SEQUENTIAL SPLIT VECTOR QUANTIZATION OF LSF PARAMETERS USING CONDITIONAL PDF

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ABSTRACT

A better performing product code vector quantization (VQ) method is proposed for coding the line spectrum frequency (LSF) parameters; the method is referred to as sequential split vector quantization (SeSVQ). The split sub-vectors of the full LSF vector are quantized in sequence and thus uses conditional distribution derived from the previous quantized sub-vectors. Unlike the traditional split vector quantization (SVQ) method, SeSVQ exploits the inter sub-vector correlation and thus provides improved rate-distortion performance, but at the expense of higher memory.

We investigate the quantization performance of SeSVQ over traditional SVQ and transform domain split VQ (TrSVQ) methods. Compared to SVQ, SeSVQ saves 1 bit and nearly 3 bits, for telephone-band and wide-band speech coding applications respectively.

Index Terms— LSF quantization, split vector quantization

1. INTRODUCTION

Most of the speech coders use linear prediction (LP) analysis and thus more effective scheme of quantizing the LP coefficients (LPCs), equivalently LSFs, is in great demand. There are many different LSF VQ methods reported in the literature; in particular, several structured VQs [2] have been proposed for telephone-band speech and further extended to wide-band speech [12]. Some of the recent techniques are parametric VQ [14], HMM based recursive quantizer [15] and two stage transform vector quantization [17]. The most cited, successful and practically used technique of LSF quantization is split vector quantization (SVQ) [4]. Originally a two sub-vector SVQ [4] was proposed, but later to reduce complexity, a three sub-vector SVQ is used in different telephone-band speech coders, such as IS-136, G.723.1 etc. [11]. For wide-band speech, Lefebvre et al. [5] and Chen et al. [9] used a seven part SVQ operating at 49 bits/vector; high quality results are reported in [13] for a four or five sub-vector SVQ at 45 bits/vector.

The independent quantization of the split sub-vectors in SVQ method does not exploit correlation between the sub-vectors, which results in a substantial loss of coding gain, referred to as “split loss”. It is shown in [16] that the use of conditional distribution results in recovering the split loss using information theoretic measure of Kullback-Leibler distance. Some of the practical approaches to exploit the conditional distribution, equivalently correlation between the split sub-vectors, including vector linear prediction [1] and delayed decision approaches ([3], [6], [10]) have been proposed. A de-correlating transform (e.g. DCT or KLT) can also be used followed by quantization of transform domain sub-vectors using SVQ technique with variance based optimum bit allocation; this method is referred to as transform domain split VQ (TrSVQ). A sequential scalar quantization (SeSQ) method is proposed in [8] which uses the conditional distribution for coding the scalar components of two or three dimensional vectors in colour image processing.

We propose sequential split vector quantization (SeSVQ) method which uses the conditional distribution of the split sub-vectors for coding the LSF parameters. The sub-vectors are quantized in sequence and thus recovers the split loss by exploiting the conditional distribution derived from the previous quantized sub-vectors. The proposed SeSVQ outperforms the traditional SVQ method. We also show that the transform domain approach of recovering the split loss, using TrSVQ method, not only fails to provide improved rate-distortion performance, but degrades the same.

2. PERFORMANCE MEASURES

The perceptually motivated objective measure used for evaluating the LSF quantization performance is the *spectral distortion* (SD) ([4], [7]). A low average SD along with minimum number of high distortion outliers are necessary for good spectrum quantization performance. For the nth frame, SD_n in dB is defined as [4]:

$$SD_n = \left\{ \frac{1}{2\pi} \int_{-\pi}^{\pi} \{10\, log_{10} P_n(\Omega) - 10\, log_{10} \hat{P}_n(\Omega)\}^2 d\Omega \right\}^{\frac{1}{2}} \quad (1)$$

where $P_n(\Omega)$ and $\hat{P}_n(\Omega)$ are the LP filter power spectra of the original LPC vector and quantized LPC vector respectively. It is known that quantization of LSF parameters retains the “local spectral sensitivity” property [4], unlike other equivalent LPC parameters. This property is successfully exploited by direct SVQ method as the sub-vectors of an LSF vector can be independently quantized without the leakage of quantization distortion from one spectral region to another [4]. On the other hand, each of the transform domain coefficients possesses contributions from all the coefficients of a particular LSF vector in TrSVQ method; quantization of a single transform domain coefficient affects the reconstruction of all the LSF's and it reflects throughout the full frequency region of the synthesis filter power spectrum. Thus, TrSVQ is unable to use the local spectral sensitivity property of LSF parameters for efficient quantization.

The local spectral sensitivity property helps to provide different weights to different LSF's for an LSF-based distance measure which is useful as some LSF's are more important than the others. Thus, to search the VQ codebook, weighted square Euclidean distance (WSED) was proposed in the literature; for the nth frame, WSED is defined as:

$$\begin{aligned} d(\mathbf{x}_n, \hat{\mathbf{x}}_n) &= (\mathbf{x}_n - \hat{\mathbf{x}}_n)^T \mathbf{W}_n (\mathbf{x}_n - \hat{\mathbf{x}}_n) \\ &= \textstyle\sum_{i=1}^{p} w_{n,i} (x_{n,i} - \hat{x}_{n,i})^2 \end{aligned} \quad (2)$$

where, for nth frame, $\mathbf{x}_n$ and $\hat{\mathbf{x}}_n$ are the p-dimensional original and quantized LSF vectors and $\mathbf{W}_n$ is a vector dependent diagonal weighting matrix as: $\mathbf{W}_n = diag\left\{[w_{n,1},\ w_{n,2}, \ldots, w_{n,p}]^T\right\}$; we use spectral sensitivity coefficients [7] as the weighting values in this paper. WSED of Eqn. 2 is a separable distance measure which is easily used for independent quantization of sub-vectors in SVQ.

Let $\mathbf{T}$ denote the de-correlating transform matrix. The transformed vector can be expressed as $\mathbf{z}_n = \mathbf{T}\,\mathbf{x_n}$; the inverse transform is given by $\mathbf{x}_n = \mathbf{T}^{-1}\,\mathbf{z}_n$. Then the WSED measure of Eqn. 2, with respect to transformed coefficients, can be written as:

$$d(\mathbf{z}_n, \hat{\mathbf{z}}_n) = (\mathbf{z}_n - \hat{\mathbf{z}}_n)^T(\mathbf{T}^{-1})^T\mathbf{W}_n\,\mathbf{T}^{-1}(\mathbf{z}_n - \hat{\mathbf{z}}_n) \qquad (3)$$

In Eqn. 3, the weighting matrix is $(\mathbf{T}^{-1})^T\mathbf{W}_n\,\mathbf{T}^{-1}$ and it is not diagonal. Thus, the weighted distance measure of Eqn. 3 is not a separable distance measure and is not easily amenable to apply for independent sub-vector quantization in TrSVQ method. Hence, TrSVQ can not use the WSED measure of Eqn. 2 for efficient LSF quantization. It is commented that quantizing the sub-vectors in transform domain may not result in better SD performance even though transform domain approach exploits correlation between the sub-vectors.

3. SEQUENTIAL SPLIT VECTOR QUANTIZATION

The proposed SeSVQ recovers the incurred split loss of SVQ using conditional distribution. SeSVQ method sequentially quantizes the sub-vectors in LSF domain; thus it provides better SD performance by exploiting the local spectral sensitivity property and using WSED measure of Eqn. 2.

Let, the nth frame LSF vector, $\mathbf{x}_n$, is split into S number of sub-vectors as: $\mathbf{x}_n = \left[\mathbf{x}_{n,1}^T\ \mathbf{x}_{n,2}^T\ \ldots\ \mathbf{x}_{n,S}^T\right]^T$, where $\mathbf{x}_{n,i}$s are column vectors and $dim\left(\mathbf{x}_{n,i}\right) = p_i$ such that $\sum_{i=1}^{S} p_i = p$. In SVQ, each of the sub-vectors is coded independently using a codebook trained from the split sub-vector's marginal pdf $f_{\mathbf{x}_{n,i}}\left(\mathbf{x}_{n,i}^\star\right)$, $1 \leq i \leq S$ and thus, the resultant product codebook is an S fold Cartesian product of the S number of sub-vector codebooks. On the other hand, for SeSVQ, the ith split sub-vector, $\mathbf{x}_{n,i}$, is coded using the codebook trained from the split sub-vector's conditional pdf derived from the previous sub-vectors and the conditional pdf is [16]:

$$f_{\mathbf{x}_{n,i}|\mathbf{x}_{n,i-1},\mathbf{x}_{n,i-2},\ldots,\mathbf{x}_{n,1}}\left(\mathbf{x}_{n,i}^\star|\mathbf{x}_{n,i-1}^\star, \mathbf{x}_{n,i-2}^\star, \ldots, \mathbf{x}_{n,1}^\star\right) \qquad (4)$$

We show that use of sequential quantization technique to code the sub-vectors allows to exploit the conditional distribution and recovers the split loss. To illustrate the effect of sequential quantization technique, an example of two dimensional correlated data is shown in Fig.1. Let, the 2-D vector is split into two sub-vectors and thus the sub-vectors are consisting of scalar components in this example. Suppose, each scalar component be allocated 2 bits. Then, the SVQ method, of quantizing the scalar components independently, leads to the product codes shown as starred points in Fig.1 (a).

In case of SeSVQ method, first $x_{n,1}$ is quantized using the same 4 levels as in Fig.1 (a), shown as partitions which are indexed by k, $1 \leq k \leq 4$, in Fig.1 (b). Next, we quantize $x_{n,2}$ using 4 levels where the necessary codebook is trained using appropriate conditional pdf $f_{x_{n,2}|\hat{x}_{n,1}:k}\left(x_{n,2}^\star|\hat{x}_{n,1}^\star : k\right)$, $1 \leq k \leq 4$. Thus, $x_{n,2}$ is quantized using the codebook trained from the conditional distribution which is confined to the columns formed from the quantization of $x_{n,1}$; the resultant product codes are shown in Fig.1 (b). Generalizing to more than two sub-vectors, it is commented that the SeSVQ method recovers the split loss.

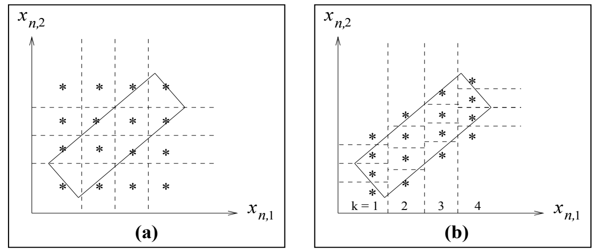

Fig. 1. *Illustration of recovering the split loss for two dimensional correlated pdf (solid rectangle) example.* (a) *Product codebook structure for the direct SVQ.* (b) *Product codebook structure for the proposed SeSVQ.*

3.1. Sequential coding in close loop

An important aspect which should be considered is that the sequential quantization needs to be performed using the past quantized sub-vectors in a close loop manner. It is also experimented and verified that the first order conditional distribution is sufficient for implementing a practical scheme. Thus, the ith sub-vector, $\mathbf{x}_{n,i}$, is coded using a codebook trained from the first order conditional pdf derived from coded $(i-1)$th sub-vector, i.e. $f_{\mathbf{x}_{n,i}|\hat{\mathbf{x}}_{n,i-1}}\left(\mathbf{x}_{n,i}^\star|\hat{\mathbf{x}}_{n,i-1}^\star\right)$.

Suppose, b_i number of bits is allocated to code $\mathbf{x}_{n,i}$; hence, the discrete random coded $(i-1)$th sub-vector, $\hat{\mathbf{x}}_{n,i-1}$, is indexed using a discrete random variable, k, which is taking integer values varying from 1 to $2^{b_{i-1}}$. Thus, the ith sub-vector, $\mathbf{x}_{n,i}$, is coded using the appropriate codebook which is chosen from the $2^{b_{i-1}}$ number of codebooks; each of the codebooks is trained using respective conditional pdf, where the conditional pdfs are:

$$f_{\mathbf{x}_{n,i}|\hat{\mathbf{x}}_{n,i-1}:k}\left(\mathbf{x}_{n,i}^\star|\hat{\mathbf{x}}_{n,i-1}^\star : k\right),\ 1 \leq k \leq 2^{b_{i-1}} \qquad (5)$$

The codebook used for quantizing each of the sub-vectors is referred to as *quantization codebook*. It is impractical to design $2^{b_{i-1}}$ number of quantization codebooks for a high resolution quantization method. To circumvent this problem, the $(i-1)$th coded sub-vector, $\hat{\mathbf{x}}_{n,i-1}$, is classified into M number of classes; thus M quantization codebooks are trained from M conditional pdfs instead of $2^{b_{i-1}}$ number of conditional pdfs. Thus, we use the conditional pdfs as follows:

$$f_{\mathbf{x}_{n,i}|\hat{\mathbf{x}}_{n,i-1}:c_{i-1,m}}\left(\mathbf{x}_{n,i}^\star|\hat{\mathbf{x}}_{n,i-1}^\star : c_{i-1,m}\right),\ 1 \leq m \leq M \qquad (6)$$

where $C_{i-1} = \{c_{i-1,m}\}_{m=1}^{M}$; C_{i-1} is the *class codebook* used for classifying $\hat{\mathbf{x}}_{n,i-1}$ and thus to choose the appropriate quantization codebook for coding $\mathbf{x}_{n,i}$. We illustrate the SeSVQ encoding algorithm for quantizing the ith sub-vector, $2 \leq i \leq S$, as follows:

(1) Reconstruct $\hat{\mathbf{x}}_{n,i-1}$ in both the encoder and decoder. Classify $\hat{\mathbf{x}}_{n,i-1}$ using class codebook C_{i-1}; the class of $\hat{\mathbf{x}}_{n,i-1}$ is indexed by $c_{i-1,m}$ which is available in both the encoder and decoder.

(2) Quantize $\mathbf{x}_{n,i}$ using the quantization codebook trained from the conditional pdf $f_{\mathbf{x}_{n,i}|\hat{\mathbf{x}}_{n,i-1}:c_{i-1,m}}\left(\mathbf{x}_{n,i}^\star|\hat{\mathbf{x}}_{n,i-1}^\star : c_{i-1,m}\right)$; the quantization codebook index of $\hat{\mathbf{x}}_{n,i}$ is transmitted. In the decoder, the same quantization codebook is used as a look up table which corresponds to $c_{i-1,m}$ and thus it is easily possible to reconstruct $\hat{\mathbf{x}}_{n,i}$.

The encoding/decoding algorithm used for SeSVQ method is illustrated in Fig. 2. In this algorithm, $\mathbf{x}_{n,1}$ is quantized using a codebook trained from $f_{\mathbf{x}_{n,1}}\left(\mathbf{x}_{n,1}^\star\right)$. The codebook index of $\hat{\mathbf{x}}_{n,1}$ is transmitted and thus it becomes available in both encoder and decoder for encoding/decoding of $\hat{\mathbf{x}}_{n,2}$. Then the above mentioned steps are repeated sequentially for the remaining sub-vectors as illustrated in Fig. 2.

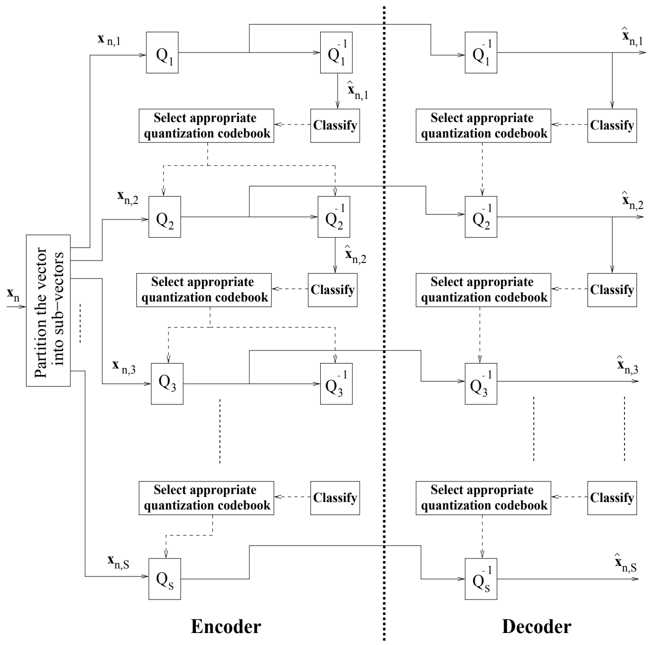

Fig. 2. *Sequential split vector quantization (SeSVQ) method.*

Table 1. *Performance of sequential split vector quantization (SeSVQ) method for telephone-band speech at different values of M*

Total bits/vector (bits allocated to sub-vectors)	Avg. SD (dB)	SD Outliers (in %) 2-4 dB	SD Outliers (in %) >4 dB	kfloats/vector (ROM)
		$M = 4$		
23 (7,8,8)	1.22	3.14	0.00	7.58
24 (8,8,8)	1.14	2.26	0.00	7.96
25 (8,9,8)	1.07	1.52	0.00	11.03
26 (8,9,9)	1.00	0.94	0.00	15.13
27 (9,9,9)	0.94	0.80	0.00	15.90
		$M = 8$		
23 (7,8,8)	1.20	3.02	0.00	14.77
24 (8,8,8)	1.12	1.98	0.00	15.16
25 (8,9,8)	1.05	1.52	0.00	21.30
26 (8,9,9)	0.99	0.84	0.00	29.49
27 (9,9,9)	0.92	0.66	0.00	30.26

3.2. SeSVQ codebook training

The class codebook, C_{i-1}, used for classifying $(i-1)$th coded sub-vector is trained using the $(i-1)$th sub-vector's training data. Using this class codebook, the ith sub-vector training data is classified and appropriately partitioned into M number of sub-sets which correspond to M number of 1-step conditional distributions. Then the quantization codebooks are designed using the respective partitioned sub-sets of training data. For illustration, C_{i-1} is the M size class codebook trained from the set of training data $\{\mathbf{x}_{n,i-1}\}_{n=1}^{N}$ (N is the number of training vectors). Then the ith split training sub-vectors, $\{\mathbf{x}_{n,i}\}_{n=1}^{N}$, are partitioned into M number of sub-sets according to the class decision of $\mathbf{x}_{n,i-1}$ using open loop approach (i.e. using unquantized data instead of using $\hat{\mathbf{x}}_{n,i-1}$) and the quantization codebooks are designed respectively. This approach repeats for designing the class and quantization codebooks for any ith split sub-vector, $2 \leq i \leq S$. In case of the first sub-vector, a single codebook is designed using the training data $\{\mathbf{x}_{n,1}\}_{n=1}^{N}$. It is informed that the SeSVQ method shows improved rate-distortion performance as M increases, but this leads to more requirement of memory.

Table 2. *Performance of traditional split vector quantization (SVQ) method for telephone-band speech*

Total bits/vector (bits allocated to sub-vectors)	Avg. SD (dB)	SD Outliers (in %) 2-4 dB	SD Outliers (in %) >4 dB	kfloats/vector (ROM)
23 (7,8,8)	1.30	4.50	0.00	2.17
24 (8,8,8)	1.22	3.30	0.00	2.56
25 (8,9,8)	1.14	2.34	0.00	3.32
26 (8,9,9)	1.07	1.58	0.00	4.35
27 (9,9,9)	1.00	1.32	0.00	5.12

Table 3. *Performance of transform domain split vector quantization (TrSVQ) method for telephone-band speech*

Total bits/vector (bits allocated to sub-vectors)	Avg. SD (dB)	SD Outliers (in %) 2-4 dB	SD Outliers (in %) >4 dB	kfloats/vector (ROM)
23 (7,8,8)	1.40	11.42	0.16	2.40
24 (8,8,8)	1.31	7.62	0.10	2.66
25 (8,8,9)	1.24	6.34	0.10	3.94
26 (8,9,9)	1.16	4.44	0.10	4.70
27 (8,9,10)	1.09	3.22	0.06	7.26

4. QUANTIZATION RESULTS

We investigate the performance[1] of SeSVQ method over TrSVQ and traditional SVQ methods for both telephone-band and wide-band speech coding applications. For TrSVQ method, we use KLT as the de-correlating transform. The square Euclidean distance (SED) is used for TrSVQ method to search the VQ codebook, whereas SeSVQ and SVQ methods use WSED of Eqn. 2. The speech data used in the experiments is from the TIMIT data base where the speech is sampled at 16 kHz. In all the experiments, 368815 number of LSF vectors are used for training and "out of training" 5000 LSF vectors are used for testing. The experiments are confined to first order conditional distribution, which is found to be sufficient.

4.1. LSF quantization for telephone-band speech

The speech is first low pass filtered to 3.4 kHz and then down sampled to 8 kHz. A 10th order LPC analysis with 20 ms Hamming windowed analysis frame is used, based on Burg method, with no successive frame overlap. A fixed 10-Hz bandwidth expansion is applied to avoid sharp spectral peaks in the LPC spectrum as in [4] and then the LP coefficients are converted to LSF parameters.

The 10-dimensional LSF vector is split into 3 parts of (3,3,4) dimensional sub-vectors for SeSVQ and SVQ methods and the sub-vector codebooks are designed using nearly uniform bit allocation[2] [4]. For TrSVQ method, the KLT is so ordered that the eigen values are in a descending order; hence the transformed vector is split into 3 parts of (2,3,5) dimensional sub-vectors and quantized using SVQ technique with variance based optimum bit allocation. Bit allocation to the sub-vectors for all the methods is shown in the respective tables.

Table 1 shows the performance of SeSVQ method at different number of classes (M). We observe that lower distortion is achieved by increasing the number of classes, but at the expense of higher memory. Table 2 and Table 3 show respectively the performance of SVQ and TrSVQ methods. TrSVQ performs worse than SVQ and thus it is observed that the use of de-correlating transform for LSF quantization results in degraded rate-distortion performance. The proposed SeSVQ saves 1 bit compared to traditional SVQ.

[1] The absolute rate-distortion performance numbers reported in the literature vary because of database, feature set etc. However, the statistical stability and relative improvement need to be consistent.

[2] The uniform bit allocation is necessary to keep the search complexity minimum ([4], [12]). If 24 bits/vector is available, then 8 bits are allocated to each of the three sub-vectors. For 25 bits/vector, the extra 1 bit is allocated to that sub-vector which results in least over-all distortion.

Table 4. *Performance of sequential split vector quantization (SeSVQ) method for wide-band speech at different values of M*

Total bits/vector (bits allocated to sub-vectors)	Avg. SD (dB)	SD Outliers (in %) 2-4 dB	SD Outliers (in %) >4 dB	kfloats/vector (ROM)
$M = 4$				
42 (8,9,9,8,8)	1.11	0.92	0.00	20.27
43 (8,9,9,9,8)	1.07	0.64	0.00	23.34
44 (9,9,9,9,8)	1.03	0.50	0.00	24.11
45 (9,9,9,9,9)	0.98	0.26	0.00	28.21
46 (9,10,9,9,9)	0.94	0.16	0.00	34.35
$M = 8$				
42 (8,9,9,8,8)	1.08	0.86	0.00	39.78
43 (8,9,9,9,8)	1.05	0.62	0.00	45.92
44 (9,9,9,9,8)	1.01	0.52	0.00	46.69
45 (9,9,9,9,9)	0.95	0.22	0.00	54.88
46 (9,10,9,9,9)	0.92	0.18	0.00	57.17

Table 5. *Performance of traditional split vector quantization (SVQ) method for wide-band speech*

Total bits/vector (bits allocated to sub-vectors)	Avg. SD (dB)	SD Outliers (in %) 2-4 dB	SD Outliers (in %) >4 dB	kfloats/vector (ROM)
42 (8,9,9,8,8)	1.23	1.96	0.00	5.63
43 (8,9,9,9,8)	1.19	1.50	0.00	6.40
44 (9,9,9,9,8)	1.15	1.38	0.00	7.16
45 (9,9,9,9,9)	1.09	0.84	0.00	8.19
46 (9,10,9,9,9)	1.05	0.58	0.00	9.72

4.2. LSF quantization for wide-band speech

We use the specification of AMR-WB speech codec [18] to produce 16-th order LP coefficients which are then converted to LSFs.

The 16-dimensional LSF vector is split into 5 parts of (3,3,3,3,4) dimensional sub-vectors for SeSVQ and SVQ methods. For TrSVQ method, the transformed vector is split into 5 parts of (2,3,3,3,5) dimensional sub-vectors. Table 4 shows the performance of SeSVQ method at different number of classes (M). Like telephone-band speech, it is observed that lower distortion is achieved by increasing the number of classes, but at the expense of higher memory. Table 5 and Table 6 show respectively the performance of SVQ and TrSVQ methods. The TrSVQ performs worse than SVQ. The proposed SeSVQ saves nearly 3 bits compared to traditional SVQ.

5. CONCLUSION

We propose sequential split vector quantization (SeSVQ) method exploiting first order conditional distribution for LSF quantization. The proposed method exploits the correlation between the split sub-vectors and thus recovers the coding loss associated with traditional split vector quantization (SVQ) method. A de-correlating transform can exploit the correlation; but it is shown that the transform domain split vector quantization (TrSVQ) method is unable to use the local spectral sensitivity property of LSF parameters and results in degraded rate-distortion performance instead of improving. The proposed SeSVQ successfully exploits the local spectral sensitivity property of LSF parameters and efficiently uses the separable weighted square Euclidean distance (WSED); SeSVQ outperforms TrSVQ and traditional SVQ methods, but at the expense of higher memory.

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Table 6. *Performance of transform domain split vector quantization (TrSVQ) method for wide-band speech*

Total bits/vector (bits allocated to sub-vectors)	Avg. SD (dB)	SD Outliers (in %) 2-4 dB	SD Outliers (in %) >4 dB	kfloats/vector (ROM)
42 (9,9,8,7,9)	1.25	5.78	0.00	6.52
43 (9,10,8,7,9)	1.19	4.16	0.00	8.06
44 (9,10,8,7,10)	1.15	3.50	0.00	10.62
45 (9,10,9,7,10)	1.11	2.74	0.00	11.39
46 (9,10,9,8,10)	1.07	2.12	0.00	11.77

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