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SEMI–LOGARITHMIC AND HYBRID QUANTIZATION OF LAPLACIAN SOURCE IN WIDE RANGE OF VARIANCES

Milan S. Savić [*] — **Zoran H. Perić** [**]
Stefan R. Panić [**] — **Aleksandar V. Mosić** [***]

A novel semilogarithmic hybrid quantizer for non-uniform scalar quantization of Laplacian source, which consist of uniform quantizer and companding quantizer is introduced. Uniform quantizer has unit gain in area around zero. Companding quantizer is defined with a novel logarithm characteristic. Also an analysis of classic semilogarithmic A-law for various values of A parameter is provided. Comparation with classic semilogarithmic A-law is performed. The main advantage of hybrid quantizer is that number of representation levels for both uniform and companding quantizer are not unambiguously determined function of the A parameter value, as it is the case with classic semilogarithmic A companding characteristic. It is shown that by using hybrid quantizer, average of signal-to-quantization noise ratio *SQNR* quality obtained by using classic A companding law can be overachieved for 0.47 dB. Numbers of representation levels of hybrid quantizer are adapted to the input signal variances, in order to achieve high *SQNR* in a wide range of signal volumes (variances). By using this adaptation higher average *SQNR* quality of 2.52 dB could be achieved compared to classic A companding law. Forward adaptation of hybrid quantizer is analyzed and obtained performances correspond to adaptive classic A companding law case but possible advantage arises in simpler practical realization of hybrid quantizers. Obtained performances correspond to classic A-law companding case, because during the adaptation process, optimal values of parameter A are chosen. For each other A parameter values proposed hybrid quantizer provides better results. For value of $A = 50$ hybrid model has higher *SQNR* value for 0.79 dB.

K e y w o r d s: hybrid semilogarithmic quantizer, forward adaptive quantization, Laplacian source

1 INTRODUCTION

Quantization denotes the process of approximating a continuous range of values by a relatively-small set of discrete symbols and plays an important role in the theory and practice of modern signal processing [1-3]. From the engineers point of view, most important issues are the design and implementation of quantizers to meet performance objectives. The quality of a quantized signal is generally influenced by the width of a quantizers support region and the number of quantization levels. Although, great number of quantization studies has been published [4-9] there is still reasonable need to continue research in this field. Main goal of our research is to find a simply quantization characteristics for quantizer model realization with high quality of performance, with maintaining robustness in wide range of input signals.

Most used types of signals (speech, audio and video) are not stationary, the exact values of above mentioned parameters are not known in advance, and in addition there is a tendency to change with time. The statistic of input signals: the statistical mean, variance (or the dynamic range), and type of input *pdf* (probability density function) constantly change with time [1–3], [9, 10]. Although, great number of quantization studies has been published [4-9] there is still reasonable need to continue research in this field.

Commonly used source model in many digital applications is Laplacian source model, due to its simplicity and fact that many parameters and characteristics can be found as the closed form relations. Also, for larger number of signal samples, the probability density function of input signal is better represented with Laplacian function [10]. In a number of papers the quantization of memoryless Laplacian source was analyzed since the *pdf* of the difference signal for an image waveform follows the Laplacian function [10, 11]. Concerning Laplacian speech model, there are two logarithmic quantizing characteristics: μ-law quantizing (used in North America & Japan) and A-law quantizing (used in Europe and the rest of the world). European ITU T G.711 standard is based upon classic semilogarithmic compression law [12].

In order to process input signal effectively it is necessary to use some kind of adaptation, forward, *ie* from the input sequence or backward, *ie* from the coded output signal. Forward adaptive technique is less sensitive to transmission errors when compared to backward adaptation. Also forward adaptation provides *SQNR* within 1 dB of the backward adaptation [13].

In this paper a new hybrid semilogarithmic model for non-uniform scalar quantization of Laplacian source is

[*] Mathematical institute of Serbian Academy of Science and Art, Kneza Mihaila 36, 11001 Belgrade, Serbia, [**] Faculty of Electrical Engineering, University of Niš, Aleksandra Medvedeva 14, Niš, 18000, Serbia [***] Faculty of Natural Sciences and Mathematics, Lole Ribara 29, Kosovska Mitrovica, 38200, Serbia, malimuzicar@gmail.com

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analyzed. First, general analysis of non-uniform scalar quantization as well as analysis of classic semilogarithmic A-law companding characteristic is presented. Then novel hybrid model which consist of uniform and companding quantizer is introduced. Comparation between quantizers is made. The main advantage of hybrid quantizer is that number of representation levels for both uniform and logarithmic part are not unambiguously determined function of the A parameter value, as it is the case with classic semilogarithmic A companding characteristic. It is shown that by using hybrid quantizer, average *SQNR* quality obtained by using classic A companding law can be overachieved for 0.47 dB. In Section 4, codebook sizes (numbers of representation levels of uniform and companding quantizers) and the width of support region (maximal amplitude of input signals) are adapted to the input signal variance. By using this adaptation, average *SQNR* quality obtained by using A-law can be overachieved for 2.52 dB.

After that, forward adaptation based on classic semilogarithm characteristic and on novel hybrid quantizer is analyzed. Since obtained performances of hybrid quantizer correspond to classic A companding law forward adaptation case another possible advantage arises in simpler practical realization of hybrid quantizer because his uniform quantizer has unit gain in area around zero. Obtained performances correspond to classic A companding law case, because during the adaptation process, optimal values of parameter A are chosen. For each other A parameter value proposed hybrid quantizer provide better results. Capitalizing on the above presented facts, the possibility of successful implementation of this hybrid model for compression of speech and other signals with Laplacian distribution is considered.

2 SEMILOGARITHMIC QUANTIZER

In this section, classic semilogarithmic A-law will be described. Assume that an input signal is characterized by continuous random variable X with probability density function (*pdf*) denoted by $p(x)$. In the rest of paper we assume that information source is Laplacian source with memoryless property and zero mean value. The *pdf* of Laplacian source is given by

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

A scalar quantizer with N levels is characterized by the set or real numbers $t_1,t_2,\dots,t_{N-1}$, called *decision thresholds*, satisfying $-\infty=t_0<t_1<\dots<t_{N-1}<t_N=+\infty$ and set of numbers $y_1,\dots,y_N$, called *representation levels*, satisfying $y_j\in\alpha_j=[t_{j-1},t_j)$ for $j=1,\dots,N$. Sets $\alpha_1,\alpha_2,\dots,\alpha_N$ form the partition of the set of real numbers R and are called *quantization cells*. The quantizer is defined as many-to-one-mapping $Q\colon R\to\{y_1,y_2,\dots,y_N\}$ deffined by $Q(x)=y_j$ where $x\in\alpha_j$. Cells $\alpha_2,\dots,\alpha_{N-1}$ are called *inner* (*or granular*) *cells* while α_1 and α_N are called *outer* (or *overload*) *cells*. In such way, cells $\alpha_2,\dots,\alpha_{N-1}$ form granular while cells α_1 and α_N form an overload region.

Compressor function for A-law is given with

$$c_1(x)=\begin{cases}\frac{A(x)}{1+\log A}, & \text{for } |x|<x_{\min},\\ \frac{x_{\max}\left(1+\log\frac{A|x|}{x_{\max}}\right)}{1+\log A}, & \text{for } x_{\min}<|x|<x_{\max}.\end{cases} \tag{2}$$

It consists of two parts: linear and logarithmic. $x_{\min}$ is border between those two parts where $x_{\max}$ is maximal amplitude of quantizer. Parameter A denotes ratio $A=x_{\max}/x_{\min}$. A-law is used in many systems, especially in PCM telephone systems in Europe, where value $A=87.6$ is used. With N_1 and N_2 are denoted numbers of representation levels in linear and logarithmic part, respectively.

N_1 and N_2 can be expressed over total number of levels N as [9]

$$N_1=\frac{N}{1+\log A}\,;\ N_2=N-N_1\,. \tag{3}$$

As it can be seen from Eq. (3), number of representation levels for both uniform and logarithmic part are unambiguously determined function of the A parameter value.

During quantization an irreversible error is made, which is expressed by distortion. Distortion is most commonly defined as mean-squared difference between original and quantized signal. Total distortion D_t consists of granular distortion D_g in granular region and overload distortion D_o in overload region, *ie*

$$D_t=D_g+D_0 \tag{4}$$

Granular distortion D_g consists of two parts: distortion in linear part D_{g1} and distortion in logarithmic part D_{g2}. D_{g1} is calculated as

$$D_{g1}=\frac{\Delta_1^2}{12}P_1 \tag{5}$$

where $\Delta_1=\frac{2x_{\min}}{N_1}$ and $P_1=\int_{x_{\min}}^{x_{\max}}p(x)\mathrm{d}x$ is probability that input signal belongs to linear part. For Laplacian distribution $P_1=1-e^{-\frac{\sqrt{2}x_{\min}}{\sigma}}$. D_{g2} can be calculated using Bennett integral as

$$D_{g2}=\frac{\Delta_2^2}{6}\int_{x_{\min}}^{x_{\max}}\frac{P(x)}{[c_1(x)]^2}\mathrm{d}x \tag{6}$$

where $\Delta_2=2x_{\max}/N$ [9].

Overload distortion is defined as [9]

$$D_0=2\int_{x_{\max}}^{\infty}(x-y_N)^2p(x)\mathrm{d}x\,. \tag{7}$$

For Laplacian distribution, applying simple mathematic calculation, we can obtain the following expressions

$$D_{g1} = \frac{x_{\min}^2}{3N_1^2}\Big(1 - e^{-\frac{\sqrt{2}x_{\min}}{\sigma}}\Big), \tag{8}$$

$$D_{g2} = \frac{(1+\log A)^2}{3N^2}\Big[e^{-\frac{\sqrt{2}}{\sigma}x_{\min}}\big(x_{\min}^2 + \sqrt{2}\sigma x_{\min} + \sigma^2\big) - e^{-\frac{\sqrt{2}}{\sigma}x_{\max}}\big(x_{\max}^2 + \sqrt{2}\sigma x_{\max} + \sigma^2\big)\Big], \tag{9}$$

$$D_0 = \sigma^2 e^{-\frac{\sqrt{2}x_{\max}}{\sigma}}. \tag{10}$$

Signal-to-quantization noise ratio ($SQNR$) is given with

$$SQNR[\text{dB}] = 10\log_{10}\frac{\sigma^2}{D_t}. \tag{11}$$

3 NOVEL HYBRID QUANTIZER

Let us propose novel hybrid quantizer model, which consists of uniform quantizer Q_1 and companding quantizer Q_2. Quantizer Q_1 has unit gain in area around zero. Quantizer Q_2 is defined with compression function

$$C_2(x) = \log\frac{|x|}{x_{\min}}\operatorname{sgn}(x), \; x_{\min} < |x| < x_{\max}. \tag{12}$$

$x_{\min}$ defines the value that separates uniform from companding quantizer, while $x_{\max}$ denotes maximal input amplitude of quantizer.

If numbers of representation levels of uniform and companding quantizers are N_1 and N_2, respectively, then $N = N_1 + N_2$ stands for the total number of representation levels.

Similarly to classic A-law, with D_{g1}, D_{g2} and D_o are denoted distortions in uniform, logarithmic and overload region. Starting from (5), (6) and (7), using, putting $c_2(x)$ instead $c_1(x)$ in (6) and approximating y_N with $x_{\max}$, following expressions are obtained

$$D_{g1} = \frac{x_{\min}^2}{3N_1^2}\Big(1 - e^{-\frac{\sqrt{2}x_{\min}}{\sigma}}\Big), \tag{13}$$

$$D_{g2} = \frac{\log\big(\frac{x_{\max}}{x_{\min}}\big)^2}{3N_2^2}\Big[e^{-\frac{\sqrt{2}}{\sigma}x_{\min}}\big(x_{\min}^2 + \sqrt{2}\sigma x_{\min} + \sigma^2\big) - e^{-\frac{\sqrt{2}}{\sigma}x_{\max}}\big(x_{\max}^2 + \sqrt{2}\sigma x_{\max} + \sigma^2\big)\Big] \tag{14}$$

$$D_0 = \sigma^2 e^{-\frac{\sqrt{2}x_{\max}}{\sigma}}. \tag{15}$$

Total distortion and $SQNR$ are calculated using expressions (4) and (11).

In order to achieve better system performances, total distortion expression can be minimized by using the method of Lagrange multipliers. First we introduce a new variable J with

$$J = D_t + \gamma(N_1 + N_2) \tag{16}$$

subject to constraint

$$N = N_1 + N_2. \tag{17}$$

Now optimization of J could be achieved by differencing (16) over N_1 and N_2

$$\frac{\partial J}{\partial N_1} = 0 \tag{18}$$

$$\frac{\partial J}{\partial N_2} = 0. \tag{19}$$

Solving (18) and (19) with respect to constraint (17) derives expressions for optimal values of codebook sizes N_1 and N_2 in the form of

$$N_1 = \frac{N}{h}\sqrt[3]{x_{\min}^2\big(1 - e^{-\frac{\sqrt{2}}{\sigma}x_{\min}}\big)}, \tag{20}$$

$$N_2 = \frac{N}{h}\sqrt[3]{2\big(\ln\frac{x_{max}}{x_{\min}}\big)^2 P} \tag{21}$$

with P and h given as

$$P = e^{-\frac{\sqrt{2}}{\sigma}x_{\min}}\big(x_{\min}^2 + \sqrt{2}\sigma x_{\min} + \sigma^2\big) - e^{-\frac{\sqrt{2}}{\sigma}x_{\max}}\big(x_{\max}^2 + \sqrt{2}\sigma x_{\max} + \sigma^2\big), \tag{22}$$

$$h = \sqrt[3]{x_{\min}^2\big(1 - e^{-\frac{\sqrt{2}}{\sigma}x_{\min}}\big)} + \sqrt[3]{2\big(\ln\frac{x_{\max}}{x_{\min}}\big)^2 P}. \tag{23}$$

By substituting (20) and (21) into (13) and (14) granular distortion, D_g can now be presented in the form of

$$D_g = \frac{h^3}{2N^2}. \tag{24}$$

It is evident from (20)–(23) that numbers of representation levels for both uniform and companding quantizer of hybrid model are not unambiguously determined function of the A parameter value, as it is the case with standard A companding characteristic.

Since number of representation levels N_1 and N_2 are defined as function of each input signal variance value, in order to simplify the quantizer designing process, only one optimized value of σ, should be chosen, *ie* σ_0, and N_1 and N_2 should be calculated with respect to it. Accurate estimate of the input signal's parameters is needed for optimizing the compressor function parameters N_1 and N_2 for a compandor implementation. This enables quantizers to be adapted to the maximal amplitudes of input signals.

Figure 1 shows comparation of $SQNR$ quality obtained by using standard A-law ($A = 87.6$) and novel hybrid quantizer, in wide range of input variance, where N_1 and N_2 are adopted to σ_0, in wide range of input signal

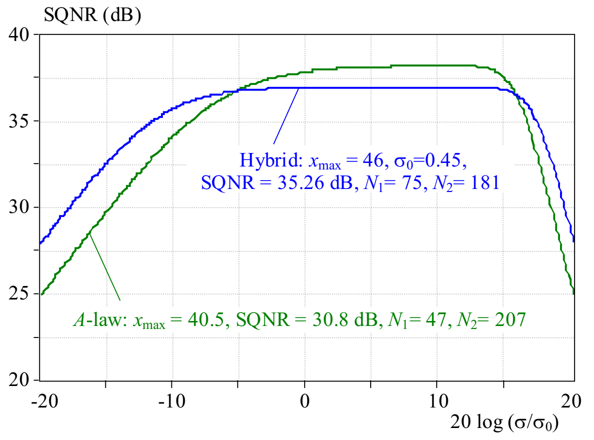

Fig. 1. Comparation of *SQNR* quality between *A*-law and fixed novel hybrid quantizer, in wide range of input variance

Table 1. Maximal and average values of SQNR obtained for various A parameter values (?=1)

	$x_{\max}^{\text{opt}}$		$SQNR_{\max}$ (dB)		$x_{\max}^{\text{opt}}$		$SQNR_{av}$ (dB)	
A	A-law	Hybrid model	A-law	Hybrid model	A-law	Hybrid model	A-law	Hybrid model
2	7.2	7.9	36.433	38.857	16.3	12.7	23.225	25.272
3	7.5	8.4	37.755	39.983	17.8	15.6	24.404	27.207
4	7.7	8.6	38.760	40.406	19.1	18.2	25.389	28.474
5	7.9	8.6	39.489	40.6	20.2	20.6	26.208	29.384
6	8.1	8.7	40.004	40.709	21.1	22.8	26.900	30.074
7	8.3	8.7	40.357	40.776	22	24.8	27.493	30.618
8	8.4	8.8	40.593	40.820	22.7	26.7	28.008	31.058
9	8.5	8.8	40.741	40.849	23.4	28.3	28.460	31.422
10	8.7	8.8	40.827	40.866	24.1	29.8	28.860	31.727
11	8.8	8.8	40.868	40.875	24.7	31.2	29.217	31.986
12	8.9	8.9	40.877	40.877	25.2	32.4	29.538	32.209
13	9.0	8.9	40.862	40.873	25.8	33.6	29.829	32.402
14	9.1	8.9	40.831	40.865	26.2	34.6	30.095	32.572
15	9.2	8.9	40.789	40.853	26.7	35.6	30.337	32.721
20	9.6	9.0	40.500	40.758	28.7	39.2	31.303	33.262
30	10.1	9.2	39.908	40.501	31.7	43.5	32.520	33.829
40	10.6	9.3	39.437	40.242	33.9	46	33.269	34.116
50	10.9	9.5	39.066	40.005	35.7	47.6	33.782	34.285
60	11.2	9.5	38.766	39.792	37.2	48.8	34.156	34.391
70	11.4	9.6	38.516	39.605	38.5	49.7	34.439	34.462

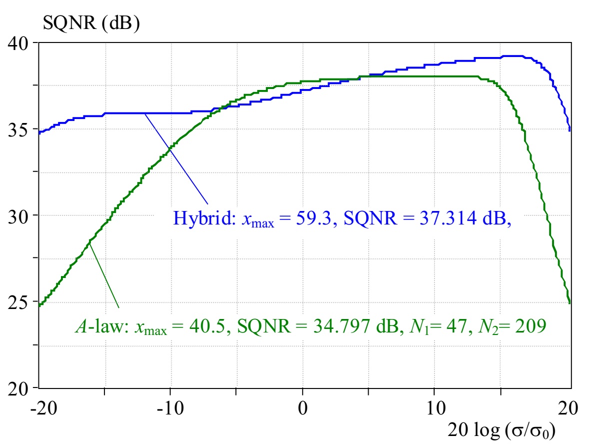

Fig. 2. Comparation of *SQNR* quality between *A*-law and novel hybrid quantizer, in wide range of input variance

statistics $[\sigma^2/\sigma_0^2]$ [dB] $= [-20, 20]$. It can be seen that by using proposed hybrid quantizer, average *SQNR* quality obtained by using A companding law can be overachieved for 0.47 dB. Obtained *SQNR* quality is achieved, due the fact, that codebook sizes, which have constant value in all input range with respect to σ_0, are optimally adopted. For the sake of comparation, it has been presumed for this case that relationship between $x_{\min}$ and $x_{\max}$ of novel hybrid model are ($x_{\min} = x_{\max}/A$). This relationship is also considered in the rest of the paper.

In Table 1 maximal and average values of *SQNR* obtained by using A-law and novel hybrid quantizer for various A parameter values are presented. It can be observed that novel hybrid quantizer provides higher *SQNR* maximums and higher average *SQNR* value in the range of lower A parameter values. This observation can be also used when there is a need for designing quantizers with low A parameter values. Since A-law is a special case of proposed hybrid quantizer it makes no sense to shown value of *SQNR* for $A > 70$. For $A > 70$ the performances between A-law and novel hybrid quantizer are almost the same.

4 FORWARD ADAPTIVE QUANTIZATION BY USING SEMI–LOGARITHMIC AND HYBRID QUANTIZERS

In this section forward adaptation of hybrid quantizer on N_1 and N_2 is given. After that forward adaptation on A-law quantizer given with $c_1(x)$ and novel hybrid quantizer, which companding quantizer characteristic is given with $c_2(x)$ is done. Given analysis is similar to analysis in [9, 14, 15].

4.1 Adaptation on N_1 and N_2

Numbers of representation levels N_1 and N_2 can be adapted to the input signal variance, by optimizing $x_{\max}$ in order to achieve high quality of signal-to-quantization noise ratio (*SQNR*) in a wide range of signal volumes (variances) with respect to its necessary robustness over a broad range of input variances

Figure 2 shows comparation of *SQNR* quality obtained by using A-law ($A = 87.6$) and novel hybrid quantizer, in wide range of input variance. It can be seen that by using proposed hybrid quantizer, average *SQNR* quality obtained by using A companding law can be overachieved for 2.52 dB, since number of representation levels N_1 and N_2 are adopted to each value of input signal variance, and have different values for each σ.

4.2 Adaptation on N_1, N_2 and $x_{\max}$

Forward adaptive lossy encoder consists of: buffer with M samples, gain estimator, log-uniform scalar quantizer with K levels for gain quantization, divider and fixed semilogarithm quantizer given with $c_1(x)$ or $c_2(x)$ designed for referent variance σ_0^2. M input samples are loaded into input buffer and average variance of these

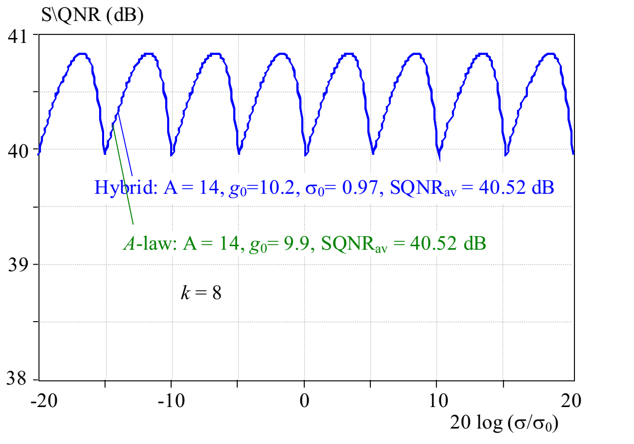

Fig. 3. Comparation of *SQNR* quality between adaptive A-law and adaptive novel hybrid quantizer, in wide range of input variance for $N_1 = 70$ and $N_2 = 186$ $(g_0 = x_{\max}/\sigma_o)$

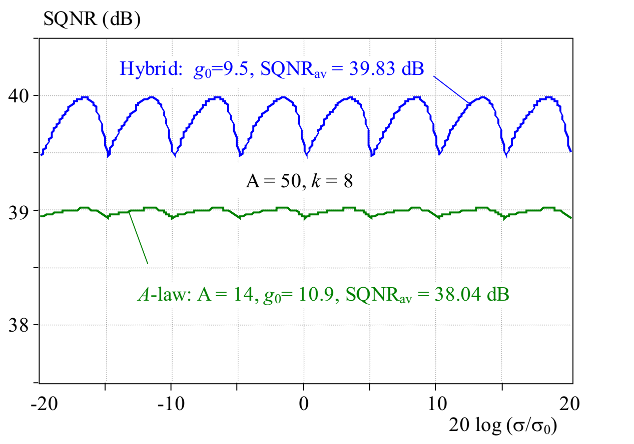

Fig. 4. Comparation of *SQNR* quality between adaptive A-law and adaptive novel hybrid quantizer, in wide range of input variance for $A = 50$ (for A-law $N_1 = 52$ and $N_2 = 204$; for Hybrid model $N_1 = 20$ and $N_2 = 236$) $(g_0 = x_{\max}/\sigma_o)$

samples, denoted with σ^2, is calculated in variance estimator. σ^2 is quantized in log-uniform scalar quantizer which is designed so that logarithmic variance $10\log(\sigma^2/\sigma_0^2)$, in range $(-20\text{dB}, 20\text{dB})$ in relation to referent variance σ_0^2, is divided on K uniform intervals. ε is the distance of input variance, where *SQNR* has maximal value, from the left intervals bound. In logarithmic domain, thresholds are

$$\alpha_i[\text{dB}] = -20 + i\Delta\,, \quad i = 0, \ldots, K \tag{25}$$

and representation levels are

$$\hat{\alpha}[\text{dB}] = -20 + (i-\varepsilon)\Delta\,, \quad i = 1, \ldots, K\,, \tag{26}$$

where $0 < \varepsilon < 1$ and $\Delta[\text{dB}] = \frac{20-(-20)}{K} = \frac{40}{K}$. In linear domain, thresholds are

$$\sigma_i = 10^{\alpha_i/20}, \quad i = 0, \ldots, K \tag{27}$$

and representation levels are

$$S_i = 10^{\hat{\alpha}_i/20}, \quad i = 0, \ldots, K\,. \tag{28}$$

So, if $\sigma \in (\sigma_{i-1}, \sigma_i)$ then σ is quantized to s_i. Gain is defined as

$$g_i = s_i/\sigma_0\,, \quad i = 1, \ldots, K\,. \tag{29}$$

Therefore, we have K discrete levels of gain. Input samples from buffer are divided with g_i and guided to fixed semilogarithmic quantizer with N levels, designed for σ_0^2. If thresholds for fixed quantizer are denoted with t_j^f, $j = 0, \ldots, N$ and representation levels with y_j^f, $j = 1, \ldots, N$, then thresholds for adaptive quantizer, for $\sigma \in (\sigma_{i-1}, \sigma_i)$, are $t_j^a = g_i t_j^f$, $j = 0, \ldots, N$ and representation levels are $y_j^a = g_i y_j^f$, $j = 1, \ldots, N$. If border between uniform and companding quantizer of fixed hybrid quantizer is denoted with $x_{\min}^f$ and maximal amplitude of this fixed quantizer is denoted with $x_{\max}^f$, then border between uniform and companding quantizer, and maximal amplitude of adaptive quantizer, for $\sigma \in (\sigma_{i-1}, \sigma_i)$, are $x_{\min}^a = g_i x_{\min}^f$ and $x_{\max}^a = g_i x_{\max}^f$.

Additional (side) information that determine which gain level (from K levels) is used, should be sent to receiver. Therefore, we need $\log_2 k$ extra bits for every frame of M samples.

In Figures 3 comparation of *SQNR* between adaptive A-law and adaptive novel hybrid quantizer, in wide range of input variance is presented. It can be seen that performances obtained by using novel hybrid quantizer corresponds to the A companding law forward adaptation case. Based on this, possible advantage arises in simpler practical realization of hybrid quantizers. Number of representation levels N_1 and N_2 does not depend on variance (in each of k uniform intervals N_1 and N_2 have the same value). Obtained performances correspond to A companding law case, because during the adaptation process, optimal values of parameter A are chosen. For each other A parameter value proposed hybrid quantizer provide better results. This is advantage of our hybrid model.

5 CONCLUSION

The novel hybrid quantizer for nonuniform scalar quantization model of Laplacian source was introduced in this paper. An analysis of classic semilogarithmic A-law for various A parameter values is also provided.

The advantage of novel hybrid quantizer is that number of representation levels for both uniform and companding quantizer are not unambiguously determined function of the A parameter value, as it is the case with classic semilogarithmic A companding law. By using this hybrid quantizing model higher average quality of transmission of 0.47 dB could be achieved for fixed quantizer compared to A companding law. Also this hybrid model provides not just higher maximal *SQNR* values but also higher average $SQNR$ values in the range of lower A parameter values. Hybrid quantizing model usage provides higher quality for fixed quantizers.

The other advantage of hybrid model is that number of representation levels of each quantizer can be adopted to input signal statistics by optimizing maximal signal amplitude $x_{\max}$. By using this adaptation, average $SQNR$ quality obtained by using A-law can be overachieved for 2.52 dB.

Adaptive characteristics for A-law and for novel hybrid quantizer are almost the same but hybrid quantizer is simpler for practical realization. The matching quality is obtained because during the adaptation process, optimal values of parameter A are chosen. For each other A parameter value proposed hybrid quantizer provides better results. For value of $A = 50$ and for side information $k = 8$ hybrid model has higher $SQNR$ value for 0.79 dB. Better performances can be reached by adapting the novel hybrid quantizer to the maximal input amplitude value and to the number of representation levels, comparing to the performances which are obtained by adapting number of quantization levels to each value of input variance.

Hybrid model presented in the paper can be applied for compression or to raise quality of continuous signals in wide range of input volumes.

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Milan S. Savić was born in Vranje, Serbia, in 1984. He received MSc degree in electrical engineering from Faculty of Electronic Engineering, Ni š, Serbia, in 2008. He joined the Department of Telecommunication, Faculty of Electronic Engineering, Ni š in 2008 as Research Assistant on joint project between Faculty of Electronic Engineering and Ministry of Science Republic of Serbia. His research interests are scalar and vector quantization techniques in speech and image coding. He is currently wit the Mathematical institute of Serbian Academy of Science and Art.

Zoran H. Perić was born in Ni š, Serbia, in 1964. He received the BSc degree in electronics and telecommunications from the Faculty of Electronic Engineering, Ni š, Serbia, Yugoslavia, in 1989, and MSc degree in telecommunications from the University of Ni š, in 1994. He received the PhD degree from the University of Ni š, also, in 1999. He is currently Professor at the Department of Telecommunications and vicedean of the Faculty of Electronic Engineering, University of Ni š, Serbia. His current research interests include the information theory, source and channel coding and signal processing. He is particulary working on scalar and vector quantization techniques in speech and image coding. He was author and coauthor in over 100 papers in digital communications. Dr Peric has been a Reviewer for IEEE Transactions on Information Theory. He is member Editorial Board of Journal "Electronics and Electrical Engineering".

Stefan R. Panić was born in Pirot, Serbia, in 1983. He received MSc and PhD degrees in electrical engineering from Faculty of Electronic Engineering, Ni š, Serbia, in 2007 and 2010. His research interests include statistical characterization of digital transmission. He was author and coauthor in over 40 papers on above. He is currently with the Department of Informatics, Faculty of Mathematics and Natural Science, University of Pri ština.

Aleksandar V. Mosić was born in Leskovac, Serbia, in 1983. He received MS degree in electrical engineering from Faculty of Electronic Engineering, Ni š, Serbia, in 2007. He joined the Department of Telecommunication, Faculty of Electronic Engineering, Ni š in 2008 as Research Assistant on joint project between Faculty of Electronic Engineering and Ministry of Science Republic of Serbia. His current research interests include the information theory, source and channel coding and signal processing. He has published several papers on the above subjects.