Quantization of Variable Dimension Spectral Vectors *

Chunyan Li, Eyal Shlomot and Vladimir Cuperman

Department of Electrical and Computer Engineering
University of California, Santa Barbara

Abstract

In this paper, we present a comprehensive study of a quantization technique for variable dimension spectral vectors that we call weighted non-square transform VQ (WNSTVQ). This technique employs generalized perceptually weighted linear dimension conversion to a fixed dimension vector followed by vector quantization (VQ). We show that the total error can be separated into the weighted modeling error and the weighted quantization error. Perceptual weighting in the modeling and the quantization of the variable dimension spectral vectors is essential for harmonic coding systems where the spectral vectors are obtained by harmonic sampling of the spectrum of the LP residual signal. The paper presents codebook search procedures for the WNSTVQ and experimental results for different types of transforms.

1. Introduction

Efficient quantization of the variable dimension spectral vectors is a crucial issue in low-bit-rate harmonic (sinusoidal) speech coders [1-5]. In these coders, the spectral magnitude vector is obtained by sampling the speech magnitude spectrum or the LP residual magnitude spectrum at multiples of the pitch frequency. This sampling procedure generates a variable-dimension vector of harmonic spectral peaks. The vector dimension, N, is inversely proportional to the pitch frequency, f_p, and is given by:

$$N = \left\lfloor \frac{F_s}{2f_p} \right\rfloor$$

where F_s is the sampling frequency, which is 8 kHz for a telephone bandwidth signal. Standard VQ cannot be directly applied to the variable-dimension vectors of harmonic spectral magnitudes. A theoretically optimal solution would employ a different codebook for each possible dimension of the spectral vectors. However, this optimal solution is quite impractical and results in prohibitive requirements on storage space for the codebooks and on the size of the training set for codebook design. The prevailing approach for the quantization of the variable-dimension spectral vectors is to convert them into fixed-dimension vectors prior to quantization. The decoder extracts the quantized fixed-dimension vector and, assisted by the quantized pitch value, converts it back into the quantized variable-dimension vector.

Several dimension conversion techniques have been developed for the quantization of the variable dimension spectral vectors. In [2,6] an all-pole (LP) model or a discrete all-pole (DAP) model is used to approximate the spectral envelope using a fixed number of parameters. The model parameters are quantized using a fixed-dimension VQ. In band-limited interpolation (BLI) [7], the variable-dimension vectors are converted into fixed-dimension vectors by sampling rate conversion which preserves the shape of the spectral envelope. The concept of spectral bins for the dimension conversion is employed in variable dimension vector quantization (VDVQ) [8]. In VDVQ, the spectral axis is divided into segments, or bins, and each spectral sample is mapped onto the closest spectral bin to form a fixed-dimension vector for quantization. Truncation method [9] and zero-padding method [5] convert the variable dimension vector to a fixed dimension vector by simply truncating or zero-padding.

We suggest classifying the dimension conversion approaches as linear or nonlinear. Such a classification can lead to a better understanding and generalization of various dimension conversion schemes.

In linear dimension conversion, the encoder converts the variable-dimension vector into a fixed-dimension vector using a (vector) linear function. Similarly, the decoder uses the inverse linear function to convert the decoded fixed-dimension vector into a variable-dimension vector. This general approach was proposed in [10] and is called non-square transform (NST) or non-square transform VQ (NSTVQ).

It was pointed in [5] that known linear dimension conversion schemes, such as BLI, VDVQ, sample truncation, and zero-padding could be treated as special cases of NSTVQ.

Nonlinear conversion schemes perform similar conversions, but use nonlinear mapping for dimension conversion. Nonlinear dimension conversion schemes are based primarily on fitting a nonlinear regression model to the harmonic spectral samples. The LP and the DAP approaches described above belong to this category.

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2. Non-square transform vector quantization

Lupini and Cuperman [10] suggested the NSTVQ for the quantization of the variable-dimension spectral vector. Fig. 1 shows an overview of the process for quantizing variable-dimension spectral magnitude vectors using NSTVQ.

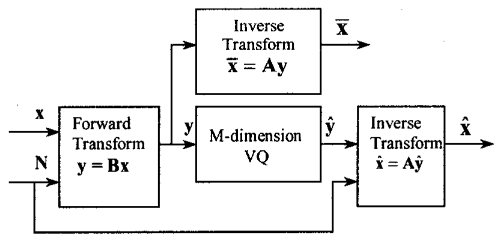

Fig. 1. NSTVQ overview

In NSTVQ, a forward transform matrix **B** maps the N elements of **x** into a fixed-length M element vector **y**:

$$\mathbf{y} = \mathbf{Bx} \tag{1}$$

For a square invertible matrix **B**, **x** can be reconstructed precisely using the inverse matrix. However, for a non-square transform, in general, only an estimate of **x**, denoted here by $\bar{\mathbf{x}}$, can be obtained:

$$\bar{\mathbf{x}} = \mathbf{Ay} \tag{2}$$

where **A** is a generalized inverse transform matrix of size $N \times M$. It is important to remember that even for fixed M, **A** and **B** belong to a family of matrices, since their dimensions depend on N. We are looking for a pair of transform matrices, **A** and **B**, which are chosen to minimize the modeling distortion D_m defined as the mean square error between the vectors **x** and $\bar{\mathbf{x}}$:

$$D_m(\mathbf{x}, \bar{\mathbf{x}}) = \|\mathbf{x} - \bar{\mathbf{x}}\|^2$$

It has been shown in [10] that, for the case $N \geq M$, D_m can be minimized by choosing the matrix **B** for given **A** such that:

$$\mathbf{B} = \left(\mathbf{A}^{\mathrm{T}}\mathbf{A}\right)^{-1}\mathbf{A}^{\mathrm{T}} \tag{3}$$

or by choosing **A** for given **B**:

$$\mathbf{A} = \mathbf{B}^{\mathrm{T}}\left(\mathbf{B}^{\mathrm{T}}\mathbf{B}\right)^{-1}$$

For the case of dimension expansion, where $N < M$, the matrix **B** can be chosen given **A**:

$$\mathbf{B} = \mathbf{A}^{\mathrm{T}}\left(\mathbf{A}\mathbf{A}^{\mathrm{T}}\right)^{-1} \tag{4}$$

or matrix A can be computed from **B** by

$$\mathbf{A} = \left(\mathbf{B}^{\mathrm{T}}\mathbf{B}\right)^{-1}\mathbf{B}^{\mathrm{T}}$$

For dimension expansion with an optimal choice of matrices, $D_m(\mathbf{x}, \bar{\mathbf{x}}) = 0$. When the rows of matrix **A** are orthonormal to each other, a very simple relationship between **A** and **B** can be obtained:

$$\mathbf{B} = \mathbf{A}^{\mathrm{T}}$$

3. Weighted harmonic spectral quantization

In practical applications to speech coding, the distortion measure has to account for perceptual weighting of the representation error. Perceptual weighting was used by Nishiguchi et al. [11], who suggested spectral vector quantization with a weighted mean squared error (WMSE) measure. This distortion measure evaluates the degree of matching between the original speech spectrum and the quantized speech spectrum based on the perceptual distortion in the speech domain. The WMSE is given by

$$D_w = (\mathbf{x} - \hat{\mathbf{x}})^{\mathrm{T}}\mathbf{W}^{\mathrm{T}}\mathbf{W}(\mathbf{x} - \hat{\mathbf{x}}), \tag{5}$$

where $\hat{\mathbf{x}}$ is the quantized version of **x**. If the variable-dimension spectral vector is obtained from the LP residual signal, the diagonal weighting matrix $\mathbf{W}^{\mathrm{T}}\mathbf{W}$ incorporates the spectral contribution of the LP synthesis filter and a perceptual weighting measure. The diagonal element of **W** at the n^{th} harmonic is given by:

$$w_{nn} = P(nf_p) \cdot \left\| \frac{1}{A(z)} \right\|_{z=e^{j\frac{2\pi n f_p}{F_s}}} \tag{6}$$

where f_p denotes the pitch frequency, F_s the sampling frequency, and $P(nf_p)$ a perceptual weighting function. Although for our application in harmonic coding of the residual signal we use a diagonal weighting matrix, in the following theoretical analysis of dimension conversion and vector quantization, **W** will not be restricted to be diagonal.

3.1. Weighted non-square transform

To derive the optimal relation between the forward and the inverse non-square transforms, we will choose a pair of transform matrices, **A** and **B**, such that $\bar{\mathbf{x}}$ defined in (2) is a "good" estimate of the original vector **x**. We are interested in matrices which minimize the weighted modeling distortion D_{wm}:

$$\begin{aligned} D_{wm} &= (\mathbf{x} - \bar{\mathbf{x}})^{\mathrm{T}}\mathbf{W}^{\mathrm{T}}\mathbf{W}(\mathbf{x} - \bar{\mathbf{x}}) \\ &= (\mathbf{x} - \mathbf{Ay})^{\mathrm{T}}\mathbf{W}^{\mathrm{T}}\mathbf{W}(\mathbf{x} - \mathbf{Ay}) \end{aligned} \tag{7}$$

Assuming that **A** is given, we can consider the minimization of the distortion D_{wm} as a function of the vector **y**. The vector $\mathbf{y}_{opt}$ which minimizes the distortion is obtained as the solution to the following set of linear equations:

$$\mathbf{A}^{\mathrm{T}}\mathbf{W}^{\mathrm{T}}\mathbf{W}\mathbf{A}\mathbf{y}_{opt} = \mathbf{A}^{\mathrm{T}}\mathbf{W}^{\mathrm{T}}\mathbf{W}\mathbf{x} \tag{8}$$

In the case when $N \geq M$ and **A** is of rank M (i.e., the M columns of A are linearly independent), the $M \times M$ matrix $\mathbf{A}^{\mathrm{T}}\mathbf{W}^{\mathrm{T}}\mathbf{W}\mathbf{A}$ is of full rank and has an explicit inverse which gives a unique solution vector $\mathbf{y}_{opt}$:

$$\mathbf{y}_{opt} = (\mathbf{A}^{\mathrm{T}}\mathbf{W}^{\mathrm{T}}\mathbf{W}\mathbf{A})^{-1}\mathbf{A}^{\mathrm{T}}\mathbf{W}^{\mathrm{T}}\mathbf{W}\mathbf{x} \tag{9}$$

Comparing (9) with (1) we see that in order for the matrix **B** to produce the fixed-length vector **y** which minimizes the weighted modeling distortion, **B** must have the form:

$$\mathbf{B} = (\mathbf{A}^T\mathbf{W}^T\mathbf{W}\mathbf{A})^{-1}\mathbf{A}^T\mathbf{W}^T\mathbf{W} \quad (10)$$

and the inverse equation which computes **A** given **B** is:

$$\mathbf{A} = (\mathbf{W}^T\mathbf{W})^{-1}\mathbf{B}^T(\mathbf{B}\mathbf{W}^{-1}\mathbf{W}^{-T}\mathbf{B}^T)^{-1} \quad (11)$$

In the case when $N<M$ and A is of rank N (i.e., the N rows of A are linearly independent), the optimal transform matrices are the same as those derived in section 2.

3.2 Weighted non-square transform VQ

As shown in Fig. 1, the non-square transform matrix **B** derived above converts a variable-dimension vector **x** into a vector **y** which can be encoded using a fixed-dimension VQ. The quantized fixed-length vector $\hat{\mathbf{y}}$ is then transformed into the quantized variable length vector $\hat{\mathbf{x}}$ using :

$$\hat{\mathbf{x}} = \mathbf{A}\hat{\mathbf{y}} \quad (12)$$

The WNSTVQ quantizer should be designed to minimize the total weighted distortion D_w defined by (5). It is easy to rewrite D_w as:

$$\begin{aligned} D_w &= (\mathbf{x}-\bar{\mathbf{x}})\mathbf{W}^T\mathbf{W}(\mathbf{x}-\bar{\mathbf{x}}) + (\bar{\mathbf{x}}-\hat{\mathbf{x}})^T\mathbf{W}^T\mathbf{W}(\bar{\mathbf{x}}-\hat{\mathbf{x}}) \\ &\quad + 2(\mathbf{x}-\mathbf{A}\mathbf{y})^T\mathbf{W}^T\mathbf{W}(\mathbf{A}\mathbf{y}-\mathbf{A}\hat{\mathbf{y}}) \\ &= D_{wm} + D_{wq} \\ &\quad + 2(\mathbf{x}-\mathbf{A}\mathbf{y})^T\mathbf{W}^T\mathbf{W}(\mathbf{A}\mathbf{y}-\mathbf{A}\hat{\mathbf{y}}) \end{aligned} \quad (13)$$

By combining (1) and (10) for the case $N \geq M$, or (1) and (4) for the case $N<M$, it can be shown that the last term in (13) is equal to zero. The total weighted distortion D_w can be hence expressed as:

$$D_w = D_{wm} + D_{wq} \quad (14)$$

The first term in (15) is the weighted modeling distortion, D_{wm}, due to the non-square transform and the second term, D_{wq}, is the quantizer distortion due to the VQ and is given by:

$$D_{wq} = (\bar{\mathbf{x}}-\hat{\mathbf{x}})^T\mathbf{W}^T\mathbf{W}(\bar{\mathbf{x}}-\hat{\mathbf{x}}) \quad (15)$$

The fact that these distortions can be separated shows that once we have chosen a transform matrix **A** or **B** the minimization of the total weighted distortion D_w is equivalent to the minimization of D_{wq}. The distortion measure used in VQ training and search, then, is given by (15).

Substituting (2) and (12) into (15), We can rewrite the weighted quantizer distortion as:

$$D_{wq} = (\mathbf{y}-\hat{\mathbf{y}})^T\mathbf{A}^T\mathbf{W}^T\mathbf{W}\mathbf{A}(\mathbf{y}-\hat{\mathbf{y}}) \quad (16)$$

The last equation shows that the minimization of D_{wq} in the variable-dimension vector domain (with the weighting matrix W) can be obtained by minimizing a weighted quantization error for the transformed fixed-dimension vector, using the weighting matrix $\mathbf{A}^T\mathbf{W}^T\mathbf{W}\mathbf{A}$.

If $\mathbf{A}^T\mathbf{W}^T\mathbf{W}\mathbf{A}$ is a diagonal matrix, the conventional vector codebook search procedure can be used by transforming the variable-dimension vector to a fixed-dimension vector, and then performing the search with modified quantization weights. In this case (16) is a simple and practical way to implement the WNSTVQ. For a diagonal **W** matrix like in (6), it is easy to show that $\mathbf{A}^T\mathbf{W}^T\mathbf{W}\mathbf{A}$ is diagonal for zero-padding, sample truncation, and VDVQ.

In this study, in order to investigate the best possible WNSTVQ scheme, we did not restrict ourselves to a diagonal $\mathbf{A}^T\mathbf{W}^T\mathbf{W}\mathbf{A}$. For a non-diagonal matrix, the search described by (16) can still be used, however, this search may result in prohibitive complexity. First, a non-diagonal matrix results in high-complexity for the computation of the WMSE in (16). Second, the input variable-dimension vector **x** is first converted to the fixed-dimension vector **y** by the forward non-square transform matrix **B** which depends on the spectral weights according to (10), and has to be recomputed for each input vector.

To avoid this problem we propose a codebook search scheme in which rather than transforming the input vector to a fixed dimension, the codebook is transformed to the variable dimension as shown in Fig. 2. The non-square transform **A** is applied to the fixed-dimension codebook $\{\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_L\}$ to obtain a new codebook, $\{\mathbf{A}\mathbf{y}_1, \mathbf{A}\mathbf{y}_2, \ldots, \mathbf{A}\mathbf{y}_L\}$, which has the same dimension as the input vector **x**. The dimensions of the transform matrix **A** depend on the input vector **x**. The search is actually performed in the new variable dimension codebook. For the case of dimension reduction, using an M-dimensional codebook of size L and the search procedure based on (16), the number of floating point operations (worst case) needed to obtain the matrix **B** using (10) is $4N_{max}^3/3 + (M+5)N_{max}^2 + MN_{max}$, where N_{max} is the maximum length of the variable-dimension spectral vector. The number of operations to transform the vector **x** into a fixed-dimension vector **y** is MN_{max}. The number of operations for codebook search in the fixed-dimension vector domain is $L(M^2+2M)$. Therefore the number of operations per vector for the search procedure based on (16) is

$$4N_{max}^3/3 + (5+M)N_{max}^2 + 3MN_{max} + L(M^2+2M)$$

The number of operations per vector for the second search procedure of Fig. 2 is

$$LMN_{max} + 2LN_{max}$$

which may result in significant savings with respect to the first search procedure.

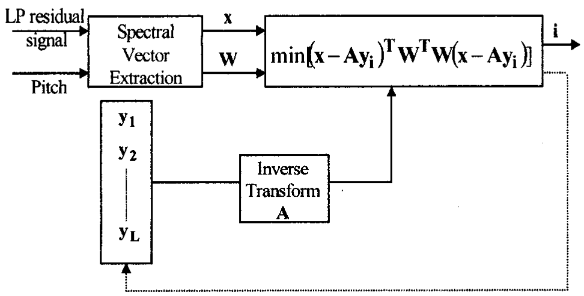

Fig. 2. Codebook search procedure for the second procedure

4. Experimental Results

In this section we present the experimental results of the WNSTVQ systems.

4.1. Distortion criteria

We used both root square spectral distortion (SD) and weighted signal to noise ration (WSNR) as distortion measures which are defined below.

- Spectral Distortion

$$SD = \frac{1}{K}\sum_{k}\sqrt{\frac{1}{N_k}\sum_{n=0}^{N_k-1}\left[10\log_{10}\frac{x_k^2[n]}{\hat{x}_k^2[n]}\right]^2} \quad [dB]$$

- Weighted SNR

$$WSNR = \frac{1}{K}\sum_{k}\frac{\sum_{n=0}^{N_k-1} w_{nn}^2 (x_k[n])^2}{\sum_{n=0}^{N_k-1} w_{nn}^2 (x_k[n]-\hat{x}_k[n])^2} \quad [dB]$$

where K is the size of the database, N_k is the dimension of the original vector $\mathbf{x}_k$, $\hat{\mathbf{x}}_k$ is the quantized version of $\mathbf{x}_k$, and $x_k[n]$ is the n^{th} element of the vector $\mathbf{x}_k$. The weights w_{nn} are defined by (6) and the weighting function used in our experiments is:

$$P(nf_p) = \left\| \frac{A(z/\gamma_1)}{A(z/\gamma_2)} \right\|_{z=e^{j\frac{2\pi n f_p}{F_s}}}$$

where $\gamma_1 = 0.94$ and $\gamma_2 = 0.7$.

4.2 Experiments and results

The speech material used in our experiments consists of sentences spoken by male and female talkers and sampled at 8 KHz. The LP residual signal was obtained by a 10^{th} order LPC filter. The spectral vectors were extracted from the residual signal every 10 ms and normalized by a gain factor. Our database includes 32396 vectors of dimension 48 or smaller. Of the 32396 vectors, 23961 vectors were used for codebook training and 8435 vectors were used for testing.

The first experiment was designed to test the performance of the WNSTVQ as a function of the codebook dimension, M. We tested the values of 10, 24, 32, and 48 for M, incorporating both dimension reduction and dimension expansion into the WNSTVQ systems for M=24 and M=32. We chose a non-diagonal transform matrix $\mathbf{A}$ based on the non-square DCT-II transform suggested in [10] with elements given by

$$\mathbf{A}(i,j) = \begin{cases} \left(\frac{2}{N}\right)^{1/2} C_i \cos\left[\frac{(2i-1)\pi(j-1)}{2N}\right] & \text{for } j = 1,\ldots,\min(N,M) \\ & \text{and } i = 1,\ldots,N \\ 0 & \text{Otherwise} \end{cases}$$

where $C_i = 1$ for all i except $C_1 = 1/\sqrt{2}$.

For each M we designed an M-dimensional 2-stage MSVQ codebook using 6 bits per stage. Figures 4 and 5 show the WSNR and the SD versus M, respectively. Increasing the value of M results in higher WSNR and lower spectral distortion. The figures show that only a minor performance gain is obtained by increasing M beyond 32. In fact the WSNR for $M=32$ is only about 0.18 dB lower than the highest WSNR obtained at $M=48$.

The second test compared the non-square DCT based WNSTVQ with the zero-padding WNSTVQ with M=48. The elements of the zero-padding matrix $\mathbf{A}$ are given by:

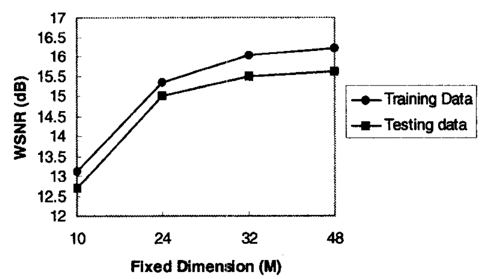

Fig. 4. WSNR vs. fixed-dimension M DCT based WNSTVQ

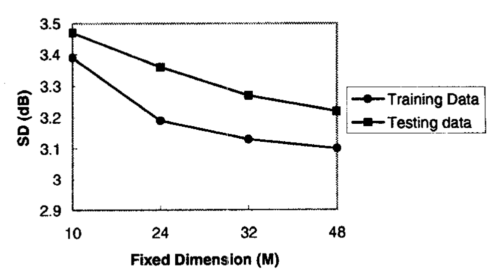

Fig. 5. SD vs. fixed-dimension M for DCT based WNSTVQ

$$\mathbf{A}(i,j) = \begin{cases} 1 & i = j \text{ and } i = 1,2,\ldots,N; \;\; j = 1,2,\ldots,N \\ 0 & \text{otherwise} \end{cases}$$

Conventional VQ search and training procedures can be applied directly in zero-padding WNSTVQ since the weighting matrix is diagonal. A 48-dimension 2-stage MSVQ codebook with 6 bits per stage was designed. We call this scheme ZP-48.

Table 1 shows that the WSNR for the ZP-48 scheme is 0.56 dB lower than that of the DCT-48 scheme, and its spectral distortion is 0.18 dB higher. However, a tradeoff exists between the performance, the complexity and the storage requirements for each transform type and different values of M. For example, DCT-10 has the lowest storage, ZP-48 the lowest complexity, and DCT-48 the best performance. For all of the quantization schemes using an M-dimension k-stage MSVQ configuration with b bits and S candidates per stage, the number of floating point operations for the codebook search is of the order of $3[(k-1)S+1]2^b M$. For the WNSTVQ with a non-diagonal weighing matrix (the DCT-M schemes), the additional complexity due to the codebook transformation is in the order of $k2^b MN_{max}$.

Table 1 Comparisons between various schemes

Schemes	WSNR (dB)	Complexity (MOPV*)	CB Storage (word)
DCT-48	16.20	0.34	6144
DCT-32	16.03	0.24	4096
DCT-24	15.32	0.19	3072
DCT -10	13.12	0.11	1280
ZP-48	15.64	0.05	6144

*MOPV : Million Operations per Vector

The theoretically optimal solution for quantization of variable dimension vectors uses a codebook for each possible dimension. In order to assess the performance improvement resulting from the use of multiple codebooks, we tested both zero-padding and non-square DCT based WNSTVQ with multi-codebook quantization schemes which are successively closer to the optimal solution.

Table 2 Dimension range for multi-codebook schemes

# of codebooks	1	2	3
dimension range #1	10-48		
dimension range #2	10-29	30-48	
dimension range #3	10-22	23-32	33-48

Table 2 shows the dimension ranges for the 3 multi-codebook quantization schemes. For example, in the first quantization scheme, all vectors are expanded to dimension 48 and a single codebook is used. For the second quantization scheme, vectors of dimension smaller than 30 were expanded into vectors of dimension 29, and vectors of dimension 30 or above were expanded into vectors of dimension 48 and two codebooks were used. For each codebook in each dimension range, we designed a 2-stage MSVQ with 6 bits per stage. Figure 6 shows the WSNR versus the number of codebooks for the zero-padding and the non-square DCT methods.

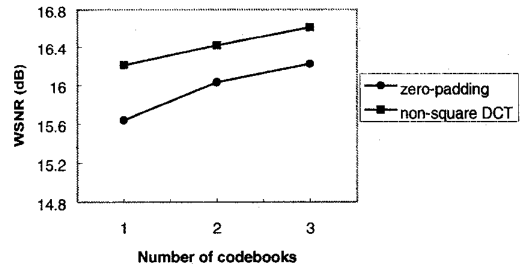

Fig. 6. WSNR vs. number of codebooks for various multi-codebook quantization systems. (12 bits/vector)

5. Conclusions

In this paper we presented a study of a weighted linear dimension conversion and quantization scheme for harmonic spectral vectors. We showed the relations between the optimal forward and inverse transform matrices and proved that the total weighted distortion can be separated into a weighted dimension conversion distortion and a weighted quantization error. We provided a complexity analysis for the possible implementation systems of our WNSTVQ, and presented simulation results showing the tradeoffs between complexity, memory storage, and performance for several WNSTVQ systems.

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