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Efficient coding of LSP parameters using Compressed Sensing on Approximate KLT Domain

***Abstract**. An efficient LSP parameters quantization scheme is proposed using the compressed sensing (CS). The LSP parameters extracted from consecutive speech frames are compressed by CS on the approximate KLT domain to produce a measurement vector, which is quantized using the split vector quantizer. Then, from the quantized measurements, the original LSP parameters are reconstructed by the orthogonal matching pursuit method. Experiments show that the scheme can obtain "transparent quality" at 5 bits/frame with drastic bits reduction compared to other methods.*

***Streszczenie.** Zaproponowano kwantyzację parametru LSP (Linear prediction coefficient) przy użyciu metody compressed sensing CS. Oryginalna wartośc LSP może być zrekonstruowana przy zastosowaniu metody ortogonalnego dopasowania. Uzyskano dobrą jakość ramki 5 bitów/ramka ze znacząca redukcją bitów w porównaniu z innymi metodami. (**Skuteczne kodowanie parametru LSP przy użyciu metody Compressed Sensing**)*

Keywords: low bit rate speech coding; line spectrum pair; compressed sensing; Karhunen-Loeve Transform (KLT)
Słowa kluczowe: kodowanie mowy, metoda Compressed Sensing.

1 Introduction

Speech coding at bit rates below 2400 bps has been widely used in digital wireless, short-wave and satellite communications. As we all known, the speech signal is often separated into a spectral envelope and a residual signal before coding, then the spectral envelope is typically represented with the Linear Prediction Coefficients (LPC) [1]. Commonly, the LPC coefficients are separately quantized using the Linear Spectrum Pair (LSP) parameters representation, which has good characteristics of quantization and interpolation.

For low bit rate speech coding applications, it is very important to quantize the LSP parameters accurately using as few bits as possible without sacrificing the speech quality. The transparent Scalar Quantization (SQ) of LSP parameters requires typically 38 to 40 bits/frame [2]. Lower bit rates can be achieved using the Vector Quantization (VQ). VQ considers the entire set of LSP parameters as an entity and allows for direct minimization of quantization distortion. Accordingly, VQ results in smaller quantization distortion than the SQ at any given bit rate, it provides 1 dB average spectral distortion using about 26 to 30 bits/frame [3,4]. However, for transparent quantization performance, VQ needs a large number of codevectors in its codebook, it means that the storage and computational requirements for VQ are prohibitively high.

It's known that there is high correlation between two neighbouring LSP frames, and between adjacent LSP parameters within a frame, so bit rates can be further reduced when both interframe and intraframe redundancy is removed. The exploitation of intraframe redundancy usually use the Split Vector Quantization (SVQ) [5] and Multi-Stage Vector Quantization (MSVQ) [6], which offer transparent quantization performance with realistic codebook storage and search characteristics at 22 to 24 bits/frame. Further compression can be obtained in principle by exploiting interframe correlation between sets of LSP parameters. In this way, the Predictive Vector Quantization (PVQ) [7,8] and Matrix Quantization (MQ) [9,10] systems have been proposed, which offer high quantization accuracy at 18 to 21 bits/frame.

Now, there are more advanced efforts to lower the bit rates below 600bps. However, with the bit rates reduce, the number of consecutive frames which are grouped together becomes larger. Such a multi-frame structure has the following two problems. Firstly, a large codebook requires prohibitively large amount of training data and the training process can take much of computation time. Secondly, the encoding complexity and storage requirement increase dramatically, and the quantization performance degrades as the bits per frame are further reduced.

To overcome these drawbacks, a novel LSP parameters quantization scheme based on compressed sensing (CS) is proposed in this paper. The recent studies of CS have shown that sparse signals or compressible on some basis can be recovered accurately using less observations than what is considered necessary by the Nyquist/ Shannon sampling principle [11,12,13,14]. Based on this theory, CS sampling and reconstruction of LSP parameters on the approximate KLT domain are realized. In the encoder, the LSP parameters extracted from consecutive speech frames are grouped into a high-dimensional vector, and then the dimension of the vector is reduced by CS to produce a low-dimensional measurement vector, the measurements are quantized using the split vector quantizer. In the decoder, from the quantized measurements, the original LSP vector is reconstructed by the orthogonal matching pursuit method [15]. Experimental results indicate that this novel quantization scheme can obtain transparent quality at 5 bits/frame with realistic codebook storage and search complexity.

The rest of this paper is organized as follows. In section 2, basic principles of compressed sensing are introduced. In section 3, the compressed sensing formulation for LSP parameters on the approximate KLT domain is proposed. In section 4, the quantization scheme is designed. Then simulation results are presented and discussed in section 5. Finally, we give out the conclusion.

2 Compressed sensing principle

Compressed sensing is a newly introduced concept of signal processing which aims at reconstructing a sparse or compressible signal accurately and efficiently from a set of few non-adaptive linear measurements.

Let $\boldsymbol{X}\in\boldsymbol{R}^{N\times 1}$ be a real-valued signal of length N, assume that $\boldsymbol{X}$ is sparse or compressible on a particular orthonormal basis $\boldsymbol{\Psi} = \{\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \dots, \boldsymbol{\phi}_N\}$, $\boldsymbol{\Psi}\in\boldsymbol{R}^{N\times N}$, i.e. $\boldsymbol{X}$ can be represented as:

$$X = \Psi\Theta = \sum_{i=1}^{N}\phi_i\theta_i \,, \quad (1)$$

where $\boldsymbol{\Theta} = \{\theta_1, \theta_2, \dots, \theta_N\}^T$ is a scalar coefficient vector of $\boldsymbol{X}$ in the orthobasis, T denotes transposition.

Clearly, $\boldsymbol{X}$ and $\boldsymbol{\Theta}$ are equivalent representations of the signal, with $\boldsymbol{X}$ in the time or space domain and $\boldsymbol{\Theta}$ in the $\boldsymbol{\Psi}$ domain. The assumption of sparsity means that only k nonzero coefficients, with $k \le N$, of $\boldsymbol{\Theta}$ are sufficient to represent $\boldsymbol{X}$. The signal $\boldsymbol{X}$ is compressible if the representation (1) has just a few large coefficients and many small coefficients.

In CS, we do not observe the k-sparse signal $\boldsymbol{X}$ directly, instead we record $M<N$ non adaptive linear measurements $\boldsymbol{Y}$, the main idea of CS is to map the signal $\boldsymbol{X}$ to a low-dimensional vector $\boldsymbol{Y}$:

(2) $$Y = \Phi X = \Phi \Psi \Theta ,$$

where $\boldsymbol{\Phi} \in \boldsymbol{R}^{M \times N}$ is a measurement matrix composed of random orthobasis vectors, $\boldsymbol{Y}$ is called the measurement vector of the original signal. CS theory states that we can reconstruct $\boldsymbol{X}$ accurately from $\boldsymbol{Y}$ if $\boldsymbol{\Phi}$ and $\boldsymbol{\Psi}$ are incoherent, this property is easily achieved when the entries of random matrix $\boldsymbol{\Phi}$ are i.i.d. Gaussian variables. If the incoherence holds, the following linear program gives an accurate reconstruction with very high probability:

(3) $$\hat{\Theta} = \arg\min \|\Theta\|_0 \ \ s.t. \ Y = \Phi \Psi \Theta ,$$

where $\| \ \|_0$ is the l_0 norm. Unfortuately, the above optimization problem is NP-hard and can not be solved efficiently. Recently, it has been shown that if the sensing matrix $\boldsymbol{\Phi}$ obeys a so called Restricted Isometry Property (RIP) [16], while $\boldsymbol{\Theta}$ is sparse enough, the solution of the combinatorial problem (3) can almost always be obtained by solving the constrained convex optimization:

(4) $$\hat{\Theta} = \arg\min \|\Theta\|_1 \ \ s.t. \ Y = \Phi \Psi \Theta .$$

The convex l_1 norm minimization problem can be solved with the traditional linear programming techniques. Unfortunately, these techniques are still somewhat slow. At the expense of slightly more measurements, fast iterative greedy algorithms have also been developed to recover the signal. Examples include the Orthogonal Matching Pursuit (OMP) [15] and tree matching pursuit algorithms. Once the optimal solution $\hat{\boldsymbol{\Theta}}$ is got, the original signal $\boldsymbol{X}$ can be recovered by:

(5) $$\hat{X} = \Psi \hat{\Theta} = \sum_{i=1}^{N} \phi_i \hat{\theta}_i .$$

Summarizing, if we wish to use CS to compress LSP parameters, three main ingredients are needed: a domain where the LSP parameters is sparse, the measurement matrix and the reconstruction algorithm. In the next section, we will give a detailed analysis of the compressed sensing formulation for LSP parameters.

3 Compressed sensing formulation for LSP parameters

3.1 LSP parameters representation

Consider the LPC analysis is applied to speech frames of D ms duration to yield coefficient vectors $\boldsymbol{a}(n) = [a_1^n, a_2^n, \ldots, a_p^n]$, where p is the order of the LPC filter and n is current LPC analysis frame, $\boldsymbol{a}(n)$ is then transformed to a LSP representation $\boldsymbol{l}(n)=[l_1^n, l_2^n, \ldots, l_p^n]$. When performed over L consecutive speech frames provides an L-by-p matrix:

(6) $$X = \begin{bmatrix} l_1^{\,n} & l_2^{\,n} & \cdots & l_p^{\,n} \\ l_1^{\,n+1} & l_2^{\,n+1} & \cdots & l_p^{\,n+1} \\ \vdots & \vdots & & \vdots \\ l_1^{\,n+L-1} & l_2^{\,n+L-1} & \cdots & l_p^{\,n+L-1} \end{bmatrix}_{L \times p} .$$

Let $N=L\times p$, the above matrix is then shaped into a N dimensinal column vector:

(7) $$\begin{aligned} X &= \left[l_1^{\,n} \ldots l_p^{\,n}, l_1^{\,n+1} \ldots l_p^{\,n+1}, \ldots, l_1^{\,n+L-1} \ldots l_p^{\,n+L-1} \right]^{\mathrm{T}} \\ &= \left[\ell_1, \ell_2, \ldots, \ell_N \right]^{\mathrm{T}} \end{aligned} .$$

Next, we will discuss some important issues in applying CS to LSP parameters. First, we need to know which domain of LSP is sparse, it is the precondition of applying CS to LSP parameters.

3.2 Sparse representation of LSP on the approximated KLT

According to the analysis in [17] and [18], the Karhunen-Loeve Transform (KLT) is an efficient data compression technique, which has been successfully used to extract the data features. The bases of KLT are the eigenvectors of the autocorrelation matrix of the signal $\boldsymbol{X}$. Assuming that $\boldsymbol{R}_x$ is the autocorrelation matrix, when the KLT is calculated over the vector $\boldsymbol{X}$, the $\boldsymbol{R}_x$ can be estimated by:

(8) $$R_x = \left\langle X X^{\mathrm{T}} \right\rangle .$$

Let $\mathbf{U}$ be a matrix whose columns constitute a set of orthonormal eigenvectors of $\boldsymbol{R}_x$, so that $\mathbf{U}^{\mathrm{T}}\mathbf{U}=\mathbf{I}$ and:

(9) $$R_x = \mathrm{U} \Lambda \mathrm{U}^{\mathrm{T}} ,$$

where $\wedge$ is the diagonal matrix of non-null eigenvalues:

(10) $$\Lambda = diag(\lambda_1, \lambda_2, \ldots, \lambda_k) .$$

For every vector $\boldsymbol{X}$, through the matrix $\mathbf{U}^{\mathrm{T}}$, we can obtain the sparse coefficients vector $\boldsymbol{\Theta}$ as:

(11) $$\Theta = \mathrm{U}^{\mathrm{T}} X .$$

Unfortunately, the KLT requires much of computation time for the eigenvector decomposition, some approximated approaches to overcome this problem have been developed [17,18]. Furthermore, in practice, we can limit the length of LSP parameters in a reasonable range.

Next, several experiments are conducted to examine the sparsity of LSP parameters on the approximated KLT domain, the Discrete Fourier Transform (DFT) domain, the Discrete Cosine Transform (DCT) domain and the Discrete Wavelet Transform (DWT) domain. As illustrated in Fig.1, we find that the approximated KLT representation of LSP parameters is sparser than representations on the other three domains.

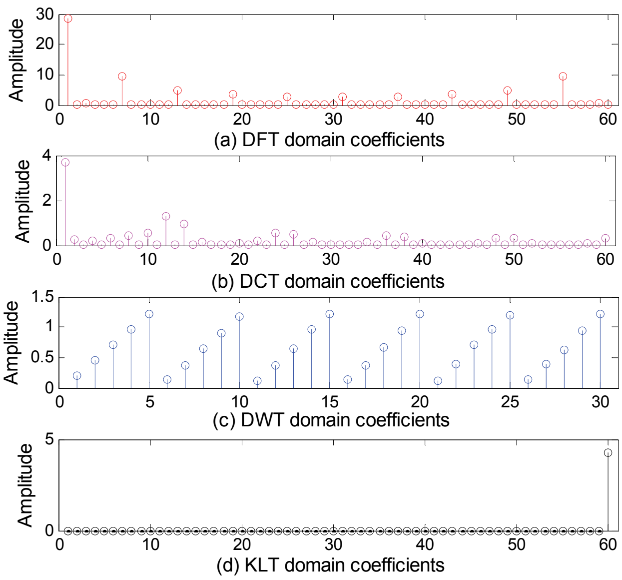


Fig.1. The transform domain of LSP parameters (L=6)

Once we get the sparse domain, another issue with LSP parameters is the sparsity. We know that the sparsity k means that the number of nonzero coefficients in $\boldsymbol{\Theta}$ which are sufficient to represent $\boldsymbol{X}$. As in Fig.1 (d), it is clearly shown that there is only 1 obvious nonzero coefficient and other coefficients are zero or close to zero. Moreover, we can use a heuristic choice of K=k+1 when the improvement in the accuracy of the reconstruction is achieved, so we can reasonably assume that the sparsity k on the approximated KLT domain is 2.

3.3 Sensing LSP with the Gaussian random matrix

The measurement matrix must allow the reconstruction of the length-N signal $\boldsymbol{X}$ from $M<N$ measurements. Since $M< N$, this problem appears ill-conditioned. However, $\boldsymbol{X}$ is k-sparse and the k locations of the nonzero coefficients in $\boldsymbol{\Theta}$ are known, then the problem can be solved efficiently. When using CS, one must choose how many samples to retain. As a rule of thumb, four times as many samples as the number of non-zero coefficients should be used [14], i.e., M=4k. Now, it is clear that the size of the measurement matrix $\boldsymbol{\Phi}$ depends uniquely on the sparsity level k. Meanwhile, for effective CS reconstruction, $\boldsymbol{\Phi}$ and $\boldsymbol{\Psi}$ must be incoherent, this property can be achieved when the measurement matrix $\boldsymbol{\Phi}$ constructed from independent and identically distributed zero-mean Gaussian variables. Consequently, the Gaussian random matrix is used as the measurement matrix throughout the paper.

3.4 LSP recovery with OMP

Although the quality of the reconstruction mainly depends on the compressibility of LSP parameters, the reconstruction algorithm is also very important. As mentioned in section 2, the Orthogonal Matching Pursuit (OMP) algorithm is an attractive method for the sparse signal recovery, which is a fast greedy algorithm that iteratively builds up a signal representation by selecting the atom that maximally improves the representation at each iteration. The OMP is easily implemented and converges quickly, which is chosen for the LSP recovery.

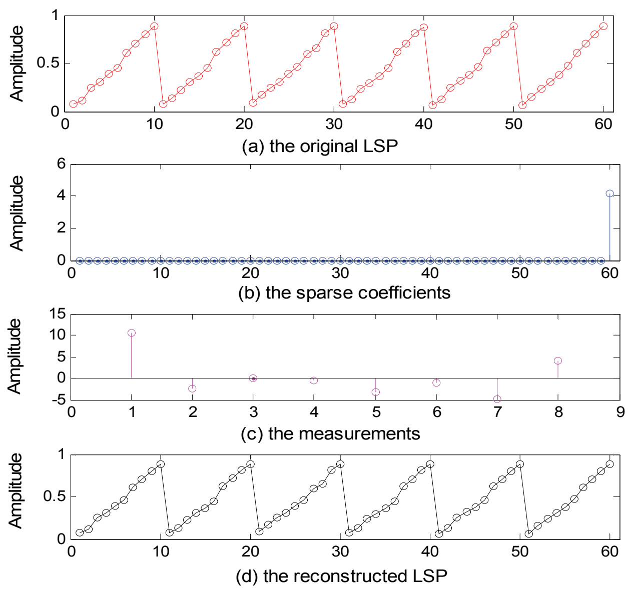


Fig.2. Example of CS recovery of LSP parameters (L=6,k=2)

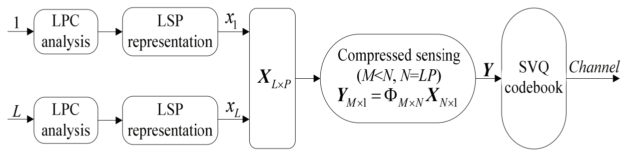
3.5 Realization of CS processing

In Fig.2, a practical example of CS recovery of LSP parameters is illustrated. Consider 60-dimensional LSP parameters (Fig.2(a)) extracted from 6 constructive speech frames, when transformed into the approximate KLT domain, the sparsity k is 2, then with the relation M=4k, 8 measurements (Fig.2(c)) are obtained. According to the 8 measurements, the original LSP parameters can be reconstructed by the OMP method. We clearly see that the reconstruction works very well, the recovered LSP signal (Fig.2(d)) match the original signal with very high accuracy.

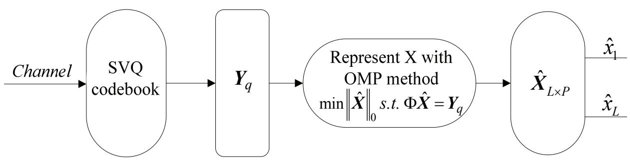
Since the LSP signal can be compressed and recovered efficiently by the compressed sensing, if, however, we encode the low-dimensional measurements instead of the original LSP signal, the coding bit rates can be definitely reduced. In other words, the quantization performance will much improved under the same coding bits as used in SVQ or MSVQ.

4 Quantization scheme

Based on the above analysis, a Compressed Sensing Vector Quantization (CSVQ) scheme for LSP parameters is proposed in this section. Fig.3 shows a block diagram of the CSVQ quantization system. Here, the p^{th} order linear prediction analysis is performed on D ms speech frame, the LSP parameters extracted from L successive frames are gathered up to form a matrix, the matrix is then converted into a N dimensional column vector.



(a) Encoder



(b) Decoder

Fig.3. CSVQ encoding and decoding process

The quantization procedure is summarized as follows:

1) Compressed sensing: the original LSP parameters are sensed by the mearsurement matrix $\boldsymbol{\Phi}$ according to (2), once $\boldsymbol{X}$ has been measured, the high-dimensional LSP parameters $\boldsymbol{X}$ can be converted into a low-dimensional measurement vector $\boldsymbol{Y}$.

2) Quantizing the measurements $\boldsymbol{Y}$ with SVQ: in CSVQ, to reduce the coding bit rates, the low-dimensional measurements $\boldsymbol{Y}$ is quantized instead of the original LSP signal. Here, the Split Vector Quantizer is utilized to quantize the measurements. As mentioned in 3.2 and 3.3, the sparsity k is 2, after compressed sensing, according to the empirical rule of thumb, four times as many samples as the sparsity is achieved, i.e. there are 8 measurements need to be quantized. To moderate the complexity and performance, in SVQ, the 8 measurements are split up into 2 subvectros, the first subvector has the first 4 measurements and the second subvetor has the remain 4 measurements. For minimizing the complexity of the SVQ, total bits available for measurements quantization are divided equally to each of the two subvectors. The total squared error (or Euclidean) distance measure is used for the SVQ operation, and the codebooks are designed using the well-known LBG algorithm to minimize the error distance based on a sufficiently rich training sequence.

3) Send: the quantized measurements $\boldsymbol{Y}_{\mathrm{q}}$ are communicated to the receiver.

4) LSP recovery with OMP: in the decoder, we consider the problem of recovering sparse signal $\boldsymbol{X}$ from a set of quantized measurements $\boldsymbol{Y}_q$. The quantized measurements are found according to the corresponding index of the codebook. Once $\boldsymbol{Y}$ has been quantized, the reconstruction of LSP parameters involves trying to recover the original LSP signal by the OMP method, the recovered LSP siganl is the ultimate quantization value of the original LSP signal.

5 Experiment results

Several experiments are conducted to examine the performance of the proposed CSVQ method, we start with the discussions on the simulation setup.

All experiments are based on the CASIA mandarin speech database, down sampled to 8 kHz. A 10^{th} order LPC analysis using the autocorrelation method is performed on every 20 ms speech frame. A fixed 15 Hz bandwidth expansion is applied to each pole of the LPC coefficient vector, and finally the LPC vectors are transformed to the LSP representation. The corresponding CSVQ codebooks are designed using the training data consist of 2×10^7 speech frames, in addition, about 2×10^5 speech frames that out of the training speech are used to evaluate the performance.

Traditionally, the objective measure that is used to assess the performance of quantization scheme is the Spectral Distortion (SD) measure:

$$\text{SD}=\frac{1}{N}\sum_{n=1}^{N}\sqrt{\frac{1}{\pi}\int_0^{\pi}[10\log_{10}S_n(\omega)-10\log_{10}\hat{S}_n(\omega)]^2 d\omega}\,, \tag{12}$$

Where N is the frame number used for SD calculation, the $S_n(\omega)$ and $\hat{S}_n(\omega)$ are the original and quantized LPC power spectrum, respectively.

5.1 Spectral distortion estimation of CSVQ

The proposed CSVQ approach has been simulated for different values of L (1-6) and quantization bits (16-30). No matter how many successive frames are gathered up, there are only 8 measurements need to be quantized. In CSVQ, the 8 measurements are always quantized using the SVQ method, which are split up into 2 subvectros, and each subvector is quantized with 8 to 15 bits.

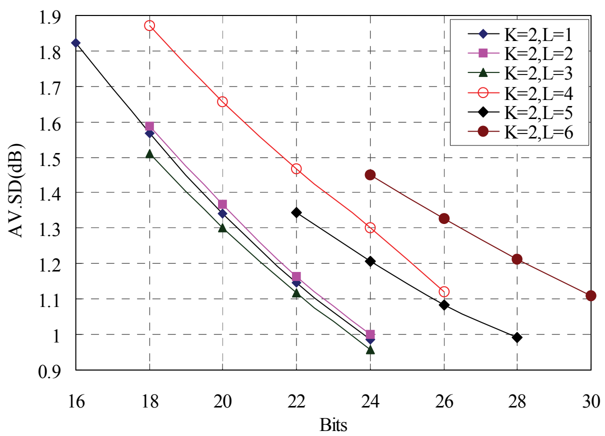


Fig.4. The Average Spectral Distortion of CSVQ

The spectral distortion and outlier results for the CSVQ are shown in Figs. 4 and 5. For the transparent quantization performance, a single frame of CSVQ needs 24 bits, which is comparable with the SVQ [5]. However, an increase of L from 2 to 3, the CSVQ totally needs 24 bits, i.e. with L=2 and L=3, the CSVQ operates transparently at 12 bits/frame and 8 bits/frame respectively. Whereas a further increase to L=4 totally needs 26 bits (6 bits/frame), L=5 totally needs 28 bits (5.6 bits/frame) and L=6 totally needs 30 bits (5 bits/frame). As to be expected, the total quantization bits used for transparent performance are increased with the L increase, the reason for this correlation is that the reconstruction error of CS becomes higher with the dimension of LSP parameters increase while at the same sparsity.

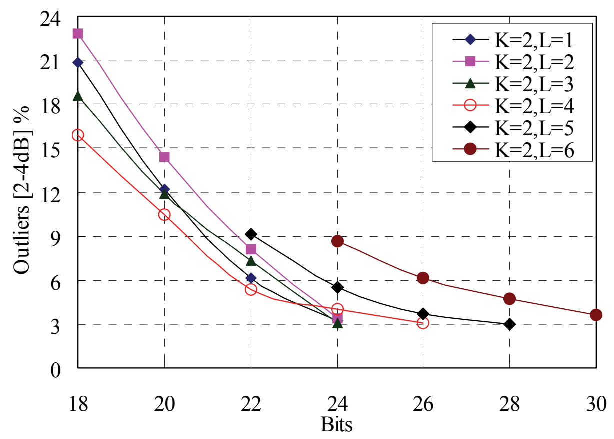


Fig.5. Outlier performance of CSVQ

Table 1 shows the detail SD performance. According to the test results, when we consider the average and outlying SDs, we can see that the performance of the combination from 24 bits/frame to 5 bits/frame is comparable to each other. As the number of successive frames L increase, the bits used for per frame decrease. There are good intuitive reasons to believe that increasing the value of L will lead to improved investigation of the potential of the compressed sensing. However, if a further increase to L=7, the CSVQ can obtain a SD very near 1 dB at a rate of 34/7 bits/frame with a low percentage of outliers. However, at 34 bits, the codebook storage and search complexity are too high to acceptable.

Table 1. The Spectral Distortion for transparent quality

CSVQ	Bits/Frame	AV.SD (dB)	Outliers [2-4 dB] (%)
L=1, k=2	24/1	0.9860	3.19
L=2, k=2	24/2	0.9913	3.38
L=3, k=2	24/3	0.9584	3.06
L=4, k=2	26/4	1.1005	3.10
L=5, k=2	28/5	0.9905	3.31
L=6, k=2	30/6	1.1090	3.64

In particular, we notice that there are two main factors involved in CSVQ that influence the spectral distortion, one is the reconstruction error of the CS, and the other is the quantization distortion of the measurements. However, the reconstruction error is far less than the quantization distortion. Increasing the number of measurements can definitely reduce the reconstruction error, however, with a cost of increased storage requirements and search complexity. Taking L=7 as a practical example, when k=2, after CS, there are 8 measurements, while k=3, there are 12 measurements. When the two combinations are uniformly quantized with the same bits, the higher k leads to a smaller SD however at expense of increasing complexity as shown in Table 2.

Table 2. The Average Spectral Distortion under different sparsity

CSVQ	Bits/Frame	AV.SD(dB)	Storage /(Words)	Complexity /MIPS
L=7, *k*=2	26/7	2.1507	65536	17.5850
L=7, *k*=3	26/7	1.7800	98304	18.1699
L=7, *k*=2	28/7	2.0306	131072	18.5850
L=7, *k*=3	28/7	1.6199	196608	19.1699

To show the benefit of CSVQ, comparing the results of CSVQ with other methods. For transparent quantization performance, the traditional SQ needs 40 bits/frame [2], the SVQ needs 24 bits/frame [5], the MSVQ needs 22 bits/frame [6] and the MQ needs 18 bits/frame [9]. In CSVQ, it is only used 5 bits/frame, the drastic bits reduction is achieved compared to other methods.

5.2 Codebook storage and search complexity

Figs.6 and 7 illustrate codebook storage and search complexity in different CSVQ configurations. The CSVQ has two subvectors, each subvector with 4 measurements is quantized using j bits, thus the total number of codebook elements is equal to $2\times2^{j}\times4$. The search complexity is defined as the number of arithmetic operations to obtain the quantized measurements [6], which is typically presented on the logarithmic scale. The simulation results clearly show that the CSVQ complexity characteristics are directly proportional to the storage requirements. The drastic bits reduction is achieved however at the expense of slightly increasing the storage requirements and search complexity. Meanwhile, the increase in storage and complexity should pose no problems with the modern DSP processors.

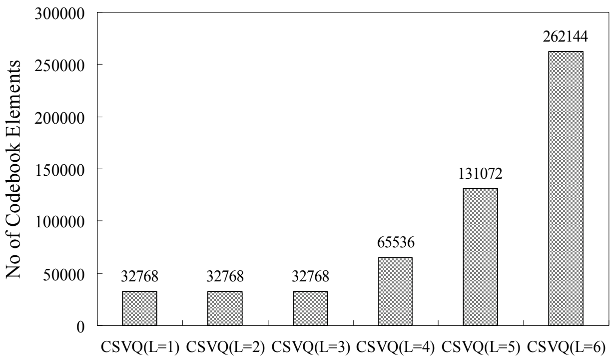


Fig.6. Storage requirements for transparent quantization

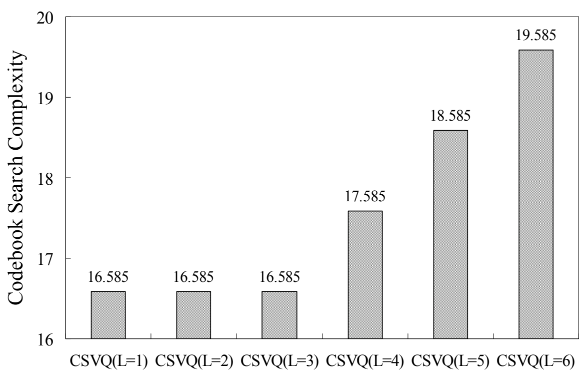


Fig.7. Search complexity for transparent quantization

6 Conclusion

In this paper, the compressed sensing formulation for LSP parameters on the approximate KLT domain is introduced. And then, a novel and efficient quantization scheme called CSVQ is presented. This is the first time that the idea of compressed sensing is applied to represent the LSP parameters, the proposed CSVQ technique involves dimension reduction and quantizer design. Simulation results show that proposed method can obtain transparent quantization performance at 5 bits/frame with realistic codebook storage and search complexity. Moreover, the performance can be further improved by finding more accurate ways to reconstruct the LSP parameters or quantizing the measurements more efficiently.

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