Fundamental frequency contour modeling using HMM and categorical multiple regression technique

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This paper proposes a novel fundamental frequency (F_0) contour modeling based on statistics aiming at text-to-speech. In the proposed modeling, the F_0 contour of a sentence is constructed by statistical minor phrase models. These models consist of a sophisticated integration of local models of normalized pitch patterns and global models of maxima and dynamic ranges. Hidden Markov Model (HMM) is introduced to determine the normalized pitch patterns (pitch-HMM). To determine the maximum and the dynamic range, categorical multiple regression technique (CMRT) is introduced. HMM is a good statistical model which directly represents the F_0 contours by several reliable states. Moreover, it is easy to take relative changes of the F_0 (ΔF_0) and phonetic environments into account. CMRT is a good statistical modeling technique which is able to deal with syntactic structures and acoustic events in a sentence simultaneously. Evaluation on the pitch-HMMs shows accent type identification rate of 91% and RMS error of 9.2 Hz. Evaluation on the maximum and the dynamic range models gives 0.901 and 0.835 for the multiple correlation coefficients, respectively. Finally, the result of the subjective evaluation indicates that the proposed modeling is superior to the conventional modeling.

Keywords: Fundamental frequency, HMM, Categorical multiple regression technique, Minor phrase, Speech synthesis

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1. INTRODUCTION

A good generation model of fundamental frequency (F_0) contours is essential for speech synthesis. Recently, several methods of F_0 contour modeling based on statistical analysis have been proposed.¹⁻⁴⁾

One approach, F_0 contour modeling based on two-stage strategy,^{2,3)} consists of a global model and a local model. These models are directly generated from F_0 contours without separating the F_0 into accentual components and phrase components. The global model characterizes global positions of F_0

shape of minor phrases such as the maximum F_0 values, and the local model characterizes local F_0 movements inside each minor phrase. Both studies apply the categorical multiple regression technique (henceforth CMRT) to generate the global model, but their methods of local modeling differ. Abe proposed a local model generated from the average F_0 and difference F_0 values of vowel parts in each syllable using CMRT.²⁾ However, this model is insufficient for capturing the local F_0 movements in a syllable (such as rise-fall or fall-rise) because only a single point pitch for each syllable is given to represent F_0 contour. Iwata used a local model ("accentual phrase pitch pattern models" defined by Iwata) generated from three fixed points of F_0

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in each vowel part.⁵⁾ The idea to represent the local movements of F_0 contour by several point pitches had an advantage compared to Abe's approach. However, there should be more reliable modeling, which suits the local movements of F_0 contour, than the fixed point modeling.

Hidden Markov Model (HMM) is well-known as a powerful method which deals with such a requirement. HMM is a good statistic model which is able to directly represent the F_0 contours by several reliable states. Moreover, it is able to use relative changes of $F_0(\Delta F_0)$ and is able to consider the phonetic environments. However, the F_0 contour modeling based on HMM has been proposed on the study of speech recognition for word accent identification⁶⁾ and phrase boundary detection,⁷⁾ while there are only a few studies of speech synthesis. Ljolje tried to generate the F_0 contours using a prosodic HMM.⁸⁾ However his method cannot be applied directly to a text-to-speech system, because his approach was tested only on monosyllabic words.

Based on these researches, we propose here a novel statistical F_0 contour modeling aiming at text-to-speech. In the proposed modeling, the F_0 contour of a sentence is constructed by statistic minor phrase models. These models consist of a sophisticated integration of local models of normalized pitch patterns and global models of a maximum and a dynamic range. HMM is introduced to determine the normalized pitch patterns (pitch-HMM). To determine the maximum and the dynamic range, CMRT is introduced, which is a good statistic method to deal with syntactic structures and acoustic events in a sentence simultaneously.

In the following sections, we first describe the proposed statistical F_0 contour modeling. These models are evaluated in section 3 and 4. Section 5 shows the result of listening tests. Section 6 discusses some important issues concerning the pitch-HMM.

2. F_0 CONTOUR MODELING

2.1 F_0 Contour Modeling using Pitch-HMMs, Maximum and Dynamic Range Models

The F_0 contour of a minor phrase, $f(t)$, which constitutes a sentence is represented by the following equation:

$$f(t) = d \cdot p(t) + m - d, \quad (1)$$

where $p(t)$ is the normalized pitch pattern generated

from normalized point pitch models; m is the maximum of $f(t)$ and d is the dynamic range, i.e. the difference between the maximum and the minimum of $f(t)$, calculated for each minor phrase. We generate $f(t)$ through the normalized point pitch models using HMM technique (pitch-HMMs) and the maximum and the dynamic range models using CMRT.

2.2 Pitch-HMMs

Pitch-HMMs are obtained from a large scale database consisting of prosodic features, segmented phoneme boundaries, and lexical information (i.e. mora count and accent type). F_0 and differenced fundamental frequency (henceforth ΔF_0) are used as prosodic features. Here, since raw F_0 values $f(t)$ vary widely among minor phrases, F_0 is normalized as follows:

$$p(t) = (f(t) - m + d) / d, \quad (2)$$

where m and d are the maximum and the dynamic range of $f(t)$. ΔF_0 is computed from $p(t)$ by linear regression.

The pitch-HMMs are trained by considering phonetic environments (e.g. accent type, mora count, mora position, phonemic category, etc.). Therefore, the pitch-HMMs can express the difference of the F_0 contours related to phonemes.⁹⁾ This is meaningful because it is reported that expressing the microscopic movements in a phoneme improves the intelligibility of a synthesized speech.¹⁰⁾ These movements in the F_0 contours can be captured by the states in the pitch-HMM.

The F_0 contour of each minor phrase $f(t)$ is generated by the following steps (See Fig. 1; the example is "/azi/(taste)").

1. Select the pitch-HMMs according to the phonetic environments (Fig. 1(a)).
2. Align the pitch-HMMs according to the segmental durations (Fig. 1(b)).
3. Determine the target point pitches and generate the normalized pitch pattern by interpolating these points (Fig. 1(c)).
4. Multiply with the dynamic range and add the bias (Fig. 1(d)):

$$f(t) = d \cdot p(t) + m - d. \quad (3)$$

Details for the pitch-HMM alignment and the normalized pitch pattern generation are described in section 3.2.2. Furthermore, advanced techniques

Fig. 1 Conceptual figure of F_0 contour generation.

for the alignment and the generation are discussed in section 6.

2.3 Maximum and Dynamic Range Models

We apply CMRT¹¹⁾ for the maximum and the dynamic range modeling. The maximum m of a minor phrase is predicted by the following equation:

$$P_i = \sum_{j=1}^R \sum_{k=1}^{C_j} \alpha_{jk} \delta_i(jk), \quad (i=1, \dots, N) \quad (4)$$

where P_i is the predicted value of the i -th sample, R is the number of factors and C_j is the number of categories of a factor j . $\delta_i(jk)$ is the characteristics function defined as

$$\delta_i(jk) = \begin{cases} 1, & \text{if the } i\text{-th sample falls into} \\ & \text{the category } k \text{ of factor } j, \\ 0, & \text{otherwise.} \end{cases} \quad (5)$$

α_{jk} is obtained by minimizing the summation of the prediction error E :

$$E = \sum_{i=1}^n (p_i - P_i)^2, \quad (6)$$

where p_i is the maximum of the i -th sample.

The dynamic range is predicted in an equivalent way.

2.4 Advantages

The proposed modeling has the following advantages. As for HMM:

- Thanks to the ability of time-warping and training with the maximum likelihood criterion, reliable point pitches are automatically determined.
- Multiple prosodic parameters (*e.g.* F_0 and ΔF_0) can be used, directly and simultaneously, which makes the model more stable.
- By taking account of phonetic environments (*e.g.* accent type, mora count, mora position, phonemic category, *etc.*), precise models can be obtained.
- Detailed movements in the F_0 contours can be captured by using larger number of HMM states.

To demonstrate the advantage of HMM based modeling, consider the three simple contours ($F_1(t)$, $F_2(t)$, $F_3(t)$) shown in Fig. 2. We compare the following three modeling approaches to calculate representative point pitches (f_1, f_2, f_3):

1. mean values sampled at the positions of $t = 1/6$, $t = 3/6$ and $t = 5/6$
(*e.g.* $f_1 = (1/3) \sum_{m=1}^3 F_m(1/6)$),
2. mean values averaged between $t=0$ and $t=1/3$, between $t=1/3$ and $t=2/3$, and between $t=2/3$ and $t=1$ (*e.g.* $f_1 = (1/3) \sum_{m=1}^3 \int_0^{1/3} F_m(t) dt$),
3. pitch-HMMs consisting of three states with a single Gaussian density function.

Three point pitches are respectively determined:

1. $f_1 = 0.36, f_2 = 0.83, f_3 = 0.36$ ($dyn = 0.71$),
2. $f_1 = 0.36, f_2 = 0.78, f_3 = 0.36$ ($dyn = 0.63$),
3. $f_1 = 0.39, f_2 = 0.89, f_3 = 0.39$ ($dyn = 0.75$),

where dyn indicates the dynamic range value, obtained by interpolation of these point pitches using a straight line between $t=0$ and $t=1$. It is seen from these results that dyn of HMM base modeling is the nearest value to the original dynamic range ($dyn = 1.0$).

CMRT is able to deal with syntactic structure (*e.g.* parts of speech and dependency structure) and

Fig. 2 Examples of contours.

acoustic events (e.g. accent type and mora count) in a sentence simultaneously. It facilitates to control the dynamics of the pitch-HMMs.

3. EVALUATION OF PITCH-HMMS

In this section, we evaluate the pitch-HMMs through two experiments. One is an accent identification experiment for investigating how appropriate the pitch-HMMs express the accent types. The other is an average of RMS error measurement for comparing the difference between the original F_0 and the one generated from the pitch-HMMs.

3.1 Conditions

For training and evaluation of the pitch-HMMs, we used the ATR 5,240 word database sampled at 12 kHz¹²⁾ uttered by one male speaker. The database contained phoneme boundary information. The lists of accent types and mora counts for these words were also prepared.

The F_0 contours were estimated by FFT cepstral analysis, with an F_0 value for every 2.5 ms. The F_0 was warped on a logarithmic scale, and then median smoothed. Additionally, half-pitch and double-pitch errors were corrected automatically. Hand correction of extraction errors was not performed, but the parameters for the smoothing algorithms were tuned to the database. The first regression coefficients of the $F_0(\Delta F_0)$ were estimated with a regression window of 77.5 ms.

Accent type, mora count, mora position and phonemic category were considered as phonetic environments. For i morae and j classes of phonemic category, the number of pitch-HMMs $N=i^2j$. Pitch-HMMs, consisting of three states with a single Gaussian density function, were trained by

Table 1 Types of phonemic category.

Model	Class of pitch-HMMs
Rough (2 classes)	vowels: *V voiced consonants: *
Detailed (15 classes)	vowels: V (no consonant), {ptk} V, {fsh} V, {bdg} V, {mn} V, rV, wV, yV, zV voiced consonants: {bdg}, {mn}, r, w, y, z

“{ptk} V” indicates any vowel preceded by any of the consonants “p,” “t,” or “k.”

the Forward-Backward algorithm.¹⁸⁾

As for the pitch-HMMs, we selected two HMM sets: one consisting of two classes of phonemic category (rough models) and the other of 15 classes of phonemic category (detailed models), as shown in Table 1. We expect that the precision of F_0 contour estimation improves by increasing the number of the pitch-HMMs according to the phonemic environments, as it has been reported that F_0 contours differ according to the phonemic environments, even if the words have same accent type and same mora count.⁹⁾

3.2 Results

3.2.1 Accent identification experiment

The appropriateness of the pitch-HMMs was evaluated by an accent identification experiment using four mora words (1,565 words) in the 5,240 word database. In this experiment, the rough pitch-HMM set was adopted and speech data with devoiced vowel and with concatenated phoneme labels were not considered.

This experiment was simply performed using the vowel parts. The accent pattern models were created by concatenating the null code model, which forces mora alignment, in between the rough pitch-HMMs (see Fig. 3). As for test data, F_0 and ΔF_0 sequences of vowel parts were extracted by using the label information, and null data was also inserted

Fig. 3 Pitch-HMM concatenation.

Table 2 Confusion matrix of accent identification of 4 mora words. The pitch-HMMs were trained by using two features, F_0 and ΔF_0 .

Accent type	0	1	2	3	ID rate
0	921	4	50	76	87.6%
1	0	143	4	0	97.3%
2	3	0	78	6	89.7%
3	4	0	20	256	91.4%

Total ID rate: 91.5%.

Table 3. Confusion matrix of accent identification of 4 mora words. The pitch-HMMs were trained by using one features, F_0 .

Accent type	0	1	2	3	ID rate
0	862	6	44	139	82.0%
1	2	144	1	0	98.0%
2	11	0	65	11	74.7%
3	48	0	22	210	75.0%

Total ID rate: 82.4%.

between each vowel part. This forced alignment allows explicit usage of the duration information in the database. The Viterbi beam search algorithm¹³⁾ was adopted for the evaluation.

Table 2 shows the experimental result using F_0 and ΔF_0 as prosodic parameters. For comparison, the result using only F_0 is shown in Table 3. The drastic improvement from 82.4% to 91.5% accuracy indicates the effectiveness of the additional ΔF_0 for the pitch-HMMs. This result shows that the pitch-HMMs trained using F_0 and ΔF_0 express accent patterns more appropriately.

3.2.2 RMS error measurement

We measured an average of RMS error between the original F_0 contours and the one generated from the pitch-HMMs using the 5,240 words. The original values of the phoneme durations (l_1 , l_2 and l_3 in Fig. 1(b)), the maxima and the dynamic ranges (m and d in Fig. 1(d)) were given to the pitch-HMMs.

In this experiment, the pitch-HMMs were simply aligned at the positions of 1/6, 3/6 and 5/6 of each phoneme duration (*i.e.* $l_{11}=l_{12}=l_{13}=l_1/3$ in Fig. 1(b)). The F_0 mean values of pitch-HMMs were used for the target point pitches (μ_{11} , μ_{12} , μ_{13} , *etc.* in

Fig. 4 Examples of the F_0 contour generation using the rough models. (a) “/sarani/ (moreover),” (b) “/ziguzagu/ (zigzag).”

Fig. 5 Examples of the F_0 contour generation using the detailed models.

Fig. 1(c)) and a simple straight line interpolation was adopted. We discuss a more reliable state alignment and a generation of the normalized pitch pattern in section 6.

As a result, the RMS error using the rough models was 1.46 semitone (equivalent to 10.2 Hz at 120 Hz). Figure 4 shows the examples using the rough models. The RMS error using the detailed models improved to 1.32 semitone (equivalent to 9.2 Hz at 120 Hz). This is about 10% improvement from the rough models. Figure 5 shows the examples using the detailed models. As shown in Fig. 5, the F_0 contours were well estimated in comparison with Fig. 4. It is also seen that the microscopic F_0 movement corresponding to a phoneme is well captured (see both /z/’s in Fig. 5(b)).

4. EVALUATION OF MAXIMUM AND DYNAMIC RANGE MODELS

In this section, we evaluate the maximum and the dynamic range models generated using CMRT.

4.1 Conditions

The maximum and the dynamic range were computed from the minor phrases in the ATR 503 sentence database.¹²⁾ As for test data, 43 sentences in another ATR database were used. These databases were uttered by the same speaker.

The F_0 contours were estimated in the same manner as described in section 3.1. The maximum and the dynamic range of each minor phrase were calculated from the F_0 contours on a logarithmic scale.

The factors and the numbers of categories for the maximum (Max) and the dynamic range (Dyn) models are shown in Table 4. Difference between mora count and accent type (*i.e.* mora count after the accentual mora) was selected because we have found from a preliminary experiment that the variance of F_0 dynamic range categorized by this factor was smaller than that categorized by accent type. The boundary environment means the combination of the preceding type (beginning of sentence, pause, continuation) and the succeeding type (end of sentence, pause, continuation). In order to smooth a potential gap between minor phrases, the preceding maximum and minimum values were utilized for the maximum model and the current maximum value for the dynamic range model.

4.2 Results

The partial correlation coefficients of both models are shown in Table 4. As shown in this table, the boundary environment and the mora count played important roles in predicting the maximum. The maximum and the minimum of the preceding minor phrase for the maximum model were also effective. For the dynamic range model, the maximum of the current minor phrase was the second most significant factor.

Table 5 shows the multiple correlation coefficients of both models. It is seen from this table that high multiple correlation coefficients for both models are obtained, *i.e.* both models are good prediction models. The averages of the RMS errors for close and open data are also shown in this table. The

Table 4 Factors, number of categories and partial correlation coefficients.

Factor	Number of categories		Partial correlation coefficients	
	Max	Dyn	Max	Dyn
Position of first mora of minor phrase within a major phrase	8	5	0.173	0.090
Mora count	6	9	0.377	0.212
Parts of speech	10	10	0.240	0.131
Dependency structure (from preceding)	2	2	0.246	0.029
Dependency structure (to succeeding)	2	2	0.112	0.005
Difference between mora count and accent type (preceding)	7	7	0.352	0.225
Difference between mora count and accent type (current)	8	8	0.271	0.648
Accent type (succeeding)	3	3	0.047	0.065
Boundary environment	8	8	0.439	0.281
Maximum (preceding)	10	—	0.209	—
Minimum (preceding)	10	—	0.140	—
Maximum (current)	—	9	—	0.496

Table 5 Multiple correlation coefficients and RMS error.

Model	Multiple correlation coefficients	RMS error semitone (Hz)	
		close	open
Max	0.901	1.77 (12.22)	2.44 (16.89)
Dyn	0.835	2.13 (14.76)	2.38 (16.50)

RMS errors of the maximum and the dynamic range models for close data came up to 1.77 semitone (equivalent to 12.22 Hz at 120 Hz) and 2.13 semitone (14.76 Hz), respectively. As for the open data, the RMS errors of both models came up to 2.44 semitone (16.89 Hz) and 2.38 semitone (16.50 Hz). The small difference between the results of the close and the open indicates that robust models are obtained.

5. SUBJECTIVE EXPERIMENTS

To evaluate the generated F_0 contours, two kinds of subjective evaluation were carried out. The first experiment (Exp. 1) was designed to evaluate the performance of the pitch-HMMs, and the second (Exp. 2) was to evaluate the total performance of

the proposed modeling.

5.1 Conditions

In both experiments, the stimuli were generated by the cepstral synthesis-analysis method.¹⁴⁾ The following three kinds of F_0 contours were prepared for comparison:

- extracted from natural speech (Original)
- generated from the proposed model (Proposed)
- generated from a conventional model¹⁵⁾ (Conventional).

In the conventional model, stress level of accent component was set to 4.0 semitone and phrase component was set to 0.4 semitone/mora. Note that a single stress level was used in this experiment, whereas Hakoda adopted five stress levels¹⁵⁾ The same durations and cepstral coefficients were given to the three stimuli.

In Exp. 1, 24 minor phrases were used as stimuli. In order to compare the pitch-HMMs with the conventional point pitches, the original maximum and the original dynamic range were given to the pitch-HMMs and to the conventional model. In Exp. 2, 20 sentences were used as stimuli. These stimuli were evaluated by a subjective opinion test of five grades with 14 listeners. The grades were “very good,” “good,” “fair,” “bad,” and “very bad,” and the score points were 5, 4, 3, 2 and 1, respectively.

The pitch-HMMs and the maximum and the dynamic range models were generated using the ATR 503 sentence database. The number of the phonemic categories was set to two (rough models) allowing for the trainability of the pitch-HMMs. Most of the conditions were the same as described in section 3.1 except prosodic parameters: a relative position in a phoneme was additionally used to F_0 and ΔF_0 . This parameter was introduced considering the following:

- Variances of F_0 contours of sentence utterances are larger than those of word utterances owing to the boundary environment, the syntactic dependency structure, *etc.*
- The pitch-HMMs are aligned at the fixed positions in our current version.

From a preliminary experiment, we confirmed that the pitch-HMMs trained using F_0 , ΔF_0 and relative positions had perceptually better quality than those trained using only F_0 and ΔF_0 .

5.2 Results

The result of Exp. 1 is shown in Fig. 6(a). The Mean Opinion Score (MOS) of the pitch-HMMs was 3.5, while the score of the conventional point pitch model was 3.2. Moreover, no listener had a higher MOS for the conventional model than for the pitch-HMM. These results demonstrate the effectiveness of the pitch-HMMs.

Figure 6(b) shows the result of Exp. 2. The scores of the proposed and the conventional models were 3.8 (close to “good”) and 2.2 (close to “bad”) respectively. The proposed modeling is significantly superior to the conventional modeling and the proposed models can generate high quality F_0 contours. As for this improvement, we believe that the global F_0 shape is playing a major role in the performance of the proposed modeling.

One word of caution: in this experiment, the proposed model was compared to the simplest conventional model (*i.e.* single stress level was used). To prove the superiority of the proposed method against the conventional methods, more sophisticated stimuli should be used.

Figure 7 shows an example of F_0 contour of open data; (a) waveform, (b) the original F_0 contour, (c) the generated F_0 contour by the proposed model. It is seen from this figure that the global F_0 features of each minor phrase (*i.e.* the maximum and the dynamic range) are well estimated. The detail movements of the F_0 contour are also well captured (*e.g.* the F_0 shapes (rise-fall) at the 1st and the 4th minor phrases are captured appropriately in spite of their accent type being type 1 (fall)).

Pitch-HMMs for up to 8 morae can be trained from the 503 sentence database. Considering application of the pitch-HMMs to a text-to-speech system, it is required to cover the actual minor phrase patterns in the real world. We investigated

Fig. 6 Subjective evaluation results.

Fig. 7 F_0 sentence contours using HMM and CMRT: (a) waveform, (b) original F_0 contour, (c) estimated F_0 contour generated by the proposed model. This sentence consists of 6 minor phrases. (5, 1) indicates the mora count and the accent type.

the coverage using 2.3 Megabyte of text corpora including many areas. As a result, the minor phrases for 8 morae or less accounted for 94.1% coverage in the corpora. The result indicates that the trained pitch-HMMs cover the real world adequately. As for the rest of 5.9%, the conventional point pitch model or integration of the pitch-HMMs and the conventional model could be utilized.

6. DISCUSSION

In this section, we discuss some important issues on the pitch-HMM, particularly the state alignment and the way to generate the normalized pitch pattern.

6.1 Alignment

In the previous experiments, the pitch-HMMs were simply aligned at the positions of 1/6, 3/6 and 5/6 in each phoneme. However, it should be more desirable to align the three states of the pitch-HMM appropriately by taking account of their own statistical information (*i.e.* mean, variance, output probabilities and transition probabilities). The statistical durations of the HMM states can be obtained from the Viterbi decoding algorithm.¹³⁾ When a phoneme duration is given, the duration of each of the three states (*i.e.* l_{11} , l_{12} and l_{13} in Fig. 1(b)) can be determined according to the ratio of the obtained statistical durations.

6.2 Interpolation

As for the interpolation, although the simple straight line interpolation was adopted in the previous experiments, various interpolating techniques (*e.g.* spline interpolation or Bézier curve) can be applied for making the F_0 contours smoother.

6.3 Pitch Pattern Generation

As for the normalized pitch pattern generation, the time series of F_0 can be computed by using the statistical information of the pitch-HMMs, in terms of maximizing the log-likelihood. For simple explanation, let us consider generating F_0 contour from a single state pitch-HMM (*e.g.* state s ($s=1, 2, 3$)). If the duration of the pitch-HMM, l , is given, a time series of normalized pitches, $\mathbf{O}_1=[O_1(1), O_1(2), \dots, O_1(l)]$, can be determined as follows.

The likelihood of F_0 , $f(\mathbf{O}_1)$, with respect to $\mathbf{O}_1$ is:

$$f(\mathbf{O}_1) = \prod_{t=1}^l (a_1)^{l-1} b_1(O_1(t)) \cdot (1-a_1), \quad (7)$$

where a_1 is a self-loop transition probability in the state s and $b_1(O_1(t))$ is an output probability. The output probability of a Gaussian probability density function is:

$$b_1(O_1(t)) = \frac{1}{\sqrt{2\pi\sigma_1^2}} \exp\left\{-\frac{(O_1(t)-\mu_1)^2}{2\sigma_1^2}\right\}, \quad (8)$$

where μ_1 and σ_1^2 are the mean and the variance of F_0 of the pitch-HMM. Similarly, the likelihood of

the ΔF_0 , $g(\mathbf{O}_2)$ is represented by a set of ΔF_0 ($\mathbf{O}_2 = [O_2(1), O_2(2), \dots, O_2(l)]$), the ΔF_0 mean (μ_2) and the ΔF_0 variance (σ_2^2).

Therefore, the log-likelihood L is:

$$\begin{aligned} L &= \log f(\mathbf{O}_1) + \log g(\mathbf{O}_2) \\ &= \sum_{t=1}^l \left\{ -\frac{(O_1(t) - \mu_1)^2}{2\sigma_1^2} \right\} \\ &\quad + \sum_{t=1}^l \left\{ -\frac{(O_2(t) - \mu_2)^2}{2\sigma_2^2} \right\} + \text{Const.} \end{aligned} \quad (9)$$

If ΔF_0 at time t , $O_2(t)$, is represented by

$$O_2(t) = \sum_{k=-M_1}^{M_2} w(k) O_1(t+k), \quad (10)$$

where

$$O_1(t) = 0, \quad i < 1 \text{ or } i > l, \quad (11)$$

and $w(k)$ is a weighted coefficient from $-M_1$ to M_2 . Using Eq. (9) to Eq. (11), the partial derivatives with respect to $O_1(t)$ of the log-likelihood L can be computed. Finally, by equating the derivatives to zero, the following linear simultaneous equations are obtained:

$$\begin{bmatrix} \frac{\partial L}{\partial O_1(1)} \\ \frac{\partial L}{\partial O_1(2)} \\ \vdots \\ \frac{\partial L}{\partial O_1(l)} \end{bmatrix} = \mathbf{A} \begin{bmatrix} O_1(1) \\ O_1(2) \\ \vdots \\ O_1(l) \end{bmatrix} = \mathbf{b}, \quad (12)$$

where $\mathbf{A}$ and $\mathbf{b}$ are an l -by- l coefficient matrix and an l -dimensional column vector. A time series of F_0 , $\mathbf{O}_1 = [O_1(1), O_1(2), \dots, O_1(l)]$, can be obtained by solving these equations. It can be also generated from multiple states in the same way.

6.4 Other Remarks

Further studies might investigate the following topics:

- The pitch-HMMs can also be utilized to select the best F_0 contour from several candidates in a database according to a maximum likelihood criterion.
- An automatic phonetic environment clustering can be performed by introducing the basic idea of the SSS algorithm.¹⁶⁾

7. CONCLUSIONS

In this paper, we have presented a new F_0 contour modeling using HMM and CMRT. In the proposed modeling, the F_0 contour of a sentence can be represented by normalized pitch patterns and maxima and dynamic ranges of minor phrases. This modeling is a sophisticated integration of the local statistical model (pitch-HMMs) represented by an HMM and the global statistical model (maximum and dynamic range models) represented by CMRT.

The experimental results for accent identification showed that the pitch-HMMs can express accent patterns appropriately and that ΔF_0 was a useful parameter to generate reliable models. In the F_0 contour generation experiments for isolated words, the detailed models (15 phonemic categories) achieved an improvement of 10% for RMS error as compared with the rough models (2 categories). Even for the rough models, however, it was shown that sufficiently precise F_0 contours could be generated by the pitch-HMMs.

To generate the maximum and the dynamic range models, we used 11 and 10 factors, respectively. Particularly, in order to smooth a potential gap between minor phrases, preceding maximum and minimum for the factor of the maximum model and current maximum value for the factor of the dynamic range model were considered. As a result, suitable models were obtained; the measured multiple correlation coefficients of both models were 0.901 and 0.835, respectively.

From the result of the subjective evaluation, the synthesized speech of the proposed F_0 contours was perceptually superior to that of the conventional model.

Through these experimental results, we showed that the proposed modeling was powerful and useful for a text-to-speech system. In this paper, we have adopted the simplest way for F_0 contour generation: fixed position alignment and straight line interpolation of the F_0 mean values. However, more sophisticated F_0 contours can be generated from the pitch-HMMs as discussed in section 6. As for future work, we will implement the proposed models into our text-to-speech system and investigate the expansion of the F_0 contour generation.

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