Normalized Two Stage SVQ for Minimum Complexity Wide-band LSF Quantization

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Abstract

We develop a two stage split vector quantization method with optimum bit allocation, for achieving minimum computational complexity. This also results in much lower memory requirement than the recently proposed switched split vector quantization method. To improve the rate-distortion performance further, a region specific normalization is introduced, which results in 1 bit/vector improvement over the typical two stage split vector quantizer, for wide-band LSF quantization.

Index Terms : Vector Quantization, LSF Coding.

1. Introduction

The split vector quantization (SVQ) [3] is a reduced complexity product code VQ method, widely used for quantizing the line spectrum frequency (LSF) parameters in speech coding. The issue of complexity becomes more important for high bitrate and high quality applications, such as in wide-band speech coding. Recently switched SVQ (SSVQ) has been proposed to improve the rate-distortion (R/D) performance over SVQ ([9], [11]). For wide-band LSF coding, the SSVQ achieves nearly 3 bits/vector advantage over the earlier SVQ scheme even at lower computational complexity. However, the real price to be paid for the SSVQ R/D performance advantage is through the increased memory, which can be as high as a factor of eight.

The goal of incorporating the product code VQ methods is to save on complexity such that an acceptable level of R/D performance is achieved at the least bit-rate. In many mobile speech coding applications, both for wide-band and telephone-band speech, it is important to reduce computation as well as memory. From the VQ literature [2], we know that multi-stage VQ (MSVQ) provides the advantages of both reduced memory and reduced complexity. However, in each stage of MSVQ, the VQ would be of full dimension equal to that of the signal vector. It is also well known that increasing the number of stages, leads to decrease in complexity, but at the expense of degraded R/D performance. Thus, we explore to develop a new method in a two stage VQ framework.

Considering the two stage VQ where the SVQ is used for the second stage, we formulate a constrained minimization of the computational complexity by the optimum bit allocation scheme. It is shown that this approach results in reduced computational complexity and much reduced requirement of memory than the SSVQ, with nearly the same gain in R/D performance over SVQ. The aim, in effective LSF quantization method, is to reduce the spectral distortion (SD) and not merely the square Euclidean distance (SED). This is possible by the use of weighted SED (WSED) in which the theoretical weights are spectral sensitivity coefficients [5]. To improve the R/D performance further, we incorporate a region specific normalization along-with the use of a modified WSED measure.

In the literature, SVQ has been used for wide-band speech LSF quantization ([4], [6]). Among the recent techniques, a split-multistage VQ (S-MSVQ) with MA predictor is used to quantize the LPC parameters in AMR-WB speech codec [12]. The SSVQ is shown to perform better than S-MSVQ [11]. We have recently proposed two stage transform VQ (T_STVQ) method [10] which provides better average SD performance than the SVQ, but suffers in poor outlier performance. In this paper, the developed normalized two stage SVQ (NT_SSVQ) method is shown to be better than the above mentioned methods considering the trade-off between average and outlier SD performances, computational and memory complexities.

2. Normalized two stage SVQ

A block diagram of the traditional two stage VQ method is shown in Fig. 1 (a) where the reproduction vector is realized as: $\hat{\mathbf{X}} = \hat{\mathbf{X}}_1 + \hat{\mathbf{E}}_2$. Suppose, the first stage quantizer ($\mathbf{Q_1}$) is allocated b_0 number of bits, by which M number of Voronoi regions (i.e. $M = 2^{b_0}$) are formed in the original vector space, whose centroids are the reconstruction vectors, $\left\{\hat{\mathbf{X}}_1\right\}$. Unlike the basic two stage VQ method in which the residual vector, $\mathbf{E}_2 = \mathbf{X} - \hat{\mathbf{X}}_1$, is quantized directly using a full dimensional quantizer in $\mathbf{Q_2}$, we split the residual vector into smaller dimensional sub-vectors and then use SVQ technique for quantization of $\mathbf{E}_2$. Thus, in the new method, the higher dimensional coding advantages [1] of VQ are exploited in the first stage ($\mathbf{Q_1}$) and the requirements of lower computational complexity and memory are achieved by using SVQ technique in the second stage ($\mathbf{Q_2}$). In the second stage, the residual vector is statistically less correlated and hence, the use of SVQ technique for coding the residual vector will not result in a substantial loss of coding gain [8]. Also SVQ, used in second stage, is a good compromise between scalar and full vector quantizer in the sense of rate-distortion performance and complexity trade-off.

In the first stage of the proposed NT_SSVQ method, the codebook consists of M mean vectors corresponding to M Voronoi regions of the signal pdf space. Thus, the first stage residual vector space is depicted as union of all the mean removed Voronoi regions having different covariance structures. Naturally, to design an effective residual codebook at the second stage, it is necessary to incorporate variance normalization procedure so that all the mean removed Voronoi regions have a common data spread (of unity variance) along all the dimensions. According to the first stage quantizer's decision, the variance normalization is carried out to explicitly take care of the Voronoi region specific signal pdf properties. Thus, we refer to

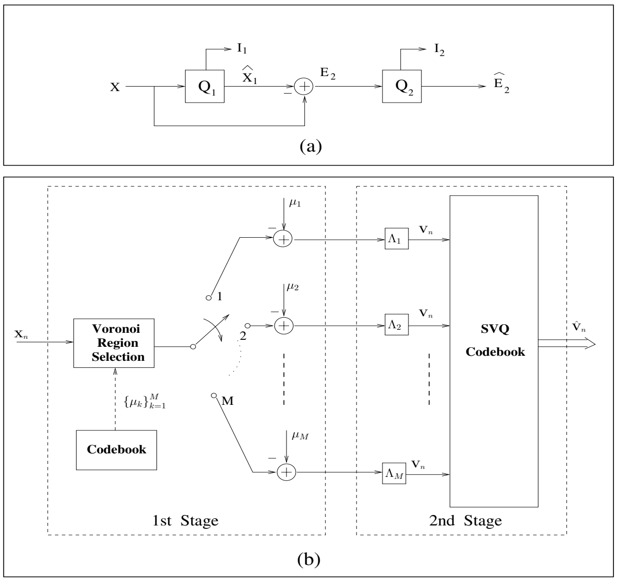

Figure 1: (a) Two stage VQ. (b) Normalized two stage SVQ (NT_SSVQ).

the proposed method as normalized two stage SVQ (NT_SSVQ).

A block diagram of NT_SSVQ is shown in Fig. 1 (b), consisting of three parts: first stage quantizer $(\mathbf{Q_1})$, variance normalization blocks specific to each of the Voronoi regions and an SVQ quantizer $(\mathbf{Q_2})$.

Let, $\mathbf{X}_n$ be the nth frame, p-dimensional LSF vector, which is quantized to μ_k using $\mathbf{Q_1}$ and thus belongs to the kth Voronoi region of the signal vector space. Then, the variance normalized residual vector is given by:

$$\mathbf{V}_n = \Lambda_k \ \ [\mathbf{X}_n - \mu_k] \tag{1}$$

where μ_k and Λ_k are respectively the mean vector and variance normalization matrix of the kth Voronoi region; $\Lambda_k = diag\left[\{1/\sigma_{k,i}\}_{i=1}^{p}\right]$, where $\{\sigma_{k,i}\}_{i=1}^{p}$ are the standard deviations associated with kth Voronoi region. Thus, the indices of the Voronoi region mean vector (μ_k) and the coded residual vector $(\hat{\mathbf{V}}_n)$ of second stage are transmitted over the channel. From Eqn. 1, we observe that the original vector is recovered by $\mathbf{X}_n = [\Lambda_k]^{-1}\mathbf{V}_n + \mu_k$; thus, the decoded vector at the receiver is realized as: $\hat{\mathbf{X}}_n = [\Lambda_k]^{-1}\hat{\mathbf{V}}_n + \mu_k$. At the receiver, the decoder uses the value of k to look up μ_k vector and Λ_k matrix, from which the coded vector is reconstructed. To achieve minimum SD, we formulate a modified weighted square Euclidean distance (WSED) measure for the $\mathbf{Q_2}$ quantization.

2.1. Voronoi region specific WSED

It is common to use WSED measure to search the VQ codebook in the context of LSF quantization ([3], [5]). For the nth frame, WSED, between the input vector $(\mathbf{X}_n)$ and the quantized vector $(\hat{\mathbf{X}}_n)$, is defined as:

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

where $\mathbf{W}_n$ is a diagonal weighting matrix with elements as $\{w_{n,i}\}_{i=1}^{p}$, which is dependent on the nth LSF vector. Throughout this paper, we use spectral sensitivity coefficients as weighting values [5].

For NT_SSVQ method, simplifying the WSED measure, given in Eqn. 2, in terms of original and quantized normalized residual vectors ($\mathbf{V}_n$ and $\hat{\mathbf{V}}_n$) at second stage, we can write:

$$\begin{aligned} d(\mathbf{X}_n, \hat{\mathbf{X}}_n) &= \left[\mathbf{X}_n - \hat{\mathbf{X}}_n\right]^T \mathbf{W}_n \left[\mathbf{X}_n - \hat{\mathbf{X}}_n\right] \\ &= \left[\mathbf{V}_n - \hat{\mathbf{V}}_n\right]^T \left[[\Lambda_k]^{-1}\right]^T \mathbf{W}_n \, [\Lambda_k]^{-1} \\ &\qquad \left[\mathbf{V}_n - \hat{\mathbf{V}}_n\right] \\ &= \left[\mathbf{V}_n - \hat{\mathbf{V}}_n\right]^T \mathbf{O}_{n,k} \left[\mathbf{V}_n - \hat{\mathbf{V}}_n\right] \\ &= d(\mathbf{V}_n, \hat{\mathbf{V}}_n) \end{aligned} \tag{3}$$

In Eqn. 3, the new weighting matrix, denoted by $\mathbf{O}_{n,k} = \left[[\Lambda_k]^{-1}\right]^T \mathbf{W}_n \, [\Lambda_k]^{-1}$, is dependent on the nth vector weighting matrix $(\mathbf{W}_n)$ and variance normalization matrix of the kth Voronoi region (Λ_k). It is also observed that both the matrices, $\mathbf{W}_n$ and Λ_k, are diagonal and thus the matrix $\mathbf{O}_{n,k}$ is also diagonal. Therefore the distance measure, characterized by Eqn. 3, is further simplified as:

$$\begin{aligned} d(\mathbf{V}_n, \hat{\mathbf{V}}_n) &= \left[\mathbf{V}_n - \hat{\mathbf{V}}_n\right]^T \mathbf{O}_{n,k} \left[\mathbf{V}_n - \hat{\mathbf{V}}_n\right] \\ &= \textstyle\sum_{i=1}^{p} o_{n,k,i} \left(v_{n,i} - \hat{v}_{n,i}\right)^2 \end{aligned} \tag{4}$$

where, $\left\{o_{n,k,i} = \sigma_{k,i}^2 \, w_{n,i}\right\}_{i=1}^{p}$ are the new Voronoi region specific weighting coefficients. This modified WSED measure is used at the second stage to quantize the normalized residual vector coefficients for coding the nth LSF vector which belongs to the kth Voronoi region. Thus, index of the Voronoi region mean vector is found by using common square Euclidean distance (SED) measure at $\mathbf{Q_1}$, whereas the normalized residual vector $(\mathbf{V}_n)$ is coded at $\mathbf{Q_2}$ using the Voronoi region specific WSED measure given in Eqn. 4.

2.2. NT_SSVQ codebook training

The LBG algorithm is first applied on the full training database to produce M centroids (or mean vectors), $\{\mu_k\}_{k=1}^{M}$, of M Voronoi regions which are the optimum code-vectors of $\mathbf{Q_1}$. All the training vectors are then classified and after that Voronoi region specific variance normalization matrices, $\{\Lambda_k\}_{k=1}^{M}$, are found out using classified data. Then, the training vectors are transformed using Eqn. 1 to create a new training database of normalized residual vector. The SVQ codebook, for the second stage quantizer $(\mathbf{Q_2})$, is designed using LBG algorithm where the normalized residual vector $(\mathbf{V}_n)$ is split into S number of sub-vectors.

2.3. Minimum complexity of NT_SSVQ

The computational steps associated with NT_SSVQ method are: Voronoi region search using SED measure at first stage, Voronoi region mean vector subtraction, variance normalization i.e. division by standard deviation values, finding Voronoi region specific weights ($\{o_{n,k,i}\}_{i=1}^{p}$) from $\{\sigma_{k,i}\}_{i=1}^{p}$ and $\{w_{n,i}\}_{i=1}^{p}$ values, SVQ codebook search using WSED measure of Eqn. 4 at second stage, multiplication by standard deviation values to realize $[\Lambda_k]^{-1}$ and Voronoi region mean vector addition for reproduction.

For a p-dimensional vector, we have already assumed that the bits allocated to $\mathbf{Q_1}$ be b_0 (i.e. $M = 2^{b_0}$). Let, the subvector dimensions in $\mathbf{Q_2}$ are $\{p_i\}_{i=1}^{S}$ with corresponding bit allocations as $\{b_i\}_{i=1}^{S}$ such that $p = \sum_{i=1}^{S} p_i$ and if the total

Table 1: Performance of the proposed normalized two stage SVQ (NT_SSVQ) method using appropriate WSED measure

Total bits/vector {Bit allocation as: $(b_0, b_1, b_2 \ldots b_5)$}	Avg. SD (dB)	SD Outliers 2-4 dB (in %)	SD Outliers >4 dB (in %)	kflops/ vector (CPU)	kfloats/ vector (ROM)
40 (5,7,7,7,7,7)	1.20	2.96	0.00	10.49	3.07
41 (5,7,8,7,7,7)	1.16	2.42	0.00	12.16	3.45
42 (5,7,8,8,7,7)	1.12	1.94	0.00	13.82	3.84
43 (6,7,8,8,7,7)	1.06	1.54	0.00	15.39	4.86
44 (6,7,8,8,8,7)	1.03	1.20	0.00	17.05	5.24
45 (6,8,8,8,8,7)	1.00	0.98	0.00	18.72	5.63
46 (6,8,8,8,8,8)	0.94	0.52	0.00	20.89	6.14

Table 2: Performance of the two stage split VQ (T_SSVQ) method (no Voronoi region normalization)

Total bits/vector {Bit allocation as: $(b_0, b_1, b_2 \ldots b_5)$}	Avg. SD (dB)	SD Outliers 2-4 dB (in %)	SD Outliers >4 dB (in %)	kflops/ vector (CPU)	kfloats/ vector (ROM)
40 (5,7,7,7,7,7)	1.25	3.96	0.00	10.43	2.56
41 (5,7,8,7,7,7)	1.21	3.08	0.00	12.09	2.94
42 (5,7,8,8,7,7)	1.17	2.38	0.00	13.76	3.32
43 (6,7,8,8,7,7)	1.11	1.64	0.00	15.32	3.84
44 (6,7,8,8,8,7)	1.08	1.28	0.00	16.99	4.22
45 (6,8,8,8,8,7)	1.04	1.02	0.00	18.65	4.60
46 (6,8,8,8,8,8)	0.98	0.62	0.00	20.83	5.12

allocated bits/vector is b, then $b = b_0 + \sum_{i=1}^{S} b_i = \sum_{i=0}^{S} b_i$. The required computation for NT_SSVQ method is (in flops)[1]:

$$\begin{aligned} \mathbf{C} &= (3p2^{b_0} + 2^{b_0}) + p + p + 2p + \\ &\quad \textstyle\sum_{i=1}^{S}(4p_i 2^{b_i} + 2^{b_i}) + p + p \\ &= 6p + (3p+1)2^{b_0} + \textstyle\sum_{i=1}^{S}(4p_i+1)2^{b_i} \end{aligned} \tag{5}$$

The optimal bit allocation scheme for NT_SSVQ method is decided by minimizing the total required computational complexity subject to the constraint of fixed bit budget as follows:

$$\min_{b_i} \ \mathbf{C} \quad \text{subject to} \quad \sum_{i=0}^{S} b_i = b \tag{6}$$

Using Lagrange optimization method, the optimal bit allocations are given as:

$$\begin{aligned} b_0 &= \tfrac{1}{S+1}\left[b + log_2\left[(3p+1)\textstyle\prod_{j=1}^{S}(4p_j+1)\right]\right] \\ &\quad -log_2(3p+1); \\ b_i &= \tfrac{1}{S+1}\left[b + log_2\left[(3p+1)\textstyle\prod_{j=1}^{S}(4p_j+1)\right]\right] \\ &\quad -log_2(4p_i+1), \qquad 1 \le i \le S. \end{aligned} \tag{7}$$

On the other hand, it is necessary to store $\{\Lambda_k\}_{k=1}^{M}$ matrices in a look up table. All the Λ_k matrices are diagonal and thus, it is required to store M number of p-dimensional standard deviation vectors. The total memory requirement for NT_SSVQ method to store Voronoi region mean vectors (in $\mathbf{Q_1}$), standard deviation vectors and the SVQ codebook (in $\mathbf{Q_2}$) is given as (in floats):

$$\mathbf{M} = p2^{b_0} + p2^{b_0} + \sum_{i=1}^{S} p_i 2^{b_i} = 2p2^{b_0} + \sum_{i=1}^{S} p_i 2^{b_i} \tag{8}$$

[1]It is assumed that each operation like addition, subtraction, multiplication, division and comparison needs one floating point operation (flop). With this assumption, the codebook search complexity for a b bits/vector VQ using SED measure is: $3p2^b + 2^b$ flops. Using WSED measure, total computation required is: $4p2^b + 2^b$ flops.

Table 3: Performance of the traditional five-part split VQ (SVQ) method

Total bits/vector {Bit allocation to sub-vectors}	Avg. SD (dB)	SD Outliers 2-4 dB (in %)	SD Outliers >4 dB (in %)	kflops/ vector (CPU)	kfloats/ vector (ROM)
42 (8,9,9,8,8)	1.23	1.96	0.00	24.32	5.63
43 (8,9,9,9,8)	1.19	1.50	0.00	27.64	6.40
44 (9,9,9,9,8)	1.15	1.38	0.00	30.97	7.16
45 (9,9,9,9,9)	1.09	0.84	0.00	35.32	8.19
46 (9,10,9,9,9)	1.05	0.58	0.00	41.98	9.72

3. Quantization experiments

To measure the LSF quantization performance, we use the traditional measure of spectral distortion (SD). The conditions for transparent quality LPC parameter quantization in telephone-band speech case are [3]: (1) the average SD is around 1 dB, (2) no outlier frame '> 4 dB' of SD, and (3) $< 2\%$ outlier frames are within the range of 2-4 dB. It is mentioned in [7] that the same conditions are also valid for transparent quality quantization of wide-band LPC parameters; thus, these conditions are used for recent study of LPC parameter quantization problem in wide-band speech coding ([9], [11]).

The speech data used in the experiments is from the TIMIT data base, where the speech is sampled at 16 kHz. We have used the specification of AMR-WB speech codec [12] to produce 16-th order LP coefficients, which are then converted to LSF parameters (i.e. $p = 16$). In the experiments, 368815 LSF vectors are used for training and "out of training" 5000 vectors are used for testing.

The performance of NT_SSVQ method, using WSED measure of Eqn. 4, is shown in Table 1; in the second stage, the variance normalized residual vector is split into 5 parts of (3,3,3,3,4) dimensional sub-vectors (i.e. $S = 5$) and then quantized using five-part SVQ. The bits are allocated optimally among the two stages and sub-vectors using Eqn. 7, which are also shown in Table 1. Table 2 shows the performance of two stage split VQ (T_SSVQ) method where the residual vector (in second stage) is not variance normalized like NT_SSVQ, but quantized using a 5 part SVQ as like NT_SSVQ; appropriate WSED measure and same bit allocation strategy of NT_SSVQ are used for implementing the T_SSVQ method. It is observed that the variance normalization of residual vector and the use of appropriate WSED measure (given in Eqn. 4) in NT_SSVQ, lead to improvement of rate-distortion performance over T_SSVQ. NT_SSVQ saves more than 1 bit/vector compared to T_SSVQ.

We compare the performance of NT_SSVQ method over traditional SVQ, and recently proposed SSVQ and T_STVQ methods. In both SVQ and SSVQ methods, we use the WSED measure of Eqn. 2. In case of traditional SVQ method, the 16 dimensional LSF vector is split into 5 parts of (3,3,3,3,4) dimensional sub-vectors[2]; the performance of SVQ is shown in Table 3. The performance of five part SSVQ, with 8 switching directions, is shown in Table 4 where the bit allocations to the switching selector and the split sub-vectors are carried out according to [11]. Table 5 shows the performance of T_STVQ method using 64 clusters [10].

Rate-distortion (average SD and 2-4 dB outliers) performances, computational complexity and memory requirement of different methods are compared in Fig. 2. NT_SSVQ outperforms the traditional SVQ method in all the aspects. Comparing with SSVQ method, the proposed NT_SSVQ nearly shows

[2]Five part SVQ is also implemented in ([9], [11]) to compare with fi ve part SSVQ.

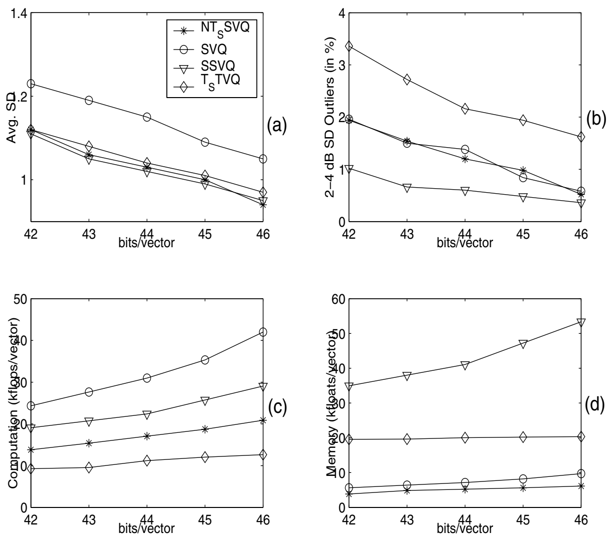

Figure 2: Comparison of different performance measures between normalized two stage SVQ (NT_SSVQ), traditional SVQ, and recently proposed switched SVQ (SSVQ) and two stage transform VQ (T_STVQ) methods. (a) Average SD (in dB) performances. (b) 2-4 dB SD outliers. (c) Computational complexities. (d) Memory requirements.

Table 4: Performance of the recently proposed five-part switched split VQ (SSVQ) method using 8 switching directions

Total bits/vector {Bit allocation to switch direction and sub-vectors}	Avg. SD (dB)	SD Outliers 2-4 dB (in %)	SD Outliers >4 dB (in %)	kflops/ vector (CPU)	kfloats/ vector (ROM)
42 (3,7,7,8,8,9)	1.11	1.02	0.00	19.08	34.94
43 (3,7,8,8,8,9)	1.05	0.66	0.00	20.74	38.01
44 (3,8,8,8,8,9)	1.02	0.60	0.00	22.40	41.08
45 (3,8,8,8,9,9)	0.99	0.48	0.00	25.73	47.23
46 (3,8,8,9,9,9)	0.95	0.36	0.00	29.06	53.37

same average SD performance, but at much lower requirements of computation and memory. The proposed NT_SSVQ provides transparent quality quantization performance at 45 bits/vector (see Table 1) like SSVQ (see Table 4); at 45 bits/vector, NT_SSVQ provides saving of computational complexity and memory requirement than SSVQ by respectively 27% and 86%. On the other hand, we note that T_STVQ could not provide transparent quality quantization performance because of its poor outlier performance; also, T_STVQ requires more memory than the NT_SSVQ method. Thus, comparing all the aspects of VQ, the proposed NT_SSVQ method can be regarded as a potential LSF quantization method in wide-band speech coding.

4. Conclusion

We develop a new normalized two stage SVQ (NT_SSVQ) method where the higher dimensional coding advantages are exploited at the first stage, and the requirements of lower computation and memory are achieved by using SVQ technique at the second stage. A Voronoi region specific weighted square Euclidean distance (WSED) measure is derived for efficient residual encoding in the second stage. The proposed NT_SSVQ method is compared with traditional SVQ, and recently proposed SSVQ and T_STVQ methods. It is observed that the NT_SSVQ provides transparent quality quantization performance at 45 bits/vector similar to SSVQ, but with lower computational complexity and much lower requirement of memory.

Table 5: Performance of the recently proposed two stage transform VQ (T_STVQ) method

Total bits/vector	Avg. SD (dB)	SD Outliers 2-4 dB (in %)	SD Outliers >4 dB (in %)	kflops/ vector (CPU)	kfloats/ vector (ROM)
42	1.12	3.36	0.02	9.26	19.58
43	1.08	2.72	0.02	9.55	19.64
44	1.04	2.16	0.02	11.21	20.03
45	1.01	1.94	0.02	12.04	20.22
46	0.97	1.62	0.02	12.62	20.35

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