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STABILITY ANALYSIS OF THE SECOND-ORDER DPCM PREDICTION FILTER AND CORRELATION WITH SIGNAL-TO-QUANTIZATION NOISE RATIO

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Abstract. *The stability study of the differential pulse code modulation system with the special focus on a predictor is given in this paper. Moreover, sufficient stability conditions for a linear prediction (recursive) filter are derived. The corresponding mathematical inequalities for the commonly used second-order predictor are derived. A method off probability estimation for the predictor coefficients is given, both deterministic and stochastic. It allows the design of the differential pulse code modulation system with the linear predictor whose coefficients meet the technical requirements. Finally, the probability of stability values for the specific second-order predictor are computed and compared with the corresponding values of the Signal-to-Quantization Noise Ratio (SQNR). The correlation between these values is verified for different frame lengths. This could be crucial for the optimal choice of predictor coefficients. Useful conclusions are drawn regarding the stability and performances of the system.*

Key words: *Normal distribution, Probability density function, Differential pulse code modulation, Linear prediction, SQNR*

1. INTRODUCTION

Differential Pulse Code Modulation (DPCM) is one of the most effective transmission signal techniques widely used in telecommunications and signal processing. Speech [1–3], and image coding [4–8], video stream data compression [9], medical research [10–14] are some of the various DPCM applications. Adaptive DPCM (ADPCM) is a DPCM which

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includes backwards adaptive quantization and/or backwards adaptive prediction [1, 3, 9]. In recent decades, new specific types of DPCM systems have been discovered such as clustered DPCM [7] and hybrid DPCM [8].

The prediction and development of prediction models for applications in various fields has become increasingly important in recent years [15, 16]. Linear prediction [1, 2, 17–20] where the prediction of the current sample is computed as a linear combination of the previous samples, is the basis of any DPCM system. A historical survey of linear prediction can be found in [21].

The DPCM transmission system is a nonlinear feedback system. Due to the negative closed loop [16], although essentially a telecommunication system, DPCM is also suitable for control systems analysis. In this context, specific properties of this system, especially its linear part (recursive, prediction filter) have already been considered. A sensitivity analysis for DPCM prediction filter of arbitrary order has been performed yet. A robustness analysis for the first and second-order prediction filter is presented in [22].

Beside above mentioned sensitivity and robustness, one of the most important properties of any real system is stability. Some stability analyses of the DPCM transmission system have already been done for the commonly used second-order predictor [23]. It was found that the stability of the predictor, which is the linear part of DPCM system, is a sufficient condition for the stability of the whole system.

In practice, every system is imperfect in some way [24]. This means that the system parameters are not deterministic but stochastic variables. In this case, the classical methods of stability analysis are not applicable, since we only know with what probability the system is stable. For these reasons, we introduced a new term: "probability of stability" [25, 26]. We have already proposed the method of stability estimation for the first-order predictor [27]. In this paper, probability of stability estimation method is presented and proven for the commonly used second-order predictor. A correlation is established between the processing quality parameter, the Signal-to-Quantization Noise Ratio (SQNR), and the Probability of Stability (P_S). This can be very important when designing a DPCM system. The optimal choice of values for the predictor coefficients guarantees better performance of the system.

The rest of this paper is structured as follows. In Section 2, we explain the theoretical background of the DPCM system. In Section 3, we analyse the stability of the linear part of this system (prediction filter) and give the stability conditions. Numerical results for the second-order predictor are given in Section 4. Appropriate values for probability of stability and SQNR are determined. We analysed the results and found the correlation between these parameters in Section 5. Concluding remarks and ideas for future work are considered in Section 6.

2. DPCM System – Theoretical Background

DPCM is a method of converting an analog signal to a digital signal by sampling the analog signal and then quantizing the difference between the actual sample value and its predicted value. The predicted value of the actual sample is based on the previous sample or samples. The basic concept of DPCM - coding a difference, is based on the fact that most source signals have significant correlation between successive consecutive samples, so the quantizer uses redundancy in sample values which in turn means a lower bit rate [1, 3, 28].

The block diagram of a DPCM/ADPCM encoder is shown in Fig. 1a. It consists of the quantizer, the inverse quantizer, and predictor. The linear prediction filters in encoder (Fig. 1a) and decoder (Fig. 1b) are of the special interest for further stability analysis. Fig. 1a also shows the additional subsystem for the adaptive prediction (buffer and predictor coefficients estimator connected with dashed lines), which forms an ADPCM encoder [1, 13]. The main idea of DPCM is to form the difference d_n between the current sample x_n and its predicted value $\hat{x}_n$:

$$d_n = x_n - \hat{x}_n . \tag{1}$$

This difference is quantized and transmitted. Let us e_n denote the quantization error which occurs due to quantization of the difference d_n. For the linear predictor, the predicted value $\hat{x}_n$ is calculated as a linear combination of the previously quantized reconstructed samples y_{n-i}. The operation of the DPCM system with the k-th order predictor is described by the following equations:

$$y_n = d_n + e_n + \hat{x}_n = x_n + e_n \tag{2}$$

$$\hat{x}_n = \sum_{i=1}^{k} a_i y_{n-i} , \tag{3}$$

where a_i, i = 1, 2,…, k are predictor coefficients.

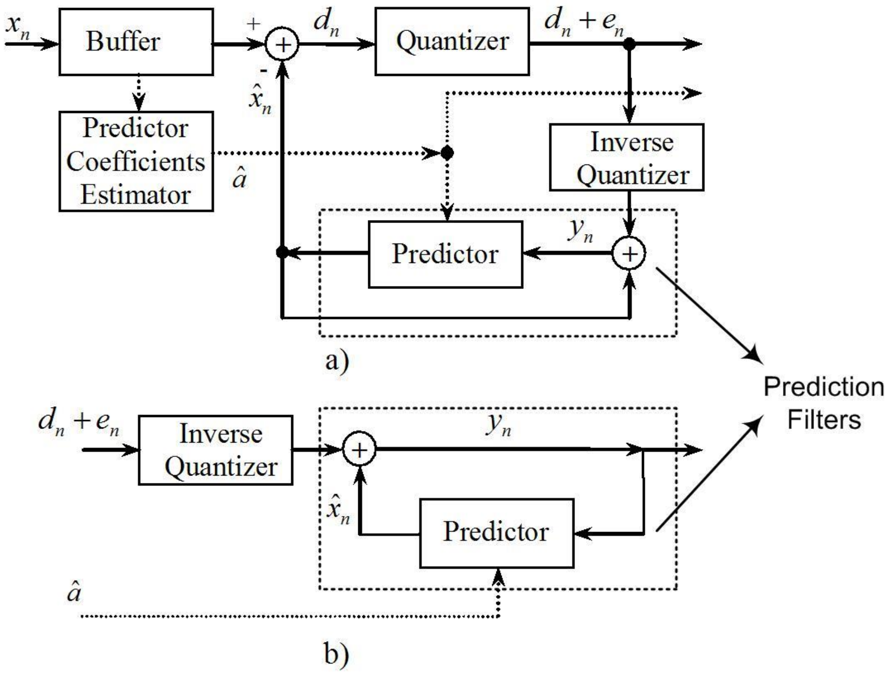

Fig. 1 DPCM/ADPCM system, a) Encoder, b) Decoder

Correlation coefficients ρ_i indicate the degree of correlation between i successive samples [1, 13]. In a DPCM system, the values of predictor coefficients are predetermined according to the class of signals under consideration and are known for both the encoder and decoder, but they are suboptimal. In Fig. 1, the predictor coefficients a_i, i=1,2,…, k are adapted according to ρ_i, i=1,2,…, k for each frame. The predictor coefficients could be determined from the correlation coefficients using the Levinson-Durbin algorithm for predictors of arbitrary order [2]. The functional dependencies between these coefficients for the second-order predictor are well known [20], and given by:

$$a_1 = \frac{\rho_1\left(1-\rho_2\right)}{1-\rho_1^2},\ a_2 = \frac{\rho_2-\rho_1^2}{1-\rho_1^2}. \tag{4}$$

DPCM systems are nonlinear feedback systems. In addition to the predictor, which is a linear element, the system contains a quantizer as a nonlinear element.

The well-known parameter – SQNR, is used to evaluate the quality of the reconstructed signal at the output of the ADPCM system [13, 29]:

$$\mathrm{SQNR}_{\mathrm{ADPCM}} = 10\log\left(\frac{\sum_{j=1}^{L}\sum_{n=1}^{M}x_{jn}^2}{\sum_{j=1}^{L}\sum_{n=1}^{M}\left(x_{jn}-y_{jn}\right)^2}\right), \tag{5}$$

where L is the number of frames and M is a frame length.

The stability analysis of the whole DPCM system is very difficult, but it is known that an element with nonlinear static characteristic with saturation stabilizes the system [30]. Consideration of the stability of the prediction filter is very important in the design of the system. The basic requirement is that the predictor coefficients are located inside stability region in parametric space or very close to this region.

The aim of this paper is to consider the stability of the prediction filter with the commonly used second-order predictor, although the proposed method is also applicable to higher order predictors with some alternative methods. We will also investigate in what way stability is related to the SQNR in this paper.

3. Stability Analysis of the Linear Prediction Filter

It is well known that the predictor is an essential part of any DPCM/ADPCM system and its coefficients have a great impact on the system performances [2, 18, 20].

We will consider the stability of the prediction filter with k-th order predictor.

The relation for the k-th order predictor is given by Eq. (3), i.e.:

$$\hat{X}(z) = \left(\sum_{i=1}^{k} a_i z^{-i}\right)Y(z), \tag{6}$$

in z-domain. Transfer function of the predictor is:

$$W_P(z)=\sum_{i=1}^{k}a_i z^{-i}\ . \tag{7}$$

Transfer function of the prediction (recursive) filter in the encoder has the following form:

$$W_R(z)=\frac{W_P(z)}{1-W_P(z)}=\frac{\sum_{i=1}^{k}a_i z^{-i}}{1-\sum_{i=1}^{k}a_i z^{-i}}\ . \tag{8}$$

Transfer function of the prediction filter in the decoder is:

$$W_R^D(z)=\frac{1}{1-W_P(z)}=\frac{1}{1-\sum_{i=1}^{k}a_i z^{-i}}\ . \tag{9}$$

Prediction filters are stable if all the poles of the transfer functions in Eqs. (8), (9) lie inside the unit circle, i.e., if the characteristic Eq. (which is the same for the both filters):

$$1-\sum_{i=1}^{k}a_i z^{-i}=0\ , \tag{10}$$

has all its zeroes inside the unit circle. Eq. (10) can be written as:

$$z^k-\sum_{i=1}^{k}a_i z^{k-i}=0\ . \tag{11}$$

The stability conditions of the system described by the characteristic Eq. (11) can be determined using various stability criteria (Jury test, Routh-Hurwitz criterion, etc. [31]). We will use the Routh-Hurwitz stability criterion in this paper. The bilinear transformation $z=(1+s)/(1-s)$ is a mapping unit circle inside the z-plane into the left half of the s-plane. After applying the bilinear transformation onto Eq. (11), we obtain:

$$b_k s^k+b_{k-1}s^{k-1}+\ldots+b_1 s+b_0=0\ , \tag{12}$$

where $b_0, b_1,\ldots, b_k$ are functions of the predictor coefficients $a_0, a_1,\ldots, a_k$, i.e.: $b_0=\Phi_0(a_1,\ldots, a_k),\ldots,b_k=\Phi_k(a_1,\ldots, a_k)$.

Remark 1: Other more general forms for the bilinear transformation can be found in the literature, but in its application in the analysis of system stability in the z-domain, the above-mentioned and very similar one $z=(s+1)/(s-1)$ occurs most frequently. We have obtained absolutely the same result if we apply it. It should be noted that both are special cases of the more general form $z=m(1+s)/(1-s)$ for $m=1$ and $m=-1$ respectively, where m is an arbitrary real number [31]. In this more general case, the region of stability in the z-plane was not a unit circle, but a circle of radius m. One more general form of the bilinear transformation is $z=(1+Ts/2)/(1-Ts/2)$ [32]. This form changes absolutely nothing, because sample period T has no influence on the analysis. In our case $T=2$.

The prediction filter (described with characteristic Eq. (11) in z-plane) is stable if all the zeroes of the characteristic Eq. (12) are inside the left half of s-plane. We form Hurwitz determinant D_k for Eq. (12):

$$D_k = \begin{vmatrix} b_{k-1} & b_{k-3} & b_{k-5} & \cdots & 0 \\ b_k & b_{k-2} & b_{k-4} & \cdots & 0 \\ 0 & b_{k-1} & b_{k-3} & \cdots & 0 \\ 0 & b_k & b_{k-2} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & b_0 \end{vmatrix}. \tag{13}$$

The necessary condition for the stability of the prediction filter in Eq. (11) is that all coefficients b_0, b_1,…, b_k are greater than zero and the sufficient condition is that all diagonal sub-determinants D_i, i=1,2,…, k, are greater than zero:

$$\begin{aligned} & D_1 = b_{k-1} > 0, \\ & D_2 = \begin{vmatrix} b_{k-1} & b_{k-3} \\ b_k & b_{k-2} \end{vmatrix} > 0, \\ & \vdots \\ & D_k > 0. \end{aligned} \tag{14}$$

The stability region of the prediction filter in Eq. (11), S_k, can be determined by the above inequalities for the first-order predictor up to the k-th order predictor.

In the case of the first-order predictor, the stability region S_1 is given by the:

$$-1 < a_1 < 1. \tag{15}$$

For the second-order predictor, the stability region S_2, in the parametric space a_1, a_2 is given by conditions:

$$\begin{aligned} & 1 + a_1 - a_2 > 0, \\ & 1 - a_1 - a_2 > 0, \\ & a_2 > -1. \end{aligned} \tag{16}$$

The stability region S_2, is the triangle shown in Fig. 2.

Remark 2: For the second order, the stability of the system can of course be easily determined, but because of the possible application of this method for higher-order predictors, we have given general conditions here by using the Routh-Hurwitz criterion [31]. We have also applied the Jury stability test mentioned above and obtained the same system of inequalities. For a third-order predictor, for example, applying both stability criteria results in the following system of inequalities: $a_1+a_2+a_3<1$, $a_1-a_2+a_3>-1$, $a_1a_3+1>-a_2+a_3^2$ and it defines the stability region S_3.

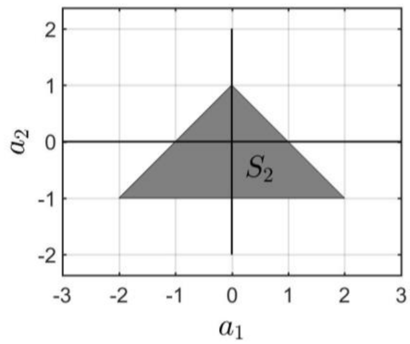

Fig. 2 The stability region of the second-order prediction filter

Previous stability analysis was performed under the assumption that the system parameters, i.e., the predictor coefficients are deterministic. This is true if the DPCM system is perfect unlike all real systems. Sometimes these imperfections have no any visible effect on the system performances, but in many cases this effect cannot be neglected. Some system properties such as stability or dynamical response are directly dependent on them. Mathematically, the imperfections are fluctuation of the system coefficients around the nominal values of the coefficients [25, 33].

The system can be either stable or unstable for constant parameter values. When the predictor coefficients are stochastic, they have some distribution. The most common distribution in the case of a real system design is the normal distribution. All calculations in this paper are performed for this type of distribution.

We now assume that the system is stable with a certain probability. This is the reason why we need to introduce the term: probability of stability instead of the traditional stability of the system. The probability of stability is defined as follows:

$$P = \int \underset{S_k}{\cdots} \int f\left(a_1,\ldots,a_k\right) da_1 \cdots da_k \,, \tag{17}$$

where $f\left(a_1,\ldots,a_k\right) = \prod_{i=1}^{k} f_i\left(a_i\right)$ is the total density function and S_k is the stability region.

Based on this, we can estimate the stability of an arbitrary order prediction filter. The proposed method can also be used for the third and higher-orders predictors, but the calculation of the integrals for the probability of stability becomes more complicated because the stability regions for which the integrals are calculated become more complex (see Eq. 17). In this sense, in addition to classical integration, it is possible to use the approximate method as a Monte Carlo to calculate complex integrals for probability estimation.

4. Numerical Results – Second-Order Predictor

The most common predictors are those of the first and second order. The second order is usually an optimal order since the prediction gain often goes into saturation for higher order predictors [2] and this is the reason why we are focused on the second order in this paper.

Stability analysis in the case of the first-order predictor was studied in [27]. The most important fact we verified is that the prediction filter is always stable in the whole range of possible values for the predictor coefficient a_1. When the system is not deterministic, i.e., when the parameter a_1 is stochastic, we obtained the probability of stability of the prediction filter for different values of the variance.

In this paper, we perform a stability analysis for the second-order predictor. We analyze a recorded speech signal of length L=10200 samples with different frame lengths, M=10, 20,…,150 samples. The ADPCM system shown in Fig. 1 was used to obtain the means and standard deviations of the predictor coefficients. The input signal is divided into frames of length M which are buffered. For each frame, the predictor coefficients a_1 and a_2 are first calculated, which are used to process the samples of that frame. In this way, we obtain round (L/M) pairs of coefficients a_1 and a_2 values that are adjusted for the corresponding frames. We form sets of coefficients a_1 and a_2 values obtained for all frames and determine their means and standard deviations, $\overline{a}_1, \overline{a}_2, \sigma_1, \sigma_2$, respectively. Based on these values and relations, we calculate the probability of stability, P_S. We set the obtained means of the predictor coefficients $\overline{a}_1$ and $\overline{a}_2$ as fixed predictor values (DPCM system), reprocess the signal and obtain the SQNR value. In this way, for the obtained values of predictor coefficients a_1 and a_2, we calculated the mean and standard deviation and SQNR for all values of M (Table I). For illustration, the distributions of the coefficients a_1 and a_2 for two of eight values of the frame length (M=10 and M=150), are shown in Figs. 3 and 4, respectively. Normal (Gaussian) distributions with the same means and standard deviations are also shown for comparison.

From these figures (as well as for other values of frame length), it can be easily demonstrated that the mean (nominal) values of the predictor coefficients $\left(\overline{a}_1, \overline{a}_2\right)$ are located into the region described by Eq. (16). This means that the linear prediction filter is stable if we assume that the predictor coefficients are deterministic, i.e., their values are equal to the desired (nominal) values.

Since the DPCM system is imperfect in practice, the predictor coefficients cannot be perfectly matched to their projected values.

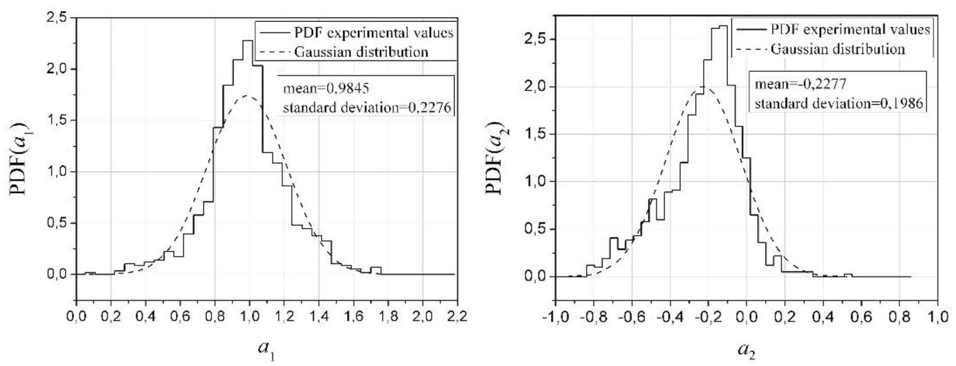

Fig. 3 The probability density function of predictor coefficients a_1 and a_2 for M=10

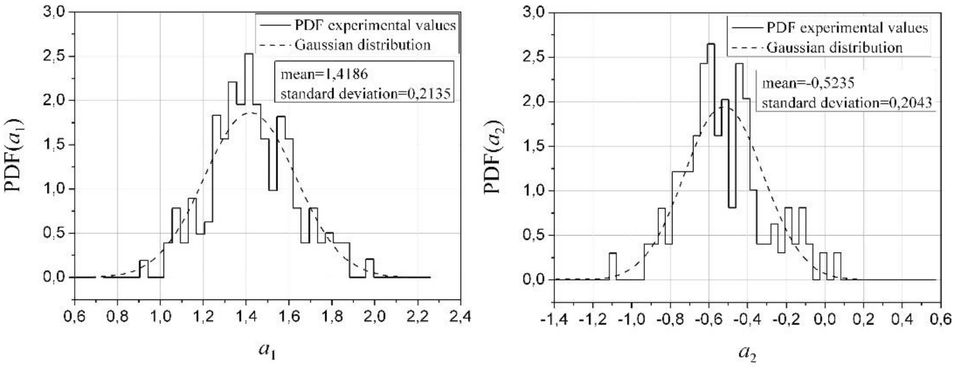

Fig. 4 The probability density function of predictor coefficients a_1 and a_2 for M=150

The probability density function (PDF) for normal distribution is given as [25, 33]:

$$f(a_1, a_2) = \frac{1}{\sigma_1\sqrt{2\pi}} \frac{1}{\sigma_2\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{a_1 - \bar{a}_1}{\sigma_1}\right)^2 - \frac{1}{2}\left(\frac{a_2 - \bar{a}_2}{\sigma_2}\right)^2 \right], \tag{18}$$

where σ_1 and σ_2 are the standard deviations, while $\bar{a}_1$ and $\bar{a}_2$ are the mean values of the predictor coefficients a_1 and a_2, respectively.

The probability of stability for the second-order system is derived from:

$$P_{S_2} = \frac{\iint\limits_{S_2} f\left(a_1, a_2\right) da_1 da_2}{\int\limits_{-\infty}^{\infty}\int\limits_{-\infty}^{\infty} f(a_1, a_2) da_1 da_2}, \tag{19}$$

where S_2 is the stability region of the prediction filter with the second-order predictor, while the integral in the denominator represents the total probability and is equal to 1. This gives the probability of stability form suitable for calculations.

The probabilities of stability and the signal-to-quantization noise ratios for different frame lengths are given in Table 1.

Table 1 The probability of stability (P_{S2}) and the signal-to-quantization noise ratio (SQNR) of the second-order prediction filter for different values of frame length

M [sample]	10	20	30	40	50	60	100	150
$\bar{a}_1$	0.984	1.125	1.220	1.231	1.281	1.329	1.377	1.419
σ_1	0.228	0.226	0.220	0.211	0.220	0.219	0.216	0.214
$\bar{a}_2$	-0.228	-0.288	-0.351	-0.356	-0.399	-0.439	-0.485	-0.524
σ_2	0.199	0.215	0.213	0.219	0.221	0.218	0.216	0.204
P_{S2}	0.790	0.699	0.664	0.658	0.644	0.634	0.629	0.629
SQNR [dB]	17.22	17.48	17.57	17.60	17.67	17.73	17.90	17.96

5. DISCUSSION

As we can see, the prediction filter is stable with some probability, unlike the ideal case when the predictor coefficients are perfectly adjusted. When the deviation from projected values of predictors is increasing, the probability of stability of the prediction filter is decreasing. However, the probability of stability is also decreasing when mean values of the predictor coefficients are approaching the limits of stability region S_2. Thus, we see that the probability of stability is the highest for M=10 samples (about 79%), although standard deviations of the parameters are not so small, but the mean values of coefficients are deep into the stability region. For M=150 we have the similar standard deviations (0.214, 0.204), but the probability of stability of the prediction filter is the smallest (62.9%). Therefore, the mean (desired) values of the predictor coefficients are closer to the boundary of the stability region more than in any other case.

The stability analysis presented above is a generalization of the classical stability considered at the beginning of this section. In the deterministic case (σ=0) we obtain a probability of stability equal to 100%, corresponding to the previous analysis for perfect systems.

We can see that the SQNR increases from M=10 up to M=150 while the probability of stability steadily decreases for the same range of frame lengths. We can conclude that SQNR is directly correlated with (1-P_S) ("probability of instability"). This is a very interested and useful conclusion. Systems where some important performance parameters (such as SQNR) are set close to the maximum may be approaching the limits of stability. Fig. 5 shows the measured dependencies of the signal-to-quantization noise ratio and the probability of stability on frame length, respectively. The aim is to optimally select the predictor coefficients in order to achieve the best system performance. The values obtained for the stability probabilities as well as the corresponding values for the signal noise can help with predetermined technical conditions.

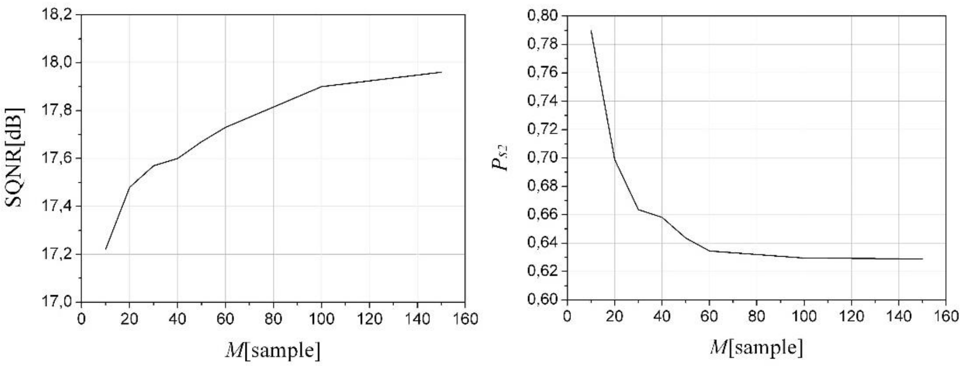

Fig. 5 Dependencies of SQNR and P_{S2} on M

6. CONCLUSIONS

Complete stability study of the prediction filter with the most commonly used second-order predictor was presented in this paper. It means that we gave relations describing the stability region via predictor coefficients, and then verified stability of the prediction filter for a concrete signal and obtained values for predictor coefficients. Finally, we generalized the stability study for a real system when the predictor coefficients are not perfectly adjusted (they are normally distributed around the projected value). Probability estimation was performed for the different frame lengths. The correlation between P_S and SQNR is given in the case of the second-order predictor in this paper. An increase in the value of the signal processing quality parameter, SQNR, with an increase in frame length is associated with a decrease in the probability of stability of the system, P_{S2}. This is very important information that has not yet been utilized so to achieve the best possible system performance when designing the system and selecting the predictor coefficient values.

Further stability study could be probability of stability estimation of the whole DPCM system. It must include a quantizer, the nonlinear part of the DPCM system. Anyway, the stability analysis of the prediction filter with predictor is the basis for this analysis.

Finally, the stability estimation of the prediction filter with predictor of higher order could be performed using the proposed method with classical integration as in this paper or by numerical integration using Monte Carlo method and find the correlation also between P_S and SQNR values.

This paper should form the basis for further research and application in today's popular science fields (machine learning, deep neural networks) where prediction models is very important.

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