Abstract—A new method is presented for the calibration and the linearity testing of analog-to-digital converters (ADCs) and dc digital instruments, such as digital voltmeters (DVMs). The test is truly static, because it uses only dc voltages with a small superimposed noise (dithering). It is much faster than that described in the IEEE Standard 1057/94 since it uses a minimal number of test signals and acquired samples in a theoretically nearly optimal manner, i.e., maximum-likelihood estimation. In addition, contrary to the test described in the IEEE Standard 1241/00, it allows offline measurements and testing of stand-alone instruments, such as DVMs. Another advantage of the proposed method is that the resolution requirements for the source of test signals are relaxed. After a review of the state of the art, this paper provides the mathematical derivation of the employed estimator. Simulations, theoretical analyses, and experimental results are also provided to illustrate the performances of the proposed test method.

Index Terms—Analog-to-digital conversion, digital voltmeters (DVMs), electric variables measurement, maximum-likelihood (ML) estimation, nonlinearities, parameter estimation, testing.

I. INTRODUCTION

TESTING the performance of analog-to-digital converters (ADCs) is of essential importance for a wide range of applications, including communication devices, measuring instruments, and radars. In recent years, attention has mainly been focused on testing under dynamic conditions, because actual applications often involve fast-varying signals, which are much more degraded by real-world ADCs, compared with constant signals used in static tests. Nonetheless, for some applications, the static test is either the most appropriate or the only possible choice. An example is the calibration of digital voltmeters (DVMs) and, in general, instruments for dc electrical quantities. It is well known that a periodical calibration of such instruments is mandatory to guarantee the quality of a laboratory or a manufacturing process.

It is easy to find technical literature relevant to the static testing of ADCs. The available methods, however, have different drawbacks, which justify some further development in this field.

The most popular static testing method is probably that described in the IEEE Standard 1057/94 for waveform recorders [1]. The problem with this method is that it is really very time consuming, because it needs the application of many different voltages for each threshold level and the acquisition of many samples for each voltage. The test duration becomes prohibitive (a tenth or even hundreds of hours) if the device under test (DUT) has a very high resolution, which is the typical situation with DVMs. In addition, a voltage source with a conveniently higher resolution with respect to the DUT is needed, which can be a serious practical problem.

The IEEE Standard 1241/00 for ADCs [2] describes a similar method with a greatly different approach with regard to the actual implementation. While the method in [1] is basically an acquisition, followed by an estimation algorithm (which can also be performed offline), the method in [2], which is thoroughly analyzed in [3], consists of realizing a dynamic system by closing the DUT in a feedback loop with a digital-to-analog converter (DAC). The average output of the dynamic systems is, under proper conditions, the actual threshold level. This way, the method is comparatively fast and is alleged to be even faster than the histogram test with sinusoidal input. The serious problem is that the correctness of the result critically depends on the round-trip delay in the feedback loop; therefore, the method is certainly unfeasible when the timing of the ADC–DAC feedback is not perfectly controllable, for example, when dealing with stand-alone instruments on a bus, with latency phenomena and delays. The method has other drawbacks, e.g., the step size of the DAC must be chosen according to the round-trip delay (which must be approximately known), and the settling time of the loop must be evaluated and taken into account. However, an important result of the simulation study on which the method is based [4] is that the DAC resolution does not need to be much higher than the ADC resolution, as required by the 1057/94 method. Indeed, the performances of the method are influenced by the ratio of the DAC resolution to the ADC internal noise.

In an effort to accelerate the static test 1057/94 without dealing with the difficult implementation of the 1241/00 method, a histogram test using small triangular waves [5] has been developed. The test requires only a dc source with low resolution and a triangular wave generator with reasonable linearity errors (since they are greatly reduced by the attenuation of the generated signal). In addition, it is really much faster than the 1057/94 method, because the triangular waves are acquired at the maximum sampling rate, and the test must stop and wait during the settling time of the dc source only a few times. However, methods based on the stimulation of the DUT by ramps or triangular waves can suffer undesired dynamic effects.
in the DUT and the signal generator. Those arising from the DUT cannot be negligible in the case of a dc instrument if the test signal does not have a sufficiently low frequency and dynamic or if the sampling intervals are not precisely controlled. Therefore, while this method can certainly be used to test an acquisition board for dynamic signals, it seems dubious for a precision dc voltmeter. Moreover, the dynamic effects arising from the signal generator can be difficult to mitigate: Excessive low-pass filtering smoothens the discontinuities in the triangular waves, increasing the number of acquired samples that must be discarded at the extremes of the signal range, whereas weak low-pass filtering (in comparison with the signal frequency) can reveal the stepwise generation of a digitally synthesized test signal.

After this brief survey of the state of the art, the aim of this paper about static testing of ADCs can clearly be understood. This paper illustrates a test with six characteristics.

1) The DUT is stimulated only by constant voltages. A small dynamic is present only due to a reasonable amount of noise (on the order of 1 LSB) superimposed on the signal.

2) The test does not require precise timing from the DUT (which is allowed to lack a trigger input and a precise sampling clock).

3) The test does not require a precise and fast response from the test bed. Test data can be collected and processed offline, if desired.

4) The method is based on a maximum-likelihood (ML) estimation of the threshold levels, so that it uses, in nearly the best possible way, the information provided by the acquired test signals.

5) As a consequence, the test uses a reduced set of input voltages (on the order of the number of threshold levels), saving time.

6) The test does not necessarily require a signal generator with a resolution higher than that of the DUT, provided that the test signals are accurately measured with a reference dc voltmeter.

II. PROPOSED METHOD

The test is based on repeated measurements of known constant signals dithered by a small amount of additive white Gaussian noise (WGN), which are obtained by the DUT. The requested noise is usually present at the DUT input as a part of the device itself, but it can also be added using a cheap noise generator. The constant signals do not need to be equally spaced. Large Gaussian signals have already been used for ADC testing [6], but in the method discussed here, the required dynamic is, instead, very small.

Let \( x^i, i = 1, \ldots, M \), be the constant input signals and \( t \) be a code transition level. Each signal is measured \( N \) times by the DUT. The value of the \( i \)th input signal at the \( n \)th measurement is denoted by \( x^i_n \), where \( i = 1, \ldots, M \) and \( n = 1, \ldots, N \), and \( c^i_n \) indicates the relevant output code produced by the DUT. Due to the addition of WGN with variance \( \sigma^2 \), it is assumed that the input signal values \( x^i_n \) are observations of independent Gaussian random variables (r.v.) \( X^i_n \) with mean \( x^i \) and variance \( \sigma^2 \). The situation is shown in Fig. 1.

The following analysis is aimed at solving the problem of estimating a code transition level \( t \) using the ADC outputs \( c^i_n \) generated by applying inputs \( x^i \). Supposing that \( t \) separates the two consecutive output codes \( k \) and \( k + 1 \), we have

\[
\begin{align*}
& c^i_n \leq k, \quad \text{iff } x^i_n \leq t, \\
& c^i_n \geq k + 1, \quad \text{iff } x^i_n > t
\end{align*}
\]

where \( x^i_n \) are the actual realizations of the r.v. \( X^i_n \). Let \( b^i \) be the number of occurrences of the events \( c^i_n \leq k \) (i.e., of the events \( x^i_n \leq t \)). Threshold \( t \) is estimated using test data \( b^i \). After introducing the probability

\[
p = P(X^i_n \leq t) = \Phi \left( \frac{t - x^i}{\sigma} \right)
\]

it is clear that, due to the hypothesis of WGN and, therefore, of the independence between measurements, quantities \( b^i \) are realizations of independent r.v. \( B^i \) with binomial distribution

\[
P(B^i = b^i) = \binom{N}{b^i} p^{b^i} (1 - p)^{N - b^i}.
\]

It is now easy to write down an ML estimator for parameters \( t \) and \( \sigma \). The likelihood function is

\[
P(B = b; x, t, \sigma) = \prod_{i=1}^{M} \binom{N}{b^i} p^{b^i} (1 - p)^{N - b^i}
\]

where the vector notations \( B = [B^1, \ldots, B^M] \), \( b = [b^1, \ldots, b^M] \), and \( x = [x^1, \ldots, x^M] \) have been used. The ML estimates are obtained by maximizing (4) or, equivalently, its logarithm (the log-likelihood function) and can therefore be expressed as follows:

\[
[t, \sigma] = \arg \max_{t, \sigma} P(B = b; x, t, \sigma)
\]

\[
= \arg \max_{t, \sigma} \sum_{i=1}^{M} f^i \log \Phi \left( \frac{t - x^i}{\sigma} \right) + (1 - f^i) \log \left[ 1 - \Phi \left( \frac{t - x^i}{\sigma} \right) \right]
\]

where \( f^i = b^i/N \) are the relative frequencies of the events \( c^i_n \leq k \). Of course, by recalculating \( b \) for different values of \( k \), the same experimental data \( c^i_n \) can be used to evaluate thresholds that are relevant to different output codes.
Fig. 2. Simulation results for the proposed test method applied to 18 not equally spaced threshold levels. It is shown that, with the eight input signals employed, only thresholds 2–16 are correctly estimated, whereas thresholds 1 and 17 and 18 are not. The estimated thresholds, indeed, must not be too far from the test signals (preferably, they should lie within the range of the inputs).

It is worth noting that, if the standard deviation \( \sigma \) is known, then only one input level (e.g., \( x^1 \)) is sufficient to estimate \( t \), with the linear formula

\[
\hat{t} = x^1 + \sigma \cdot \Phi^{-1}(f^1).
\] (6)

Moreover, if the standard deviation \( \sigma \) is unknown and two input levels are used (the minimum required to perform the estimation), it is easily demonstrated that the estimate is obtained by solving a system of two equations of the form (6)

\[
\begin{bmatrix}
1 & -\Phi^{-1}(f^1) \\
1 & -\Phi^{-1}(f^2)
\end{bmatrix}
\begin{bmatrix}
\hat{t} \\
\sigma
\end{bmatrix}
= \begin{bmatrix} x^1 \\ x^2 \end{bmatrix}.
\] (7)

Of course, using more input levels yields, in general, more accurate estimates. In the general case \( M > 2 \), (5) can be solved by using iterative methods. This is a simple task, because it can be demonstrated that the likelihood function has only one local maximum. In some cases (i.e., for some realizations \( b \)), the maximum is asymptotically reached, and the estimates diverge. It can be demonstrated that the condition for the finiteness of the estimates is

\[
\text{cov} (x, b) < 0
\] (8)

### III. SIMULATION RESULT

#### A. Sample Simulated Test

To illustrate the proposed method, the results of a simulated test are shown in Fig. 2. \( M = 8 \) constant input signals with additive WGN of standard deviation \( \sigma = 1 \) LSB have been employed. Each signal has been converted \( N = 1000 \) times using the 18 not equally spaced thresholds illustrated in the figure. The range covered by the right input signals is roughly from the fourth to the 15th output code bin; nevertheless, the estimation of all the 18 threshold levels has been tried.

Fig. 2 shows that the thresholds have accurately been estimated, except when they noticeably lie outside the range of the employed test signals. This is, of course, an expected behavior, because, in this case, the acquired samples are not informative enough about the position of the threshold. The average of the estimated standard deviations is \( \hat{\sigma} = 0.986 \) LSB, which is quite near the true value \( \sigma = 1 \) LSB.

Some notes must be added about the actual implementation of the method. All the thresholds have independently been estimated, except when they noticeably lie outside the range of the employed test signals. This is, of course, an expected behavior, because, in this case, the acquired samples are not informative enough about the position of the threshold. The average of the estimated standard deviations is \( \hat{\sigma} = 0.986 \) LSB, which is quite near the true value \( \sigma = 1 \) LSB.

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### B. Uncertainty of the Proposed Method

The root mean square error (RMSE) of the estimator \( \hat{T} \) (which gives the estimates \( \hat{t} \)) has been calculated, for different test conditions, to evaluate the uncertainty of the method as

\[
\text{RMSE}(\hat{T}) = \sqrt{\text{var}(\hat{T}) + \text{bias}^2(\hat{T})}
\] (9)

where \( \text{bias}(\hat{T}) = E[\hat{T}] - t \). In the following analysis, \( x \) is assumed to be known with a negligible uncertainty.
Fig. 3. Evaluation of the bias for \( N = 1000 \) and \( M = 2 \).

Fig. 4. Evaluation of the uncertainty for \( N = 1000 \) and \( M = 2 \). It can be seen that the optimal value of \( \sigma \) is about \( 0.5 \cdot \Delta x \) and that the position \( X_m \) of the input signals has only a small effect on the uncertainty.

In all the test conditions, the input signals \( x^i \) are assumed to be equally spaced with a conventionally fixed mutual distance \( \Delta x = x^{i+1} - x^i = 1 \), and the position \( t \) of the threshold level is conventionally zero. The results have been grouped, with each group having the same number \( N \) of acquired samples and the same number \( M \) of equally spaced input signals. Different values of the noise standard deviation \( \sigma \) and of the position \( X_m \) (with respect to the threshold) of the mean of the input signals \( x^i \) have been considered in each group.

Fig. 3 shows the bias, and Fig. 4 shows the RMSE for the case \( (N = 1000, M = 2) \). It must be noted that, with \( \Delta x = 1 \), the values of \( \sigma, X_m, bias, \) and RMSE must be seen as normalized with respect to \( \Delta x \). The results reported here show that there is an optimal ratio \( \sigma/\Delta x \) of about 0.5. Smaller or greater values of this ratio imply a greater uncertainty in the estimate. Moreover, the position \( X_m \) of the input signals has only a small effect on the uncertainty.

Other results, which are not reported here for the sake of conciseness, have shown that the sensitivity of the RMSE with respect to \( X_m \) is even smaller if \( M \) increases. In addition, for fixed values of \( \sigma, X_m, N, \) and \( \Delta x \), the RMSE decreases only down to a lower bound, even if \( M \) increases. The value of
Fig. 5. RMSE of an efficient (and correct) estimator of $t$. The plot shows the CRLB for the problem of estimating parameters $t$ and $\sigma$. The two lines refer to the maximum and minimum of the RMSE when varying $X_m$. The CRLB is plotted in Fig. 5. Here, $M$ is calculated according to (10), and $N = 1$. Again, the values of $\sigma$ and RMSE must be seen as normalized with respect to $\Delta x$. The values of the RMSE for any choice of $N$ can easily be calculated, because the RMSE is proportional to $1/\sqrt{N}$. Moreover, with $X_m$ being allowed to vary according to (11), the maximum and minimum of the RMSE are plotted. It is apparent that, for $\sigma/\Delta x \geq 0.4$, the RMSE does not change with $X_m$, provided that (11) is satisfied.

The reported analysis and Fig. 5 allow the design of the test under a given uncertainty constraint. A more comprehensive theoretical analysis can be found in [7].

M over which the RMSE does not significantly decrease has been determined by calculating the Cramer–Rao lower bound (CRLB) since the ML estimator asymptotically approaches this theoretical optimum. It can be found [7] that this limit value for $M$ is approximately

$$M = 1 + \left[2\sigma/\Delta x + 2c/\Delta x\right], \quad \text{for } \sigma/\Delta x \geq 0.4$$

where $c$ is the worst-case displacement between the mean of the input signals and the true (but unknown) threshold $t$, i.e.,

$$|X_m - t| \leq c.$$

A sensible choice is $c/\Delta x = 0.5$.

The CRLB is plotted in Fig. 5. Here, $M$ is calculated according to (10), and $N = 1$. Again, the values of $\sigma$ and RMSE must be seen as normalized with respect to $\Delta x$. The values of the RMSE for any choice of $N$ can easily be calculated, because the RMSE is proportional to $1/\sqrt{N}$. Moreover, with $X_m$ being allowed to vary according to (11), the maximum and minimum of the RMSE are plotted. It is apparent that, for $\sigma/\Delta x \geq 0.4$, the RMSE does not change with $X_m$, provided that (11) is satisfied.

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IV. EXPERIMENTAL RESULT

The performance of the method has also been experimentally verified by testing a physical digitizer. The first experimental results, as presented in [8], have been completed with a more detailed data analysis. The DUT is an oscilloscope HP 54603B, with a full-scale range of 1 V/div (from $-4$ to 4 V) and a sweep time of 5 ms (i.e., 0.5 ms/div). The constant test signals have been generated using an Agilent 33250A arbitrary waveform generator. It must be noted that this instrument is not intended to provide very accurate dc voltages; therefore, the constant signals were not equally spaced nor accurately corresponding to the programmed signals. However, performing the test requires only accurately measuring the signals $x^i$ with a reference dc instrument. An Agilent 34401A digital multimeter (6.5 digits) has been used for this purpose. Each signal has been measured ten times before and ten times after the acquisitions by the DUT; the results have been averaged to give the values $x^i$.

With the chosen settings, the LSB of the DUT was $Q = 0.03125$ V. In the test, a nominal step $\Delta x = 0.031$ V has been used, i.e., a step approximately equal to the LSB. To measure the 254 threshold levels in the range $[-4, 4]$ V, only $M = 270$ different input values have been used, covering the slightly larger range of $[-4.16, 4.18]$ V. For each input signal, a set of $N = 2000$ samples (one sweep of the oscilloscope) has been acquired. A Gaussian noise with a standard deviation of about 0.0313 V has been added to the input. The noise was generated using an Agilent 33220A arbitrary waveform generator. The standard deviation $\sigma$ of any set of 2000 samples is about 0.048 V (excluding the quantization noise). The time spent for the test was on the order of a few minutes.

To obtain an independent measurement of the threshold levels to use as a comparison, we have also implemented a classical histogram test. Here, the DUT, with the same settings, has been used to acquire 800,000 points of a sinusoidal waveform, with an amplitude of about 4.2 V (an overshoot of about 5%) and a frequency of 200 Hz. It must be noted from previous experiments that, with such input frequencies and sweep time, the oscilloscope under test has a completely static behavior.

Figs. 6 and 7 show the measured integral nonlinearity (INL) and differential nonlinearity (DNL). The results of the proposed
Fig. 6. Comparison between the INL measurement obtained via the proposed method and that measured via the histogram test.

Fig. 7. Comparison between the DNL measurement obtained via the proposed method and that measured via the histogram test.

static test are compared with those provided by the histogram test. It can be seen that they are in very good agreement.

In Fig. 8, two consecutive tests, which are executed with the proposed method, are compared. There is no evidence of non-stationarity. The collected experimental data allow the coarse statistical evaluation of the standard uncertainty \( u \) obtained by averaging the variance between the two vectors of estimated thresholds, i.e.,

\[
 u^2 = \frac{1}{N} \sum_k \text{var}(\hat{t}_{k,1}, \hat{t}_{k,2}) \tag{12}
\]

where \( \hat{t}_{k,1} \) and \( \hat{t}_{k,2} \) are the two different estimations of the \( k \)th threshold. It is obtained \( u = 0.022 \) LSB. It is interesting to compare \( u \) with the theoretical estimator RMSE, which is evaluated in the hypothesis of estimator efficiency (and correctness) and WGN. With the help of Fig. 5, it is found that, for \( \sigma/\Delta x = 1.5 \), the normalized RMSE is 0.93. The RMSE is then \( 0.93 \cdot \Delta x/\sqrt{N} = 0.021 \) LSB, which differs from \( u \) by about 7%. These results illustrate the use of Fig. 5 and the validity of the theoretical uncertainty analysis given in Section III-B.

For the purpose of completing the description of the test conditions, Fig. 9 shows the normal quantile–quantile plot of the record of samples \( c_{151} \) (which is expressed in volts). The figure illustrates the distribution of the quantized noisy input with a mean \( x^{151} \) of about 0.49 V. The test conditions, with
regard to the amount of added noise, have been chosen to have no apparent deviation from the quantile–quantile plot of a quantized Gaussian noise, even though the method seems to be robust for distributions with different tails.

V. DISCUSSION

A. Choice of the DUT

It is worth highlighting that, in the reported experiment, we used a particular DUT, which shows the same nonlinearity with a low-frequency sinusoidal input and with dc input signals. This does not only allow the comparison and the experimental validation of the proposed test but also implies that, for this DUT, the proposed test is not of great usefulness (since the histogram test can be used). The proposed test is very useful, instead, for instruments such as DVMs and slow, high-resolution ADCs, which cannot be tested using dynamic signals.

B. Choice of the Signal Generator

Common signal generators can be used to execute the static test. There are two main requirements.

1) The dc voltage must be stable during the use of that test signal. This is, however, a limited amount of time in comparison with the total test time.
2) All the test signals actually used in the determination of a given threshold must be dithered by noise with the same standard deviation. However, there are signal generators that, in the default configuration, automatically optimize the internal signal path, selecting different arrangements of amplifiers or attenuators. This default behavior must be turned off, because it can lead to a change in the noise amount.

C. Generalization of the Method

Two requirements of the test, i.e., the knowledge of the test signal values (obtained using a reference DVM) and the constancy of the noise standard deviation, can be relaxed by using a powerful generalization of the test derived employing the methodology already illustrated in Section II. The likelihood function (4) is replaced by the probability of observing \( b \), given \( x, t \), and \( \sigma \)

\[
P(B = b; x, t, \sigma) = \prod_{i=1}^{M} \frac{N!}{\prod_{k=1}^{K} b_{k,i}!} \left[ \Phi \left( \frac{t_{k} - x_i}{\sigma_i} \right) - \Phi \left( \frac{t_{k-1} - x_i}{\sigma_i} \right) \right]^{b_{k,i}} \tag{13}
\]

where \( \sigma = [\sigma_1, \sigma_2, \ldots, \sigma^M] \), \( \sigma_i \) is the standard deviation of the noise superimposed to the signal \( x_i \), \( K \) is the number of the ADC output codes, \( t = [t_1, t_2, \ldots, t^{K-1}] \) is the vector of ADC thresholds, \( b \) is the array of observed absolute frequencies, and \( B \) is the relevant random array. The element \( b_{k,i} \) of \( b \) counts the occurrences of the \( k \) code when the ADC is stimulated by the signal \( x_i \). The more general problem that we can solve is obtaining the ML estimates of the parameters \( x, t, \) and \( \sigma \), i.e., the parameters that maximize (13). In this case, \( x, t \) can be determined to be less than the offset and scaling factor, but this is enough to completely characterize the ADC’s nonlinearity (and the signal generator nonlinearity), without using a reference DVM. It is noteworthy that different problems can be solved by considering some parameters known in (13) and estimating the others. For example, the outputs of a DAC under test (unknown \( x \)) can be determined against a reference ADC (known \( t \)) by ML estimation. Therefore, the method can also lead to improvements in the field of DAC testing.

Recently, the same methodology has been applied to improve the classical sine wave test described in [2]. In [9], a parametric sinusoidal model for the test signal is used, instead of constant signals, leading to a likelihood function similar to (13). The main difference is that parameters \( x_i \) are replaced by the samples of the parametric sinusoid. These parameters, as well as the ADC thresholds, are estimated by maximizing the likelihood function.

D. DVM Calibration

DVM calibration usually consists of determining and correcting only gain and offset errors. Only a few points per range (typically, the two extremes of the full range) are measured and compared with the known output value of a calibrator or of a voltage standard (e.g., a 10-V Zener reference). Additional test points are available upon request at calibration facilities but may also entail additional costs. The proposed method, instead, makes the measurement of the quantization scale of the DVM (or portions of it) feasible, allowing a more complete characterization, which includes also linearity assessment. Moreover, the use of calibrators, whose price can be one order of magnitude greater than that of the DVM under test, is unnecessary. In fact, a cheaper signal generator in conjunction with a reference DVM can be used instead. This results in a decrease in the test costs. The proposed method and the discussed generalizations pave the way to an affordable transfer of accuracy of a reference DVM to a DVM under test, by using a signal generator as the vector.

VI. CONCLUSION

This paper illustrates an improved static test for dc digital instruments and ADCs. The main features of the test are that it is truly static, using only dc voltages with a small superimposed noise; that it does not require precise timing (offline data processing is also allowed); that it uses a minimal number of input signals and acquired samples in a theoretically nearly optimal manner (ML estimation); and that the resolution of the test signal generator need not be better than that of the DUT. The test is very convenient in terms of the time and instrumentation required and is, therefore, a possible candidate, in the authors’ opinion, for future replacement of the static test that is currently described in IEEE Standard 1057/94.

The uncertainty of the method has theoretically and experimentally been examined. Both simulations and experiments have shown that the test can certainly attain any reasonably desired accuracy with reasonable means and time.

REFERENCES

Attilio Di Nisio was born in Bari, Italy, in 1980. He received the M.S. degree in electronic engineering from the Polytechnic of Bari in 2005. He is currently working toward the Ph.D. degree in electronic engineering with the Laboratory for Electric and Electronic Measurements, Department of Electrics and Electronics, Polytechnic of Bari. Since 2005, he has been working on research projects in the field of ADC testing and automatic vision inspection. His research interests include ADC/DAC modeling and testing, identification of error models in acquisition channels, automatic test equipment software, estimation theory, and image processing. Mr. Di Nisio is a member of the Italian Group of Electrical and Electronic Measurements (GMEE).

Nicola Giaquinto was born in Bari, Italy, on September 29, 1966. He received the M.S. and the Ph.D. degrees in electronic engineering from the Polytechnic of Bari in 1992 and 1997, respectively. Since 1993, he has been working in the field of electrical and electronic measurements, doing research mainly on the field of digital signal processing for measurement systems. From 1997 to 1998, he was with the Casaccia Research Center, Rome, Italy, as a grant holder of the Italian Agency for New Technologies (ENEA), where he was concerned with real-time geometric measurements for autonomous robots. In 1998, he rejoined the Polytechnic of Bari, where he has been an Assistant Professor and then an Associate Professor in electric and electronic measurements with the Laboratory for Electric and Electronic Measurements, Department of Electrics and Electronics. Since then, he has been the leading researcher of his working group in the field of ADC-DAC characterization and optimization. His current research interests include ADCs and DACs, linear and nonlinear estimation methods, uncertainty evaluation, and the design of sensors for agriculture, medicine, quality control, and transportation. Dr. Giaquinto is a member of the Italian Group of Electrical and Electronic Measurements (GMEE).

Laura Fabbiano received the M.S. degree in electrical engineering in 2003 from the Polytechnic of Bari, Bari, Italy, where she is working toward the Ph.D. in electric engineering. Since 2003, she has been working on a research project with the Electrics and Electronics Measurement Group, Laboratory for Electric and Electronic Measurements, Department of Electrics and Electronics, Polytechnic of Bari. Her research interests include environmental sensors and electronics and electronic measurements on instruments and devices. Ms. Fabbiano is a member of the Italian Group of Electrical and Electronic Measurements (GMEE).

Giuseppe Cavone was born in Bari, Italy, in 1955. He received the M.S. degree in electrical engineering from the State University of Bari in 1988. He then joined the Laboratory for Electric and Electronic Measurements, Department of Electrics and Electronics, Polytechnic of Bari. He is currently a Technical Coordinator at the Polytechnic of Bari, where he works on the optimization of spectral estimation algorithms for the monitoring of distortion levels in power systems and robotics and diagnostics of electrical drives. He was also involved with filtering design techniques to increase the performance of digital measuring instrumentation. His current research interests include the characterization of A/D converters, DSP techniques for time–frequency measurements on stochastic signals, and the characterization of intelligent instruments.

Mario Savino (M’86) was born in Bari, Italy, in 1947. He received the M.S. degree in electrotechnical engineering from the University of Bari. He is currently with the Laboratory for Electric and Electronic Measurements, Electrotechnical Institute (now the Department of Electrics and Electronics), Polytechnic of Bari, where he was a Researcher from 1971 to 1973, an Assistant Professor from 1973 to 1982, an Associate Professor from 1982 to 1985, and where he has been a Full Professor since 1985. He has also been the Dean of the Faculty of Engineering, Polytechnic of Bari. He is the author or coauthor of more than 100 papers published in international scientific reviews or proceedings. His research interests include electric and electronic measurements, particularly digital signal processing and artificial intelligence in measuring systems. Prof. Savino is a member of the Italian Electrotechnical and Electronic Society (AEI). He is currently the Honorary Chairman of the TC–4 technical committee of the International Measurement Confederation (IMEKO).