ADC Testing With Verification

Balázs Fodor and István Kollár, *Fellow, IEEE*

***Abstract*—An important method for analog-to-digital-converter (ADC) testing is sine wave fitting. In this method, the device is excited with a sine wave, and another sine wave is fitted to the samples at the output of the ADC. The acquisition device can be analyzed by looking at the differences between the fitted signal and the samples. The fit is done using the least-squares (LS) method. If the samples of the error (the difference between the fitted signal and the samples) were random and independent of each other and of the signal, the LS fit would have very good properties. However, when the error is dominated by quantization error, particularly when a low bit number is used or the level of the measured noise is low, these conditions are not fulfilled. The estimation will be biased, and therefore, it must be corrected. The independence of the error samples is more or less true if the sine wave is noisy or dither is used. In these cases, the correction is not necessary. Therefore, it is reasonable to analyze the effect of the potentially unnecessary correction to noisy data, and it is desirable to determine the magnitude of the noise from the measurements. In this paper, these two questions are investigated. The variance of the corrected estimator is investigated, and a new noise estimation method is developed and analyzed.**

***Index Terms*—ADC test, analog-to-digital converter (ADC), effective number of bits (ENOB), elimination of samples, IEEE Standard 1241-2000, least-squares (LS) fit, noise estimation, sine wave fitting, sine wave test.**

I. Introduction

SINE FITTING may be the most important method in the testing of analog-to-digital converters (ADCs) under IEEE Standard 1241-2000. The essence of this method is the fitting of a sine wave to the samples that appear at the ADC output. The errors of the converter can be analyzed by looking at the difference between the fitted signal and the samples.

Fitting is executed using the least-squares (LS) method. Error $\mathbf{e}$ is defined as the difference between observations $\mathbf{y}$ and model $\mathbf{m}$. The observations are the samples, and the model is the test signal, whose parameters are unknown. Minimizing the sum of e_n^2, the LS fit is performed, i.e.,

$$\min_m \sum_n (y_n - m_n)^2 = \min_m \sum_n e_n^2. \quad (1)$$

Manuscript received July 5, 2007; revised May 23, 2008. First published August 1, 2008; current version published November 12, 2008. This work was supported by the Hungarian Scientific Research Fund (OTKA) under Grant TS49743. The Associate Editor coordinating the review process for this paper was Dr. Richard Thorn.

B. Fodor is with the Institute of Communications Technology, Braunschweig Technical University, 38106 Braunschweig, Germany (e-mail: balazs.fodor@web.de).

I. Kollár is with the Department of Measurement and Information Systems, Budapest University of Technology and Economics, 1521 Budapest, Hungary (e-mail: kollar@mit.bme.hu).

Digital Object Identifier 10.1109/TIM.2008.928404

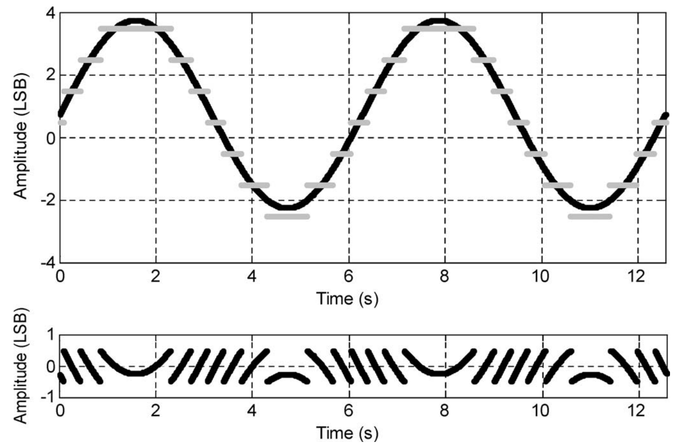


Fig. 1. Original sine wave, quantized samples, and quantization error ($B = 3$ bits, dc $\neq 0$).

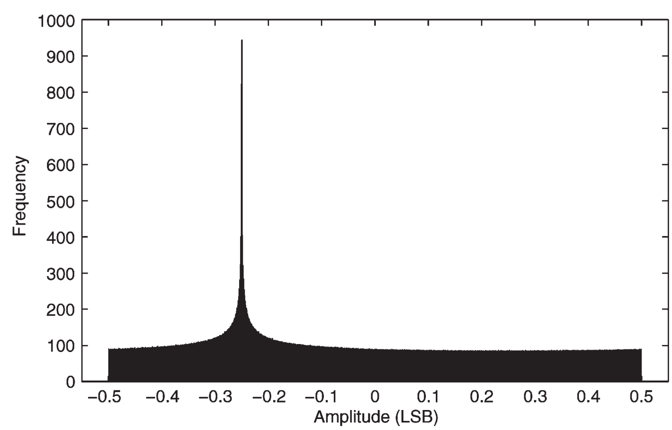


Fig. 2. PDF of the quantization error. ($B = 3$ bits, and the dc component of the sine is nonzero.)

The LS method has very good properties, particularly when the error is random and zero-mean Gaussian, and the samples are independent. However, when error $\mathbf{e}$ is dominated by quantization noise, neither of these is true. The main problem is that, even by ideal quantization, the quantization error strongly depends on the input signal (see Fig. 1).

Therefore, the estimated parameters, particularly the estimated amplitude, will usually be biased. An easy-to-see example is the case when the dc level of the input signal is not zero. The peak in the probability density function (pdf) of the quantization error (the part that is related to the peaks of the sine wave) is no longer at the middle, and the mean value of the error is no longer zero (see Fig. 2).

This causes an error in the amplitude estimation. However, the amplitude estimation can still be erroneous, even if the error distribution is symmetric to zero.

A possible solution to avoid this mis-fit is to eliminate the samples that belong to the almost-constant curves in the quantization error [2], [3]. This method indeed decreases bias; however, it increases the variance of the estimator since information is lost because of the elimination of some samples. Therefore, it is reasonable to analyze how the variance changes as a consequence of sample elimination.

If the sine wave is noisy or dither is used, the samples of the error will be more or less independent of the input signal. The estimation will be unbiased, and no manipulation, such as sample elimination, is necessary. However, one needs to have information about the signal-to-noise ratio (SNR) at the input to know whether sample elimination needs to be used. If sample elimination is blindly applied in the noisy case, the otherwise-zero bias remains unchanged, but the variance of the estimation increases. This is not good. In the second part of this paper, a new signal-to-noise estimation method that works for the ADC output samples only will be shown. When the SNR is known, one can decide whether the sample elimination is necessary.

The basis of the noise-estimation method is the measurement of the oscillatory parts in the output samples. The length of these oscillations depends on the magnitude (standard deviation) of the noise. This is the best method of estimation because the available information on the noise is considered.

II. LS Fit

According to the IEEE standard [1], the following expression is minimized:

$$\min_{A_0,B_0,C_0,\omega} \sum_{n=1}^{M} e_n^2 = \min_{A_0,B_0,C_0,\omega} \sum_{n=1}^{M} [y_n(n) - A_0\cos(\omega t_n) - B_0\sin(\omega t_n) - C_0]^2 = \min_{A_0,B_0,C_0,\omega} (\mathbf{y}-\mathbf{D}\mathbf{x})^T(\mathbf{y}-\mathbf{D}\mathbf{x}) \quad (2)$$

where $\mathbf{y}$ is the vector of samples, and M is the length of $\mathbf{y}$. If ω is known, three-parameter sine fitting can be applied. Minimizing the expression, the estimator of the input signal is obtained as

$$\hat{\mathbf{x}} = (\mathbf{D}^T\mathbf{D})^{-1}\mathbf{D}^T\mathbf{y} = \begin{bmatrix} \hat{A}_0 \\ \hat{B}_0 \\ \hat{C}_0 \end{bmatrix}. \quad (3)$$

Assuming an independent identically distributed error, the covariance matrix of the estimator is given as follows:

$$\mathrm{cov}\{\hat{\mathbf{x}},\hat{\mathbf{x}}\} = E\left\{(\hat{\mathbf{x}}-\mathbf{x})(\hat{\mathbf{x}}-\mathbf{x})^T\right\} = \sigma^2\left(\mathbf{D}^T\mathbf{D}\right)^{-1} \quad (4)$$

where σ^2 is the variance of noise $\mathbf{e}$. The elements of matrix $(\mathbf{D}^T\mathbf{D})^{-1}$ are given as follows:

$$\mathrm{cov}\{\hat{\mathbf{x}},\hat{\mathbf{x}}\} = \sigma^2 \begin{bmatrix} \mathrm{var}\{\hat{A}_0\} & \mathrm{cov}\{\hat{A}_0,\hat{B}_0\} & \mathrm{cov}\{\hat{A}_0,\hat{C}_0\} \\ \mathrm{cov}\{\hat{B}_0,\hat{A}_0\} & \mathrm{var}\{\hat{B}_0\} & \mathrm{cov}\{\hat{B}_0,\hat{C}_0\} \\ \mathrm{cov}\{\hat{C}_0,\hat{A}_0\} & \mathrm{cov}\{\hat{C}_0,\hat{B}\} & \mathrm{var}\{\hat{C}_0\} \end{bmatrix}. \quad (5)$$

If sampling is coherent, i.e., the sampled record contains an integer number of periods, the columns of $\mathbf{D}$ are orthogonal; thus, the entries outside the main diagonal in the covariance matrix become zero.

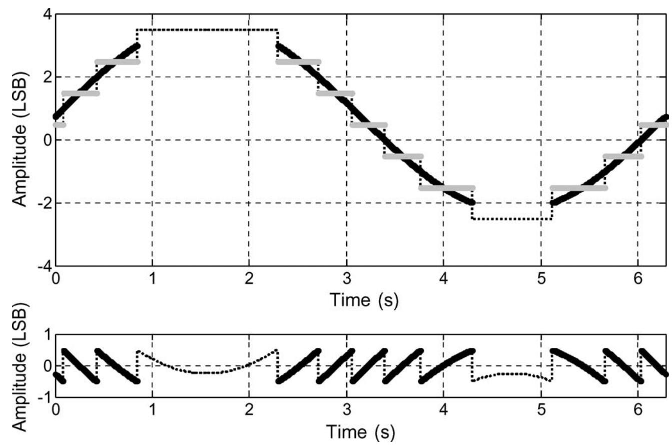


Fig. 3. Effect of sample elimination from $\mathbf{y}$, as illustrated in the time-domain quantization error.

The calculated main diagonal entries are given as follows:

$$\mathrm{var}\{\hat{A}_0\} = \frac{1}{\sum_{n=1}^{M}\cos^2(\omega t_n)} = \frac{2}{M} \quad (6)$$

$$\mathrm{var}\{\hat{B}_0\} = \frac{1}{\sum_{n=1}^{M}\sin^2(\omega t_n)} = \frac{2}{M} \quad (7)$$

$$\mathrm{var}\{\hat{C}_0\} = \frac{1}{\sum_{n=1}^{M}1} = \frac{1}{M}. \quad (8)$$

For noncoherent sampling or when samples are eliminated, the orthogonality of the columns of $\mathbf{D}$ is not true. This means that the estimated parameters become correlated.

Thus, in the general case, when eliminating samples, the sums in (6)–(8) decrease, and the variances increase.

III. Increase in the Variance When Eliminating Some Samples

When the phase φ of the excitation signal is zero (a simplifying assumption without loss of generality), $\hat{A}_0$ becomes the amplitude estimator, i.e.,

$$\hat{\mathbf{x}} = \begin{bmatrix} \hat{A}_0 \\ \hat{B}_0 \\ \hat{C}_0 \end{bmatrix} = \begin{bmatrix} \hat{A}\cdot\cos(0) \\ -\hat{A}\cdot\sin(0) \\ \hat{C} \end{bmatrix} = \begin{bmatrix} \hat{A} \\ 0 \\ \hat{C} \end{bmatrix}. \quad (9)$$

For simplicity, the number of periods has been reduced to one. The effect of the sample elimination is shown in Fig. 3.

When the input signal has a dc component, the quantization error is not of zero mean (asymmetric). When eliminating the samples from the observations, the distribution of the quantization error becomes more or less uniform (see Fig. 4), leading to the ideal quantization noise model.

According to the observation equation ($\mathbf{y} = \mathbf{D}\cdot\mathbf{x}$), the elimination of samples from $\mathbf{y}$ influences matrix $\mathbf{D}$. Therefore,

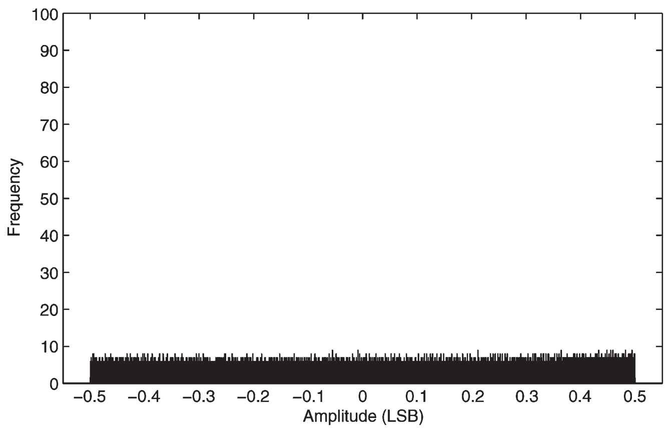


Fig. 4. PDF of the quantization error after the elimination.

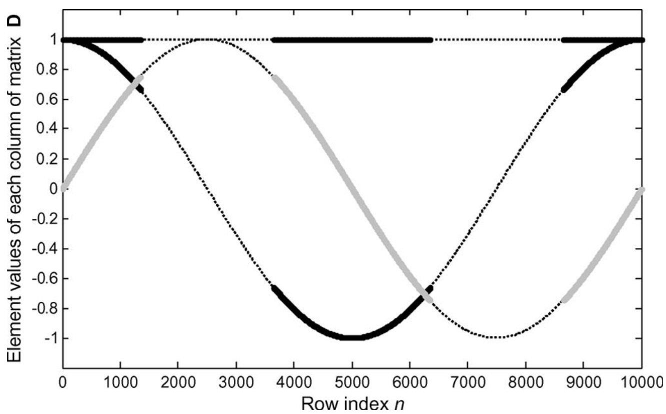


Fig. 5. Elimination of rows (i.e., the values from the cosine, sine, and ones series [1, eq. (17)]) from matrix $\mathbf{D}$ ($\varphi = 0$). (Dotted line) Eliminated samples. (Solid line) Remaining samples.

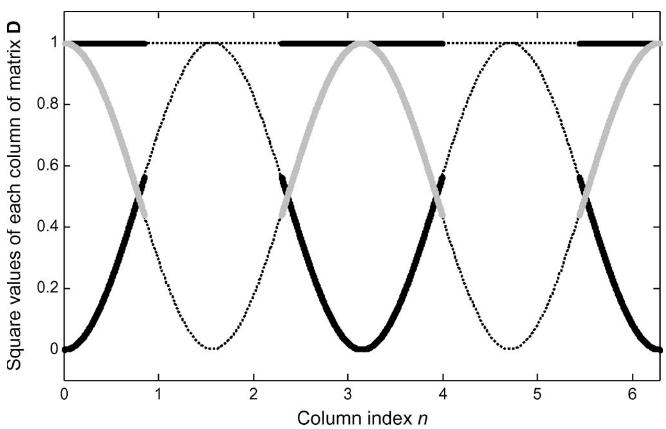


Fig. 6. Change of each element (denoted by the sum of each curve) in the main diagonal of $\mathbf{D}^T\mathbf{D}$ ($\varphi = 0$). (Dotted line) Eliminated samples. (Solid line) Remaining samples.

if samples are eliminated from $\mathbf{y}$, the corresponding rows from $\mathbf{D}$ should also be eliminated. This is shown in Fig. 5.

The elimination of rows from matrix $\mathbf{D}$ changes the main diagonal values of $\mathbf{D}^T\mathbf{D}$ (see Fig. 6).

After dropping some samples from the observations, it is interesting to investigate the change in the variance of the individual parameters.

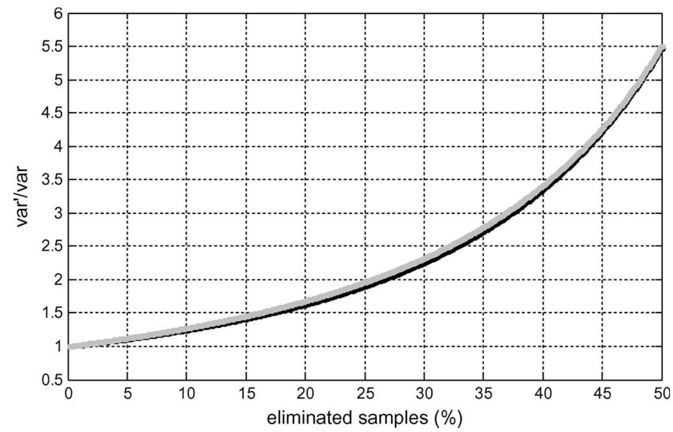


Fig. 7. Ratio of the amplitude A variance versus the proportion of the eliminated samples. (Gray curve) Approximate formula. (Black curve) Theoretical formula.

A. Change in $\mathrm{var}\{\hat{A}_0\}$

Assume that $k/2$ ($k < M$) maximum and minimum samples of the observation are eliminated. When $\varphi = 0$, and just one period was measured, the samples are eliminated in a symmetrical manner around positions $M/4$ and $3M/4$. Therefore, the following equation is obtained:

$$\mathrm{var}\left\{\hat{A}_0^{\mathrm{elim}}\right\} = \frac{1}{\sum_{n=1}^{M}\sin^2(\omega t_n) - 2\cdot\sum_{i=M/4-k/4}^{M/4+k/4}\sin^2(\omega t_i)}. \tag{10}$$

This causes a significant modification (increase in the variances) because the samples are left from near the maximum of the $\sin^2$ function. After some manipulation, the new variance is obtained as

$$\mathrm{var}\left\{\hat{A}_0^{\mathrm{elim}}\right\} = \frac{2}{M - k - 2\sum_{n=-k/4}^{k/4}\cos(2\omega t_n)}. \tag{11}$$

To see how much of the variance of the amplitude estimator increased, it is assumed that k samples are left from M (which are all close to $M/4$ and $3M/4$), i.e.,

$$\frac{\mathrm{var}\left\{\hat{A}_0^{\mathrm{elim}}\right\}}{\mathrm{var}\{\hat{A}_0\}} = \frac{1}{1 - \frac{k}{M} - \frac{2}{M}\sum_{n=-k/4}^{k/4}\cos(2\omega t_n)}. \tag{12}$$

This can be approximated as

$$\frac{\mathrm{var}\left\{\hat{A}_0^{\mathrm{elim}}\right\}}{\mathrm{var}\{\hat{A}_0\}} \cong \frac{1}{\left(1 - 1.15\cdot\frac{k}{M}\right)^2}. \tag{13}$$

In Fig. 7, the result of both formulas can be seen. According to this plot, the variance increases to a value that is 1.5 times larger when approximately 17% of the samples are left and doubles when about 26% of the samples are left. Fortunately, these values are not reached with practical bit numbers. The

TABLE I
WORST-CASE VALUES OF THE ELIMINATING RATIOS ACCORDING TO THE ELIMINATION ALGORITHM

ADC bit number	eliminated samples
6	18.65%
8	9.22%
10	4.59%
12	2.29%
16	0.57%
24	0.04%

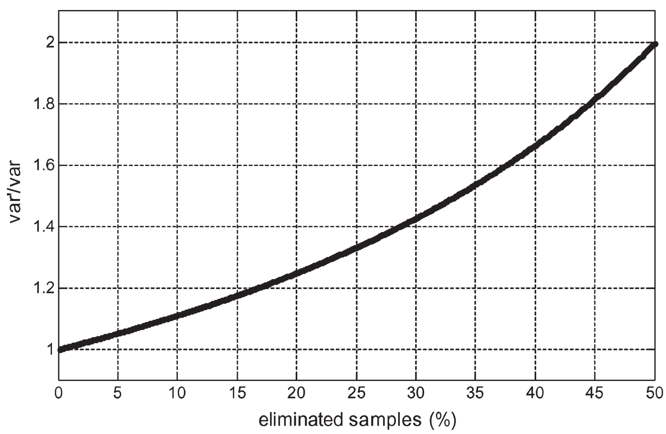


Fig. 8. Ratio of the offset C variance versus the proportion of the eliminated samples.

worst-case values, according to the elimination algorithm [2], [3], are given in Table I.

B. Change in $\mathrm{var}\{\hat{C}_0\}$

The new variance of $\hat{C}_0$ after eliminating k samples is

$$\mathrm{var}\{\hat{C}_0^{\mathrm{elim}}\} = \frac{1}{\sum_{n=1}^{M} 1 - \sum_{i=1}^{k} 1} = \frac{1}{M-k}. \tag{14}$$

The ratio of the variances is

$$\frac{\mathrm{var}\{\hat{C}_0^{\mathrm{elim}}\}}{\mathrm{var}\{\hat{C}_0\}} = \frac{M}{M-k} = \frac{1}{1-\frac{k}{M}}. \tag{15}$$

Fig. 8 shows how the ratio of the offset C variances increases after the elimination of the observation samples.

IV. SIMULATION

The previous calculations have been verified by simulation using MATLAB. In these simulations, only the worst case is considered, i.e., the four outmost histogram bins of the observation samples have the maximum values. In this scenario, the samples correspond to these four outmost histogram bins (i.e., the most samples surrounding the peaks) are eliminated.

In the simulation, all observation data are contaminated by additive Gaussian noise. The standard deviation σ of this noise was approximately equal to the least significant bit (LSB). The condition $\sigma > 0.5$ LSB assures that Quantization Theorem II [5] is satisfied. The quantization error was, therefore, approximately uniformly distributed. As expected, the input signal was uncorrelated with $\mathbf{e}$.

The properties of the input signal and the quantizer during the simulation are given as follows:

1) $M = 1000$ (number of samples);
2) $A = 1$, $\varphi = 0$, and $C = 0$;
3) quantizer: 6 bits, linear, and ideal.

The simulation routine with sample elimination was repeated 100 times, and that without elimination was repeated 100 times (using all the samples for the fit). The simulation results are given as follows.

A. Simulation Results With All Samples

$$\mathrm{mean}\{\hat{\mathbf{x}}\} = \begin{bmatrix} 0.9771 \\ -0.0001 \\ 0.0002 \end{bmatrix} \rightarrow \begin{array}{c} A = 0.9771 \\ \varphi = 0.0054^\circ \\ C = 0.0002 \end{array} \tag{16}$$

$$\mathrm{cov}\{\hat{\mathbf{x}}, \hat{\mathbf{x}}\} = \sigma^2 \begin{bmatrix} 2\cdot 10^{-3} & 0 & 0 \\ 0 & 2\cdot 10^{-3} & 0 \\ 0 & 0 & 1\cdot 10^{-3} \end{bmatrix}. \tag{17}$$

B. Simulation Results With Sample Elimination

Number of ADC bits: see previous discussion.
Mean number of the eliminated samples: 173.
Mean number of the remaining samples: $M_{\mathrm{elim}} = 827$.

$$\mathrm{mean}\{\hat{\mathbf{x}}\} = \begin{bmatrix} 0.9718 \\ 0.006 \\ 0.0002 \end{bmatrix} \rightarrow \begin{array}{c} A = 0.9718 \\ \varphi = -0.3525^\circ \\ C = 0.0002 \end{array} \tag{18}$$

$$\mathrm{cov}(\hat{\mathbf{x}}, \hat{\mathbf{x}}) = \sigma^2 \begin{bmatrix} 3.0024\cdot 10^{-3} & 7.7\cdot 10^{-6} & 4.8\cdot 10^{-6} \\ 7.7\cdot 10^{-6} & 2.026\cdot 10^{-3} & 5\cdot 10^{-7} \\ 4.8\cdot 10^{-6} & 5\cdot 10^{-7} & 1.2097\cdot 10^{-3} \end{bmatrix}. \tag{19}$$

The variances were increased. Using (12)

$$\sigma^2 \mathrm{var}\left\{\hat{A}_0^{\mathrm{elim}}\right\} = \sigma^2 \frac{2}{M-k-2\sum_{n=-k/4}^{k/4} \cos(2\omega t_n)} = 0.003\sigma^2. \tag{20}$$

Comparing this to (19), it can be seen that the formula works well.

C. Comparison of the Two Cases

The ratio of the two variances is given as follows:

$$\frac{\sigma^2 \mathrm{var}\left\{\hat{A}_0^{\mathrm{elim}}\right\}}{\sigma^2 \mathrm{var}\{\hat{A}_0\}} = \frac{0.0030024\sigma^2}{0.002\sigma^2} \cong 1.5. \tag{21}$$

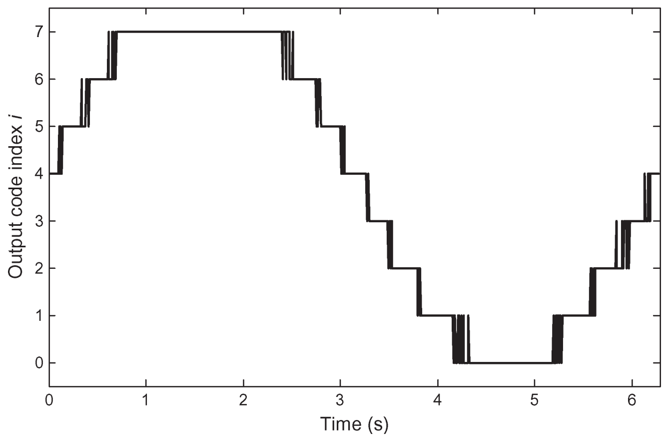


Fig. 9. Output samples of a 3-bit ADC ($\sigma_{\text{additive noise}} = 0.1$ LSB).

This means that about 50% more samples are needed to reach the same variance, i.e.,

$$M_{\text{needed}} = \frac{\text{var}_{\text{elim}}}{\text{var}} M_{\text{elim}} = 1.5 M_{\text{elim}}. \tag{22}$$

V. Estimation of the Noise Level From the Output Samples

The preceding analysis illustrates that, in the presence of noise, sample elimination increases the variance. On the other hand, noise removes bias; thus, with noise, sample elimination is not necessary. Therefore, it is of interest to determine the input noise level from the output samples without extra measurements.

The model is as follows: We have an input that is a sine wave, which is corrupted by Gaussian white noise and quantized by an ADC. In the rest of the examples, the ADC is considered ideal. However, later, it will be shown that this is not a requirement. A typical output signal is shown in Fig. 9.

The noise is exhibited by the oscillating parts around the quantization levels. It makes sense to analyze the length of the oscillations because their length directly depends on the standard deviation of the noise.

In Fig. 10, one oscillatory part can be seen. The local slope of the sine is more or less constant, and the change of the sine is much slower than the change of the noise. In this case, it can be said that the sine is a "drift" component of the noise.

The lengths of the oscillations are difficult to extract because of their stochastic behavior. Therefore, these lengths will be determined based on the "standard deviations" of the oscillatory patterns. For this, first, the centers of the oscillatory parts $\mathbf{z}$ have to be calculated. An example of oscillatory parts is shown in the lower graph of Fig. 10. $\mathbf{z}$ is a part of the observations (output samples) $\mathbf{y}$, and $\mathbf{z}_i$ contains the information that the ADC output code is i or $i+1$ (see the lower graph of Fig. 10). $\mathbf{z}$ should be determined for each neighbor output level $(i = 1, \ldots, 2^B - 1)$ and for each period of the excitation sine wave, i.e.,

$$z_i = \left\{z_n^i\right\}_{n=1}^{N} \tag{23}$$

where n is the number of the current samples from vector $\mathbf{z}_i$, and N is the length of $\mathbf{z}_i$. A reasonable tool for determining the center point of each oscillatory part $\mathbf{z}_i$ is calculating the "center of mass" of the absolute transition vector $\mathbf{d}_i$, which is defined as

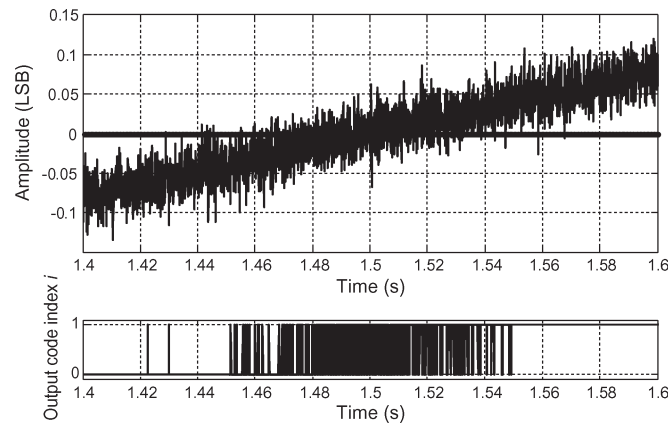


Fig. 10. Synthesis of an oscillatory part at the output of the ADC. (Upper) Input signal of the ADC. The horizontal black line at the zero amplitude is a comparison level of the ADC. (Lower) Output signal of the ADC.

$$\mathbf{d}_i = \left\{d_n^i\right\}_{n=1}^{N-1} \tag{24}$$

$$d_n^i = \begin{cases} 0, & z_n = z_{n+1} \\ 1, & \text{else} \end{cases}, \qquad n = 1, \ldots, N-1 \tag{25}$$

where d_n^i is one element from $\mathbf{d}_i$, and N is the length of $\mathbf{z}_i$. The central point of one oscillatory part can be determined as follows:

$$c_i = \frac{\sum_{n=1}^{N-1} n \cdot d_n^i}{\sum_{n=1}^{N-1} d_n^i} \tag{26}$$

where d_n^i is an element of the absolute transition vector $\mathbf{d}_i$. The length of an oscillatory part can be determined as follows:

$$\sigma_i = \sqrt{\frac{1}{N-2} \sum_{n=1}^{N-1} d_n^i (c_i - n)^2}. \tag{27}$$

The oscillation lengths obtained must be averaged to have a good estimate of the standard deviation of the noise. For this, they need to be weighted because the lengths of the oscillations depend on the local slope of the sine. This weighting can be done using the local slope of the sine. The dependence of this average on the standard deviation of the noise can be seen in the simulation results in Fig. 11.

The nature of this curve is similar for all the bit numbers investigated (see Table II).

If this curve is known (as it is from Fig. 11), the standard deviation of the noise can be computed from the measured length of the oscillations.

A possible approximation of the curve in Fig. 11 can be done by making an LS fit with a cosine function

$$f_i = A \cdot \cos\left(2 \cdot \pi \cdot P \cdot \frac{i}{M}\right) + C. \tag{28}$$

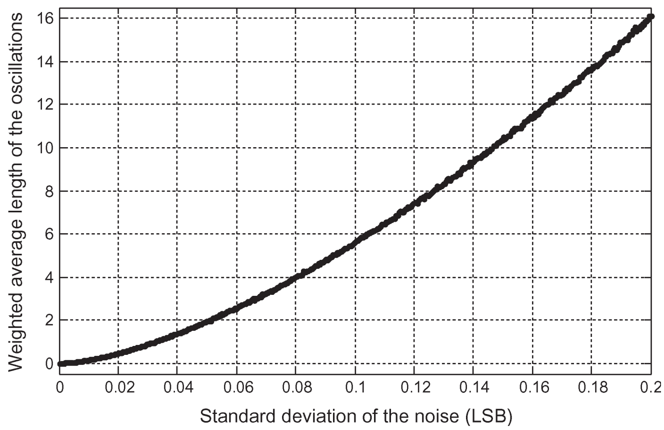


Fig. 11. Standard deviation of the noise versus the average length of the oscillations ($M = 8000$ samples, $B = 3$ bits).

TABLE II
PARAMETERS OF THE FITTED COSINE (THE NUMBER OF REGISTERED ADC OUTPUT SAMPLES IS $M = 8000$)

	Amplitude (sample) A	Period (LSB) P	Offset (sample) C
3 bit	-10.432	0.32752	10.873
4 bit	-3.8301	0.32563	3.9769
5 bit	-1.4071	0.32087	1.4511
6 bit	-0.52826	0.30706	0.53915
8 bit	-0.0887	0.23132	0.0885

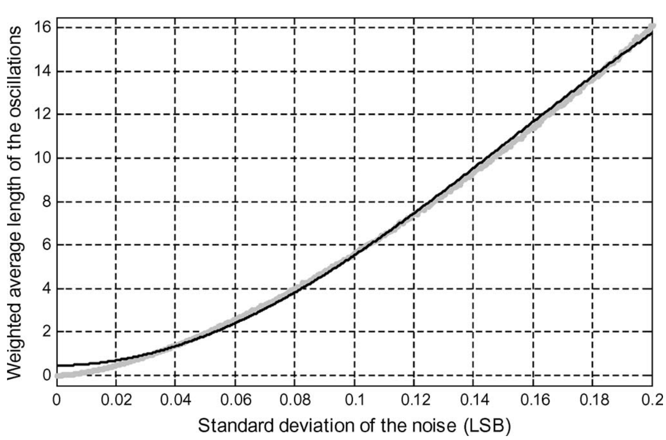


Fig. 12. Comparison of the simulation results and the modified fitted curve ($M = 8000$ samples, $B = 3$ bits).

The parameters (amplitude A, period P, and offset C) of the cosine can be found in Table II.

The phase of the cosine is zero in all cases.

The LS method causes an apparent error at the beginning of the fitted curve. A solution to this is to force the error around zero to be small in the fit (amplitude $A =$ offset C). The modified fit can be seen in Fig. 12.

An approximate formula for the amplitude of the cosine is given as follows:

$$\hat{A} = \hat{C} \cong 1.246 \cdot 10^{-4} \cdot M \cdot (-210.2 \cdot e^{-b}) \tag{29}$$

where M is the number of samples, and b is the number of bits.

To estimate the SNR using the observations (the output samples of an ADC), four steps can be suggested.

1) Measure the oscillation lengths at the output of the ADC.
2) Form a weighted average: The weights are the local slope of the sine.
3) Determine the cosine curve using Table II or (28) and (29).
4) Determine the standard deviation of the noise with the help of the inverse cosine function.

The signal-to-noise estimation was evaluated by the data measured on ADC-type DC270 (8-bit resolution) [7]. Only a data portion of 8000 samples was taken. The center and the length of the oscillatory parts for every ADC output bin were calculated using (26) and (27), respectively. For each ADC output bin, the length of the oscillations was weighted with the local slope of the sine, which was fitted to the output samples. The average of the weighted lengths was 0.0343, which corresponds to a standard deviation of 0.1258, according to Table II and (28). By considering the typical case of the ADC testing, in which the device under test must be directly excited with a low-noise sine generator [1], the low standard deviation principally confirms the functionality of the proposed algorithm.

VI. CONCLUSION

The sample elimination method [2], [3] can be well used for the enhancement of the sine wave fit. The samples around the sine peaks have to be eliminated, and to have estimates with the same variance, more samples have to be taken. The necessary number of samples can be determined from the increase in the variance.

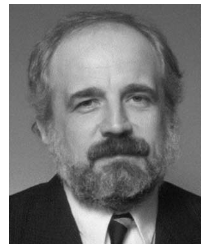
To verify the results without sample elimination, the standard deviation of the noise has to be measured. For this, an algorithm that is usable in practice was given.

REFERENCES

[1] *IEEE Standard for Terminology and Test Methods for Analog-to-Digital Converters*, IEEE Std. 1241-2000, Dec. 6, 2000.
[2] I. Kollár and J. J. Blair, "Improved determination of the best fitting sine wave in ADC testing," *IEEE Trans. Instrum. Meas.*, vol. 54, no. 5, pp. 1978–1983, Oct. 2005.
[3] I. Kollár, "Improved residual analysis in ADC testing," in *Proc. 13th Int. Symp. Meas. Res. Ind. Appl., 9th Workshop ADC Modeling Test.*, Athens, Greece, Sep. 29–Oct. 1, 2004, pp. 869–874.
[4] B. Widrow and I. Kollár, *Quantization Noise*, ch. 19: Dither, Cambridge, U.K.: Cambridge Univ. Press, Jul. 2008. [Online]. Available: http://www.mit.bme.hu/books/quantization/
[5] B. Widrow, I. Kollár, and M.-C. Liu, "Statistical theory of quantization," *IEEE Trans. Instrum. Meas.*, vol. 45, no. 2, pp. 353–361, Apr. 1996.
[6] B. Fodor and I. Kollár, "ADC testing with verification," in *Proc. IMTC*, Warsaw, Poland, May 1–3, 2007, pp. 1–6.
[7] *ADC Test Data Evaluation Program for Matlab*. [Online]. Available: http://www.mit.bme.hu/projects/adctest/

Balázs Fodor was born in Esztergom, Hungary, in 1982. He received the M.S. degree in electrical engineering from the Technical University of Budapest, Budapest, Hungary, in 2007. He is currently working toward the Ph.D. degree with the Institute of Communications Technology, Braunschweig Technical University, Braunschweig, Germany.

His current research interests include digital signal processing and digital speech enhancement.



István Kollár (M'87–SM'93–F'97) was born in Budapest, Hungary, in 1954. He received the M.S. degree in electrical engineering from the Technical University of Budapest, in 1977 and the "Candidate of Sciences" and "Doctor of the Academy" degrees from the Hungarian Academy of Sciences, Budapest, in 1985 and 1998, respectively.

From 1989 to 1990 and during the spring of 2005, he was a Visiting Scientist with the Vrije Universiteit Brussels, Brussels, Belgium. From 1993 to 1995, he was a Fulbright Scholar and Visiting Associate Professor with the Department of Electrical Engineering, Stanford University, Stanford, CA. He is currently a Professor of electrical engineering with the Department of Measurement and Information Systems, Budapest University of Technology and Economics. He has authored about 130 scientific papers and the Frequency-Domain System Identification Toolbox for MATLAB. He is a coauthor of the books *Technology of Electrical Measurements* (New York: Wiley, 1993) and *Quantization Noise* (Cambridge University Press, 2008). His research interests are digital and analog signal processing, measurement theory, and system identification.

Dr. Kollár is an active member of the European Project for ADC-based devices Standardization (EUPAS) of the International Measurement Confederation (IMEKO). He was also the Technical Cochairman of the IEEE Instrumentation and Measurement Technology Conference in 2001.