A NOVEL CHANNEL DISTORTION MEASURE FOR VECTOR QUANTIZATION AND A FUZZY MODEL FOR CODEBOOK INDEX ASSIGNMENT

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10.21437/Eurospeech.1999-393

ABSTRACT

Vector quantization is very efficient for data compression of speech and image. The channel distortions are introduced due to channel noise. Assigning suitable indices to codevectors can reduce distortion due to an imperfect channel. Several codebook index assignment algorithms were proposed. Unfortunately, no algorithm is always better than the others for any bit error rate due to these algorithms are operated under the assumption of some fixed channel bit error rate which is not realistic. In this paper, a novel channel distortion measure is proposed by computing the expected chanel distortion using Belta distribution function. All codebook index assignment algorithms can be optimized based on this distortion measure. Besides, a fuzzy channel optimized vector quantization for codebook design and index assignment is also derived in this paper.

1. INTRODUCTION

Vector quantization is an efficient approach for the compression of speech signal [1]. The codevector index may be changed due to the channel noise. The overall distortion due to the channel noise may be reduced by properly assigning the indices for the codevectors. Lots of index assignment algorithms were proposed to reduce the channel distortion. The binary switching algorithm (BSA) [2] was proposed to improve the codevector index assignment by Zeger and Gersho. The main idea of binary switching algorithm is to calculate the expected distortion due to the single bit error in the index of codevectors for every index swapping and swap the index pair that makes the largest improvement in distortion. Obviously, the binary switching algorithm is the descent algorithm. It is difficult to reach the global optimum and always get trap in the local optimum. The simulated annealing technique was applied to design the codevector indices by Farvardin [3]. An initial temperature is set and the initial state b of the indices for codevectors is chosen at random. Randomly choose another state b' (perturbation of state b) and calculate $\mathrm{d}D = D(b') - D(b)$. If $\mathrm{d}D < 0$, replace b by b'; otherwise replace b by b' with probability $\exp(\frac{-\mathrm{d}D}{T})$. If the number of average distortion drops exceeds a prescribed number or if too many unsucessful perturbations occur, then check the termination condition. The procedure will be terminated if the temperature is below some prescribed freezing temperature or a stable state is reached.

Wu and Barba [4] developed an efficient index allocation algorithm by using the information of a priori probability of codevectors. Potter and Chiang [5] adopted a minimax design criterion instead of the mean squared error for codevector index assignment. The worst case performance is greatly improved which maintains good average performance by applying the minimax design criterion. Channel optimized vector quantization was also developed for indices assignment to get promising results [6,7]. Both the codebook generation and the codevector indices assignment are optimized together by iterative algorithm in the channel-optimized vector quantizer which is different from the separated optimization approaches.

Rosebrock and Besslich proposed a design procedure for the shape-gain vector quantization to improve robustness against channel noise at a moderate degradation in the noiseless case [15]. Moriya proposed a two-channel conjugate vector quantization in an attempt to reduce quantization distortion for noisy channels. The proposed scheme is confirmed to be effective for a medium bit-rate speech waveform coder [16]. Phamdo et al. presented a unified approach to tree-structured and multistage vector quantization for noisy channels [17].

Genetic algorithms [8] are adaptive methods which can be used in the search and optimization problems. In genetic algorithms, a set of solutions to a problem is called chromosomes. A chromosome (string of solution) is composed of genes. Usually, the individual of the whole population contains only one chromosome. The performance of the solution is called fitness. The fitness of chromosomes are evaluated and ordered, then new chromosomes are produced by using the selected candidates as parents and applying mutation and crossover operations. The new set of chromosomes is then evaluated and ordered again. This cycle continues until a suitable solution is found. Data parallelism can be easily applied to genetic algorithms by dividing the population into several groups and running the same algorithm for each group at the same time using different processors which is called parallel genetic algorithm (PGA). The parallel genetic algorithm was applied to improve the codevector indices assignment by Pan et. al. [9,10]. The chromosome is composed of the string of the codevector indices. Several population groups are generated randomly. The individuals in each group are evaluated. Then the selection, crossover and mutation schemes are applied to each group separately. For some fixed generations, some promising individuals in each group are migrated to the neighbor groups. This procedure guarantees a better optimum will be reached easily from the experiments.

The tabu search approach was proposed by Glover [11]. The basic idea of the tabu search is to explore the search space of all feasible solutions by a sequence of moves. The spirit of this method is embedded in its short-term memory process. The elements of the move from the current solution to its selected neighbor are partially or completely recorded in the tabu list for the purpose of forbidding the reversal of the replacement in a number of future iterations. The search will cycle between the first encountered local minimum and its neighbor without this assurance.

The tabu search scheme starts with test solutions generated randomly and evaluated the objective function for these solutions. If the best of these solutions is not tabu or if it is tabu, but satisfies the aspiration criterion, then select this solution to be the new current solution to generate test solutions for next iteration. The process is terminated if the predefined objective value or the number of iterations have been reached. It is called aspiration criterion if the test solution is a tabu solution but the objective value is better than the best value of all iterations. The tabu search approach was applied to codebook index assignment over noisy channels by Pan and Chu [12]. Unfortunately, it rarely happens that one index assignment algorithm is always better than the other one for any bit error rate due to the channel mismatch that the index assignment algorithms are operated under the assumption of some fixed channel bit error rate which is not realistic. In this paper, a novel channel distortion measure is proposed by computing the expected channel distortion using Beta distribution function. Besides, a fuzzy model for VQ codebook design and index assignment over noisy channels is also derived and the property of this model is also described.

2. ENSENBLE AVERAGE DISTORTION

Assume that N codevectors C_i, $i = 1,2,\ldots,N$, are assigned codevector indices with an m bit string $b(c_i)$, where $N = 2^m$. Let $P(c_i)$ and $d(c_i, c_j)$ denote the probability of sending codevector C_i and the distortion between codevector C_i and C_j, i, $j = 1,2,\ldots,N$. A memoryless binary symmetric channel with bit error probability ε is simulated in this paper. For a random assignment of the codevector indices $b = (b(c_1), b(c_2), \ldots, b(c_N))$, the average distortion for any possible bit errors caused by the channel noise is derived as [9]

$$\overline{D} = \frac{1-(1-\varepsilon)^m}{N-1}\sum_{i=1}^{N} P(c_i)\sum_{j=1}^{N} d(c_i, c_j) \qquad (1)$$

The objective performance for the transmission of indices $b(c_i)$, i=1,2,…,N, can be written as

$$D = \sum_{i=1}^{N} P(c_i)\sum_{i=1}^{m}\varepsilon^{l}(1-\varepsilon)^{m-1}\sum_{b(c_j)\in N^{l}(b(c_i))} d(c_i, c_j) \qquad (2)$$

where $N^{l}(b(c_i)) = \{b(c_j)\in I, H(b(c_i), b(c_j)) = l\}$, is the lth neighbour set of $b(c_i)$. If the channel bit error probability ε is assumed to be sufficiently small ($m\varepsilon << 1$), then the error probability due to more than one bit error can be ignored and the bit error probability of the channel model can be expressed as

$$P(b(c_j)/b(c_i)) = \begin{cases} \varepsilon, & H(b(c_i), b(c_j)) = 1 \\ 1-m\varepsilon, & H(b(c_i), b(c_j)) = 0 \\ 0, & H(b(c_i), b(c_j)) > 1 \end{cases} \qquad (3)$$

Based on this channel model, the average distortion caused by the channel noise for a given assignment of indices, $b(b(c_1), b(c_2), \ldots, b(c_N))$, can be expressed as

$$D = \sum_{i=1}^{N}\sum_{j=1}^{N} P(c_i)P(b(c_j)/b(c_i))d(c_i, c_j) \qquad (4)$$

$$= \varepsilon\sum_{i=1}^{N} P(c_i)\sum_{j:H(b(c_i),b(c_j))=1} d(c_i, c_j), \qquad (5)$$

and the ensemble average distortion is

$$\overline{D} = \frac{\varepsilon}{N!}\sum_{i=1}^{N} P(c_i)\sum_{all\ b}\ \sum_{j:H(b(c_i),b(c_j))=1} d(c_i, c_j) \qquad (6)$$

$$= \frac{\varepsilon m}{N-1}\sum_{i=1}^{N} P(c_i)\sum_{j=1}^{N} d(c_i, c_j). \qquad (7)$$

3. EXPECTED CHANNEL DISTORTION MEASURE

Given the channel bit error rate ε, the number of codevector N and the Hamming distance $h(i, j)$ for index i and j, the channel distortion can be expressed as following:

$$D_c = \frac{1}{k}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p_i \varepsilon_{ij} d(c_i, c_j)$$
$$\varepsilon_{ij} = \varepsilon^{h(i,j)}(1-\varepsilon)^{m-h(i,j)}$$

where $N = 2^m$, p_i is the occupancy probability for the codevector c_i and k is the number of dimension for the codevector. By using the probability density function

$$g(\varepsilon) = \frac{\varepsilon^{\alpha-1}(1-\varepsilon)^{\beta-1}}{B_{0.5}(\alpha,\beta)}, \quad 0 < \varepsilon < 0.5 \tag{8}$$

$$B_{0.5}(\alpha,\beta) = \int_0^{0.5} t^{\alpha-1}(1-t)^{\beta-1}\, dt, \tag{9}$$

the expected channel distortion for the channel bit error rate $0 \le \varepsilon \le 0.5$ is

$$\begin{aligned} E(D_c) &= \int_0^{0.5} D_c g(\varepsilon) d\varepsilon \\ &= \frac{1}{k}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p_i d(c_i, c_j) \frac{B_{0.5}(\alpha + h(i,j), B + m - h(i,j))}{B_{0.5}(\alpha,\beta)} \end{aligned} \tag{10}$$

where α and β can be chosen to match the channel noise distribution. In this paper, the binary switching algorithm, simulated annealing algorithm and the tabu search approach are optimized and compared under the proposed expected channel distortion measure. The average channel distortion for the random assignment is

$$\begin{aligned} \overline{D} &= \int_0^{0.5} \frac{1-(1-\varepsilon)^m}{N-1} \sum_{i=0}^{N-1} p_i \sum_{j=0}^{N-1} d(c_i, c_j) g(\varepsilon) d\varepsilon \\ &= \frac{\sum_{i=0}^{N-1} p_i \sum_{j=0}^{N-1} d(c_i, c_j)}{N-1}\left[1 - \frac{B_{0.5}(\alpha, \beta + m)}{B_{0.5}(\alpha,\beta)}\right] \end{aligned} \tag{11}$$

4. FUZZY CHANNEL OPTIMIZED MODEL

Assume that N codevectors C_i, $i = 1, 2, \ldots, N$, are assigned codevector indices with an m bit string $b(c_i)$, where $N = 2^m$, D_{tj} is the distortion between the training data X_t and the codevector C_j. Let $P(b(c_j)/b(c_i))$, $i, j = 1, 2, \ldots, N$, denote the probability that the index $b(c_j)$ is received given the index $b(c_i)$ is sent. If the total number of training data is T, by using the Lagrange Multiplier Technique, the optimized codevector and membership function can be derived as follows:

$$C_j = \frac{\sum_{i=1}^{T}\sum_{j=1}^{N} \mu_{ti}^{\tau} P(b(c_j)/b(c_i)) X_t}{\sum_{t=1}^{T}\sum_{i=1}^{N} \mu_{ti}^{\tau} P(b(c_j)/b(c_i))}, \tag{12}$$

$$\mu_{ti} = \frac{1}{\sum_{\lambda=1}^{N}\left(\frac{\sum_{j=1}^{N} P(b(c_j)/b(c_i)) D_{tj}}{\sum_{j=1}^{N} P(b(c_j)/b(c_\lambda)) D_{tj}}\right)^{\frac{1}{\tau-1}}} \tag{13}$$

This fuzzy model has the following properties:

1. For error free condition,

$$P(b(c_j)/b(c_i)) = \begin{cases} 1, & \text{if } i = j \\ 0, & \text{if } i \ne j \end{cases}$$

then $$\mu_{ti} = \left(\frac{1}{\sum_{\lambda=1}^{N} \frac{D_{ti}}{D_{t\lambda}}}\right)^{\frac{1}{\tau-1}} \tag{14}$$

$$C_j = \frac{\sum_{t=1}^{T} \mu_{tj}^{\tau} X_t}{\sum_{t=1}^{T} \mu_{tj}^{\tau}}. \tag{15}$$

This is Fuzzy C-means clustering algorithm [13].

2. If $\mu_{ti} = \begin{cases} 1, & \text{if } X_t \in S_i \\ 0, & \text{if } X_t \notin S_i \end{cases}$

then $$C_j = \frac{\sum_{i=1}^{N} P(b(c_j)/b(c_i)) \sum_{t: X_t \in S_i} X_t}{\sum_{i=1}^{N} P(b(c_j)/b(c_i)) |S_i|} \tag{16}$$

It is channel optimized vector quanitzation, [6,7] where S_i is the ith partitioned set and $|S_i|$ is the number of the training data belonged to the ith partitioned set.

3. For error free condition and $\mu_{ti} = \begin{cases} 1, & \text{if } X_t \in S_i \\ 0, & \text{if } X_t \notin S_i \end{cases}$,

then $C_j = \frac{\sum_{t: X_t \in S_j} X_t}{|S_j|}$, it is LBG algorithm [14].

Several well known methods can be generalized using this fuzzy model.

5. EXPERIMENTAL RESULTS

The test materials for these experiments consisted of 7,500 training data vectors. The training data vectors are generated from the 1st-order Gauss-Markov process with zero mean and unit variance. These training data vectors are used to generate 64 codevectors by using the well known LBG algorithm [14]. Experiments are carried out to test the performance of the binary switching algorithm [2], the simulated annealing [3] and the tabu search approach [12] by employing the expected channel distortion (ECD) with $a = 1$ and $b = 40$. The expected channel distortion of the random assignment is also computed. For the simulated annealing method, the parameters are the same as in paper [3]. As shown in Table 1, the performance of the tabu search approach is better than the binary switching algorithm (BSA) and the simulated annealing (SA) method for the limited experiments (10 runs). Since the measure of the expected channel distortion is independent of the channel bit error rate, it can be used to overcome the channel mismatch problem and compared the codebook index assignment algorithms fairly.

Random	0.893867		
Seed	BSA	SA	TABU
1	0.389143	0.463292	0.381861
2	0.385566	0.456199	0.381141
3	0.392812	0.461574	0.378954
4	0.396317	0.462924	0.380427
5	0.385237	0.470554	0.381840
6	0.395086	0.456274	0.377419
7	0.396830	0.457251	0.384321
8	0.389858	0.458813	0.379186
9	0.382603	0.431468	0.379186
10	0.385992	0.442840	0.378299
Average	0.389944	0.456119	0.380263

Table 1: Performance comparison of binary switching algorithm, simulated annealing method, tabu search approach and random assignment using the measure of expected channel distortion

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