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FORWARD ADAPTIVE SPEECH CODING WITH LOW BIT RATES AND VARIABLE WORD LENGTH

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Abstract. *In this paper, two scalar quantizers for the memoryless Laplacian source with low number of levels are designed and discussed. The nonuniform quantizer is designed according to the Lloyd-Max's algorithm since it can provide an optimal performance in the minimum distortion sense. Two variants of the uniform dead-zone quantizer are designed according to the criterion of minimal distortion and the simultaneous criterion of minimal distortion and minimal bit rate. Joint design of quantizer and Huffman encoder is considered in all proposed solutions. In addition, forward adaptation of the observed quantizers is performed on frame-by-frame basis. The best performance from the point of practical implementation is obtained using a uniform dead-zone quantizer that satisfies the criterion of minimal distortion and minimal bit rate at the same time. Moreover, the theoretical results are verified via the experimental results obtained on a real speech signal.*

Key words: *Lloyd-Max's quantizer, uniform dead-zone quantizer, forward adaptation technique, Huffman code, Laplacian source*

1. INTRODUCTION

Quantization is the process of approximating a continuous range of values with a finite (preferably small) range of discreet values known as codewords. It is realized in two phases. In the first phase, quantization is employed for the purpose of analog to digital signal conversion, whereas in the second phase, it is used to achieve signal compression. In this paper we elaborate on the latter phase. From the point of compression, the most suitable are scalar quantizers with a low number of quantization levels *N*.

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The quantities that are usually used to evaluate the quantizer performance are SQNR (signal to quantization noise ratio) and bit rate R. One of the most important methods of scalar quantization is the Lloyd-Max's algorithm that maximizes SQNR for the referent probability density function [1, 9]. In particular, the Lloyd-Max algorithm iteratively computes the optimized quantization parameters (representative levels and decision boundaries) by minimizing the mean square distortion. The optimality holds for the fixed rate quantizers, where each quantization level is represented by the same amount of bits, leading to a bit rate determined as $R=\log_2 N$. However, iterative Lloyd-Max's algorithm is convenient for utilization when small N (low bit rate quantizers) is at disposal, due to the increased design complexity when dealing with large N [1].

Regarding the low-rate quantizer, performance improvement in bit rate can be achieved when we take into account variable-length coding (VLC) of its outputs rather than fixed-length coding. Lossless compression can be realized by employing entropy codes that involve variable-length code words. Some of the most popular entropy coding techniques include Lempel-Ziv, arithmetic and Huffman coding [2]. In this paper, we have decided to incorporate Huffman code on the quantizer output, due to its high efficiency when working with low number of quantization levels [2]. In contrast to the design of Lloyd-Max quantizer, the problem of quantizer design when VLC is used requires a different approach. In this scenario, the design implies determining the quantizer parameters that minimize the mean squared distortion for a given rate R. The authors in [10] present the performance analysis of several types of quantizers for low and moderate bit rate, when Huffman code is applied. It was shown that the best performance offers the hybrid quantizer combined with the uniform and Lloyd-Max quantizer. In addition, the low bit rate or low resolution scalar quantizers are considered in [5]. The focus of this paper is on design of the asymmetrical scalar quantizers for Laplacian and Gaussian source including the analysis of entropy when distortion approaches one.

In this paper, we present two scalar quantizers with N=5 levels designed for unit variance of the input signal. The distribution of the input speech signal is assumed to be Laplacian. Joint design of the quantizer and lossless encoder is done in all proposed models of quantizer. Firstly, we introduce the nonuniform model of quantizer. The idea behind the model we propose is found from the fact that quantizers with N=5 levels are not observed for the fixed-length code words [1], therefore we design it for the variable-length code words using the VLC Huffman code. Moreover, Lloyd-Max's algorithm is utilized to achieve the highest performance of the proposed nonuniform quantizer, since it provides the optimal performance for any number of quantization levels and is particularly efficient for low number of quantization levels.

Furthermore, we have proposed the uniform quantizer with dead-zone which is located in the centre of the quantizer characteristic and involves zero level [8]. In particular, the optimal choice of the dead-zone improves SQNR performance of the uniform quantizer [7]. We have introduced this model encouraged by the fact that Huffman code can be effectively implemented on the available outputs. The uniform quantizer is designed when two criterions are satisfied: the criterion of minimal distortion and the simultaneous criterion of minimal distortion and minimal bit rate. Hence, our analysis is focused on determining the values of Δ and Δ_1 that respectively define the step size and the dead-zone in uniform quantizer in accordance with the aforementioned criteria.

We applied our models in speech coding algorithms based on forward adaptation technique. It is known that speech signal modeled by Laplacian distribution has a wide dynamic range [9]. Therefore, forward adaptation is used in order to provide the appropriate performance in the entire range of input variances of interest. Situation where the forward adaptation outperforms the backward adaptation in terms of SQNR performance by 1 dB is shown in [4].

The obtained theoretical results indicate that proposed quantizers offer improved performance in comparison to the theoretical solutions suggested so far. Moreover, among the analyzed models designed with VLC Huffman code, the most suitable for practical application is the uniform dead-zone quantizer which satisfies two simultaneous conditions. More specifically, the advantage of the uniform dead zone quantizer over the proposed Lloyd-Max quantizer is confirmed on the basis of special criterion for choosing the best quantizer. Also, it will be shown that it outperforms the conventional uniform quantizer having N=5 levels. Additionally, we performed experiments on speech signal in order to test the performance of the proposed quantizers in a real environment.

The remainder of this paper is organized as follows: in Section 2 the proposed models of quantizer along with the numerical results are presented. In Section 3 forward adaptation of the presented quantizers is performed. Section 4 summarizes experimental results and finally we give concluding remarks in Section 5.

2. DESCRIPTION OF MODELS

An N-level scalar quantizer Q is specified by the parameters referred to as decision thresholds $t_1, \ldots, t_{N-1}$ such that $t_0 = -\infty < t_1 < \ldots < t_{N-1} < t_N = \infty$ and $t_i \in R$, and representative levels $Y=\{y_1, y_2, ..., y_N\}$, such that $y_1 < y_2 < \ldots < y_N$, where N is a codebook size. Quantization cells denoted with α_i are defined by $\alpha_i = (t_{i-1}, t_i]$ $i = 1,\ldots, N$. Each cell α_i is represented by the level $y_i \in \alpha_i$. If the input signal value x falls into the interval (cell) α_i, that value is quantized by the level y_i. Hence, a scalar quantizer can be described by a function Q: R → Y that maps the value x into the level y_i where $Q(x) = y_i$, for $x \in \alpha_i$. In addition, for the assumed nonlinear source at the input, cells $\alpha_2,\ldots, \alpha_{N-1}$ form the granular region and are called granular cells while α_1 and α_N constitute an overload region and are called overload cells.

We assume throughout this paper, that the information source is memoryless and Laplacian with zero mean and variance σ^2. The probability density function of this source is:

$$p(x,\sigma) = \frac{1}{\sqrt{2}\sigma} e^{-\frac{\sqrt{2}|x|}{\sigma}} . \quad (1)$$

An important objective measure of quantizer performance is signal to quantization noice ratio, which can be determined from:

$$\mathrm{SQNR}(\sigma) = 10\log_{10}\left(\frac{\sigma^2}{D}\right). \quad (2)$$

where D is distortion inserted by the quantizer.

A design procedure of the proposed scalar quantizers, nonunform and uniform dead-zone quantizer, having equal number of representational levels (N=5) will be described in the following subsections. Both quantizers are designed for the case of unit variance ($\sigma^2=1$).

2.1. Nonuniform quantizer

The main idea displayed here includes the design of optimal quantizer for a given N, i.e. Lloyd-Max's quantizer, followed by the incorporation of Huffman code at its output. A nonuniform quantizer with N=5 levels is illustrated in Fig. 1. The proposed quantizer is symmetrical and involves zero level y_3. Due to the symmetry thresholds and the levels in the negative part of quantizer's characteristic are symmetrical to those in the positive part, i.e. $-t_2=t_3$, $-t_1=t_4$ and $-y_2=y_4$, $-y_1=y_5$. It is obvious that the design of the proposed model of quantizer is completed by determining only the positive thresholds and levels, in accordance with the criterion of minimal distortion or maximal SQNR.

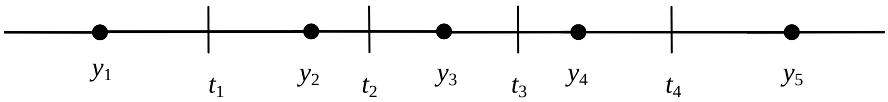

Fig. 1 The proposed nonuniform quantizer

Lloyd-Max's algorithm is implemented using the following algorithm:

Step 1. Define the initial values for thresholds $\{t_3^{(0)}, t_4^{(0)}\}$ and levels $\{y_4^{(0)}, y_5^{(0)}\}$.

Step 2. New values for levels $\{y_4, y_5\}$ and thresholds $\{t_3, t_4\}$ are iteratively calculated using:

$$y_4^{(i+1)} = \frac{\int_{t_3^{(i)}}^{t_4^{(i)}} xp(x)dx}{\int_{t_3^{(i)}}^{t_4^{(i)}} p(x)dx}, \quad y_5^{(i+1)} = t_4^{(i)} + \frac{1}{\sqrt{2}}, \quad i = 0,1,\ldots, \tag{3}$$

$$t_3^{(i+1)} = \frac{y_3^{(i+1)} + y_4^{(i+1)}}{2}, \quad t_4^{(i+1)} = \frac{y_4^{(i+1)} + y_5^{(i+1)}}{2}, i = 0,1,\ldots. \tag{4}$$

Step 3. Lloyd-Max's algorithm interrupts when next iteration does not produce any change in distortion.

The distortion D is the measure of the irreversible error incurred by the quantization procedure. The total distortion can be decomposed into granular distortion and overload distortion. Granular distortion D_g is given by:

$$D_g = 2\int_0^{t_3} x^2 p(x)dx + 2\int_{t_3}^{t_4} (x-y_4)^2 p(x)dx, \tag{5}$$

while overload distortion D_o is defined by:

$$D_o = 2\int_{t_4}^{\infty} (x-y_5)^2 p(x)dx. \tag{6}$$

It is obvious that $D=D_g+D_o$. Now, according to equation (2) SQNR can be easily determined.

To be able to fully assess performance of the quantizer, it is necessary to determine its bit rate R:

$$R=\sum_{i=1}^{N} p\left(y_i\right) l_i \ , \tag{7}$$

where l_i is the length of Huffman codeword corresponding to the level y_i and p_i is the probability of y_i occurring:

$$p(y_i)=\int_{t_{i-1}}^{t_i} p(x)dx=\frac{1}{2}(e^{-\sqrt{2}t_{i-1}}-e^{-\sqrt{2}t_i}) \ . \tag{8}$$

Specifically, the quantizer outputs are encoded with Huffman code since it can provide the optimal length of codewords for a given probability model [2].

2.2. Uniform dead-zone quantizer

The quantizer design in this case is quite different than the one described in previous subsection. Huffman code is exploited to represent the quantizer outputs as well. In Fig. 2 we illustrate the proposed symmetrical uniform dead-zone quantizer with odd number of levels $N=2L+1$, where for the considered case $L=2$ [8]. All quantization cells are of equal size Δ in the proposed uniform quantizer, except cell $\Delta_1=(-t_1, t_1)$ which defines the dead-zone. The dead-zone is located in the quantizer characteristic so that it involves zero level y_0. Since the quantizer is symmetrical, we can observe only positive thresholds and levels. In addition, $t_{\max}$ represents the upper bound between granular and overload region.

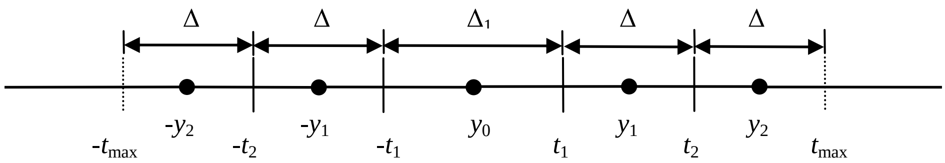

Fig. 2 The proposed uniform dead-zone quantizer

It is obvious that the total distortion D, inserted by the uniform dead-zone quantizer, can be obtained as the sum of the distortions in the inner (dead-zone) D_{DZ} and the outer part D_{OP}:

$$\begin{aligned} D_{OP} &= 2\int_{t_1}^{t_1+\Delta}(x-y_1)^2 p(x)dx+2\int_{t_1+\Delta}^{t_{\max}}(x-y_2)^2 p(x)dx+2\int_{t_{\max}}^{\infty}(x-y_2)^2 p(x)dx= \\ &=\frac{1}{2}\frac{e^{-\sqrt{2}(t_1+\Delta)}}{(e^{\sqrt{2}\Delta}-1)^2}(e^{3\sqrt{2}\Delta}+2\Delta^2-2e^{2\sqrt{2}\Delta}(1+\Delta^2)+e^{\sqrt{2}\Delta}(1+2\Delta^2)) \end{aligned} \ , \tag{9}$$

$$D_{DZ}=2\int_0^{t_1} x^2 p(x)dx=1-e^{-\sqrt{2}t_1}(1+t_1(\sqrt{2}+t_1)) \ . \tag{10}$$

Substituting D in equation (2) we obtain SQNR, while the bit rate, as in preceding case, can be calculated from equation (7), using the following probability model:

$$p(y_0) = 2\int_0^{t_1} p(x)dx = 1 - e^{-\sqrt{2}t_1} \;, \tag{11}$$

$$p(y_1) = p(-y_1) = \int_{t_1}^{t_1+\Delta} p(x)dx = \frac{1}{2} e^{-\sqrt{2}t_1}(1 - e^{-\sqrt{2}\Delta}) \;, \tag{12}$$

$$p(y_2) = p(-y_2) = \int_{t_1+\Delta}^{\infty} p(x)dx = \frac{1}{2} e^{-\sqrt{2}(t_1+\Delta)} \;. \tag{13}$$

It is evident from equations (9)-(13) that parameters t_1 and Δ play an essential role in the uniform dead-zone quantizer performance. Additionally, the performance is investigated when following criterions are fulfilled: the criterion of minimal distortion and the simultaneous criterion of minimal distortion and minimal bit rate. Accordingly, the appropriate values of t_1 and Δ are numerically determined with respect to the mentioned criteria.

2.3. Numerical results

In this subsection we present numerical results to compare the performance of the proposed quantizers. Table 1 summarizes the performances of the joint Lloyd-Max quantizer and Huffman encoder (Q_{LM}), along with the uniform dead-zone quantizer which fulfills the criterion of minimal distortion (Q_{DZ1}) and the uniform dead-zone quantizer which satisfies the criterion of minimal distortion and minimal bit rate at the same time (Q_{DZ2}).

Table 1 Theoretical performance of the proposed quantizers with N=5 levels

σ^2=1	Δ_{opt}	Δ_{1opt}	$p(y_1)= p(y_5)$	$p(y_2)=p(y_4)$	$p(y_3)$	D	SQNR[dB]	R[b/s]
Q_{LM}	-	-	0.0561	0.2200	0.4478	0.1198	9.2152	1.9966
Q_{DZ1}	1.26	0.8914	0.0448	0.2214	0.4676	0.1272	8.9556	1.9331
Q_{DZ2}	1.26	1.3370	0.0327	0.1616	0.6115	0.1442	8.4096	1.6808

Regarding the quantizer Q_{DZ1}, it is a special case of the proposed uniform dead-zone quantizer when the parameters Δ and Δ_1 are chosen so that the highest quality of the quantized signal is provided. In this case, the performances of uniform dead-zone quantizer are searched for in Δ range from 0.1 to 2 with step 0.01 and in t_1 range from t_3^{LM} to 2 t_3^{LM} with step $t_3^{LM}/10$. The optimal threshold value of quantizer Q_{LM} is denoted by t_3^{LM}. Based on the conducted performance analysis, the optimal values of Δ and Δ_1 (denoted by Δ_{opt} and Δ_{1opt} (t_{1opt})) are selected.

In addition, the quantizer Q_{DZ2} is another special case of the uniform dead-zone quantizer, but with more complex design than the preceding one. More specifically, it minimizes the bit rate under the constraint that the maximal possible increasing in SQNR is achieved for a given type of quantizer. For this scenario, the performance analysis of the uniform dead-zone quantizer is carried out in t_1 range from t_{1opt} to 2 t_{1opt} with step t_{1opt} /10, while the step size is assumed to be Δ=Δ_{opt}. Selection of the optimal uniform dead-zone quantizer is presented in Table 2, where highlighted values denote an optimal quantizer design.

Table 2 Selection of the optimal uniform dead-zone quantizer

σ^2=1	SQNR [dB]	R [b/s]
t_1= 0.4457	8.9556	1.9331
t_1= 0.4903	8.9231	1.8761
t_1= 0.5348	8.8482	1.8225
t_1= 0.5794	8.7345	1.7723
t_1= 0.6240	8.5865	1.7251
t_1= **0.6685**	**8.4096**	**1.6808**
t_1= 0.7131	8.2088	1.6392
t_1= 0.7577	7.9896	1.6002
t_1= 0.8023	7.7566	1.5635
t_1= 0.8468	7.5141	1.5291
t_1= 0.8914	7.2658	1.4968

The best quantizer in Table 2 is chosen by using the following criterion:

$$\frac{\Delta R}{\Delta \mathrm{SQNR}} > \frac{\Delta R^{\mathrm{e}}}{\Delta \mathrm{SQNR}^{\mathrm{e}}} = \delta \,. \tag{14}$$

The left side of inequality is the slope of the curve R(SQNR) found among quantizers designed for different values of threshold t_1, while the right side of inequality corresponds to the expected value of the slope found among standard Lloyd-Max's quantizers with N=2 and N=4 levels and amounts to 0.2203 [1]. In other words, this criterion compares two quantizers (the first one has a higher SQNR) and quantizer having the best performance is selected in the following way: if the slope value is higher than the expected one the second quantizer is a better solution, otherwise the first one is preferred. Highlighted raw in Table 2 corresponds to the quantizer which satisfies criterion of minimal distortion and minimal bit rate at the same time.

SQNR versus bit rate R for proposed quantizers is shown in Fig. 3. Blue line represents the standard Lloyd-Max quantizers with N=2 and N=4 levels having the bit rates R=1 b/s and R=2 b/s, respectively. It can be seen that SQNR curve increases linearly when the bit rate is raised for 1 b/s, and has a slope of 4.54 dB [1, 2]. The marked points above the curve indicate the obtained performance of the discussed quantizers, i.e. Q_{LM}, Q_{DZ1} and Q_{DZ2} (as in Table 1). Note that the proposed models of quantizer provide improved performance when compared to the theoretical solution suggested so far. Particularly, the quantizer Q_{LM} gives 1.69 dB higher SQNR for the respective bit rate, in comparison to the expected SQNR value (specified by a point on a blue curve). Additionally, the gains of quantizers Q_{DZ1} and Q_{DZ2} are 1.72 dB and 2.32 dB, respectively.

Furthermore, we will determine the best quantizer solution from the aspect of practical application, when VLC Huffman code is used. Namely, when we compare quantizers Q_{LM} and Q_{DZ2}, it may be noted that when the bit rate is reduced by 0.32 b/s, SQNR drops by 0.81 dB. One can perceive, by using 4.54 dB/bit rule, that with the same reduction of the bit rate, SQNR reduction of 1.43 dB is achieved. This result proves that the quantizer Q_{DZ2} has a better performance in regard to the quantizer Q_{LM}. Furthermore, the advantage of the quantizer Q_{DZ2} over the quantizer Q_{LM} can be confirmed by applying the recommended criterion (14), where the value of the slope amounts 0.392.

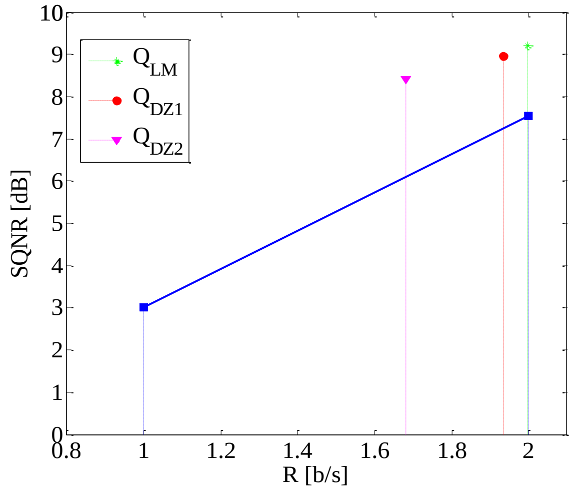

Fig. 3 Attained performances of different quantizers

Additionally, it will be beneficial to compare the attained performance (SQNR and *R*) of the quantizer Q_{DZ2} with the ones of *N*=5 levels uniform scalar quantizer (in this case the decision thresholds are equally spaced by Δ and the representative levels are the midpoints of the respective cells) followed with Huffman encoder. Particularly, it provides the following: SQNR=8.76 dB and *R*=1.92 b/s. Now, using the criterion (14) the slope value of 0.69 is obtained, showing the superiority of the proposed quantizer Q_{DZ2} compared to the uniform one having equal number of levels.

3. Forward Adaptation

Forward adaptation performed on frame-by-frame basis is often reported in literature [1, 4], hence we will give only a brief overview. The block diagram of the forward adaptive coding scheme is shown in Fig. 4. The proposed coding scheme involves a buffer, a variance estimator, a log-uniform quantizer with *L* levels for the quantization of frame variance and an adaptive quantizer with *N* levels.

The quantizer is adapted to the short-term estimate of the input signal variance for each frame. The following procedure is conducted. Frame consisted of *M* input samples is stored in buffer and variance σ^2 is determined in the variance estimator. The quantization of σ^2 is employed using the log-uniform quantizer (Q_{LU}). The main reason for utilization of such a quantizer lies in the fact that it provides better SQNR performance in a wide range of input variances in comparison to the uniform one [9].

In this paper, we have designed a log-uniform quantizer with *L* levels to quantize logarithmic variance $10\log_{10}(\sigma^2/\sigma_0^2)$ in the range (-30 dB, 30 dB) with respect to the referent variance σ_0^2. Thresholds of the considered log-uniform quantizer are determined as:

$$l_i[\text{dB}] = -30 + \Delta_L i \text{ , } i = 0, 1, \ldots, L, \tag{15}$$

while levels are determined as:

$$r_i[\text{dB}] = -30 + \Delta_L\left(i - \frac{1}{2}\right),\ i=1,\ldots, L. \tag{16}$$

where Δ_L [dB] = 60/L is the quantizer step size

In linear domain, thresholds and levels are respectively given by:

$$\sigma_i = 10^{l_i/20},\ i= 0, 1,\ldots, L, \tag{17}$$

$$\hat{\sigma}_i = 10^{r_i/20},\ i= 0, 1,\ldots, L, \tag{18}$$

It is clear that the equality $Q_{LU}(\sigma^2)=\hat{\sigma_i}$ holds for $\sigma^2 \in (\sigma_{i-1}, \sigma_i)$.

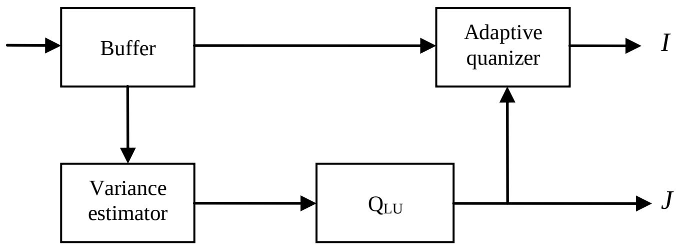

Fig. 4 Forward adaptive coding scheme

Furthermore, the quantized value of the frame variance is used to update the parameters of the adaptive quantizer. The decision thresholds and representative levels of the adaptive quantizer, for $\sigma^2 \in (\sigma_{i-1}, \sigma_i)$, can be respectively determined as $t_j^a = g_i t_j^f$, j=0, 1, …, N and $y_j^a = g_i y_j^f$, j=1, …, N, where $g_i = \sqrt{\hat{\sigma}_i}$. With t_j^f, j=0, 1, …, N and y_j^f, j=1, …, N we denote thresholds and levels of the non-adaptive (fixed) quantizer, respectively. After that, M samples within the current frame are quantized using the adaptive quantizer.

Indices I and J are transferred to the receiver, as depicted on Fig. 4. Index I denotes the codeword index obtained as the result of the encoding procedure. Index J carries information about the level of the log-uniform quantizer that has been used for the frame variance quantization. Note that J is transmitted as additional or side information and involves $\log_2 L$ bits per frame.

Consequently, bit rate for adaptive quantizer is given by:

$$R^a = R^f + \frac{\log_2 L}{M}. \tag{19}$$

where R^f denotes the bit rate of fixed quantizer.

Fig. 5 plots SQNR of several forward adaptive quantizers across the entire range of input variances of interest. The results are provided when L=32 levels log-uniform quantizer is employed for the frame variance quantization, while the referent variance is fixed at $\sigma_0^2 = 2 \times 10^{-3}$. The results for Q_{LM}, Q_{DZ1} and Q_{DZ2} comply with theoretical results shown in Fig. 3. It can be observed that SQNR behaves fairly constantly in the whole variance range. Note that our models exceed SQNR curve of the standard Lloyd-Max quantizer with N=4 levels ($Q_{LM,N=4}$), as expected.

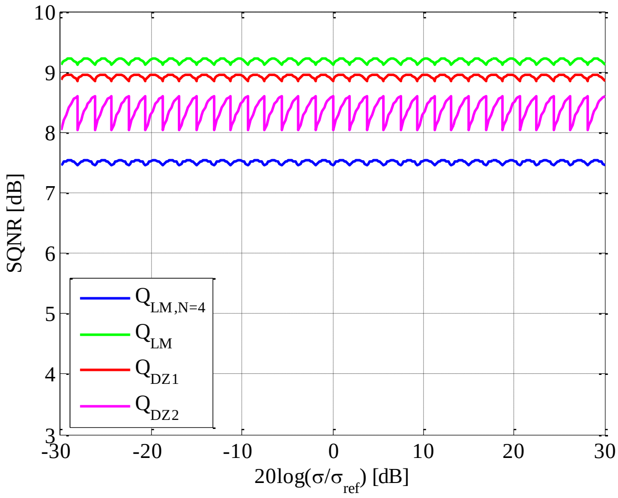

Fig. 5 SQNR dependence on the input variances

4. Experimental Results

In this section, the analysis on real speech signal is performed with a goal to verify the theoretical results obtained in Section 2. In our experiment, the input speech is divided into frames of length M. We assumed that the input signal consists of a finite number of speech frames F.

Experimental values of signal to quantization noise ratio within each of F frames are determined from the expression:

$$\mathrm{SQNR}_j^e = 10\log_{10}\left(\frac{(\sigma_j^e)^2}{D_j^e}\right),\ j=1,\ldots,F, \tag{20}$$

where $(\sigma_j^e)^2$ is the average variance of the j-th frame, j=1,…,F:

$$(\sigma_j^e)^2 = \frac{1}{M}\sum_{i=1}^{M} x_{ji}^2,\ j=1,\ldots,F, \tag{21}$$

and D_j^e is the average distortion for the j-th frame, j=1,…,F:

$$D_j^e = \frac{1}{M}\sum_{i=1}^{M}(x_{ji}-y_{ji}^a)^2,\ j=1,\ldots,F. \tag{22}$$

where x_{ji} and y_{ji}^a are samples of the considered input speech and the outputs of the adaptive quantizer, respectively.

Finally, we performed averaging of the signal to quantization noise ratios in equation (20) over all frames to obtain experimental results:

$$\mathrm{SQNR}^{ex} = \frac{1}{F}\sum_{j=1}^{F}\mathrm{SQNR}_j^{e} \ . \tag{23}$$

Table 3 contains experimental results, together with the values of R^a for several types of quantizers. Experimental results are obtained using the speech signal sampled at 16 kHz (approximately 1 milion of speech samples in total) with different frame lengths (M = 80, 160, 200, 240 and 320). We observe that the experimental results are in agreement with the theoretical results presented in this paper (difference is less than 1 dB). Hence, the correctness of our models is ascertained. Note that bit rate slightly increases when the frame length decreases. In addition, one can perceive that the highest SQNR^{ex} values are obtained for M=80. This is expected as the parameters of the quantizer are updated more frequently.

Table 3 Experimental results and bit rate for the proposed quantizers

	Q_{LM}		Q_{DZ2}		$Q_{LM,N=4}$	
	SQNR^{ex}[dB]	R^a [b/s]	SQNR^{ex}[dB]	R^a[b/s]	SQNR^{ex}[dB]	R^a[b/s]
M=80	10.2426	2.0591	9.1815	1.7433	8.8000	2.0625
M=160	10.2020	2.0278	9.0453	1.7121	8.7608	2.0313
M=200	10.1799	2.0216	9.0072	1.7058	8.6811	2.0250
M=240	10.1584	2.0174	8.9826	1.7016	8.7195	2.0208
M=320	10.0944	2.0122	8.9385	1.6964	8.6118	2.0156

5. Conclusion

In this paper, a joint design of the quantizer and Huffman encoder is presented and its performances with N=5 quantization levels have been analyzed and compared to the standard quantizer solutions. It is found that the proposed joint Lloyd-Max quantizer and Huffman encoder, as well as uniform dead zone quantizer significantly improve performance of the theoretical solutions exposed so far, in terms of the gains in SQNR, mainly due to the incorporation of variable-length code. The best quantizer solution among the proposed ones is the uniform dead-zone quantizer satisfying the criterion of minimal distortion and minimal bit rate at the same time. In addition, forward adaptation of the developed quantizers is performed in order to ensure the appropriate SQNR in a wide range of input variance. Finally, we have provided the experimental results on a real speech signal to validate the theoretical results. Therefore, we can conclude that the proposed quantizers are efficient solutions for compression of speech signal, especially the uniform dead-zone quantizer which is found to outperform the other proposed models.

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