社団法人 電子情報通信学会
THE INSTITUTE OF ELECTRONICS,
INFORMATION AND COMMUNICATION ENGINEERS

信学技報
TECHNICAL REPORT OF IEICE.

統計的系列-フレーム写像に基づく音声変換

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あらまし 話者変換の目的はある話者の声を別の話者の声に変換することである。これは二つの話者区間において音声時系列のマッピング関数を求めることとして考えられる。GMM を用いた統計的マッピング方法 [1], [2] は話者変換のタスクにおいてよく使われている。ただし、GMM を用いた変換技術はフレームからフレームへのマッピング関数を使用しているので、音声時系列のコンテキスト情報が十分には使われていない。HMM は音声時系列の有効なモデルであり、音声認識や音声合成においてよく使われている。本研究は HMM を用いた音声変換を研究対象とする。我々は HMM を用いた回帰、シーケンスからフレームの変換関数を導出した。先行の HMM を用いた音声変換方法 [3]〜[5] は強制切り出し (forced alignment) によって音声を分割し、各区間に対して変換を行う。それらの方法と異なって，我々の変換関数は線形変換の重みつけの和として導出される。重みは各フレームの HMM 事後確率である。変換パラメータを推定するために、我々は最小２乗誤差基準及びと最大尤度基準を提案した。実験結果は提案手法の有効性を示した。

キーワード 音声変換、線形回帰、シーケンスからフレームへ変換、HMM,

Statistical sequence-to-frame mapping techniques for voice conversion

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Abstract Voice conversion, a task to transform one speaker's voice to another's, can be regarded as a problem to find a mapping function between voice spaces of two speakers. GMM-based statistical mapping methods [1], [2] have been widely used for voice conversion. However, the classical GMM-based techniques make use of a frame-to-frame mapping function, which largely ignores the contextual information existing over a speech sequence and usually causes over-smoothness of converted speech. It is well known that HMM yields an efficient method to model the density of a whole speech sequence and has found successes in speech recognition and synthesis. Inspired by this fact, this paper studies how to use HMM for voice conversion. We derive an HMM-based sequence-to-frame mapping function with statistical analysis. Different from previous HMM-based voice conversion methods [3]〜[5] that used forced alignment for segmentation and transform frames aligned to a state with its associated linear transformation, our method has a soft mapping function as a weighted summation of linear transformations. The weights are calculated as the HMM posterior probabilities of frames. We also propose and compare two methods to learn the parameters of our mapping functions, namely least square error estimation and maximum likelihood estimation. We carried out experiments to examine the proposed HMM-based method for voice conversion.

Key words Voice conversion, linear regression, sequence-to-frame mapping, HMM

1. Introduction

Voice conversion (VC) [1], [2], [6], [7] is a task to transform a speaker's voice into the one that sounds like another speaker while the linguistic contents are preserved. VC has many important applications and is receiving intensive attentions in the field of speech synthesis. Since utterances of two speakers differ from each other in many aspects, such as speech rate, duration, pitch, formant frequencies and speaking style etc., the ideal VC technique should take account of all these aspects. However, this is difficult in practice, some of these features are difficult to calculate and some are difficult to convert. For this reason, many VC techniques seek to use a transformation function between the spectral spaces of source and target speakers, and only conduct simple modifications for prosody features such as F0. We follow this framework in this paper.

The GMM-based statistical mapping techniques proposed by Stylianou et al. [1] and Kain [2] have been widely used to convert spectral features between different speakers. These techniques make use of GMM to model the densities of source cepstral vectors [1] or joint cepstral vectors [6]. The mapping function is a weighted summation of linear transformations for each Gaussian component while the weights are calculated as posterior probabilities of source vectors. The parameters of the linear transformations are estimated by minimizing squared errors. The efficiency of GMM-based mapping and its advantage to other spectral conversion methods such as mapping codebooks and artificial neural network, have been demonstrated in many previous studies [1], [2], [6], [7]. However, GMM only describes the density of frame vectors and cannot take account of the contextual (dynamic) information. Although one can incorporate delta or delta-delta features into GMM, these features still only provide local dynamic information. On the other hand, HMM is a density model for sequences and the transition probabilities of HMM allow it to account for the dynamics in speech. This paper studies an HMM-based mapping method for voice conversion. We deduce the formulas for sequence-to-frame mapping based on HMM by using statistical analysis. We use least square error (LSE) and maximum likelihood (ML) criteria to estimate the parameters of the mapping function. We find that the LSE estimation has a closed form solution, while the ML estimation leads to a nonlinear optimization problem. For this reason, we develop an EM-based algorithm for the ML estimation of HMM-based mapping. We conduct experiments to examine the performances of LSE estimation and ML estimation for HMM-based voice conversion. The results show the usefulness of the proposed method.

We notice that several studies tried to apply HMMs to voice conversion [3]∼[5]. In [3], Kim et al. introduced a hidden Markov VQ model for voice conversion, where the mapping function is determined by the codebook and the optimal states of a source utterance. Different from this method, we use normal HMMs and our mapping function is a weighted summation of several linear transformations. Duxans et al. [4] used HMMs to model the densities of source vectors and joint vectors, and estimated a linear transformation for each state of an HMM to convert an input utterance. In [5], Wu et al. proposed duration-embedded DeBi-HMM for expressive voice conversion. Unlike the methods in [4] and [5] where the mapping functions only depend on the optimal states obtained by forced alignment, our method has a more strict statistical framework and the mapping function is derived by combining the linear transformations of different states using weights of posterior probabilities of states. This 'soft' mapping function allows us to deal with the problem of spectral jumps at the boundaries of segments resulted from forced alignment [3], [4].

2. HMM-based voice conversion

Voice conversion can be regarded as a problem to determine a mapping function from an utterance of a source speaker to that of a target speaker denoted by $Y = F(X)$, where F denotes the mapping function and X, Y represent speech sequences of source and target speakers, respectively. Let $X = [x_1, x_2, ..., x_T]$ and $Y = [y_1, y_2, ..., y_{T'}]$, where x_t $(1 \leqq t \leqq T)$ and y_t $(1 \leqq t \leqq T')$ represents d-dimensional frame vectors. However, to find a direct mapping between two sequences is very difficult, since a sequence usually contains a large number of elements and the length of sequences X and Y can be different. For this reason, many researchers reduced the sequence mapping to a frame-to-frame conversion problem, which is denoted by $y_t = f(x_t)$. A popular approach of this kind is to make use of the GMM-based statistical mapping, where GMM is used to model the density of frame vectors [1] of a source speaker or joint vectors of source and target speakers [2], and the final mapping function is the weighted combination of linear transformations estimated for each Gaussian component. In a recent study, we proposed a method called Mixture of Probabilistic Linear Regressions (MPLR) [8], which unifies the two GMM-based voice conversion techniques [1], [2] and leads to a better method for estimating mapping parameters. Although the frame-to-frame mapping is simple, it only considers the current frame x_t for conversion and doesn't take account of the contextual (dynamic) information to derive a mapping function, which plays a important role for speech perception.

GMM is a density model of frame vectors, and GMM-based mapping is a frame-to-frame conversion, which cannot account for the contextual information over a speech sequence. Partially for this reason, it is observed that the classical GMM-based mapping usually generates overly smoothed utterances [7]. To overcome this problem, Toda et al. [7] took consideration of the dynamic features with a trajectory model and alleviate the overly smoothing problem by

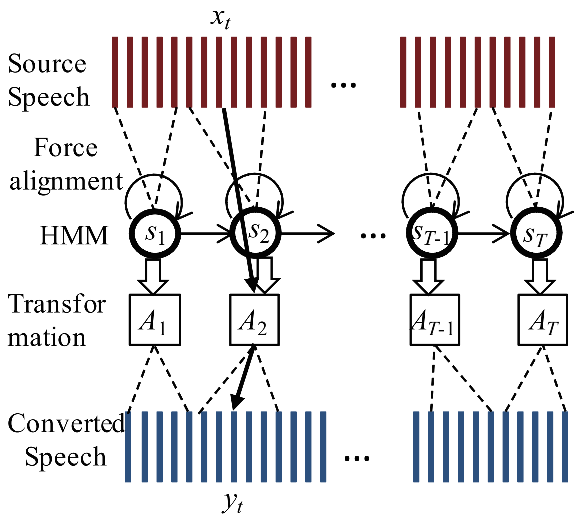

図 1 Framework of voice conversion with forced alignment.

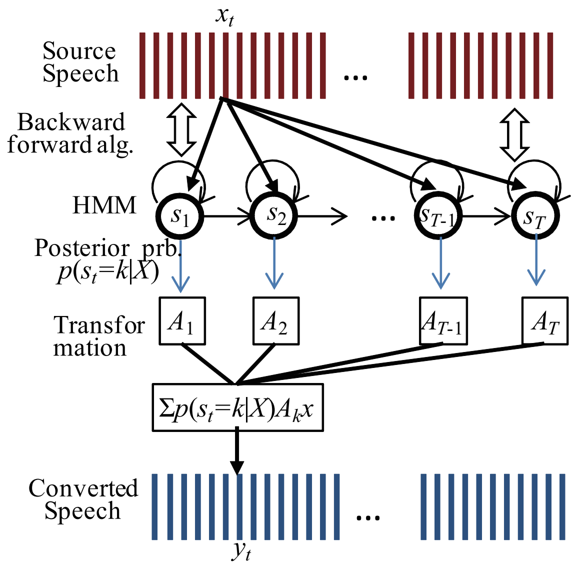

図 2 Framework of proposed HMM-based voice conversion.

considering a global variance feature. In this paper, we try to solve this problem by using HMM. Different from GMM, HMM provides a probability model for sequences and accounts for the dynamic information by using transition probabilities. The effectiveness of HMM has been demonstrated in both speech recognition and speech synthesis. Motivated by these facts, we study the HMM-based spectral mapping techniques in this paper (注1). Perhaps the most simplest idea for applying HMM to voice conversion is to 1) prepare a transformation for each state, 2) determine the optimal state of each frame of an input utterance to be converted with forced alignment (Viterbi decoding), and 3) convert each frame vector by the transformation associated with its optimal state (Fig. 1). This idea was adopted by previous works [3]∼[5]. However, forced alignment gives a hard segmentation of the speech sequence. And this usually leads to spectral jumps at the boundaries of segments, and diminishes the smoothness of converted speech. In this paper, we deal with this problem by introducing a 'soft' mapping function. This soft mapping function is a weighted summation of the linear transformations of all states, where the weights are posterior probabilities of states given a source sequence.

2.1 HMM-based sequence-to-frame mapping

This section describes the formal formulation of HMM-based sequence-to-frame mapping. Consider an HMM with K states. Let $p(x|s)$ denote a state-observation probability of frame vector x given state s, and $p(s'|s)$ represent a state-transition probability from state s to s'. In HMM, the joint probability of speech sequence $X = [x_1, x_2, ..., x_T]$ and its corresponding state sequence $S = [s_1, s_2, ..., s_T]$ $(1 \leqq s_t \leqq K)$ can be calculated by,

$$\begin{aligned} p(X, S) =& P(X|S)P(S) \\ &= \prod_{t=1}^{T} p(x_t|s_t)p(s_1) \prod_{t=2}^{T} p(s_t|s_{t-1}). \end{aligned} \tag{1}$$

Given state s and source vector x, we assume that target vector y has the following linear-Gaussian distribution,

$$p(y|s, x) = N(y|B_s x + b_s, \Sigma_s), \tag{2}$$

where B_s, b_s denote the linear transformation parameters, and Σ_s represents the covariance matrix of the above linear-Gaussian distribution. Then the expectation (mean) of y is given by $E_{p(y|s,x)}[y] = B_s x + b_s$.

With the HMM of source sequence X, we can calculate the conditional probability of the t-th target vector y_t given sequence X as

$$p(y_t|X) = \sum_{S \in \mathbb{S}} p(y_t, S|X) = \sum_{S \in \mathbb{S}} p(y_t|S, X)p(S|X), \tag{3}$$

where $\mathbb{S}$ is the set of possible state sequences for X.

When state s_t is given, we assume that target vector y_t only depends on its corresponding source vector x_t. This allows us to make the following simplification,

$$p(y_t|S, X) = p(y_t|s_t, x_t) = N(y_t|B_{s_t} x_t + b_{s_t}, \Sigma_{s_t}). \tag{4}$$

Under this assumption, we can deduce the probability of Eq. 3 as

(注1): Generally, the length of source utterance T has not to be equal to the length of target utterance T'. However, in this paper we assume that $T = T'$ in the HMM-based mapping for simplicity.

$$
\begin{aligned}
&\sum_{S\in\mathbb{S}} p(y_t|S,X)p(S|X)\\
&=\sum_{s_t}\left[\sum_{/s_t} p(y_t|s_t,x_t)p(S^{/s_t}|X)\right]\\
&=\sum_{s_t} p(y_t|s_t,x_t)\sum_{S^{/s_t}} p(S^{/s_t}|X)\\
&=\sum_{k=1}^{K} p(y_t|s_t=k,x_t)p(s_t=k|X), \qquad (5)
\end{aligned}
$$

where $S^{/s_t} = s_1,...s_{t-1}s_{t+1}...s_T$. Noted that posterior probability $p(s_t = k|X)$ can be calculated efficiently by the famous backward and forward algorithm of HMM [9]. With Eq. 5, the mapping of sequence X to frame y_t can be estimated by

$$
\begin{aligned}
f_{\text{HMM}}(X,t) =& E_{p(y_t|X)}[y_t]\\
=& \sum_{k=1}^{K} p(s_t=k|X)(B_k x_t + b_k). \qquad (6)
\end{aligned}
$$

The above formula includes the multiplication of two parts, one is the posterior probabilities of t-th state beining with state k $p(s_t = k|X)$, and the other is the linear transformations $B_k x_t + b_k$. The framework of our HMM based conversion is depicted in Fig. 2.

2.2 Estimation of mapping parameters

In this section, we discuss how to calculate the parameters of HMM-based mapping function of Eq. 6 from a set of training sequence pairs $(X_n, Y_n)_{n=1}^N$, where source sequence $X_n = [x_1^n, ..., x_{T_n}^n]$ and target sequence $Y_n = [y_1^n, ..., y_{T_n}^n]$. We assume that X_n, Y_n have been aligned by dynamic time warping, and thus both have the same length denoted by T_n. We can train an HMM from the utterances of source speaker by the well known Baum-Welch algorithm [9] at first. And posterior probability $p(s_t^n = k|X_n)$ (s_t^n denotes the state of frame x_t^n in X_n) can be calculated with the backward and forward algorithm of HMM. Then the problem here is how to estimate the transformation parameters $\{B_s, b_s, \Sigma_s\}$ for state s. In the following, we describe two approaches for estimating these parameters. One is least square error (LSE) estimation and the other is maximum likelihood (ML) estimation. For convenience, we introduce notation $r_{t,k,n} = p(s_t^n = k|X_n)$.

2.2.1 Least square estimation

The objective function of least square estimation is,

$$
\begin{aligned}
&\min_{\{B_k,b_k\}} \sum_{n=1}^{N}\sum_{t=1}^{T_n} |f_{\text{HMM}}(X_n,t) - y_t^n|^2\\
&=\sum_{n=1}^{N}\sum_{t=1}^{T_n} |\sum_{k=1}^{K} r_{t,k,n}(B_k x_i^n + b_k) - y_i^n|^2. \qquad (7)
\end{aligned}
$$

This is a linear optimization problem, which can be solved directly. For simplicity, we introduce argument vector $\hat{x} = [x^T, 1]^T$ and set $A_k \hat{x}_t^n = B_k x_t^n + b_k$. Further, the following notations are used $X_k^n = [r_{1,k,n}\hat{x}_1, r_{2,k,n}\hat{x}_2, ..., r_{T_n,k,n}\hat{x}_{T_n}]$, $X_k = [X_k^1, ..., X_k^N]$, $\mathbb{X} = [X_1^\top, X_2^\top, ..., X_K^\top]^\top$, $Y_n = [y_1, y_2, ..., y_{T_n}]$, and $\mathbb{Y} = [Y_1, Y_2, ..., Y_N]$, where '$\top$' denotes matrix transpose. The optimal matrices $\{A_k^*\}$ for Eq. 7 are given by

$$
[A_1^*, A_2^*, ..., A_K^*] = \mathbb{Y}\hat{\mathbb{X}}^\top(\hat{\mathbb{X}}\hat{\mathbb{X}}^\top)^{-1}. \qquad (8)
$$

However, this is very computationally expensive, since matrix $\hat{\mathbb{X}}$ has a size of $K(d+1)\times\sum_n T_n$. To overcome this limitation, we use the following decomposition method. Remind $\sum_k r_{t,k,n} = 1$ and $r_{t,k,n} > 0$. According to Jensen's inequality, we have $|\sum_k r_{t,k,n}(y_t^n - A_k\hat{x}_t^n)|^2 \leqq \sum_k r_{t,k,n}|y_t^n - A_k\hat{x}_t^n|^2$. Therefore, Eq. 7 can be approximated by the following upper bound,

$$
\arg\min_{\{A_k\}} \sum_k\sum_n\sum_t r_{t,k,n}|y_t^n - A_k\hat{x}_t^n|^2. \qquad (9)
$$

This can be further decomposed into K independent linear optimization problems,

$$
\arg\min_{A_k} \sum_n\sum_t r_{t,k,n}|y_t^n - A_k\hat{x_t^n}|^2. \qquad (10)
$$

The optimal matrix for Eq. 10 is given by $A_k^\# = \mathbb{Y}X_k^\top(X_k X_K^\top)^{-1}$. These calculations are closely related to those discussed in our previous work on MPLR [8].

2.2.2 Maximum likelihood estimation

Although least square estimation is simple and has a closed form solution, it doesn't consider the covariance matrices $\{\Sigma_s\}$ in Eq. 2. In the section, we make use of maximum likelihood (ML) estimation to overcome this problem. For linear regression, LSE and ML estimations lead to the same estimations. However, as we will see shortly this is not the case for our problem. Formally, ML estimation is defined as,

$$
\begin{aligned}
&\max_{B_k,b_k,\Sigma_k} \prod_n\prod_t p(y_t^n|X_n)\\
&=\prod_n\prod_t\sum_{k=1}^{K} p(s_t^n=k|X_n)N(y_t^n|B_k x_t^n + b_k, \Sigma_k). \qquad (11)
\end{aligned}
$$

Then log likelihood function is given by,

$$
\begin{aligned}
&\mathcal{L}(\{B_k, b_k, \Sigma_k\})\\
&=\sum_n\sum_t \log\left(\sum_{k=1}^{K} p(s_t^n=k|X_n)N(y_t^n|B_k x_t^n + b_k, \Sigma_k)\right). \qquad (12)
\end{aligned}
$$

For convenience, we introduce parameters $\gamma_{t,k,n}$ and $\beta_{t,k,n}$ as follows

Algorithm 1 EM algorithm for ML estimation

1: **Initialize** transformation parameters $\{B_k, b_k, \Sigma_k\}$.

2: **E-step:** Calculate hidden parameters $\{\gamma_{t,k,n}\}$ and $\{\beta_{t,k,n}\}$.

3: **M-step:** Estimate the following parameters.

$$N_k = \sum_n \sum_t \beta_{t,k,n}, \tag{18}$$

$$\bar{x}_k = \frac{1}{N_k} \sum_n \sum_t \beta_{t,k,n} x_t^n, \tag{19}$$

$$\bar{y}_k = \frac{1}{N_k} \sum_n \sum_t \beta_{t,k,n} y_t^n, \tag{20}$$

$$\Sigma_k^{xx} = \frac{1}{N_k} \sum_n \sum_t \beta_{t,k,n} (x_t^n - \bar{x}_k)(x_t^n - \bar{x}_k)^\top, \tag{21}$$

$$\Sigma_k^{yx} = \frac{1}{N_k} \sum_n \sum_t \beta_{t,k,n} (y_t^n - \bar{y}_k)(x_t^n - \bar{x}_k)^\top, \tag{22}$$

$$\Sigma_k^{yy} = \frac{1}{N_k} \sum_n \sum_t \beta_{t,k,n} (y_t^n - \bar{y}_k)(y_t^n - \bar{y}_k)^\top. \tag{23}$$

Update transformation parameters as

$$B_k^* = \Sigma_k^{yx} (\Sigma_k^{xx})^{-1}, \tag{24}$$

$$b_k^* = \bar{y}_k - B_k^* \bar{x}_k, \tag{25}$$

$$\Sigma_k^* = \Sigma_k^{yy} - \Sigma_k^{yx} (\Sigma_k^{xx})^{-1} (\Sigma_k^{yx})^\top. \tag{26}$$

4: **Evaluate** the log likelihood $L(\{B_k, b_k, \Sigma_k\})$.

5: **Terminate** the procedure when convergence, otherwise go to step 2.

$$\gamma_{t,k,n} = N(y_t^n | B_k x_t^n + b_k, \Sigma_k), \tag{13}$$

$$\beta_{t,k,n} = \frac{\gamma_{t,k,n} r_{t,k,n}}{\sum_j \gamma_{t,j,n} r_{t,j,n}}. \tag{14}$$

To maximize Eq. 11, we calculate the derivatives of log likelihood $\mathcal{L}$ as,

$$\frac{\partial \mathcal{L}}{\partial b_k} = \sum_n \sum_t \beta_{t,k,n} (\Sigma_k)^{-1} (y_t^n - B_k x_t^n - b_k) = 0, \tag{15}$$

$$\frac{\partial \mathcal{L}}{\partial B_k} = \sum_n \sum_t \beta_{t,k,n} (\Sigma_k)^{-1} (y_t^n - B_k x_t^n - b_k) x_t^{n\top} = 0, \tag{16}$$

$$\frac{\partial \mathcal{L}}{\partial \Sigma_k} = \sum_n \sum_t \frac{1}{2} \beta_{t,k,n} \{ (\Sigma_k)^{-1} (y_t^n - B_k x_t^n - b_k) (y_t^n - A_k x_t^n - b_k)^\top (\Sigma_k)^{-1} - (\Sigma_k)^{-1} \} = 0. \tag{17}$$

The above formulas don't have closed form solutions, since $\{\beta_{t,k,n}\}$ include the parameters $\{B_k, b_k, \Sigma_k\}$. Then we develop the following EM algorithm for parameter estimation.

3. Experiments

We carried out experiments to evaluate the proposed two HMM-based voice conversion methods. We made use of the ATR-503 phoneme balanced sentences in the experiments. The data set used contains 503 utterances from a male speaker and another 503 utterances from a female speaker with the same linguistic contents. The sampling frequency is 16k Hz. For each utterance, we calculated its 24-D cepstrum sequence. We made the conversion from female voice to male voice. As a preparation, the training utterances of the source speaker and the target speaker are aligned by dynamic time warping (DTW). In all the following experiments, ergodic HMMs are trained for the utterances of a source speaker. The cepstrum distortion [1] between the target cepstrum vector $[y_t^1, ..., y_t^{24}]$ and the converted cepstrum vector $[y_c^1, ..., y_c^{24}]$ is defined by,

$$\mathrm{CD[dB]} = \frac{10}{\ln 10} \sqrt{2 \sum_d (y_t^d - y_c^d)^2}. \tag{27}$$

And we calculate the average cepstrum distortion as an objective evaluation measure.

表 1 Average cepstrum distortions [dB] of LSE and MLE. (N is the number of training utterances. M is the number of states.)

	N ($M = 10$)					
Method	10	20	30	50	100	200
LSE	5.030	4.881	4.832	4.784	4.758	4.735
MLE	5.037	4.884	4.836	4.786	4.759	4.736
	M ($N = 150$)					
Method	5	7	9	15	30	50
LSE	4.780	4.766	4.760	4.751	4.741	4.745
MLE	4.781	4.767	4.761	4.754	4.742	4.746

3.1 Comparison of LSE and MLE

We make comparison between the two parameter estimation methods, least square estimation (LSE) and maximum likelihood estimation (MLE). We changed the number of training utterances and the number of states. In both experiment, the testing set are 50 new utterances. The results are sumarized in Table 1. As one can see, LSE and MLE have very similar performance, but the cepstrum distortion of LSE is a bit smaller than that of MLE. This is because LSE directly minimizes squared errors. Note that as MLE requires EM iterations, MLE is much more computationally expensive than LSE.

3.2 Experiment 2

In this experiment, we made comparison between the proposed HMM-based mapping method with LSE estimation and the previous HMM-based mapping method [4]. We conducted two experiments. In the first experiment, we fixed the states of HMM as 5 and changed the number of training utterances. In the second experiment, we changed the number of states of HMM while 150 training utterances were used for training. The test set includes 50 different utterances. The results are shown in Fig. 3 and Fig. 4. As one can see that the proposed method always outperforms the previous HMM-based conversion method. We can also find that the difference between the two methods enlarges as state number increases. This is because as state number increases, the

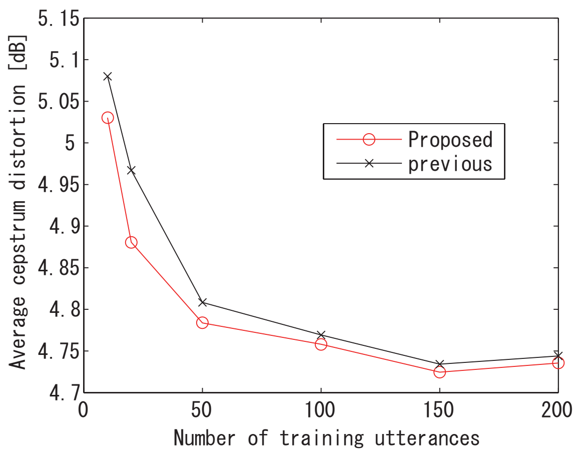

図 3 Comparison of the proposed method and the previous forced alignment based mapping method with various numbers of training utterances.

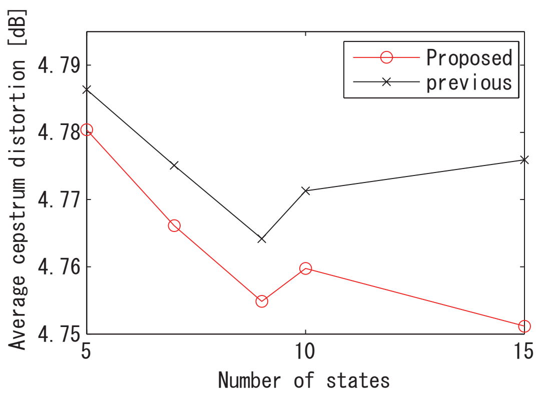

図 4 Comparison of the proposed method and the previous forced alignment based mapping method with various numbers of states.

forced alignment of the previous method leads to more segments and thus more boundaries with spectral jumps, which affects its performance. We also conducted experiments to make comparison with GMM-based mapping. The cepstral distortions of both methods are similar. The experimental results are still limited here. We will examine the proposed method with bigger database and a larger number of states in the future.

4. Conclusions

This paper studies a HMM-based sequence-to-frame mapping method for voice conversion. The objective of using HMM is to model the dynamic and contextual information in speech sequence. We derive a novel HMM-based mapping function with statistical analysis. The mapping function is composed of the weighted summation of linear transformations estimated for each state, where the weights are calculated as posterior probabilities using forward and backward algorithms. We develop two methods to estimate transformation parameters of the mapping function, one is least square estimation (LSE) and the other is maximum likelihood estimation (MLE). The former can be reduced to a linear optimal problem, and has its closed form solution. For the latter, we develop an EM-based algorithm to calculate the optimal parameters. Compared with the previous GMM-based voice conversion techniques, the use of HMM allows us to account for contextual information in speech signals. Compared to the previous HMM-based voice conversion method, our method use a soft mapping function to avoid spectral jumps at state boundaries. We carried out experiments to compare LSE and MLE. The results show that both methods have very similar performance. We also conducted a comparative experiment with the previous HMM-based mapping method [4]. The results indicate that our method has a better performance in terms of cepstrum distortion. We also conducted comparison experiments with GMM-based methods, but found the cepstrum distortions of both methods are near. Finally, it is noted that experimental results are only limited in the current version. Several experiments with more data and a larger number of states are still on the way. We are also going to carry out a subjective test to assess the proposed methods.

謝辞 The first author would like to thank the Japan Society for the Promotion of Science (JSPS) for the fellowship under P19.07078.

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