method against the HMM-based Speech Synthesis System (HTS) as well as against a template-based variant of FONN ("DRIFT") by imposing contours generated by the methods onto natural speech and obtaining quality ratings. Test sets varied in degree of coverage by training data. Contours generated by DRIFT and FONN were strongly preferred over HTS-generated contours, especially for poorly-covered test items, with DRIFT slightly preferred over FONN. We conclude that the new methods hold promise for high-quality F0 contour generation while making efficient use of training data.

Index Terms: Prosody, Intonation modeling, Text-to-Speech synthesis, Artificial Neural Networks

1. Introduction

Generating fundamental frequency (F0) in text-to-speech synthesis (TTS) takes many forms, from rule-based methods in older systems where F0 is generated by rule and then imposed on concatenated sequences of stored acoustic units [1], to HMM based synthesis in which F0 is generated frame-wise in parallel with spectral frame generation and is, again, imposed on the spectral frames [2], to unit selection systems with enough recordings that stored F0 can be used as-is [3].

A fundamental issue is whether frame-based methods are able to capture a key property of F0 movement, which is that they have — except where perturbed or interrupted by obstructions — a smooth suprasegmental shape with typically no more than two inflection points. A recent study explicitly addressing this issue [4] considered various phonological units in a statistica...
curves in the training data, we expect DRIFT to have a relative advantage over FONN in well-covered test data because such data would provide ample stored templates that closely match the test context in terms of the selection features, but the reverse in poorly-covered test data.

2. Model-driven, frame-based F0 generator
Multi-space probability distribution HMM (MSD-HMM) [21] is a special case of using HMM to model observed $F_0$ values. MSD-HMM includes discrete and continuous mixture HMMs to model $F_0$. We used the HTS toolkit (version 2.2) [20] to perform HMM-based TTS synthesis. HTS uses the Festival speech synthesis architecture to extract a sequence of contextual and phonological features at several levels, such as, for a given utterance, the phrase, word, syllable, phoneme, and frame levels. As a result, there are many combinations of contextual features to consider when obtaining models. HTS employs decision-tree (DT) based context clustering for handling a large number of feature combinations. The left panel in Figure 1 shows independent DT-based context clustering for $F_0$ and duration, respectively.

3. DRIFT: Data-driven, foot-based F0 generator

3.1. Intonation model
In a previous study [8], we proposed a new method to decompose a continuous $F_0$ contour — interpolated in unvoiced regions — into component curves in accordance with the GSM: a phrase curve and a sum of one or more accent curves (one accent per foot).

In this method, the phrase curve consists of two log-linear curves, between the phrase start and the start of the phrase-final foot, and between the latter and the end point of the last voiced segment of the phrase, respectively. We use a combination of the skewed normal distribution and a sigmoid function to model three different types of accent curves. First, the skewed normal distribution is employed to model rise-fall accents that occur in non-phrase-final positions as well as, in statements, in utterance-final positions. Second, a sigmoid function is used to model the rise at the end of a yes/no question utterance. And, third, the sum of the skewed normal distribution and the sigmoid function is used to model continuation accents at the end of a non-utterance-final phrase. (for details, see [8]).

3.2. Analysis
In order to segment training utterances (training and test set selection explain in subsections 5.1 and 5.2) into foot sequences, this method uses three contextual features: accent labels, syllable labels, and phrase boundaries, to automatically create foot boundaries. In contrast with HTS, which uses a large number of contextual features, we only extract five contextual features per foot:

\[
\text{Set} = \begin{cases} 
\text{PT}: \text{phrase type (statement, continuation)} \\
\text{FPo s}: \text{foot position in phrase (initial, final, other)} \\
\text{SNum}: \text{number of syllables in foot (1, 2, >2)} \\
\text{OD}: \text{onset duration of stressed accented syllable} \\
\text{RD}: \text{rime duration of stressed accented syllable}
\end{cases}
\]

A curve inventory is created as follows. For each training utterance, we extract $F_0$ and then fit the intonation model described in subsection 3.1 to compute the phrase curve and the accent curves. We store the vector comprising the estimated accent curve parameters and the values of OD and RD in the inventory. The inventory contains twelve sub-inventories defined in terms of the Set features PT, FPos, and SNum (middle panel of Figure 1). Because the data were not tagged for y/n (or any) questions, we did not include a y/n question sub-inventory.

3.3. Synthesis
In this method, an input sentence is segmented into phrases, each phrase is segmented into a foot sequence, and for each foot the Set features are extracted from text data. The three first features are extracted from text data, and the value OD and RD are predicted using force alignment applied on original utterances [22]. A suitable accent sub-inventory is chosen for that foot by traversing the proposed DT using the first three features: PT, FPos, and SNum (middle panel of Figure 1). We calculate the euclidean distance between the OD, and RD of the current foot and the stored accent curves in the chosen sub-inventory. The five candidate accent curves with the low-
est distance in that sub-inventory are retrieved. To minimize the differences between successive accent curve heights in a phrase, we apply a Viterbi search to the sequence of candidate accent curves; the observation matrix consists of the normalized duration distances and the transition matrix consists of the normalized accent curve height differences.

4. FONN: Foot-based F0 Generator using Neural Networks

4.1. Intonation model

We employ the same intonation model as the DRIFT method (Section 3.1). In this model, the phrase curve consists of two linear curves. We use the combination of the skewed normal distribution and the sigmoid function to model the three different types of accent curves.

4.2. Analysis

For each utterance of trainSET (described in Section 5.1, 5.2), we extract $F_0$ and then fit the intonation model described in subsection 5.1 to compute the phrase curve and the accent curves. We store two vectors as input and target vector for each foot. The input vector comprised of the features from feature SetC. We normalize the OD and RD by foot duration. The target vector comprises of the parameters of the estimated accent curve. Before storing the target vector, we normalize the parameters.

We use the input and target vector to train an Artificial Neural Network (ANN) [23]. The ANN consists of two layers as shown in the right panel of Figure 1. The input and output dimensions are 10 and 7, respectively. The hidden layer size is 200. The activation function in the hidden layer is sigmoid and the activation function in the output layer is linear.

4.3. Synthesis

Like the DRIFT method (Section 3.3), an input sentence is segmented into phrases, each phrase is segmented into a foot sequence, and for each foot the SetC features are extracted from text data. These feature vectors sequentially are given to the trained ANN to predict accent curves parameters. We use the predicted parameters to create accent curves for each foot.

5. Experiments

5.1. Databases

We use a US English female speaker of the CMU arctic database (SLT) [24]. This corpus contains 1132 utterances, which are recorded at 16bit 32KHz, in one channel. The database is automatically labelled by CMU Sphinx using FestVox labeling scripts. No hand corrections are made.

5.2. Set coverage

In data driven approaches, data sparsity is a pervasive challenge [25]. To investigate the effects of sparsity, we employ an algorithm [10] to select four subsets of the data: trainSET, containing the training data; wellSET, containing test data that are well covered by trainSET; poorSET, containing test data that are poorly covered by trainSET; and randomSET, a random selection from the test data. The algorithm iterates to find a wellSET and poorSET that are maximally different in terms of their coverage by trainSET.

5.3. Evaluation

For subjective evaluation of the intonation generation performance of the three approaches, we design a test that measures naturalness. We use Amazon Mechanical Turk [26], with participants who have approval ratings of at least 95% and were located in the United States.

We prepare three separate tests to compare each pair of three approaches combination (HTS Vs. DRIFT, HTS Vs. FONN, and DRIFT Vs. FONN). For each pairs, We use a comparison test to evaluate the naturalness of the $F_0$ contours synthesized by the two approaches. In this test, listeners hear two stimuli with the same content back-to-back and then are asked which they prefer using a five-point scale consisting of -2 (definitely First one), -1 (probability First one), 0 (unsure), +1 (probably Second one), +2 (definitely Second one). We randomly switch the order of the two stimuli. The experiment includes 50 utterance pairs for each of the three test sets (total 150 pairs). We employed 150 listeners, that each listener only can chose one test set (i.e., poorSET, randomSET, and wellSET) to judge. Three trivial-to-judge utterance pairs are added to the experiment to filter out unreliable listeners.

We evaluate the two approaches by imposing the $F_0$ contours generated by the two approaches onto recorded natural speech, thereby ensuring that the comparison strictly focused on the quality of the $F_0$ contours and is not affected by other aspects of the synthesis process [27]. To ensure that the $F_0$ contours are properly aligned with the phonetic segment boundaries of the natural utterance, the contours are time warped so that the predicted phonetic segment boundaries correspond to the segment boundaries of the natural utterance. Note that the predicted phonetic segment boundaries are the same for the two approaches. To compute the segment boundaries of the natural utterance, we used the HTS state duration and phoneme duration. Finally, we use PSOLA to impose the synthetic contour onto the natural recording.

Figure 2 shows the results of the pair-wise comparisons between the naturalness of the $F_0$ contours synthesized by the two configuration pairs (HTS-DRIFT, HTS-FONN, and DRIFT-FONN). In general, perceptual results indicated superior performance of DRIFT and FONN over HTS. DRIFT over-performed FONN in random and well coverage cases. For significance testing, we first compute a score for each utterance using Equation 1, and then, separately for each test set, apply a one-sample t-test (results are summarized in Table 1). In Equation 1, $j$, $n$, $m$, and $C_{ji}$, stand for $j^{th}$ utterance of current test set, number of listeners, number of utterance of current test set, and the rating of the $j^{th}$ listener for the $i^{th}$ utterance, respectively, and $\mu^i_{ji}$ is the average rating across all listeners for the $j^{th}$ utterance of the $i^{th}$ test set.

<table>
<thead>
<tr>
<th></th>
<th>Poor Randomization</th>
<th>randomSET</th>
<th>wellSET</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>t-test</strong></td>
<td><strong>t-value(df), p-value</strong></td>
<td><strong>mean SD</strong></td>
<td><strong>t-value(df), p-value</strong></td>
</tr>
<tr>
<td>HTS vs. DRIFT</td>
<td>t(49) p-value</td>
<td>mean SD</td>
<td>t(49) p-value</td>
</tr>
<tr>
<td></td>
<td>7.9034 2.6854e-10</td>
<td>1.3227 1.2454</td>
<td>5.9978 2.3584e-7</td>
</tr>
<tr>
<td></td>
<td>4.9139 1.0386e-5</td>
<td>0.6584 1.4475</td>
<td>0.0208 0.1571</td>
</tr>
<tr>
<td>HTS vs. FONN</td>
<td>6.7803 1.4528e-8</td>
<td>0.4120 1.2189</td>
<td>5.7140 6.4363e-7</td>
</tr>
<tr>
<td></td>
<td>2.0512 0.0456</td>
<td>0.5868 0.9294</td>
<td>-2.3892 0.0208</td>
</tr>
<tr>
<td>DRIFT vs. FONN</td>
<td>-0.6974 0.4888</td>
<td>-0.8512 0.8353</td>
<td>4.2792 0.0270</td>
</tr>
</tbody>
</table>

Table 1: Results of one-sample t-tests [t-value(df), p-value], and mean and standard deviation (SD) of the randomization-based t-statistic distribution for three pairwise comparisons in three test sets that vary in how well they are covered by the training data.
indicates the absolute value.

\[
score_j = \frac{\sum_{i=1}^{m} (C_{ji}|C_{ji}|)}{\sum_{j=1}^{n} \left( \sum_{i=1}^{n} (|C_{ji}|) \right)} \quad , C_{ji} \in \{-2, -1, 0, 1, 2\} \quad (1)
\]

Conventional t-test results for the first and second comparisons (Table 1, first and second rows) show that the scores for DRIFT and FONN are significantly better than those for HTS for all test sets. The third comparison (Table 1, last row) indicates that the scores for DRIFT and FONN differ significantly from each other for two test sets (random and well), but are the same for poor test set. The superiority of FONN over HTS, but not that of DRIFT over HTS, is reduced in the well\textit{SET}.

For showing the robustness of the t-test results, we also perform a randomization test for each comparison in each test set. We randomly change the signs of all ratings, compute the scores for each utterance, and then calculate the t statistic. We repeat these steps 2000 times. The means and standard deviations of the resulting distributions are reported in Table 1, confirming the conventionally obtained significance levels. For example, the t-value of the first comparison (HTS-DRIFT) for poor\textit{SET} is far from the chance (e.g., 7.90 deviates by 5.3 standard deviations from the randomization mean of 1.33, for a normal t(49)-distribution with mean 1.33 and SD of 1.24, this yields a chance of $5.79 \times 10^{-8}$).

In another experiment, we perform a test in which we compare the systems based on the impact of coverage. We first compute a difference score for each utterance, defined by the difference between the scores for the two approaches, and subsequently perform a two-sample t-test comparing these difference scores between the poor\textit{SET} and well\textit{SET} data. Only for HTS-FONN comparison, statistically significant results were found ($t(49) = -3.5675$, $p = 2.8036 \times 10^{-4}$, one-tailed; these results were again confirmed using a randomization tests). This result shows a powerful significant trend for the impact of coverage to be stronger for the HTS approach than for FONN. Figure 2 (gray curve, right y-axis) also shows the results of comparing the two systems in terms of the impact of coverage.

6. Conclusion

We proposed a neural network foot-based intonational approach (FONN) for $F_0$ generation, with these key characteristics. First, like DRIFT, usage of a superpositional model in which selected accent curves are added to a phrase curve [8]. Second, also like DRIFT, usage of a structured inventory of fitted accent curves. Third, unlike DRIFT which uses accent curve parameter templates, usage of a trainable parametric method to compute accent curve parameters. Both FONN and DRIFT methods result in $F_0$ curves that are guaranteed to have the desired smooth suprasegmental shapes, and are well-suited to handle sparse training data as well. Perceptual results indicated superior performance of FONN and DRIFT compared to a frame-based approach (HTS). Using a test data selection algorithm, we were able to evaluate the impact of sparsity, with results that tentatively confirmed, as we predicted, the ability of the FONN to handle sparse training data better than HTS. However, there was a trend for DRIFT to outperform FONN except in poor\textit{SET}. We surmise that, for speech synthesis, template based approaches such as DRIFT that create accent curves that inherently preserve natural detail are to be preferred over approaches that compute accent curves. It remains to be seen, however, whether FONN may nevertheless outperform template based approaches in exceptionally sparse data conditions where several slots in the template tree are missing.

Figure 2: Each group-bars (poor, random, and well) represent the histogram (in percentage (left y-axis)) of the related preference point: The five-point scale consisting of -2 (definitely first version), -1 (probability first), 0 (unsure), +1 (probability second ), +2 (definitely second). Dotted line and confidence intervals correspond to the values (right y-axis) computed via Equation 1.
7. References


