



Speech Prosody Generation for Text-to-Speech Synthesis Based on Generative Model of F_0 Contours

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Abstract

This paper deals with the problem of generating the fundamental frequency (F_0) contour of speech from a text input for text-to-speech synthesis. We have previously introduced a statistical model describing the generating process of speech F_0 contours, based on the discrete-time version of the Fujisaki model. One remarkable feature of this model is that it has allowed us to derive an efficient algorithm based on powerful statistical methods for estimating the Fujisaki-model parameters from raw F_0 contours. To associate a sequence of the Fujisaki-model parameters with a text input based on statistical learning, this paper proposes extending this model to a context-dependent one. We further propose a parameter training algorithm for the present model based on a decision tree-based context clustering. **Index Terms:** Speech F_0 contours, stochastic model, Fujisaki model, hidden Markov model, EM algorithm

1. Introduction

The fundamental frequency (F_0) contour of speech is a feature that represents the intonation of an utterance. One important challenge of the text-to-speech synthesis research involves developing a reasonable model and method for generating a natural-sounding F_0 contour from a text input.

Thanks to the increasing availability of speech databases, speech synthesis systems based on statistical models such as hidden Markov models (HMMs) have attracted particular attention in recent years. In the HMM-based speech synthesis system [2], a sequence of spectra, F_0 s and their delta and acceleration components is modeled simultaneously within a unified HMM framework. At the synthesis stage, a sequence of these parameters is generated according to the output probabilities of the trained HMM given an input sentence. The constraints of the dynamic parameters are considered during parameter generation in order to guarantee the smoothness of the generated spectral and F_0 trajectories. However, conventional HMM based speech synthesis systems tend to produce over-smoothed F_0 contours, which often result in a synthesis that sounds “emotionless” to human listeners.

In speech synthesis technology, one important challenge involves synthesizing an F_0 contour that is not only linguistically appropriate but also physically likely to be generated via the control mechanism of phonation. The Fujisaki model [1] is a well-founded mathematical model, that describes the process by which the whole F_0 contour of a speech utterance is generated. This model is known to approximate actual F_0 contours of speech well when the parameters are chosen appropriately. In the Fujisaki model, F_0 contour on a logarithmic scale is assumed to be the superposition of three components: a phrase component, an accent component and a base-line component. The phrase component consists of the major-scale pitch variations over the duration of the prosodic units, and the accent component consists of the smaller-scale pitch variations in accented syllables. To avoid synthesizing over-smoothed and physically unlikely F_0 contours, one reasonable approach would be to incorporate the Fujisaki model into the statistical model for speech synthesis so that we can separately take the average of each of these components according to the

assigned context labels. Thus, the Fujisaki model can potentially be a good model for F_0 contour synthesis. However, since the Fujisaki model does not take the form of a statistical (automatically trainable) model, using the Fujisaki model for synthesizing F_0 contours within a statistical framework is not straightforward. Indeed, estimating (learning) the Fujisaki model parameters from raw F_0 contour observations has been a difficult task. Several techniques have already been developed (e.g., [3, 4, 5, 6]), but so far with limited success due to the difficulty in searching for optimal parameters under the constraints imposed in the Fujisaki model.

We have previously formulated a statistical model of speech F_0 contours by translating the Fujisaki model into a probabilistic model described as a discrete-time stochastic process [7, 8]. This formulation has allowed us not only to derive an efficient parameter inference algorithm utilizing powerful statistical methods but also to obtain an automatically trainable version of the Fujisaki model. The aim of this paper is to further extend this model to a context-dependent one so as to be able to learn and generate the Fujisaki parameters from input sentences.

The rest of this paper is organized as follows. Sec. 2 briefly reviews the original Fujisaki model and a discrete-time stochastic counterpart to the Fujisaki model, that we have introduced in [7, 8]. Sec. 3 proposes to extend it to a context-dependent one. Sec. 4 proposes a parameter training algorithm for the present model based on decision tree-based context clustering. Sec. 5 shows some results of a speech synthesis experiment conducted using real speech data excerpted from the ATR speech database. Sec. 6 concludes this paper.

2. Generative model of speech F_0 contours

2.1. Original Fujisaki Model

The Fujisaki model [1] assumes that an F_0 contour on a logarithmic scale, $y(t)$, where t is time, is the superposition of three components: a phrase component $y_p(t)$, an accent component $y_a(t)$, and a base component y_b :

$$y(t) = y_p(t) + y_a(t) + y_b. \quad (1)$$

The phrase component $y_p(t)$ consists of the major-scale pitch variations over the duration of the prosodic units, and the accent component $y_a(t)$ consists of the smaller-scale pitch variations in accented phrases. These two components are modeled as the outputs of second-order critically damped filters, one being excited with a command function $u_p(t)$ consisting of Dirac deltas (phrase commands), and the other with $u_a(t)$ consisting of rectangular pulses (accent commands):

$$y_p(t) = G_p(t) * u_p(t), \quad (2)$$

$$G_p(t) = \begin{cases} \alpha^2 t e^{-\alpha t} & (t \geq 0) \\ 0 & (t < 0) \end{cases}, \quad (3)$$

$$y_a(t) = G_a(t) * u_a(t), \quad (4)$$

$$G_a(t) = \begin{cases} \beta^2 t e^{-\beta t} & (t \geq 0) \\ 0 & (t < 0) \end{cases}, \quad (5)$$

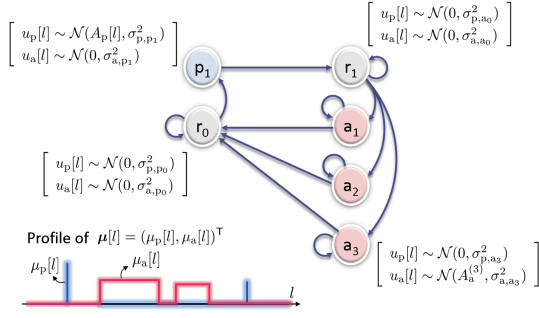


Figure 1: Previous HMM topology for command function modeling.

where $*$ denotes convolution over time. The baseline component y_b is a constant value related to the lower bound of the speaker's F_0 , below which no regular vocal fold vibration can be maintained. α and β are natural angular frequencies of the two second-order systems, which are known to be almost constant within an utterance as well as across utterances for a particular speaker. It has been shown that $\alpha=3$ [rad/s] and $\beta=20$ [rad/s] can be used as default values.

It is interesting to note that the phrase and accent commands, which we will henceforth refer to as the Fujisaki-model parameters, can be interpreted as quantities related to linguistic information. In the Japanese language, a phrase command and an accent command typically occur at the beginning of each breath group and over the range of accent nucleus in each accental phrase, respectively.

2.2. Probabilistic formulation of F_0 contour model

Here, we briefly review our probabilistic pitch contour model based on the discrete-time version of the Fujisaki model [7, 8].

In the original Fujisaki model, the phrase commands and accent commands are assumed to consist of Dirac deltas and rectangular pulses, respectively. In addition, they are not allowed to overlap each other. To incorporate these requirements, we find it convenient to model the $u_p[k]$ and $u_a[k]$ pair, i.e., $\mathbf{o}[k] = (u_p[k], u_a[k])^T$, using a hidden Markov model (HMM). In [7, 8], we have assumed that $\{\mathbf{o}[k]\}_{k=1}^K$ is a sequence of outputs generated from an HMM with the specific topology illustrated in Fig. 1. In state r_0 , $\mu_p[k]$ and $\mu_a[k]$ are both constrained to be zero. In state p_1 , referred to as the ‘‘phrase state,’’ $\mu_p[k]$ can take a non-zero value, $A_p[k]$, whereas $\mu_a[k]$ is still restricted to zero. At the phrase state, no selftransitions are allowed. In state r_1 , $\mu_p[k]$ and $\mu_a[k]$ become zero again. This path constraint restricts $\mu_p[k]$ to consisting of isolated deltas. State r_1 leads to states a_1, \dots, a_N , referred to as the ‘‘accent states.’’ At each accent state, $\mu_a[k]$ can take a different non-zero value $A_a^{(n)}$, whereas $\mu_p[k]$ is forced to be zero. A direct state transition from an accent state to a different state without passing through state r_1 is not allowed. This path constraint restricts $\mu_a[k]$ to consisting of rectangular pulses. The output distribution of each state is assumed to be a Gaussian distribution

$$\mathbf{o}[k] \sim \mathcal{N}(\mathbf{o}[k]; \mathbf{c}_{s_k}, \mathbf{\Upsilon}_{s_k}), \quad (6)$$

where s_k indicates the state variable. Namely, the mean vector $\boldsymbol{\mu}[k] = (\mu_p[k], \mu_a[k])^T = \mathbf{c}_{s_k}$ and covariance matrix $\boldsymbol{\Sigma}[k] = \mathbf{\Upsilon}_{s_k}$ are considered to evolve in time as a result of the state transition s_1, \dots, s_K . The definition of the above HMM can be summarized as follows:

Output sequence:	$\{\mathbf{o}[k]\}_{k=1}^K$
State sequence:	$\{s_k\}_{k=1}^K$
Output distribution:	$P(\mathbf{o}[k] s_k) = \mathcal{N}(\mathbf{o}[k]; \mathbf{c}_{s_k}, \mathbf{\Upsilon}_{s_k})$
Mean sequence:	$\boldsymbol{\mu}[k] = (\mu_p[k], \mu_a[k])^T = \mathbf{c}_{s_k}$
Transition probability:	$\phi_{i',i} = \log P(s_k = i s_{k-1} = i')$

Given the state sequence $\mathbf{s} = \{s_k\}_{k=1}^K$, the above HMM generates the $u_p[k]$ and $u_a[k]$ pair. From (2) and (4), $u_p[k]$ and $u_a[k]$ are then fed through different critically damped fil-

ters, $G_p[k]$ and $G_a[k]$, to generate the phrase and accent components, $y_p[k]$ and $y_a[k]$:

$$y_p[k] = u_p[k] * G_p[k], \quad (7)$$

$$y_a[k] = u_a[k] * G_a[k], \quad (8)$$

where $*$ denotes convolution over k . An F_0 contour is then given by

$$y[k] = y_p[k] + y_a[k] + y_b, \quad (9)$$

where y_b denotes the baseline value.

3. Context Dependent Generative Model of F_0 Contours

3.1. Context dependent phrase and accent command

As discussed in Sec. 2.1, phrase and accent command is closely associated with linguistic information such as breath group or accent nucleus. Thus we assume that we can obtain an appropriate F_0 contour from a text input by allocating a phrase command to the beginning of each breath group and an accent command to the range of each accent nucleus. Here, the problem is how to determine the magnitudes of the phrase and accent commands. In this paper, we treat the magnitude of each command as a model parameter to be trained using training data. We can assume that commands depend on the types of the preceding, current and succeeding breath groups and accental phrases because of the fact that F_0 contours represent the intonation of natural speech. Hence, the phrase and accent commands should be determined according to the types of the preceding, current and succeeding breath groups and accental phrases. We henceforth call those environments context. In Sec. 3, we propose a decision-tree based context clustering algorithm, which allows us to train the decision tree along with the model parameters using the context labels.

In this paper, the following contextual factors are taken into account:

- Contextual factors that are relevant to accent commands
 - mora count and accent type of {preceding, current, succeeding} accental phrase
 - position of current accental phrase in current breath group
 - position of current accental phrase in sentence
 - {preceding, current, succeeding} mora count of breath group
 - position of current breath group in sentence
 - mora count in sentence
- Contextual factors that are relevant to phrase commands
 - {preceding, current, succeeding} mora count of breath group
 - accental phrase count in {preceding, current, succeeding} breath group
 - position of current breath group in sentence
 - mora count in sentence

3.2. Probabilistic F_0 contour model including context dependent phrase and accent command with HMM

To extend the model presented in Subsec. 2.2 to a context-dependent one, we consider the HMM described in Fig. 2. In this HMM, we would like the phrase and accent states to be grouped into clusters via context clustering. We use M and N to denote the numbers of the phrase states and accent states, respectively. Thus, the present HMM can be summarized as follows:

problem, which can be dealt with using the EM algorithm. The log-likelihood function of θ given \mathbf{x} is written as

$$\begin{aligned} \log P(\mathbf{x}|\theta) &\stackrel{c}{=} \frac{1}{2} \log |\Lambda^{-1}| - \frac{1}{2} (\mathbf{x} - \mathbf{m})^T \Lambda^{-1} (\mathbf{x} - \mathbf{m}), \\ \mathbf{x} &= \begin{bmatrix} \mathbf{y}_p \\ \mathbf{y}_a \\ \mathbf{y}_b \end{bmatrix}, \quad \mathbf{m} = \begin{bmatrix} \mathbf{A}^{-1} \boldsymbol{\mu}_p \\ \mathbf{B}^{-1} \boldsymbol{\mu}_a \\ \boldsymbol{\mu}_b \mathbf{1} \end{bmatrix}, \\ \Lambda^{-1} &= \begin{bmatrix} \mathbf{A}^T \boldsymbol{\Sigma}_p^{-1} \mathbf{A} & \mathbf{O} & \mathbf{O} \\ \mathbf{O} & \mathbf{B}^T \boldsymbol{\Sigma}_a^{-1} \mathbf{B} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} & \boldsymbol{\Sigma}_b^{-1} \end{bmatrix}. \end{aligned} \quad (12)$$

In this case the Q function is thus given by

$$\begin{aligned} Q(\theta, \theta') &\stackrel{c}{=} \frac{1}{2} \left[\log |\Lambda^{-1}| - \text{tr}(\Lambda^{-1} \mathbb{E}[\mathbf{x}\mathbf{x}^T | \mathbf{y}; \theta']) \right. \\ &\quad \left. + 2\mathbf{m}^T \Lambda^{-1} \mathbb{E}[\mathbf{x} | \mathbf{y}; \theta'] - \mathbf{m}^T \Lambda^{-1} \mathbf{m} \right]. \end{aligned} \quad (13)$$

In above equation, a prior probability $\Pr(\theta)$ is constant since θ is uniformly distributed and the state sequence \mathbf{s} is fixed.

$\mathbb{E}[\mathbf{x} | \mathbf{y}; \theta]$ and $\mathbb{E}[\mathbf{x}\mathbf{x}^T | \mathbf{y}; \theta]$ are given explicitly as

$$\begin{aligned} \mathbb{E}[\mathbf{x} | \mathbf{y}; \theta] &= \mathbf{m} + \Lambda \mathbf{H}^T (\mathbf{H} \Lambda \mathbf{H}^T)^{-1} (\mathbf{y} - \mathbf{H} \mathbf{m}), \\ \mathbb{E}[\mathbf{x}\mathbf{x}^T | \mathbf{y}; \theta] &= \Lambda - \Lambda \mathbf{H}^T (\mathbf{H} \Lambda \mathbf{H}^T)^{-1} \mathbf{H} \Lambda \\ &\quad + \mathbb{E}[\mathbf{x} | \mathbf{y}; \theta] \mathbb{E}[\mathbf{x} | \mathbf{y}; \theta]^T, \end{aligned}$$

by using the relationship $\mathbf{y} = \mathbf{H}\mathbf{x}$, where $\mathbf{H} = [\mathbf{I}, \mathbf{I}, \mathbf{I}]$. These are the values to be updated at the E step. Let $\mathbb{E}[\mathbf{x} | \mathbf{y}; \theta]$ be partitioned into four $K \times 1$ blocks such that $\mathbb{E}[\mathbf{x} | \mathbf{y}; \theta] = (\bar{\mathbf{x}}_p^T, \bar{\mathbf{x}}_a^T, \bar{\mathbf{x}}_b^T)^T$.

In the M step, There is no need to update the state sequence parameter \mathbf{s} since we set restriction that it is always fixed. Hence the M step update is equivalent to the procedure that maximize with respect to $A_p^{(m)}$ and $A_a^{(n)}$ and is as follows.

$$\begin{aligned} A_p^{(m)} &= \frac{1}{|\mathcal{T}_{p_m}|} \sum_{k \in \mathcal{T}_{p_m}} [\mathbf{A} \bar{\mathbf{x}}_p]_k, \quad \mathcal{T}_{p_m} = \{k | s_k = p_m\}, \\ A_a^{(n)} &= \frac{1}{|\mathcal{T}_{a_n}|} \sum_{k \in \mathcal{T}_{a_n}} [\mathbf{B} \bar{\mathbf{x}}_a]_k, \quad \mathcal{T}_{a_n} = \{k | s_k = a_n\}. \end{aligned}$$

4.3. Parameter generation process

To obtain F_0 contour from input text, we firstly extract the state sequence by using context and constructed decision trees by training. Then, according to state sequence \mathbf{s} and model parameters θ , we can obtain the F_0 contour by determining \mathbf{y} so as to maximize $P(\mathbf{y} | \mathbf{s}, \theta)$ with respect to \mathbf{y} .

5. Preliminary experiment for proposed method

5.1. Experimental conditions

As a preliminary experiment, we implemented a simplified version of the present method to demonstrate the proof of concept of the present method. The simplified version we have implemented consists of two stages: First, we extract phrase and accent commands using the method described in [8] from the raw F_0 contours of the training data (the first 450 sentences of HTS ver 2.1 demo script [9]). Second, the values of the extracted phrase and accent commands were clustered using a decision tree based context clustering. The decision tree was constructed

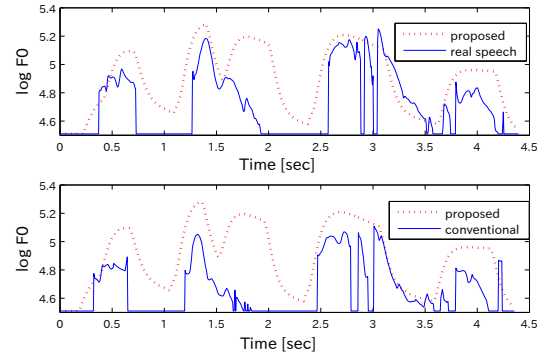


Figure 4: An example of generated F_0 contours of a Japanese utterance “ippyo no kakusa wa sarani hirogaru darou”. The top graph shows the F_0 contour generated by the simplified version of the present method described in 5.1 along with the F_0 contour of real speech. The bottom graph shows the F_0 contour generated by HTS [2].

according to the following criterion:

$$MDL = \frac{1}{2} \sum_{d=1}^{D_j} \left\{ \log(2\pi\sigma_j^2) + \frac{(x_i - \mu_j)^2}{\sigma_j^2} \right\} + cJ \log W \quad (14)$$

where x_i indicates the magnitude of each command, J indicates the number of nodes in each tree, j indicates node index, and D_j indicates the state occupancy of j -th node. We used the HTS label sequence in [9] in order to extract the beginning of each breath group and the range of each accentual phrase. In the method [8], the constant parameters were fixed respectively at $t_0 = 8$ ms, $\alpha = 3.0$ rad/s, $\beta = 20.0$ rad/s, $v_n^2[k] = 10^{15}$ for unvoiced regions and $v_n^2[k] = 0.2^2$ for voiced regions. μ_b was set at the minimum $\log F_0$ value in the voiced regions.

5.2. Experimental results

Fig. 4 shows an example of the F_0 contours generated using the last 53 sentences in the speech database available at [9], the raw F_0 contours of real speech extracted with the straight analysis [10] and the F_0 contours generated by HTS [2]. Since the conventional method is not ensured to generate an F_0 contour that follows the generating process of F_0 contours, it tended to sometimes generate unnatural-sounding F_0 contours. On the other hand, most of the F_0 contours generated by the present method sounded reasonably natural. This may be due to the fact that the Fujisaki model is able to express human F_0 contours consistently well. Some examples of the synthesized speech generated by the present and conventional methods are demonstrated in our demo site {<http://hil.t.u-tokyo.ac.jp/~kadowaki/Demos.htm>}. We can also confirm from these results that the over-smoothing of F_0 contours rarely occurred with the present approach.

6. Conclusion

This paper proposed a method for generating the F_0 contour of speech from a text input for text-to-speech synthesis. We previously introduced a statistical model describing the generating process of speech F_0 contours, based on the discrete-time version of the Fujisaki model. To associate a sequence of the Fujisaki-model parameters with a text input based on statistical learning, we extended this model to a context-dependent one. This idea was motivated by our expectation that averaging these parameters would not directly cause the over-smoothing of the F_0 contours, unlike the conventional method. We further proposed a parameter training algorithm for the present model based on a decision tree-based context clustering. The preliminary experimental results revealed that the present method was able to generate natural-sounding F_0 contours. Future work includes implementing the unified training algorithm described in Sec. 4 and conducting subjective evaluations.

7. References

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