Comparison of Prediction Based LSF Quantization Methods using Split VQ

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Abstract

Further improvement in performance, to achieve near transparent quality LSF quantization, is shown to be possible by using a higher order two dimensional (2-D) prediction in the coefficient domain. The prediction is performed in a closed-loop manner so that the LSF reconstruction error is the same as the quantization error of the prediction residual. We show that an optimum 2-D predictor, exploiting both inter-frame and intra-frame correlations, performs better than existing predictive methods. Computationally efficient split vector quantization technique is used to implement the proposed 2-D prediction based method. We show further improvement in performance by using weighted Euclidean distance.

Index Terms : LSF Quantization, Predictive Methods.

1. Introduction

On going speech coding research has been pushing bit-rates further downward and thus there is a requirement of finding more efficient LPC parameter quantization technique. Among many representations of LPC, line spectrum frequency (LSF) parameters are well suited for quantization [5]. Since the full search vector quantization (VQ) is complexity limited, various structured VQ methods have been proposed in the past to encode the LSF parameters. One of the most cited and practically used techniques is split VQ (SVQ) [5]. A three sub-vector SVQ technique is used in different coders, such as IS-136, G.723.1 etc. [12].

Since speech spectra are slowly time-varying, the LSF parameters show a significant *inter-frame* correlation between successive frames. To exploit this, several predictive schemes have been proposed in the past ([2], [6], [8], [9]). We refer to these methods as inter-frame correlation based predictive methods (1-D methods). In addition to the inter-frame correlation, there exists a strong *intra-frame* correlation [3] between the LSF components of a particular frame. Therefore, the predictive methods can exploit both the inter-frame and intra-frame correlations simultaneously. Hence, 2-D prediction method is proposed in [4] and further explored in ([7], [11]). The 2-D method uses both the LSFs of the previous frames and some of the LSFs of the current frame to remove the linear redundancy. Another approach to linear redundancy removal is through a de-correlating transform, such as applying DCT [3]. Hence intra-frame redundancy can be reduced through the DCT of LSF vector. A similar approach for inter-frame redundancy removal will require large coding delay, which may not be acceptable. Hence, one has to explore a hybrid of transform domain inter-frame prediction [3].

In using VQ for LSF, there is also the issue of complexity, for which sub-optimum SVQ has been widely used. However, the 1-D and 2-D prediction schemes use quantized priors and hence for limited complexity, it is worth to explore the effectiveness of applying SVQ technique in different predictive schemes as well as in hybrid predictive scheme. Towards this, we have found as optimum order 2-D prediction scheme (combined inter-frame and intra-frame) which outperforms the 1-D, 2-D prediction schemes, as well as hybrid transform domain prediction scheme. The optimum 2-D predictor provides nearly 3 bit performance advantage over the regular SVQ scheme.

2. Predictive LSF quantization

Let the nth frame 10th dimensional LSF vector be $\underline{\omega}(n) = [\omega_1(n)\ \omega_2(n)\ \ldots\ \omega_{10}(n)]^T$. The earliest of predictive scheme for LSF is the vector LP [2], in which $\underline{\omega}(n)$ is predicted as $\tilde{\underline{\omega}}(n) = \underline{A}\ \hat{\underline{\omega}}(n-1)$; where $\underline{A}$ is 10×10 prediction matrix. Later, $\underline{A}$ is simplified to a diagonal matrix (pp. 504 of [9]), leading to $\tilde{\omega}_i(n) = a_i \hat{\omega}_i(n-1),\ 1 \le i \le 10$, resulting in the 1-D predictor. We refer this method using SVQ technique as 1-D predictive SVQ method (1DPSVQ).

The 2-D predictor [4] uses both inter-frame and intra-frame components for joint prediction as: $\tilde{\omega}_i(n) = b_i \hat{\omega}_i(n-1) + c_i \hat{\omega}_{i-1}(n),\ 1 \le i \le 10$. Because of the joint prediction, it is expected to provide better prediction gain than pure 1-D predictor or only inter-frame prediction. This method, using SVQ technique, is referred as 2-D predictive SVQ method (2DPSVQ).

The intra-frame redundancy can also be removed through linear transforms, such as applying DCT [3] or KLT [10] on LSF vector; i.e. using $\underline{u}(n) = \mathbf{D}\ \underline{\omega}(n)$, where $\mathbf{D}$ is a 10×10 DCT or KLT matrix. The de-correlating transform removes the intra-frame redundancy and hence intra-frame prediction can be avoided. Therefore, the hybrid predictive scheme uses the prediction in the transformed domain as: $\tilde{u}_i(n) = h_i \hat{u}_i(n-1),\ 1 \le i \le 10$. We refer this method, using SVQ technique, as transform domain 1DPSVQ method (T1DPSVQ).

3. Optimum 2-D predictor

A general 2-D predictor, using the past coded coefficients to predict the current coefficients, can be expressed as:

$$\tilde{\underline{\omega}}(n) = \sum_{k=1}^{M} \underline{A}_k\ \hat{\underline{\omega}}(n-k) + \underline{B}\ \hat{\underline{\omega}}(n) \qquad (1)$$

where $\underline{A}_k$s are the prediction matrices associated with past coded frames' LSF vectors (exploiting inter-frame correlation) and $\underline{B}$ is the matrix associated with the current frame LSF vector (exploiting intra-frame correlation). This $\underline{B}$ matrix is a constrained lower triangular matrix with main diagonal elements as zeros to achieve the causality relation of the predictor formulation. So, $\omega_i(n)$ can

Table 1: *Open loop performance using different predictive methods with different orders*

Scheme	Coefficients used to predict $\omega_i(n)$	Model order, p	Avg. G_p	Further Improvement
1-D Predictive Methods				
1	$\omega_i(n-1)$	1	3.19	-
2	$\omega_i(n-1), \omega_i(n-2)$	2	3.23	no
3	$\omega_{i-1}(n-1), \omega_i(n-1)$ and $\omega_{i+1}(n-1)$	3	3.49	minor
2-D Predictive Methods				
4	$\omega_i(n-1), \omega_{i-1}(n)$	2	4.69	major
5	$\omega_i(n-1), \omega_{i+1}(n-1)$ and $\omega_{i-1}(n)$	3	4.98	minor
6	$\omega_i(n-1), \omega_{i-1}(n-1)$ and $\omega_{i-1}(n)$	3	5.50	major
7	$\omega_{i-1}(n-1), \omega_i(n-1)$ $\omega_{i+1}(n-1)$ and $\omega_{i-1}(n)$	4	5.67	minor
8	$\omega_{i-1}(n-1), \omega_i(n-1)$, $\omega_{i+1}(n-1), \omega_{i-1}(n)$ and $\omega_{i-2}(n)$	5	5.68	no
9	$\omega_{i-2}(n-1), \omega_{i-1}(n-1)$, $\omega_i(n-1), \omega_{i+1}(n-1)$, $\omega_{i+2}(n-1)$ and $\omega_{i-1}(n)$	6	5.71	no

be predicted using past coded components of the same nth frame, i.e. $\{\omega_{i-k}(n)\}_{k=1}^{i-1}$, in addition to the past coded components of the previous frames. Since a first order inter-frame predictor is sufficient [9] to exploit the inter-frame correlation, Eqn. 1 is modified as:

$$\underline{\tilde{\omega}}(n) = \underline{A}_1 \ \underline{\hat{\omega}}(n-1) + \underline{B} \ \underline{\hat{\omega}}(n) \tag{2}$$

An optimum solution of the prediction matrices in Eqn. 2, with the condition that of $\underline{B}$ is possessing a special constrained structure, is mathematically intractable. However, treating the vector sequence in a 2-D plane, we can form a causal nearest neighbor scalar predictor formulation. We find experimentally the optimum 2-D predictor as:

$$\begin{aligned}\tilde{\omega}_i(n) = d_i\hat{\omega}_{i-1}(n-1) + e_i\hat{\omega}_i(n-1) + f_i\hat{\omega}_{i+1}(n-1)\\ +g_i\hat{\omega}_{i-1}(n),\ 1 \le i \le 10\end{aligned} \tag{3}$$

where d_i, e_i, f_i and g_i are the prediction coefficients. The boundary values are fixed as: $\hat{\omega}_0(n) = \hat{\omega}_0(n-1) = 0.005$ and $\hat{\omega}_{11}(n) = \pi$. We call this new 2-D prediction scheme, using SVQ technique, as optimum PSVQ method (OPSVQ).

Without any quantization, we first study the open loop[1] performance gain improvements achieved by different predictors. A training data of 5,000 frames is used to find the corresponding optimum prediction coefficients[2] for each of the methods and 5,579 frames of "out of training" data is used for testing[3]. Table 1 shows the average prediction gain (Avg. G_p in dB) performance of different methods. Some of these schemes are elucidated in Fig. 1. The observations from Table 1 are:

(a) All 2-D methods are better than 1-D methods, indicating the advantage of jointly exploiting inter-frame and intra-frame correlations.

(b) Among the 1-D predictors, the marginal improvements are essentially due to increase of the model order and thus scheme-1 is sufficient for 1-D prediction as reported in [9].

(c) Among the 2-D predictors there is 1 dB average gain improvement from model order $p = 2$ to $p = 6$. Also, we note that $p = 2$ in 2-D is much better than $p = 3$ in 1-D.

(d) It is clear that $p = 4$ in 2-D methods provides most of the prediction gain improvement and there is no need for the higher complexity of $p = 5$ and $p = 6$; hence this combination (scheme-7) is chosen to represent an optimum 2-D predictor as OPSVQ, characterized by Eqn. 3.

We further investigate the open loop prediction gains of different LSF components for three main schemes, which are shown in Table 2. It is observed that scheme-4 performs better than scheme-1. But, scheme-7 provides higher prediction gains for each of the LSF coefficients throughout the whole frequency region compared to scheme-4 and scheme-1. Therefore, it is expected that, OPSVQ, corresponding to scheme-7, will show better performance.

[1]Open loop is used to de-link the prediction from the performance of the quantizer.

[2]These 5,000 frames are always used to find the corresponding prediction coefficients of all the prediction based methods for all the experiments carried out. Increasing the number of training vectors to find the optimum prediction coefficients did not yield any tangible prediction gain improvement.

[3]Speech frames are 20 ms Hamming windowed with no successive overlap.

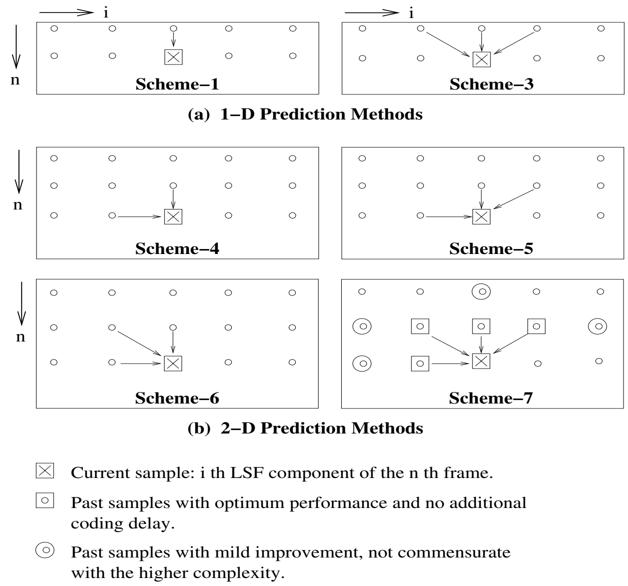

Figure 1: *LSF coefficient prediction neighborhood for some of the schemes shown in Table 1. (a) 1-D prediction methods, (b) 2-D prediction methods. Here 'n' is the frame index and 'i' is the LSF coefficient index.*

Table 2: *Open loop prediction gains (G_p in dB) of different schemes for each LSF coefficient*

Method	LSF coefficient										Avg. G_p
	1	2	3	4	5	6	7	8	9	10	
Scheme-1	2.2	2.1	2.5	3.8	4.9	4.4	4.3	3.9	2.2	1.3	3.1
Scheme-4	2.2	2.7	4.5	5.3	6.0	6.3	5.6	6.2	3.1	4.6	4.6
Scheme-7	2.8	3.7	5.2	6.3	6.6	7.4	6.3	7.5	3.8	6.5	5.6

Table 3: *Performance of different quantization methods (in dB) using Euclidean distance*

Method	Avg. SD	Outliers (in %) 2-4 dB	Outliers (in %) >4 dB	RMS SDM	Avg. SD	Outliers (in %) 2-4 dB	Outliers (in %) >4 dB	RMS SDM
	22 bits/frame				23 bits/frame			
SVQ	1.46	12.36	0.30	1.45	1.38	8.37	0.14	1.37
1DPSVQ	1.37	12.51	0.17	1.43	1.28	9.26	0.16	1.34
T1DPSVQ	1.33	9.49	0.21	1.36	1.23	7.08	0.34	1.30
2DPSVQ	1.33	8.87	0.14	1.38	1.24	6.27	0.17	1.29
OPSVQ	1.25	7.00	0.23	1.31	1.17	4.94	0.17	1.22
	24 bits/frame				25 bits/frame			
SVQ	1.30	6.63	0.14	1.30	1.21	4.92	0.10	1.22
1DPSVQ	1.19	7.11	0.14	1.26	1.12	5.62	0.05	1.20
T1DPSVQ	1.18	5.87	0.21	1.24	1.12	4.83	0.12	1.17
2DPSVQ	1.16	4.83	0.08	1.20	1.09	3.54	0.05	1.13
OPSVQ	1.08	3.99	0.14	1.14	1.02	3.29	0.07	1.08
	26 bits/frame				27 bits/frame			
SVQ	1.13	3.54	0.01	1.15	1.07	2.79	0.01	1.09
1DPSVQ	1.05	4.10	0.05	1.12	0.98	3.38	0.05	1.06
T1DPSVQ	1.03	3.20	0.07	1.09	1.00	3.02	0.05	1.06
2DPSVQ	1.02	2.56	0.03	1.06	0.95	2.11	0.03	1.01
OPSVQ	0.95	2.36	0.05	1.01	0.89	1.95	0.01	0.95

4. Quantization results

To measure the LSF quantization performance, we use the traditional measure of Spectral Distortion (SD) [5] . We also use a perceptually relevant dynamic distortion measure of Spectral Distortion with Interframe Memory (SDM), recently proposed in [13]. The conditions for transparent quality LPC parameter quantization ([5], [13]) are: (1) the average SD is around 1 dB (2) no outlier frame '$>$ 4 dB' of SD (3) $< 2\%$ of outlier frames are with in the range of 2-4 dB of SD and (4) an rms SDM is around 1 dB.

The speech data used in the experiments is from the TIMIT data base. 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. In order to avoid sharp spectral peaks in the LPC spectrum a fixed 10-Hz bandwidth expansion is applied as in [5]. In the experiments 71,707 LSF vectors are used for training and "out of training" 5,579 frames are used for testing.

We study comparative quantization performance of proposed OPSVQ over 1DPSVQ, T1DPSVQ, 2DPSVQ and memory-less regular SVQ methods. In all the methods, we have used three split arrangement of the 10 dimensional vector. We use 3-3-4 split segmentation for SVQ, 1DPSVQ, 2DPSVQ and OPSVQ methods. Since the DCT packs most energy into lower-index coefficients, the DCT residual vectors are split using 2-3-5 segmentation for the case of T1DPSVQ. In all the methods, the codebooks are designed using the LBG algorithm[4] [1]. The results of different methods using Euclidean distance (ED) are reported in Table 3.

We observe from Table 3 that the proposed OPSVQ shows better performance in all the respects than the other methods. In most of the cases, 1DPSVQ reduces average SD compared to SVQ, but fails to reduce the outliers. Also 1DPSVQ fails to show considerable improvement in the sense of rms SDM measure. But OPSVQ not only reduces average SD, but also the percentage of outliers as well as rms SDM compared to all other methods. It is observed that in the sense of only average SD, 1DPSVQ saves nearly 1 bit from the SVQ. T1DPSVQ shows either comparable or marginal improvement in performance over 1DPSVQ. 2DPSVQ method performs better than the 1DPSVQ and T1DPSVQ and thus justifies the importance of exploiting intra-frame correlation. But, the OPSVQ saves another 1 bit compared to its close contender 2DPSVQ, both in terms of average SD and rms SDM measures.

[4]The bit allocation to sub-vectors is nearly uniform to keep the search complexity minimal [5]. If 21 bits are available for the full vector, then 7 bits are allocated to each sub-vector. If 22 bits are available, then 1 bit is allocated to that sub-vector which results in least quantization distortion.

Table 4: *Performance of different quantization methods (in dB) using weighted Euclidean distance*

Method	Avg. SD	Outliers (in %) 2-4 dB	Outliers (in %) >4 dB	RMS SDM	Avg. SD	Outliers (in %) 2-4 dB	Outliers (in %) >4 dB	RMS SDM
	22 bits/frame				23 bits/frame			
SVQ	1.41	9.49	0.19	1.39	1.33	6.38	0.07	1.32
1DPSVQ	1.32	10.27	0.19	1.38	1.23	8.08	0.14	1.29
2DPSVQ	1.27	6.29	0.14	1.31	1.19	4.71	0.12	1.23
OPSVQ	1.20	5.25	0.16	1.25	1.12	4.08	0.10	1.17
	24 bits/frame				25 bits/frame			
SVQ	1.25	4.82	0.07	1.25	1.17	3.47	0.03	1.17
1DPSVQ	1.14	6.07	0.10	1.21	1.08	4.51	0.07	1.15
2DPSVQ	1.11	3.33	0.10	1.15	1.04	2.11	0.05	1.08
OPSVQ	1.04	2.74	0.07	1.09	0.97	1.81	0.05	1.03
	26 bits/frame				27 bits/frame			
SVQ	1.09	2.36	0.00	1.10	1.03	1.77	0.00	1.05
1DPSVQ	1.00	3.29	0.03	1.07	0.94	2.74	0.03	1.01
2DPSVQ	0.97	1.59	0.01	1.01	0.90	1.23	0.00	0.95
OPSVQ	0.91	1.48	0.03	0.96	0.85	1.20	0.00	0.90

In the context of LSF quantization, it is common to use weighted Euclidean distance (WED) to search the VQ codebook ([5], [10]). For the nth frame, WED is:

$$d(\underline{\omega}, \underline{\hat{\omega}}) = (\underline{\omega} - \underline{\hat{\omega}})^T \mathbf{\Sigma} (\underline{\omega} - \underline{\hat{\omega}}) = \sum_{\mathbf{i}=\mathbf{1}}^{\mathbf{10}} \sigma_{\mathbf{i}} (\omega_{\mathbf{i}} - \hat{\omega}_{\mathbf{i}})^{\mathbf{2}} \quad (4)$$

where $\mathbf{\Sigma}$ is a diagonal sensitivity matrix whose diagonal elements, $\{\sigma_i\}$, are the necessary weights [10]. Let $\mathbf{D}$ denotes the DCT matrix. The transformed coefficients can be expressed as $\underline{u} = \mathbf{D}\,\underline{\omega}$; the inverse transform is given by $\underline{\omega} = \mathbf{D}^{-1}\,\underline{u}$. Then the distance measure with respect to transformed coefficients can be written as:

$$d(\underline{u}, \underline{\hat{u}}) = (\underline{u} - \underline{\hat{u}})^T (\mathbf{D}^{-1})^T \mathbf{\Sigma}\, \mathbf{D}^{-1} (\underline{u} - \underline{\hat{u}}) \quad (5)$$

In Eqn. 5, the weighting matrix is $(\mathbf{D}^{-1})^T \mathbf{\Sigma}\, \mathbf{D}^{-1}$ and it is not diagonal. Therefore, the weighted distance measure, characterized by Eqn. 5, is not easily amenable to apply for transformed domain sub-vectors using SVQ technique in T1DPSVQ method. On the other hand, WED, characterized by Eqn. 4, can be easily applied to all other methods except T1DPSVQ, using SVQ technique. Hence, further improvement of T1DPSVQ using WED measure is not explored. For the other methods, we have used WED where the weights are Modified Inverse Harmonic Mean Weight (MIHMW) [16]. The results of different methods using WED are shown in Table 4.

It is observed that use of WED improves the performance in Table 4 compared to Table 3. OPSVQ always performs better than the other methods and provides near transparent quality quantization performance at 25 bits/frame according to the requirements discussed earlier. Therefore, the OPSVQ method should be considered as a potential candidate for LSF quantization. It is noted that all the methods use nearly same memory; but predictive methods need higher computational complexity compared to memoryless method. OPSVQ results in maximum complexity among the predictive methods.

5. Conclusions

We observe that, an optimum two dimensional predictive method, exploiting both the inter-frame and intra-frame correlations of LSF parameters, outperforms the commonly used one dimensional predictive method which only exploits inter-frame correlation. It is noticed that a transform domain predictive approach, i.e. removing the intra-frame correlation of LSF parameters by a transform and then applying inter-frame prediction, is not providing a considerable improvement. A point to be noted that SVQ is inferior to unconstrained full-vector quantization, due to the independent treatment of sub-vectors [14]. But, 2-D predictor tries to mitigate this loss through intra-frame prediction and thus provides better quantization performance. Future work includes to explore the performance of switched 2-D predictor with channel noise robustness issues and sensitivity of bit errors.

6. Appendix

In searching the optimal residual code vector, WED is used where $\{\sigma_i\}$ are the MIHMW weights. If $\sigma_i = 1$, then the distance measure becomes an Euclidean distance (ED) measure. Let q dimensional pth sub-vector of nth frame LSF vector $\underline{\omega}(n)$ is, $\underline{\omega}_p(n) = [\omega_{p,1}(n)\ \ \omega_{p,2}(n) \ldots \omega_{p,q}(n)]^T$; X_p and Y_p be two pth sub-vector error codebooks of size 2^{B_p} with index sets K_p and L_p respectively for 1DPSVQ and OPSVQ.

(a) *Encoding of 1DPSVQ*: Using the equation $\tilde{\omega}_i(n) = a_i \hat{\omega}_i(n-1)$,

$$\forall j \in K_p,\ \ \hat{\omega}_{p,i}^j(n) = a_{p,i}\hat{\omega}_{p,i}(n-1) + x_{p,i}^j;\ \ 1 \le i \le q \qquad (6)$$

where $\mathbf{x}_p^j = [x_{p,1}^j\ \ x_{p,2}^j\ \ldots\ x_{p,q}^j]$ is the jth residual code vector in 1DPSVQ error codebook X_p. Then the optimum codeword j_p^* can be found by exhaustive codebook search,

$$j_p^* = \arg\min_{j \in K_p} \left\{ \sum_{i=1}^{q} \sigma_{p,i}[\omega_{p,i}(n) - \hat{\omega}_{p,i}^j(n)]^2 \right\} \qquad (7)$$

(b) *Encoding of OPSVQ*: The encoding algorithm is based on [4], which is modified and used. Given the encoded value of $\hat{\omega}_{p,0}(n)$, $\hat{\omega}_{p,0}(n-1)$ and $\hat{\omega}_{p,q+1}(n-1)$ and using Eqn. 3,

$$\begin{aligned}\forall j \in L_p,\ \ \hat{\omega}_{p,i}^j(n) &= d_{p,i}\hat{\omega}_{p,i-1}(n-1) + e_{p,i}\hat{\omega}_{p,i}(n-1) \\ &+ f_{p,i}\hat{\omega}_{p,i+1}(n-1) + g_{p,i}\hat{\omega}_{p,i-1}^j(n) + y_{p,i}^j;\ \ 1 \le i \le q \qquad (8)\end{aligned}$$

where $\mathbf{y}_p^j = [y_{p,1}^j\ \ y_{p,2}^j\ \ldots\ y_{p,q}^j]$ is the jth code vector in OPSVQ error codebook Y_p. Then the optimum codeword j_p^* can be found by the same way as in Eqn. 7, but using codebook Y_p with index set L_p.

For more details on this encoding algorithm, the reader is referred to [15]. The same encoding algorithmic structure of OPSVQ is used for 2DPSVQ method using equation $\tilde{\omega}_i(n) = b_i\hat{\omega}_i(n-1) + c_i\hat{\omega}_{i-1}(n)$ in lieu of Eqn. 3 and searching the corresponding codebook.

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