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Compression of the Highly Correlated Measurement Signals using DPCM Technique

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***Abstract*—Compression of highly correlated measurement signals is considered using DPCM/ADPCM (Difference Pulse Code Modulation/Adaptive Difference Pulse Code Modulation) technique. It is important since very often transmission and storage of measurement signals are needed. Theory is applied on ECG (Electrocardiogram) signal, as an example of highly correlated signals. Very good performances are achieved: high compression rate and high improvement of performances are obtained.**

***Index Terms*—ECG signal compression, DPCM system, linear prediction, logarithmic μ-law quantizer.**

I. Introduction

Measurement signals should be stored or transmitted to some distant location for further processing. Due to limited resources, the compression of the measurement signals is desirable [1]. One of the most effective techniques for signal compression is the prediction, where the prediction of the current sample is formed based on the previous samples, and after that the difference between the current sample and its prediction is quantized and transmitted. The prediction is based on the fact that samples of the most real signals are correlated. Using prediction, decorrelation of the signal is done, i.e. the redundancy of the signal is removed. The efficiency of the prediction depends on the degree of correlation between samples: the prediction is more effective if samples are more correlated. DPCM technique is based on the linear prediction, where the prediction of the current sample is calculated as the linear combination of previous samples [1]–[4].

The linear prediction is mostly used due to its simplicity. If the degree of correlation between consecutive samples varies with time, then ADPCM can be used, where adaptation of the predictor coefficients is done according to the correlation between samples [3], [4].

In this paper the compression of the high correlated measurement signal is considered using prediction. The design of DPCM/ADPCM system is analyzed. Since the variance of the measurement signals can vary in time, the robust quantizer should be used as a part of DPCM system since it will give nearly constant SQNR regardless on the variance [3], [4]. We choose to use the logarithmic companding quantizer with μ compression law within DPCM system, due to its robustness. Furthermore, this logarithmic μ-law quantizer has one more advantage: its thresholds and representation levels can be expressed in the closed form, which is not the case with some other quantizers (for example, the integral equations should be solved to find thresholds and representation levels of the optimal companding quantizer) [3]. The quantizer is designed for Gaussian distribution since it can is usually used for modelling of measurement signals [5].

As an example of highly correlated signal, we consider ECG signal, which is a very important diagnostic method in cardiology. Much important information about heart working can be obtained from ECG signal and many diseases can be detected. Usually, multichannel recording of ECG signal is done, using up to 12 channels [6], which increases recording data. For diagnostic purposes, recording of ECG signal can be done continually in some period of time (e.g. Holter monitoring lasts at least 24 hours), collecting a large amount of data which should be stored. Also, due to development of telemedicine, ECG recording can be done out of hospital. Namely, the device for ECG monitoring can be mounted on the patient body, recording and transmitting ECG signal to the hospital. Therefore, in modern systems for ECG monitoring, a large amount of data should be stored or transmitted, which requires application of some compression technique [1], [7]–[10]. Due to the high correlation of ECG signal, high degree of compression can be achieved using prediction.

The main contribution of this paper is appropriate choice of quantizer (robust logarithmic quantizer) and optimization of correlation coefficient for ECG signal. Therefore, very good performances are obtained: high quality of quantized ECG signal and high level of compression. Our model gives better performances compared to the model described in [1], where Lloyd-Max quantizer was used.

This paper is organized as follows. Section II describes the DPCM system and provides some theoretical explanations. The logarithmic μ-law quantizer is described in Section III. Numerical results are presented in Section IV. Section V concludes the paper.

II. DPCM/ADPCM System

DPCM is a technique of converting an analog into a

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digital signal in which an analog signal is sampled and then the difference between the actual sample value and its predicted value is quantized. Predicted value of the actual sample is based on previous sample or samples. Basic concept of DPCM - coding a difference, is based on the fact that most source signals show significant correlation between successive samples so that quantizer uses redundancy in sample values which implies lower bit rate [3], [4].

The block diagram of the DPCM encoder is shown in Fig. 1(a)), which consists of the quantizer, inverse quantizer and predictor. Also, in Fig. 1(a)) the additional subsystem for the adaptive prediction is shown (buffer and predictor coefficients estimator which are connected with dotted lines), forming an ADPCM encoder. Firstly, we will consider the DPCM encoder. The main idea of the DPCM is to form the difference d_n between the current sample x_n and its predicted value $\hat{x}_n$, and to quantized and transmit this difference. Let's e_n denotes the quantization error which is made by quantization of the difference d_n. For the linear predictor, the predicted value $\hat{x}_n$ is calculated as a linear combination of the previous quantized samples y_n. The functioning of the DPCM system with the *P*-th order predictor is described with the following equations:

$$d_n = x_n - \hat{x}_n, \quad (1)$$

$$y_n = d_n + e_n + \hat{x}_n = x_n + e_n, \quad (2)$$

$$\hat{x}_n = \sum_{i=1}^{P} a_i y_{n-i}, \quad (3)$$

where a_i are predictor's coefficients.

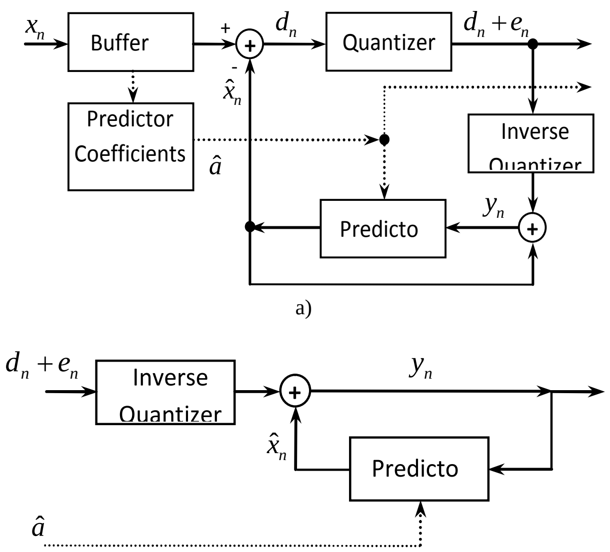

Fig. 1. DPCM/ADPCM system: a) Encoder; b) Decoder.

Due to simplicity, we will consider the first order predictor, where the predicted value $\hat{x}_n$ is calculated based on the quantized value y_{n-1} of the previous sample x_{n-1}, i.e. $\hat{x}_n = a_1 y_{n-1}$. For the first order predictor it holds that the coefficient of the predictor is equal to the correlation coefficient *ρ*, which represents the degree of the correlation between the two consecutive samples. It is defined as

$$\circ = \frac{\sum_{j=1}^{S-1} x_j x_{j+1}}{\sum_{j=1}^{S} x_j^2}, \quad (4)$$

where *S* denotes the total number of signal samples. In DPCM system, value of a_1 is defined in advance, according to the class of signals which are considered and it is known both in the encoder and in the decoder.

The quality of the prediction is defined with the prediction gain

$$\mathrm{G_p[dB]} = 10\log\left(\frac{\sum_{n=1}^{S} x_n^2}{\sum_{n=1}^{S} d_n^2}\right). \quad (5)$$

The degree of the correlation between consecutive samples can vary with time. Then, an ADPCM system should be used, where the adaptation of the coefficient of the predictor to the changes of the correlation coefficient *ρ* is done during the time. ADPCM works in the frame-by-frame basis. There is a buffer where frames of *M* samples are formed. The correlation coefficient for the samples in the buffer is estimate and the predictor coefficient a_1 is adjusted to this value. Also, this value should be quantized and transmitted to the receiver as additional information, for adaptation of the predictor in the decoder.

Figure 1(b) shows the DPCM/ADPCM decoder. In the feedback of the decoder is the predictor which is the same as the predictor in the feedback of the encoder. ADPCM decoder uses the additional information for the adaptation of the predictor coefficient.

The quality of the reconstructed signal for the DPCM system is defined with two parameters [3], [11], [12]:

$$\mathrm{SQNR_{DPCM}[dB]} = 10\log\left(\frac{\sum_{n=1}^{S} x_n^2}{\sum_{n=1}^{S}\left(x_n - y_n\right)^2}\right), \quad (6)$$

$$PRD_{DPCM}\,[\%] = 100\sqrt{\frac{\sum_{n=1}^{S}\left(x_n - y_n\right)^2}{\sum_{n=1}^{S} x_n^2}}. \quad (7)$$

For the ADPCM system, these two parameters are defined as

$$\mathrm{SQNR_{ADPCM}[dB]} = 10\log\left(\frac{\sum_{j=1}^{L}\sum_{n=1}^{M} x_{jn}^2}{\sum_{j=1}^{L}\sum_{n=1}^{M}\left(x_{jn} - y_{jn}\right)^2}\right), \quad (8)$$

$$PRD[\%] = 100\sqrt{\frac{\sum_{j=1}^{L}\sum_{n=1}^{M}\left(x_{jn}-y_{jn}\right)^{2}}{\sum_{j=1}^{L}\sum_{n=1}^{M}x_{jn}^{2}}}, \qquad (9)$$

where L is the number of frames. The aim of the designing process is to maximize SQNR or to minimize PRD.

III. Logarithmic Quantizer with μ Compression Law

For the quantization of the difference d_n between the actual value of the sample and its predicted value (Fig. 1a)), the logarithmic companding quantizer with μ compression law will be used, due to its robustness. Let's N denotes the number of quantization levels and $x_{\max}$ denotes the maximal amplitude of the quantizer. $x_{\max}$ is defined as

$$x_{\max} = k \cdot ±_{x}, \qquad (10)$$

where $±_{x}$ denotes the standard deviation of the original signal x, and k is the loading factor of the quantizer. Optimal value of k is found by minimization of the distortion.

The compression function of the μ-law logarithmic quantizer is defined with the following expression

$$c(x) = \frac{x_{\max}}{\ln(« + 1)} \ln\left(1 + \frac{«|x|}{x_{\max}}\right), \qquad (11)$$

where $|x| \le x_{\max}$.

Thresholds x_i and representation levels y_i of this quantizer in the positive part of the real axis are defined in the closed form in the following way

$$x_i = \frac{x_{\max}}{«}\left((« + 1)^{2i/N} - 1\right), \qquad (12)$$

where $i = 0, ..., N/2$.

$$y_i = \frac{x_{\max}}{«}\left((« + 1)^{(2i-1)/N} - 1\right), \qquad (13)$$

where $i = 1, ..., N/2$.

Thresholds and representation levels in the negative part of the real axis are symmetric to those in the positive part. The parameter μ determines the degree of the robustness of the quantizer. Higher values of μ provide more robust quantizers. Since we need very robust quantizer, we will use high value of $« = 255$. This value is also chosen since it is used in the G.711 standard.

IV. Numerical Results

Results shown in this section are obtained by the simulation of DPCM and ADPCM systems. These systems are applied for the compression of ECG signals, which are examples of highly correlated measurement signals. We use ECG signals from the referent MIT-BIH database [13].

The dependence of SQNR on the parameter k is shown in Fig. 2. for the two bit-rates R = 4 bps and R = 6 bps, where $R = \log_2 N$. We can see that the maximal SQNR is obtained for k = 1.2.

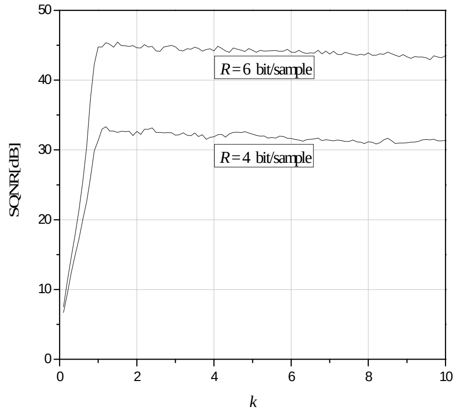

Fig. 2. The dependence of SQNR on the parameter *k*.

For DPCM system, the dependences of parameters SQNR and PRD on the predictor coefficient a_1 are shown in Fig. 3 and Fig. 4. Analysis is done for two values of the bit-rate: R = 4 bps and R = 6 bps.

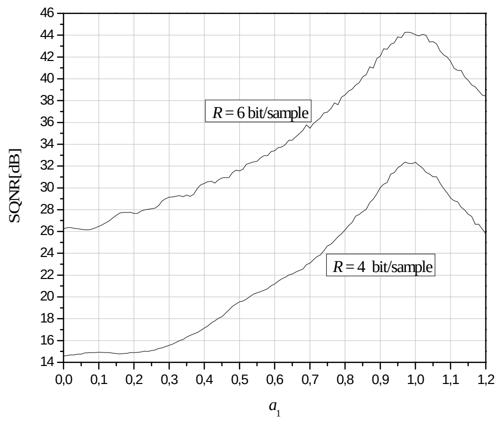

Fig. 3. The dependence of $SQNR_{DPCM}$ on the predictor coefficient a_1.

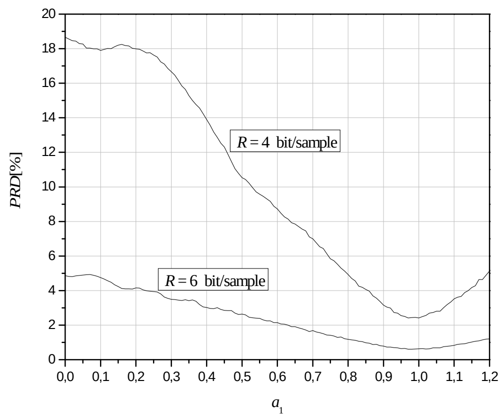

Fig. 4. The dependence of PRD_{DPCM} on the predictor coefficient a_1.

We can see that the optimal performances of the DPCM system are obtained for a_1 = 0.98, in both cases, using $SQNR_{DPCM}$ or PRD_{DPCM} as a measure of quality. These optimal performances are: $SQNR_{DPCM}$ = 32.27 dB and PRD_{DPCM} = 2.41 % for R = 4 bps and $SQNR_{DPCM}$ = 44.17 dB and PRD_{DPCM} = 0.61 % for R = 6 bps. High prediction gain G_p is achieved, i.e. high increasing of SQNR compared to the system without prediction (a_1 = 0). For R = 4 bps the prediction gain is G_p = 17.69 dB while for R = 6 bps the prediction gain is G_p = 17.91 dB.

Performances of our model are better than performances of the model described in [1]. In Fig. 5(b) of paper [1] is shown that performances PRD_{DPCM} = 3.39 % and PRD_{DPCM} = 4.72 % are achieved using the first and the second order predictor, respectively, for R = 4 bps , which is worse compared to PRD_{DPCM} of our model for 0.98 % and 2.31 %. Our model is better than the model in [1] from two reasons.

i) Firstly, we make better choice of quantizer – since ECG signal has very high dynamic range, it is much better to use the robust quantizer such us the logarithmic μ-law quantizer used in this paper than non-robust Lloyd-Max quantizer used in [1]. It can be seen from Fig. 5 that the logarithmic μ-law quantizer has much higher the average SQNR in the wide range of variances than Lloyd-Max quantizer. For example, in the range of variances $(\pm_0^2[\mathrm{dB}]-30\,\mathrm{dB}, \pm_0^2[\mathrm{dB}])$, the μ-law logarithmic quantizer has higher the average SQNR for 6.38 dB.

ii) Secondly, we optimize the correlation coefficient for ECG signal while in [1] they used coefficients from [3] which are optimal for speech but not for ECG signal.

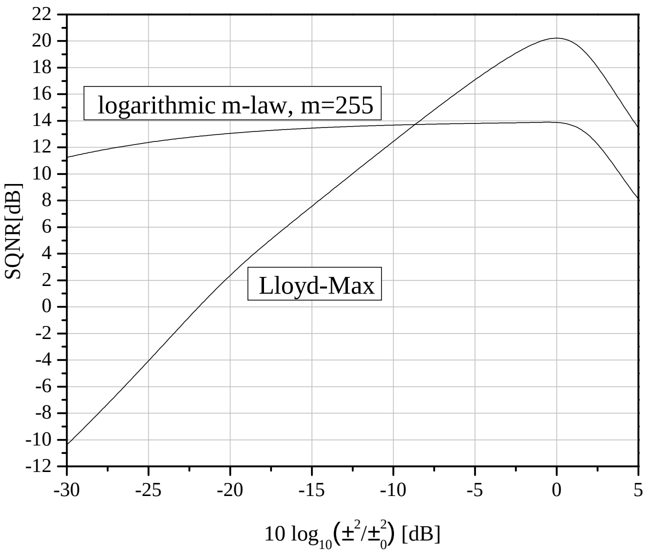

Fig. 5. Comparison of the quantizers characteristics.

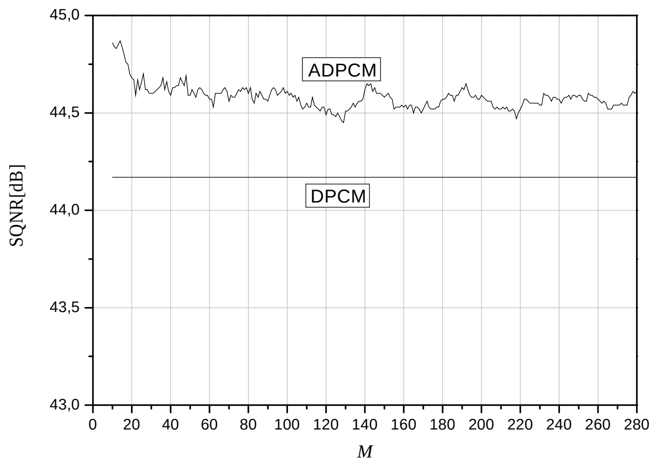

Fig. 6. The dependence of $SQNR_{DPCM}$ and $SQNR_{ADPCM}$ on the length of frame of the input signal.

Comparison of the DPCM and ADPCM system is shown in Fig 6. In this figure is given the dependence of $SQNR_{DPCM}$ and $SQNR_{ADPCM}$ on the length of frame of the input signal. $SQNR_{DPCM}$ is independent of the M and it is given for comparison with $SQNR_{ADPCM}$. We can see that $SQNR_{ADPCM}$ is slightly higher compared with $SQNR_{DPCM}$, up to 0.75 dB for lower values of M.

V. CONCLUSIONS

We considered high-quality transmission of ECG signal, which is achieved by appropriate choice of the quantizer, i.e. using the robust logarithmic μ-law quantizer since the ECG signal is nonstationary. Also, due to the optimization of the correlation coefficient of ECG signal, high value of prediction gain (about 18 dB) is achieved. It was shown that this model has better performances than the model described in [1]. ADPCM slightly improves performances compared to DPCM, for about 0.5 dB, but ADPCM system is more complex. Since ECG signal is highly correlated and correlation coefficient is almost constant, it is not necessary to use ADPCM instead of DPCM since the increasing of complexity is higher than the improvement of performances.

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