SPEECH LSF QUANTIZATION WITH RATE INDEPENDENT COMPLEXITY, BIT SCALABILITY AND LEARNING.

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ABSTRACT

A computationally efficient, high quality, vector quantization scheme based on a parametric probability density function (PDF) is proposed. In this scheme, speech line spectral frequencies (LSF) are modeled as i.i.d realizations of a multivariate Gaussian mixture density. The mixture model parameters are efficiently estimated using the Expectation Maximization (EM) algorithm. An efficient quantization scheme using transform coding and bit allocation techniques which allows for easy and computationally efficient mapping from observation to quantized value is developed for both fixed rate and variable rate systems. An attractive feature of this method is that source encoding using the resultant codebook involves very few searches and its computational complexity is minimal and independent of the rate of the system. Furthermore, the proposed scheme is bit scalable and can switch between memoryless and quantizer with memory seamlessly. The performance of the memoryless quantizer is 2-3 bits better than conventional quantization schemes.

1. INTRODUCTION

Realistic bandwidth and memory restrictions compel one to perform quantization on a continuous valued source. For the purposes of transmission and storage, there is a need to build quantizers with reasonable search and computational complexity that provide good performance relative to a relevant distortion measure. Conventional schemes have always tried and reasonably succeeded in attaining the best performance-complexity tradeoff. However, there is room for improvement and significant gains can be made by addressing the following aspects.

1. *Computational Complexity* :
   Full search quantization schemes have considerable computational and search complexity. Vector quantizers, in particular, are known to have huge memory and computational costs [6]. This has lead to current schemes such as the MSVQ [5] which employ sub-optimal search and design techniques which then lead to sub-optimal quantizers. Inspite of these suboptimalities, current schemes still have exponential search and memory complexity.
2. *Rate Dependence* :
   The complexity of conventional schemes is dependent on the rate of the system. In particular, the complexity of vector quantizers varies exponentially with the rate of the system [6]. This implies that current schemes are infeasible in high bit-rate applications as is likely in internet telephony.
3. *Bit Scalability* :
   The current schemes are not easily bit scalable. This means that quantizer design is usually done for a specific bit rate and in case we need to operate at a different bit-rate, the whole training process needs to be repeated. At best, with additional memory complexity, current schemes allow for quantization at a few distinct rates but do not allow for scalability in a continuum of rates.
4. *Variable rate coding* :
   The current quantizers do not allow for easy adaptation to variable-rate coding which holds promise in wireless CDMA communication environments.
5. *Interoperability* :
   Conventional quantization schemes are usually inflexible. They do not allow for easy switching between memoryless quantizers and quantizers with memory depending on channel conditions.
6. *Learning* :
   Conventional quantization schemes are typically unsuitable for operation in a learning environment. This is because the structure of codebooks in the current schemes do not allow for efficient adaptation with the varying statistics of the source.

This paper proposes a novel source coding scheme which efficiently and effectively addresses all the above mentioned drawbacks of present day quantizers without compromising on the quality of the output of the source coder.

Section 2 provides a broad overview of the overall source coding scheme. Section 3 explains the quasi-parametric density estimation using mixture models. Section 4 provides the details of the quantizer design for both fixed-rate and variable-rate systems. Section 5 discusses the salient features of this new scheme such as rate-independent complexity and bit scalability. Section 6 presents the experimental results.

2. OVERALL SOURCE CODING SCHEME

The problem of quantizer design for a random source may be conveniently broken down into one of estimating the probability den-

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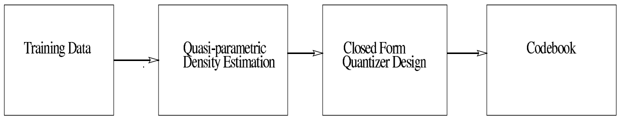

Fig. 1. Overall source coding scheme

sity function (pdf) of the random source and then efficiently quantizing the estimated pdf. This approach has several advantages over conventional VQ design and was first suggested in [3] for scalar quantization, the pdf being estimated using a non-parametric model. This paper extends the design to the important vector case and presents a vector quantizer design scheme which is based on an estimate of the multidimensional pdf of a vector source using a parametric model.

Figure 1 depicts the overall source coding scheme. Irrespective of the distortion measure used, the pdf of a random source has all the necessary and sufficient information to build an optimal finite rate quantizer for that source. Further, when the pdf of the source is estimated parametrically, the density estimation parameters form an alternate compact representation for the source. In addition, if the quantizer design block can be realized in closed form, the density estimation parameters become an alternate and compact representation of the quantizer codebook. This division of labor into density estimation followed by quantizer design has additional advantages. With varying bit rates, the density estimation block remains unaltered. All that is necessary is to use a different closed form expression for the quantizer design part. The same analogy also holds for interoperability between fixed rate and variable rate systems. When the statistics of the source varies with time, the closed form expression used in the quantizer design block remains unaltered. Only the density estimation parameters needs to be re-estimated in order to represent the current statistics of the source. The re-estimation may be done recursively using the old density estimation parameters and current data for easy implementation. Hence, parametric density estimation followed by closed form quantizer design gives us the advantages of bit scalability, variable rate coding, interoperability and learning. Minimal and rate independent computational complexity is acheived by a clever implementation of the quantizer design block.

The success of the quantization scheme presented in this paper depends on an efficient methodology for density estimation using mixture models followed by an efficient mapping from density to quantizer. For the purposes of source coding, the mixture models employed in this paper have two specific advantages,

- Simple and stable estimation algorithms such as the EM algorithm [1] can be conveniently put to use to reliably estimate the mixture model parameters from the training data.
- As shown in the paper, they lend themselves to efficient quantization schemes using transform coding and bit allocation techniques that results in codebooks that involve very few searches in the decoder stage and have their computational complexity independent of the rate of the system.

3. DENSITY ESTIMATION

In this scheme, quasi-parametric density estimation is done using using Gaussian mixture models. In this approach, the unknown pdf of speech LSF's is modeled as a mixture of Gaussian parametric pdf's, i.e.,

$$f\left(\mathbf{x} \mid \mathbf{\Phi}\right) = \sum_{i=1}^{m} \alpha_i N_i \left(\mathbf{x} \mid \phi_{\mathbf{i}}\right) \tag{1}$$

$$\Phi = [m, \alpha_1, \ldots, \alpha_m, \phi_1, \ldots, \phi_m] \tag{2}$$

where α_i are non-negative constants and $\sum_{i=1}^{m} \alpha_i = 1$. $N_i\left(\mathbf{x} \mid \phi_{\mathbf{i}}\right)$ is an individual p-dimensional Gaussian density parameterized by $\phi_i = [\Sigma_i, \mu_i]$. We shall refer to $N_i\left(\mathbf{x} \mid \phi_{\mathbf{i}}\right)$ as *cluster* i. m is the number of clusters. Φ is the parameter set which defines the quasi-parametric model.

The mixture modeling approach to density estimation combines the parametric advantage of efficient estimation with small number of observations with the non-parametric advantage of consistent estimates. In fact, Eq. 1 may be interpreted as the functional decomposition of the unknown pdf in terms of known parametric pdfs, the parametric pdfs serving as basis functions for this decomposition.

The EM algorithm [1] efficiently computes the maximum likelihood estimate of Φ by the iterative application of the Expectation step and the Maximization step which are available in closed form. [1]

4. QUANTIZER DESIGN

The codebook design scheme may be broadly explained as follows. We consider the specific case of the Gaussian mixture model. Each of the clusters in the mixture model is quantized separately. The number of bits used to quantize a particular cluster depend on three factors

- whether the system is fixed rate or variable rate
- the covariance matrix of the cluster
- the cluster probability α_i

Within a cluster, transform coding and bit allocation techniques are used to allocate bits amongst the p cluster components (the source is p-dimensional and hence the covaraiance matrix of each cluster has size $p \times p$). For each cluster component, a compander (compressor followed by uniform quantizer) is used to build the codebook. A given observation is quantized by identifying an appropriate cluster among the m clusters and then quantizing using the codebook of that cluster. For the quantizer with memory, well known linear prediction techniques are used to remove the temporal correlation in the source prior to density estimation. In order to avoid quantizer error propagation, an error control scheme is used.

We now explain the details of the quantization scheme. Let b_{tot} be the total number of bits used to quantize the source. Let b_i represent the number of bits used to quantize cluster $i, 1 \leq i \leq m$. Let $D_i(b_i)$ represent the mean square distortion of an optimal b_i bit transform coder of cluster i. We use the high resolution expression for $D_i(b_i)$ [4]. In high resolution, it is well known that when the vector components are jointly Gaussian, the Karhunen-Leove transform is the best possible transform for minimizing the overall distortion [4]. We shall first derive the bit allocation scheme among the clusters for both fixed rate and variable rate systems for a memoryless quantizer.

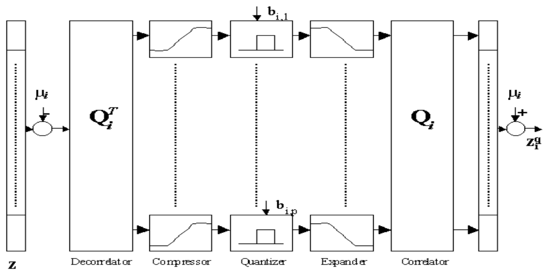

Fig. 2. Cluster Quantization

4.1. Cluster Bit Allocation

4.1.1. Fixed rate

In a fixed rate quantizer, the total number of codepoints in the codebook is fixed. This implies $2^{b_{tot}} = \sum_{i=1}^{m} 2^{b_i}$. Since α_i is an estimate of the probability of occurrence of cluster i, the total average distortion of the quantization scheme is upperbounded by

$$D_{tot} = \sum_{i=1}^{m} \alpha_i D_i(b_i) \tag{3}$$

The bit allocation scheme for the fixed rate case is decided by minimizing the total average distortion subject to the constraint that the total number of codepoints is fixed, i.e.,

$$\min_{b_i} \; D_{tot} = \sum_{i=1}^{m} \alpha_i D_i(b_i), \quad \text{subject to} \quad 2^{b_{tot}} = \sum_{i=1}^{m} 2^{b_i} \tag{4}$$

The high resolution expression for $D_i(b_i)$ in the Gaussian case is given as

$$\begin{aligned} D_i(b_i) &= \frac{\sqrt{3}\pi}{2} p c_i 2^{-2b_i/p} && (5) \\ c_i &= \left[\prod_{k=1}^{p} \lambda_{i,k}\right]^{\frac{1}{p}}, 1 \le i \le m && (6) \\ \Lambda_i &= \mathrm{diag}(\lambda_{i,1}, \lambda_{i,2}, \ldots, \lambda_{i,p}) && (7) \\ \Sigma_i &= Q_i \Lambda_i Q_i^T && (8) \end{aligned}$$

where the last equation is the eigen value decomposition of the Σ_i, the covariance matrix of cluster i [4].

Theorem 1 (Optimal Fixed-rate Cluster Bit Allocation) *The optimal bit allocation scheme that minimizes the total average mean square distortion $D_{tot} = \sum_{i=1}^{m} \alpha_i D_i(b_i)$, subject to the fixed rate constraint, $2^{b_{tot}} = \sum_{i=1}^{m} 2^{b_i}$, is given by*

$$2^{b_i} \;=\; 2^{b_{tot}} \frac{(\alpha_i c_i)^{p/p+2}}{\sum_{i=1}^{m} (\alpha_i c_i)^{p/p+2}}, \;\; 1 \le i \le m \tag{9}$$

Proof : See [9].

4.1.2. Variable rate

In a variable rate quantizer, the average rate of the quantizer is fixed. Let b_c be the number of bits used to identify a particular cluster. Further, in the present scheme, if a particular observation is quantized with cluster i, then b_i bits are transmitted for that observation. The variable rate constraint is then given by $b_q = b_{tot} - b_c = \sum_{i=1}^{m} \alpha_i b_i$. The expression for total average distortion is the same as the one used for the fixed rate case.

Theorem 2 (Optimal Variable-rate Cluster Bit Allocation) *The optimal bit allocation scheme that minimizes the total average mean square distortion $D_{tot} = \sum_{i=1}^{m} \alpha_i D_i(b_i)$, subject to the variable rate constraint, $b_q = \sum_{i=1}^{m} \alpha_i b_i$, is given by*

$$b_i = b_q + \frac{p}{2}\left[log_2 c_i - \sum_{i=1}^{m} \alpha_i log_2 c_i\right] \tag{10}$$

Proof : See [9].

4.2. Quantization scheme

The overall quantization scheme is explained by the following steps.

1. A given observation, z, is quantized using all the clusters. Fig 2 depicts the details of how the observation z is quantized using cluster i. It consists of the following steps
   - We subtract the mean of the cluster, μ_i, from the observation, z, and then decorrelate it using the the matrix Q_i^T.
   - Each of the p scalar components is then passed through a compressor and then a uniform quantizer whose number of levels is given by the bit allocation among the cluster components. For example, the uniform quantizer of the j^{th} scalar component has $2^{b_{i,j}}$ levels.
   - The quantized value in the transformed domain is then passed through an expander and a correlator, Q_i, and the cluster mean, μ_i, is finally added to obtain z_i^q, the quantized value of z from cluster i.
2. Among the m probable quantized values, we choose the one which minimizes the relevant distortion measure. In the speech coding case, we choose that quantized value which minimizes the Log spectral distortion [2].
3. We transmit the index of the appropriate cluster codepoint to the reciever. The reciever does a simple table look-up to obtain the quantized value.

5. SALIENT FEATURES

5.1. Rate-Independent Computational Complexity

In the proposed scheme, the given observation is quantized using all the clusters. Cluster quantization can be accomplished is closed form since the compressor function as well as the uniform quantizer have closed form expressions in terms of the given observation. Hence, the only complexity involved is comparing the m prospective candidates after cluster quantization. This can be accomplished using m searches. Hence, the proposed scheme has a search complexity of m searches to quantize a given observation.

For a given source, the number of clusters used to model the probability density function of the source is a design parameter. However, once the number of clusters required to model the source has been determined, it remains fixed and need not be changed with the rate of the system. This implies that the search complexity of the proposed scheme is only m searches, *independent of the rate of the system.*

Let us now calculate the memory requirements of the proposed scheme. The number of real numbers the encoder and the decoder need to store can be calculated as follows. For every cluster, we need the cluster probability, α_i, (a real number), the mean, μ_i, (p real numbers), the diagonal eigen-value vector, Λ_i, (p real numbers) and the decorrelating matrix, Q_i, (p^2 real numbers). The number of parameters which define the mixture model is given as $N_{par} = m(1 + 2p + p^2) = m(1 + p)^2$, where, m is the number of clusters and p is the dimension of the source. In the proposed scheme, these are the only values that need to be stored by the source encoder. This is because, for a given rate, the bit allocation among the clusters and the cluster components can be computed online using these values and the cluster quantization can be accomplished. Hence the number of parameters that need to be stored at the source encoder in order to quantize a given observation is independent of the rate of the system. These values are sufficient for decoding at the receiver too, provided the receiver has prior knowledge about the rate of the system. Summarizing, the proposed scheme has search complexity and memory requirements which are constant and independent of the rate of the system.

5.2. Scalability

The proposed scheme is scalable. Once the mixture model parameters which model the pdf of the source have been identified, varying bit-rates corresponds directly to varying bit allocation among the clusters and cluster components. This means that as the bit-rate of the system changes, the new quantizer can be identified effortlessly without any need for re-training.

6. EXPERIMENTAL RESULTS

We have done several experimental studies and the results are very promising. Speech is broken down into 20ms frames, each frame providing a p =10 dimensional LSF vector. A database of 400,000 frames of speech is used to estimate a mixture model consisting of eight clusters. As an example, for a 24 bit VQ, each cluster gets around $2^{24}/2^3$ quantization levels, which is equal to 21 bits per cluster or approximately two bits per cluster component (provided the clusters are equally important which is not necessarily true.). The quantizer is tested on a database of 80,000 frames of speech. Table 1 lists the results of a variable rate memoryless quantizer. Table 2 lists the results of a fixed rate memoryless quantizer. Table 3 lists the results of a variable rate quantizer with memory. In this quantizer, we quantize the difference between consecutive LSF's and use an error control scheme. Table 4 lists the results of a fixed rate quantizer with memory. The fixed rate memoryless quantizer performs about 2-3 bits better than the MSVQ [5]. The variable rate quantizer performs better than the fixed rate quantizer. The quantizer with memory acheives transparent speech quality at 20 bits/frame. The above results indicate that the pdf optimized VQ provides a very computationally efficient method for quantization.

Table 1. Variable rate memoryless quantizer

bits/frame	LSD dB	2-4 dB	>4 dB
21	1.2134	5.57	0.03
22	1.1489	4.18	0.01
23	1.0697	2.77	0.00
24	1.0140	2.27	0.00

Table 2. Fixed rate memoryless quantizer

bits/frame	LSD dB	2-4 dB	>4 dB
21	1.2400	6.7	0.03
22	1.1615	5.83	0.01
23	1.0945	4.14	0.00
24	1.0295	3.05	0.00

Table 3. Variable rate quantizer with memory

bits/frame	LSD dB	2-4 dB	>4 dB
17	1.1990	5.23	0.07
20	1.0116	2.86	0.03
21	0.8842	1.49	0.00
22	0.8158	1.21	0.00

Table 4. Fixed rate quantizer with memory

bits/frame	LSD	2-4 dB	>4 dB
16	1.4013	12.27	0.07
17	1.3330	10.28	0.03
18	1.1180	5.15	0.00
22	0.9943	2.75	0.00

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