Statistical Error Compensation Techniques for Spectral Quantization

Seung Ho Choi* · Hong Kook Kim**

ABSTRACT

In this paper, we propose a statistical approach to improve the performance of spectral quantization of speech coders. The proposed techniques compensate for the distortion in a decoded line spectrum pairs (LSP) vector based on a statistical mapping function between a decoded LSP vector and its corresponding original LSP vector. We first develop two codebook-based probabilistic matching (CBPM) methods based on linear mapping functions according to different assumption of distribution of LSP vectors. In addition, we propose an iterative procedure for the two CBPMs. We apply the proposed techniques to a predictive vector quantizer used for the IS-641 speech coder. The experimental results show that the proposed techniques reduce average spectral distortion by around 0.064dB.

Keywords: speech coding, vector quantization, probabilistic matching, spectral distortion

1. Introduction

In low-bit-rate speech coding, spectral parameters are employed to model a vocal tract of the speech production system. Therefore, accurate design of a vector quantizer (VQ) at low rates is important to decoded speech quality. To efficiently quantize the spectral parameters, lots of schemes have been proposed such as a split VQ, a multi-stage VQ, a predictive VQ and so on [1]. Nonetheless, the performance of spectral quantizers used for the current standard speech coders is required to be improved in a view of transparent speech quality suggested by [2].

In order to improve the performance of spectral quantization, we compensate for the spectral distortion in a decoded spectral parameter vector, typically, line spectrum pairs (LSP) [3] used

* Dept. of Electronics and Information Eng., Seoul National University of Technology.
** Dept. of Information and Communications, Gwangju Institute of Science and Technology (GIST).

for the spectral parameters in speech coding. This can be done by using a statistical mapping between the decoded LSP vector and its corresponding original LSP vector. Actually, a decoded LSP vector is an element of a finite set because it is already quantized as one of the codewords. In other words, the vector is a point of the Voronoi region [4] constructed by a vector quantizer. At first, we match the two probabilities of the original and decoded LSP vectors. For this end, a mapping function is designed on the basis of vector quantization. In this paper, we develop linear mapping functions based on the codebook-based probabilistic matching algorithms in case of completely correlated observations (CBPM-CC) and mean-square estimation (CBPM-MS). Furthermore, iterative methods are proposed for CBPM-CC and CBPM-MS, respectively. We applied the proposed techniques to a predictive vector quantizer used for the IS-641 speech coder [5].

Following this Introduction, we propose a codebook-based probabilistic matching method in Section 2. Here, we describe two algorithms such as CBPM-CC and CBPM-MS. And then, we will extend each method in an iterative version. In Section 3, we will show the performance improvement of the proposed methods, and then we conclude this paper in Section 4.

2. Codebook-based Probabilistic Matching

To begin with, it is assumed that a p-dimensional original LSP and its corresponding decoded LSP vectors follow with multivariate Gaussian probability distribution functions (pdfs) [6], defined as

$$f(\vec{\omega}(n) \mid \phi_i^{\Omega}) = N(\omega_{i,k}(n); \mu_{i,k}, \Sigma_{i,k}), \tag{1}$$

$$f(\vec{\omega}'(n) \mid \phi_i^{\Omega'}) = N(\omega'_{i,k}(n); \mu'_{i,k}, \Sigma'_{i,k}), \tag{2}$$

where $N(x;\mu,\Sigma) = \frac{1}{(2\pi)^{p/2}|\Sigma|^{1/2}} \exp\{-\frac{1}{2}(x-\mu)^t \Sigma^{-1}(x-\mu)\}$, $\vec{\omega}(n) = (\omega_1, \cdots, \omega_p)^t$ and $\vec{\omega}'(n) = (\omega'_1, \cdots, \omega'_p)^t \in (0,\pi)^p$ are the original and decoded LSP vectors, respectively. In addition, $\phi_i^{\Omega} = (\vec{\mu}_i, \Sigma_i)$ is the Gaussian mixture density of the i-th cluster for the original LSP vector with the mean vector and the covariance matrix of the i-th cluster as $\vec{\mu}_i = (\mu_{i,1}, \cdots, \mu_{i,p})^t \in (0,\pi)^p$ and $\Sigma_i = diag\{\sigma_{i,1}, \cdots, \sigma_{i,p}\}$ Also, $\phi_i^{\Omega'} = (\vec{\mu}_i, \Sigma_i)$ is the Gaussian mixture density of the i-th cluster for the decoded LSP vector where the mean vector and the covariance matrix are $\vec{\mu}_i' = (\mu_{i,1}', \cdots, \mu_{i,p}')^t$ and $\Sigma_i' = diag(\sigma_{i,1}', \cdots, \sigma_{i,p}')$. From the uncorrelatedness property of LSP [7], we can set covariance matrices as diagonal.

In order to achieve a probabilistic matching, a linear function T from Ω' to Ω is considered and defined as

$$\hat{\vec{\omega}}(n) = T(\vec{\omega}'(n)) = A\vec{\omega}'(n) + \vec{b}, \quad (3)$$

where A is a linear transform matrix with a rank of p, and $\vec{b}$ is a constant bias vector. Since $T(\cdot)$ is a linear function, $\hat{\vec{\omega}}(n)$ is also a multivariate Gaussian random vector [8].

2.1 Completely Correlated Observations

In order to match the pdf of $\vec{\omega}(n)$ and $\hat{\vec{\omega}}(n)$, it is sufficient to solve the equation of

$$A\Sigma_i' A^t = \Sigma_i, \quad (4)$$

$$A\vec{\mu}_i' + \vec{b} = \vec{\mu}_i, \quad (5)$$

where we assume that $\vec{\omega}(n)$ and $\hat{\vec{\omega}}(n)$ are generated from the parameters of ϕ_i^{Ω} and $\phi_i^{\Omega'}$, respectively. By solving (4) and (5), we obtain A and $\vec{b}$ as

$$A = \Sigma_i^{1/2} \Sigma_i'^{-1/2}, \quad (6)$$

$$\vec{b} = \vec{\mu}_i - \vec{\mu}_i' \Sigma_i^{1/2} \Sigma_i'^{-1/2}. \quad (7)$$

The covariance matrices are diagonal and thus their square roots are also diagonal. Therefore, A must be diagonal. We can estimate $\vec{\mu}_i$, Σ_i, $\vec{\mu}_i'$, and Σ_i' by using a clustering technique whose step-by-step procedure is described below.

Algorithm 1 Codebook-based Probabilistic Matching – Completely Correlated Observations (CBPM-CC)

It is assumed that we have enough decoded LSP vectors and their corresponding original LSP vectors so that the parameters can be sufficiently estimated. Let N be the total number of the decoded and original LSP vector pairs for estimating the mean and covariance matrices parameters.

Step 1) Cluster decoded LSP vectors by a VQ codebook design algorithm [9]. Let $\{C'_1,\cdots,C'_M\}$ be the M clusters for decoded LSP vectors. Also, we denote $\{C_1,\cdots,C_M\}$ as the M clusters for original LSP vectors. A decoder LSP vector is assigned to one of M clusters such that $\vec{\omega}'(n)\in C'_i$ if $f(\vec{\omega}'(n)\mid\phi_i^{\Omega'})>f(\vec{\omega}'(n)\mid\phi_j^{\Omega'})$ for $i,j=1,\cdots,M$ and $i\neq j$. Therefore, estimates of $\vec{\mu}'_i$ and Σ'_i for $1\le i\le M$ are represented as

$$\vec{\mu}'_i=\frac{1}{N(i)}\sum_{\vec{\omega}'(n)\in C'_i}\vec{\omega}'(n), \tag{8}$$

$$\Sigma'_i=\frac{1}{N(i)}\sum_{\vec{\omega}'(n)\in C'_i}(\vec{\omega}'(n)-\vec{\mu}'_i)(\vec{\omega}'(n)-\vec{\mu}'_i)^t, \tag{9}$$

where $N(i)=\#C'_i$ is the cardinal of C'_i.

Step 2) Construct the M clusters for the original LSP vectors. By a simple rule of

$$\vec{\omega}(n)\in C_i \text{ if } \vec{\omega}'(n)\in C'_i, \tag{10}$$

we also estimate the mean and variance for each cluster in original LSP vector domain as

$$\vec{\mu}_i=\frac{1}{N(i)}\sum_{\vec{\omega}(n)\in C_i}\vec{\omega}(n), \tag{11}$$

$$\Sigma_i=\frac{1}{N(i)}\sum_{\vec{\omega}(n)\in C_i}(\vec{\omega}(n)-\vec{\mu}_i)(\vec{\omega}(n)-\vec{\mu}_i)^t, \tag{12}$$

where $\#C_i=\#C'_i=N(i)$.

In order to compensate the quantization distortion for a given decoded LSP vector $\vec{\omega}'(n)$, the compensated LSP vector by CBPM-CC is obtained by

$$\bar{\vec{\omega}}'(n)=\Sigma_i^{1/2}\Sigma_i'^{-1/2}(\vec{\omega}'(n)-\vec{\mu}'_i)+\vec{\mu}'_i \tag{13}$$

$$\text{if } f(\vec{\omega}'(n)\mid\vec{\mu}'_i,\Sigma'_i)>f(\vec{\omega}'(n)\mid\vec{\mu}'_j,\Sigma'_j) \text{ for all } i\neq j. \tag{14}$$

We can also rewrite (13) in component-wise as

$$\overline{\omega}_k(n) = (\frac{\omega'_k(n) - \mu'_{i,k}}{\sigma'_{i,k}})\sigma_{i,k} + \mu_{i,k}, \text{ for } 1 \le k \le p. \quad (15)$$

2.2 Mean Square Estimation

In the CBPM-CC algorithm described above, we assumed that $\vec{\omega}(n)$ and $\vec{\omega}'(n)$ are completely correlated and thus we could exactly match the two statistics. However, this is not true. Therefore, another method should be proposed for considering less correlated effect.

We can find the linear function of (3) which minimizes the mean square (MS) estimation error between $\vec{\omega}(n)$ and $T(\vec{\omega}'(n))$ such as

$$A^*, \vec{b}^* = \min_{A,\vec{b}} E[(\vec{\omega}(n) - A\vec{\omega}'(n) - \vec{b})'(\vec{\omega}(n) - A\vec{\omega}'(n) - \vec{b})]. \quad (16)$$

By setting the derivatives of (16) to zero, the constants A and $\vec{b}$ are obtained as

$$A^* = R_i \Sigma_i'^{-1}, \quad (17)$$

$$\vec{b}^* = \vec{\mu}_i - A^* \vec{\mu}_i', \quad (18)$$

where it is also assumed that $\vec{\omega}(n)$ and $\vec{\omega}'(n)$ are jointly generated from the parameters of $\phi_i^{\Omega}, \phi_i^{\Omega'}$ and R_i. Here, R_i is a crosscorrelation matrix between $\vec{\omega}(n)$ and $\vec{\omega}'(n)$. If two vectors are completely correlated each other, then $R_i = \Sigma_i^{1/2}\Sigma_i'^{-1/2}$. Thus (17) and (18) are equal to (6) and (7), respectively.

Algorithm 2 Codebook-based Probabilistic Matching – Mean Square Estimation (CBPM-MS)

In addition to the processing of CBPM-CC, we estimate the crosscorrelation of the i-th cluster, R_i, as

$$R_i = \frac{1}{N(i)} \sum_{\vec{\omega}(n) \in C_i} (\vec{\omega}(n) - \vec{\mu}_i)(\vec{\omega}(n) - \vec{\mu}_i)'. \quad (19)$$

where R_i's should also be diagonal. If $\vec{\omega}'(n)$ is included in C_i, the vector compensated by CBPM-MS is represented as

$$\bar{\omega}_k(n) = \left(\frac{\omega'_k(n) - \mu'_{i,k}}{\sigma'_{i,k}}\right) r_{i,k}{}^2 + \mu_{i,k} \quad \text{for } 1 \le k \le p, \tag{20}$$

where $R_i = diag\{r_{i,1}{}^2, \cdots, r_{i,p}{}^2\}$.

2.3 Iterative Methods

The procedure for the proposed iterative CBPM (ICBPM) is as follows:

Step 1) Construct the same codebook with a size of M as CBPM-CC or CBPM-MS. Let l be the iteration number. Set l = 1.

Step 2) Estimate the parameters of $\vec{\mu}_i(l), \vec{\mu}'_i(l), \Sigma_i(l)$, and $R_i(l)$ of the l-th iteration for each cluster.

Step 3) Transform every decoded vector into a probabilistically matched vector by using CBPM-CC or CBPM-MS. Let $\bar{\vec{\omega}}(n)$ be the transformed vector at frame n. Replace all the decoded vectors with the transformed vectors as $\vec{\omega}'(n) = \bar{\vec{\omega}}(n)$ for all n.

Step 4) Evaluate the cost function of ε to test if the iterative CBPM (ICBPM) has to be terminated or not. The ε function is defined as

$$\varepsilon = \iint (\vec{\omega} - \bar{\vec{\omega}})^t (\vec{\omega} - \bar{\vec{\omega}}) f(\vec{\omega}, \vec{\omega}' | \phi^{\Omega}, \phi^{\Omega'}, l) d\vec{\omega}\vec{\omega}' \tag{21}$$

$$= \sum_{n=1}^{N} \{(\vec{\omega}(n) - \bar{\vec{\omega}}(n))^t (\vec{\omega}(n) - \bar{\vec{\omega}}(n)) \frac{1}{(2\pi)^p \sqrt{|W_i(l)|}} = \exp\{-\frac{1}{2}(\vec{\omega}(n), \vec{\omega}'(n))^t W_i^{-1}(l)(\vec{\omega}(n), \vec{\omega}'(n))\}\}.$$

Instead of using the exact formula shown in Appendix 1, we can use the following Euclidean distance measure because the means and variances of $\vec{\omega}(n)$ and $\vec{\omega}'(n)$ have been matched from step 3.

$$\varepsilon \approx \sum_{n=1}^{N} \| \vec{\omega}(n) - \bar{\vec{\omega}}(n) \| \tag{22}$$

Step 4) Repeat these steps with l = l +1 until the change between this value and that of the previous iteration reaches below a predefined threshold.

When we use CBPM-CC in the parameter estimation of step 2, the above procedure is called ICBPM-CC. Meanwhile, it is called ICBPM-MS when CBPM-MS is applied in step 2. ICBPM-CC is a special case of ICBPM-MS by letting $R_i = I$ because we use (22) for obtaining a cost function and classification of codebook clusters.

3. Performance Evaluation

3.1 Spectral Distortion

In this work, we choose the IS641 standard coder as a baseline coder [5]. The coder employs a predictive vector quantizer with fixed prediction coefficients. The vector obtained by subtracing the predicted vector from the original vector, is quantized by a three-dimensional split VQ, where each tenth order LSP vector is split into three subvectors of 3, 3 and 4 each, and hence the subvectors are quantized into 8, 9, and 9 bits. Fig. 1 shows the block diagram of the spectral quantization process used in the speech coder. Spectral quantization error compensation schemes can be located in two different points for (a) compensating the residual quantization error and (b) compensating whole LSP quantization error. The second approach is more general than the first one, and it can be adopted for other speech coder. The former approach is expected to reduce the spectral quantization error furthermore because the spectral quantizer confines the domain into a finite space of $\{0,1\}^{26}$. On the other hand, the latter one can utilize the correlation information with the adjacent frames.

We call the former and the latter approaches the codebook-based probabilistic matching of LSP (CBPM/LSP) and that of residual LSP (CBPM/RLSP), respectively. Tables 1 and 2 show the spectral distortions between an original LSP vector ($\vec{\omega}(n)$) and others that are the decoded LSP vector from IS-641 ($\vec{\omega}'(n)$), the mean vector classified from the VQ ($\tilde{\vec{\omega}}'(n) = \vec{\mu}'$), and the transformed vector by each CBPM ($\bar{\vec{\omega}}(n)$). The average spectral distortion (SD) is defined [2] as

$$SD^2 = \frac{1}{N}\sum_{n=1}^{N}\left(\frac{100}{\pi}\int_0^{\pi}\left[\log_{10}\frac{|P_{\vec{\omega}(n)}(\omega)|}{|P_{\vec{\omega}'(n)}(\omega)|}\right]^2 d\omega\right), \tag{22}$$

where $P_{\vec{\omega}(n)}(\omega)$ and $P_{\vec{\omega}'(n)}(\omega)$ represent the LPC power spectra obtained from $\vec{\omega}(n)$ and $\vec{\omega}'(n)$, respectively.

The database is composed of 200 connected digit strings, where each string consists of 14 digits. Among the data, the first 100 strings were used for training VQ (tagged as close set) and the others were for testing VQ (tagged as open set). The number of vectors is 43,164 and 36,125 each. When the codebook size is 512, for the close set, the average SDs after being processed by CBPMs are lower than that of the IS-641 spectral quantizer. Especially, ICBPM-MS has the smallest average SD. Both CBPM-CC and CBPM-MS reduced the outliers of the SD between

2 and 4 dB as well as those of the SD greater than 4 dB, and ICBPM-MS reduced the outliers of the SD between 2 and 4 dB but slightly increased those of the SD greater than 4 dB. The experimental results show that the transparent condition of the SD less than 1 dB can be obtained by the proposed methods and the improvement of 0.064 dB in the SD has the effect of bit rate reduction more than 1 bit/frame [2].

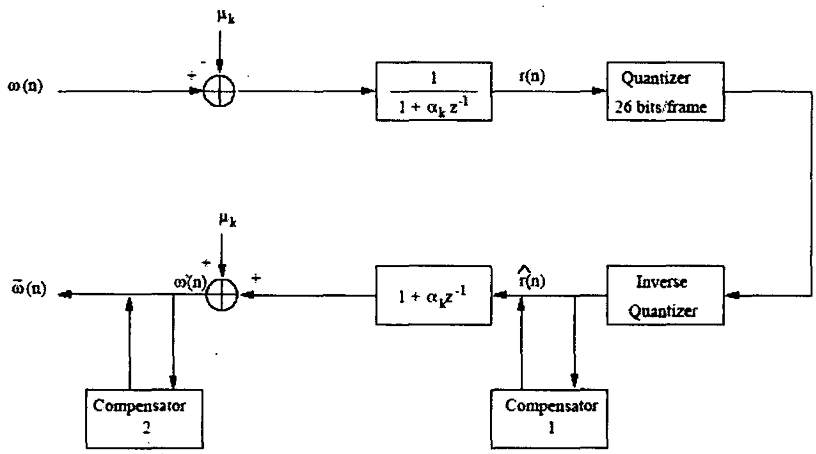

Fig. 1: Block diagram of the IS-641 spectral quantizer.

Table 1: Performance of CBPMs whose codebook size is 512: close set test (43,164 frames)

Methods	Average SD (dB)	Outliers (%)	
		2 ~ 4 dB	> 4 dB
No Processing	1.043	0.725	0.0
CBPM-CC	1.022	0.533	0.0
CBPM-MS	0.982	0.487	0.0
ICBPM-MS	0.979	0.459	0.021

Table 2: Performance of CBPMs whose codebook size is 512: open set test (36,125 frames)

Methods	Average SD (dB)	Outliers (%)	
		2 ~ 4 dB	> 4 dB
No Processing	1.067	0.786	0.0
CBPM-CC	1.061	0.789	0.0
CBPM-MS	1.023	0.642	0.0
ICBPM-MS	1.021	0.620	0.030

Next, we changed the codebook size from 8 to 2,048 in a step of power of 2. Fig. 2 shows the performance for CBPM-CC according to different VQ codebook sizes. When the codebook size is greater than 2^4, the SD decreases for both close set and open set. This trend stays until the codebook size is beyond 512.

Figs. 3 and 4 also show the performance of CBPM-MS and ICBPM-MS, respectively. The results show that the CBPM-MS and ICBPM-MS have the similar tendency in reducing the average spectral distortion to CBPM-CC.

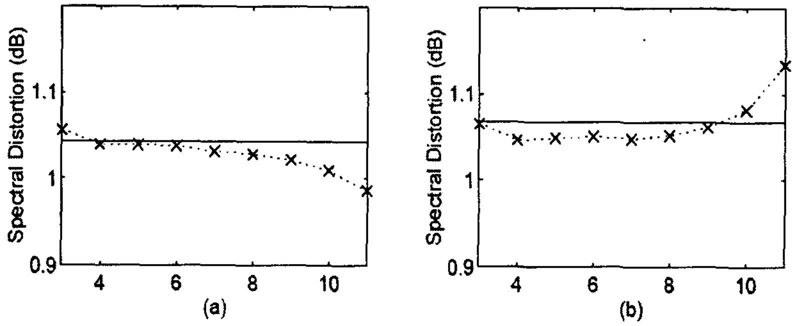

Fig. 2: Performance comparison of CBPM-CC by varying the codebook size from 8 to 2,048 in a step of power of 2: (a) close set and (b) open set.

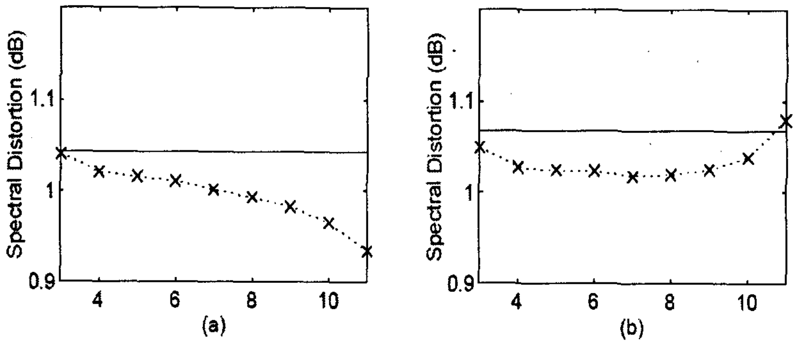

Fig. 3: Performance comparison of CBPM-MS by varying the codebook size from 8 to 2,048 in a step of power of 2: (a) close set and (b) open set.

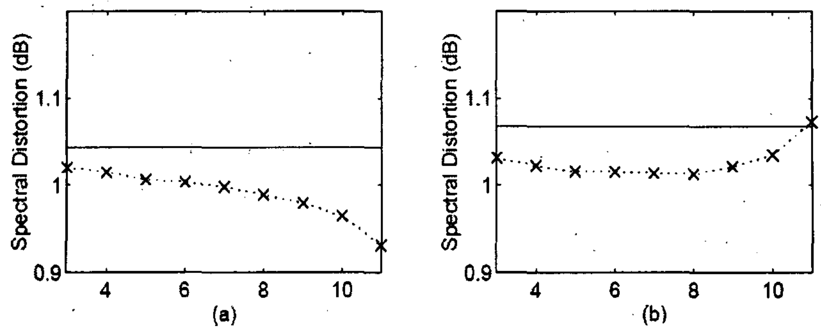

Fig. 4: Performance comparison of ICBPM-MS by varying the codebook size from 8 to 2,048 in a step of power of 2: (a) close set and (b) open set.

4. Conclusions

In this paper, we proposed statistical error compensation techniques in order to improve the performance of spectral quantization of speech coders. The proposed techniques are based on linear mapping functions and we developed the codebook-based probabilistic matching algorithms in case of completely correlated observations (CBPM-CC) and mean square estimation (CBPM-MS). Moreover, iterative methods were incorporated to CBPM-CC and CBPM-MS, respectively. These techniques were applied to the spectral quantizer employed in the IS-641 standard speech coder, and it was shown that the performance of the proposed methods was improved in a view of the average SD of the spectral quantizer.

5. Appendix

In (20), the covariance matrix W_i is partitioned as

$$W_i = \begin{bmatrix} \Sigma_i & R_i \\ R_i & \Sigma'_i \end{bmatrix}, \tag{23}$$

where $\Sigma_i = diag\{\sigma_{i,1}^2, \cdots, \sigma_{i,p}^2\}$, $\Sigma'_i = diag\{\sigma_{i,1}'^2, \cdots, \sigma_{i,p}'^2\}$, and $R_i = diag\{r_{i,1}^2, \cdots, r_{i,p}^2\}$. From the matrix inversion lemma of a partitioned matrix, we can obtain the determinant as

$$|W_i| = \prod_{k=1}^{p}(\sigma_{i,k}^2\sigma_{i,k}'^2 - r_{i,k}^4), \tag{24}$$

and the inverse of the matrix as

$$W_i^{-1} = \begin{bmatrix} D_{i,11} & D_{i,12} \\ D_{i,12} & D_{i,22} \end{bmatrix}, \tag{25}$$

where $D_{i,11} = (\Sigma_i - R_i\Sigma_i'^{-1}R_i)^{-1} = [\frac{\sigma_{i,k}'^2}{\sigma_{i,k}^2\sigma_{i,k}'^2 - r_{i,k}^4}]k$, $D_{i,12} = -(\Sigma_i - R_i\Sigma_i'^{-1}R_i)^{-1}R_i\Sigma_i'^{-1}$, $D_{i,22} = (\Sigma_i' - R_i\Sigma_i^{-1}R_i)^{-1} = [\frac{\sigma_{i,k}^2}{\sigma_{i,k}^2\sigma_{i,k}'^2 - r_{i,k}^4}]k$, where $[d]_k$ means that the matrix is diagonal and the k-th component is d Also, we assume that each vector is re-ordered according to the class C_i' so that $\vec{\omega}'(n)$ is included in the class of $C'_{\{i|n-\sum_{l=1}^{i}N(l)<0\}}$.

$$\log f(\vec{\omega},\vec{\omega}' \mid \phi^{\Omega},\phi^{\Omega'}) = \sum_{i=1}^{M}\sum_{n=1}^{N(i)}\log f(\vec{\omega}(n),\vec{\omega}'(n) \mid \vec{\mu}_i,\Sigma_i,\vec{\mu}_i',\Sigma_i',R_i)$$

$$= -pN\log 2\pi - \frac{1}{2}\sum_{i=1}^{M}\sum_{n=1}^{N(i)}\sum_{k=1}^{p}\log(\sigma_{i,k}^2\sigma_{i,k}'^2 - r_{i,k}^4) - \frac{1}{2}\sum_{i=1}^{M}\sum_{n=1}^{N(i)}\sum_{k=1}^{p}\{(\omega_k(n)-\mu_{i,k})^2\frac{\sigma_{i,k}'^2}{\sigma_{i,k}^2\sigma_{i,k}'^2 - r_{i,k}^4}$$
$$-2(\omega_k(n)-\mu_{i,k})(\omega_k'(n)-\mu_{i,k}')\frac{r_{i,k}^2}{\sigma_{i,k}^2\sigma_{i,k}'^2 - r_{i,k}^4} + (\omega_k'(n)-\mu_{i,k}')^2\frac{\sigma_{i,k}^2}{\sigma_{i,k}^2\sigma_{i,k}'^2 - r_{i,k}^4}\}. \tag{26}$$

By setting the partial derivatives of (26) with respect to $\mu_{i,k}, \mu_{i,k}', \sigma_{i,k}, \sigma_{i,k}'$ and $r_{i,k}$ for $1 \le i \le M$ and $1 \le k \le p$ to zero, we can obtain their estimates as

$$\bar{\mu}_{i,k} = \frac{1}{N(i)}\sum_{n=1}^{N(i)}\omega_k(n) \tag{27}$$

$$\bar{\sigma}_{i,k}^2 = \frac{1}{N(i)}\sum_{n=1}^{N(i)}(\omega_k(n)-\mu_{i,k})^2 \tag{28}$$

$$\bar{\mu}_{i,k}' = \frac{1}{N(i)}\sum_{n=1}^{N(i)}\omega_k'(n) \tag{29}$$

$$\bar{\sigma}_{i,k}'^2 = \frac{1}{N(i)}\sum_{n=1}^{N(i)}(\omega_k'(n)-\mu_{i,k}')^2 \tag{30}$$

$$\bar{r}_{i,k}^2 = \frac{1}{N(i)}\sum_{n=1}^{N(i)}(\omega_k(n)-\mu_{i,k})(\omega_k'(n)-\mu_{i,k}'). \tag{31}$$

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Received: 2004. 11. 01
Aceepted: 2004. 11. 30

▲ Seung Ho Choi
Dept. of Electronics and Information Eng., Seoul National University of Technology, 172 Kongneung-2 Dong, Nowon-Gu, Seoul 139-743, Korea
서울산업대학교 전자정보공학과 (우: 139-743)
Tel: +82-2-970-6461 (O), Fax: +82-2-979-7903
E-mail: shchoi@snut.ac.kr

▲ Hong Kook Kim
Dept. of Information and Communications, Gwangju Institute of Science and Technology, 1 Oryong-Dong, Buk-Gu, Gwangju, 500-712, Korea
광주과학기술원 정보통신공학과 (우: 500-712)
Tel: +82-62-970-2228 (O), Fax: +82-62-970-2204
E-mail: hongkook@gist.ac.kr