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Ultrasonic Distance Sensor Improvement Using a Two-Level Neural Network

Alessio Carullo, Franco Ferraris, Salvatore Graziani, *Member, IEEE,* Ugo Grimaldi, and Marco Parvis

***Abstract*—This paper discusses the performance improvement that a neural network can provide to a contactless distance sensor based on the measurement of the time of flight (TOF) of an ultrasonic (US) pulse. The sensor, which embeds a correction system for the temperature effect, achieves a distance uncertainty (rms) of less than 0.5 mm over 0.5 m by using a two-level neural network to process the US echo and determine the TOF in the presence of environmental acoustic noise. The network embeds a "guard" neuron that guards against gross measurement errors, which would be possible in the presence of high environmental noise.**

I. Introduction

Ultrasound-based distance measurement is now recognized as being a simple and inexpensive answer to many typical demands of industrial manufacturing [1]–[7]. Nevertheless, the wide use of such a technique in an industrial environment is often prevented by several drawbacks, such as poor resolution and sensitivity to temperature and environmental noise.

The temperature effect can be satisfactorily compensated by adding a small circuit to the sensor [8], [9]. As far as the distance resolution of US sensors is concerned, it has been shown [2], [10] that quite good results can, in principle, be obtained if suitably shaped pulses are employed to drive the transmitting transducer. Unfortunately, the low energy of the US echoes obtained with low-cost commercial devices makes the issue of the noise sensitivity of chief importance.

It has already been shown that a neural network, namely a multilayer perceptron (MLP), can provide quite good accuracy improvement when low environmental noise is present [11]. The purpose of this paper is to present the performance improvement provided by a two-level neural network in the presence of higher noise levels.

II. Distance Measurement Issues

In TOF-based measurements, the distance to be measured is obtained by the relationship

$$d = k \cdot v \cdot T_F \tag{1}$$

where d is the measured distance; k is a constant whose value, which depends on the geometry of the signal path, is close to 0.5; v is the propagation velocity in the medium; and T_F is the signal TOF.

The measurement uncertainty $u_c(d)$ can be determined [12] by taking into account the rms values of the quantities involved in the measurement and their sensitivity functions c_i. Making reference to the measurement model (1), where the velocity of sound v significantly depends on the average air temperature θ and on the air relative humidity RH, the measurement uncertainty $u_c(d)$ is obtained from

$$u_c^2(d) = [c_\theta u(\theta)]^2 + [c_{RH} u(RH)]^2 + [c_{T_F} u(T_F)]^2 \tag{2}$$

where the contribution of k is omitted, since uncertainty of k can be made negligible by a preliminary calibration. The sensitivity coefficients vary with the actual temperature; their maximum values in the range of 0–40°C are

$$\begin{aligned} c_\theta &\approx d \cdot 1.8 \cdot 10^{-3}\,\mathrm{K}^{-1} \\ c_{RH} &\approx d \cdot 4.3 \cdot 10^{-5} (\%\mathrm{RH})^{-1} \\ c_{T_F} &\approx 180\,\mathrm{m/s} \end{aligned} \tag{3}$$

where d is expressed in meters. The relative humidity effect is usually neglected, while several authors have already developed distance measurement systems including a thermal compensation, e.g., [8], [9], which is based on a direct measurement of the air temperature.

The TOF uncertainty $u(T_F)$ is mainly affected by the frequency of the employed ultrasound and decreases as the frequency increases. In this work the authors employed 40 kHz piezoelectric transducers which permitted an inexpensive sensor to be built, since the cost of the transducers is about one dollar, and very cheap hardware is sufficient to perform the measurement. Furthermore, the relatively low attenuation of sound in air at that frequency allows measurements of up to a few meters, and the probability of diffraction in most common environments is quite low, as the pulse wavelength is about 8 mm.

On the other hand, although it is not possible to foresee the value of the standard uncertainty $u(T_F)$, because the measured TOF distribution varies according to the different measurement conditions, one should note that an error in the echo detection of one period of the echo waveform corresponds to a distance error of about 4 mm.

A distance accuracy that is considerably better than such a value can therefore be obtained only if a considerably better TOF accuracy than one period of the echo waveform is achieved. This can be obtained by employing a threshold detector (TD), an analog-to-digital converter (ADC) and a

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A. Carullo, F. Ferraris, U. Grimaldi, and M. Parvis are with Politecnico di Torino, I-10129 Torino, Italy.
S. Graziani is with the Dipartimento Elettrico, Elettronico e Sistemistico, University of Catania, Catania, Italy.
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post-processing unit. The TD triggers the ADC, which acquires a suitable number of samples; the post-processing is used to estimate the TOF by evaluating the time interval to be added to the TD firing time. In the sensor developed one hundred samples at 500 kHz are acquired: this allows the meaningful part of the echo to be correctly described.

The compensation of the temperature effect is based on a direct measurement of the air temperature, carried out by means of a low-cost solid-state commercial sensor that exhibits a temperature uncertainty of 0.5°C: the correction is implemented during the computations performed by the post-processing unit.

The sensor contains a noise measurement circuit, which detects the peak amplitude of the noise in time intervals where no echo is present [13]: this is used to characterize the statistical reliability of the measurements, as discussed later.

III. Neural Post-Processing

A two-level neural network, fed with the acquired samples of each echo received, is employed for the post-processing. A competitive layer (CL) is first used to determine which period of the echo waveform made the threshold detector fire. Then an MLP is used to determine the actual echo position. This allows one to set up different but very simple MLP's, one for each echo cluster that results from the threshold detector firing in correspondence of different periods of the echo waveform.

A. Competitive Layer

The neural network size, as well as the training method, can easily be decided by considering that the CL can be trained using echoes whose characteristics are all well known, because they are generated in stated and known conditions. This allows the network to be trained in a supervised manner, e.g., by applying a learning vector quantization (LVQ) method.

The CL network is based on the computation of some kind of "distance" between the input signal and the neuron weight vectors: the neuron whose weight has a shorter distance from the input signal is declared to be the winner [14]. The authors employed the "city-block" distance, defined as

$$D_{cb} = \sum_{i=1}^{N} |w_i - e_i| \tag{4}$$

where w_i and e_i are the ith values over N samples of the neuron weight and of the received echo, respectively.

Other choices would lead to similar results [15], but the city-block distance has the advantage of not implying multiplications, thus allowing a much lower computational complexity to be achieved. The weights are therefore a sort of "mean" of the signals that make the neuron win: such "mean signals" characterize the class each neuron can recognize.

The number of neurons required to correctly identify the different echoes (i.e., the number of classes that have to be drawn out of the mentioned clusters) therefore depends on the distances between the echoes themselves. The phenomenon that plays a crucial role in spreading the echoes over the classes and clusters, rather than the amplitude noise, is the phase noise in which the former is transformed by the threshold detection (for a more detailed discussion of the effects of the noise on the echoes dealt with in this work, see [13]).

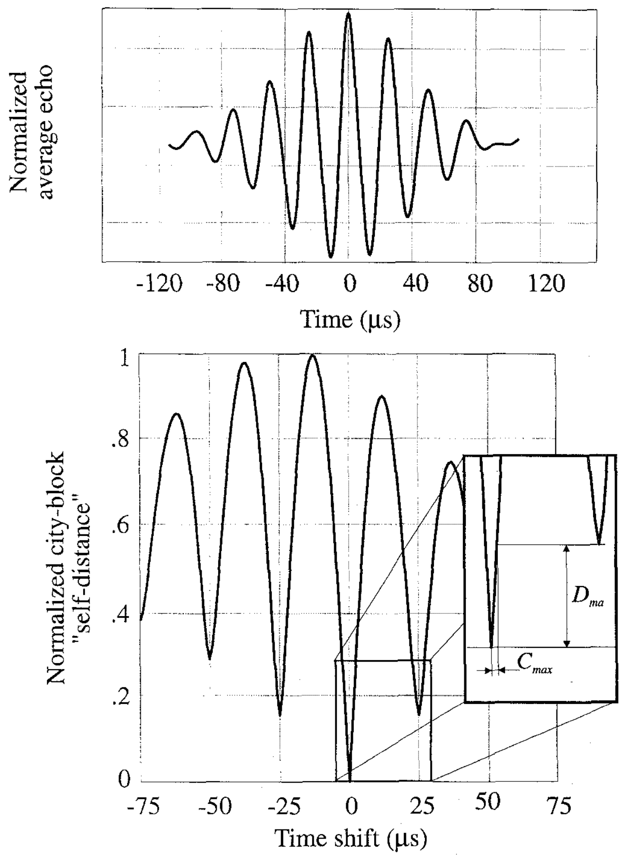

Fig. 1. Average echo and relevant city-block "self-distance" function.

It is possible to predict the behavior of the network with reasonable accuracy by computing the city-block "self-distance" function of the echo that is expected in the absence of noise (Fig. 1): the null distance refers to an echo that matches the neuron weight. The CL can correctly identify the echoes only if the self-distance corresponding to the amplitude of each class is reasonably less than the self-distance D_{ma}, which corresponds to the local minima adjacent to the absolute one. In the case described, the distance corresponding to such adjacent local minima is reached at a time shift $C_{\max} \approx 2\,\mu$s. Therefore, 1 μs wide classes were chosen as a reasonable compromise between network complexity and safety of discrimination in noisy conditions. This resulted in five or six classes (i.e., neurons) for each cluster; however, as the maximum number of clusters is limited by the number of echo periods, the maximum possible neuron number is less than twenty. The use of 1 μs wide classes implies an intrinsic standard uncertainty, due to the time quantization, that can be evaluated in 0.28 μs by hypothesizing a rectangular distribution within each class.

B. Multilayer Perceptron

The MLP is used to perform an interpolation within each class, thus reducing the uncertainty obtained with the CL. The

MLP input vectors are the outputs of the CL neurons which represent the distance of the received echo from the "mean signals" characterizing each class.

The MLP therefore has to be trained to estimate the actual TOF of the current echo by examining those distances. The number of neurons of the MLP's hidden layer cannot be determined theoretically, as in the case of the CL, due to the inherent characteristics of the MLPs: however, the problem complexity only requires that a few neurons be employed.

One MLP is implemented for each cluster: only one MLP is thus activated once the CL has detected the cluster that the echo belongs to. In this way the computational complexity, both in the training and the retrieval phases, is strongly reduced.

C. The "Guard" Neuron

The CL always has a winning neuron; unfortunately, in the presence of large noise, it is possible that all the neuron outputs are quite high, and therefore, although a winner is of course declared, it has a very low probability of being the correct one. It is thus necessary to provide the CL with some form of protection against such possible gross errors that could greatly degrade the sensor performance. This can be obtained by adding an additional "guard" neuron to the CL.

The guard neuron is a fixed-output neuron: it wins if the outputs of the other neurons are higher than its output; in this case an error flag is set and the measurement is discarded. Unfortunately, this implies that several measurements, in which the CL output would have been correct, are also discarded. Thus, the guard level, i.e., the output of the guard neuron, has to be chosen as a compromise between the affordable error probability and the affordable discarded fraction of the measurements; although it is possible to find a guard level which zeros the error probability under the hypotheses that are true in most real cases, this results in a measurement discard rate that is too high.

The guard level can be set by an experimental determination of both the error probability (as a function of the noise-induced distance in real conditions) and the fraction of measurements that are discarded (as a function of both the noise amount and the guard level). The authors employed the following procedure.

- An ideal noiseless echo is generated by time-shifting the weight of a neuron that is therefore marked as the correct winner. The shift is 0.5 μs, which is half the interclass time distance: the noiseless echo that maximizes the output of the chosen neuron, still belonging to its class, is thus generated as the worst case for that class.
- A series of measurement sessions is carried out without generating the US pulse, so that only the noise is sensed by the receiver; the received noise is recorded. Each session is carried out under different noise conditions and consists of a fixed number of acquisitions; the session is flagged with the noise peak amplitude, which is detected by the noise measurement circuit.
- The noise examples are summed to the noiseless echoes in order to simulate the real noisy echoes, which are then fed into the CL.

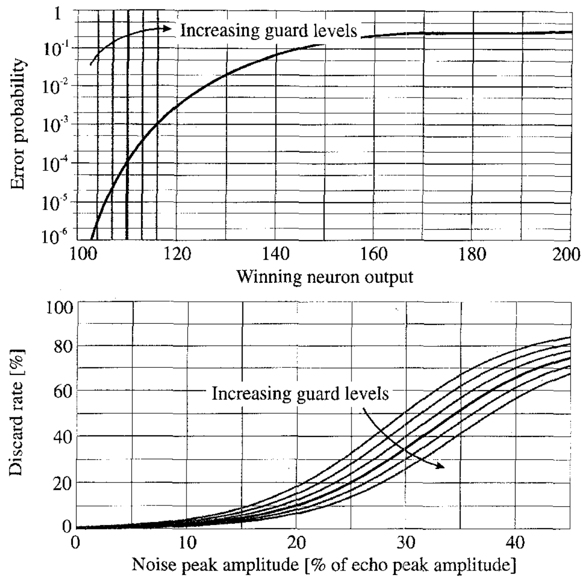

Fig. 2. Example of error probability and discard rate in the case of the developed sensor. Some different guard levels and their effect are shown: the level chosen is indicated with the solid black line.

- The error probability is computed as the ratio between the number of misclassified examples and the total number of examples fed into the CL. The error probability is then plotted as a function of the output of the winning neuron. In this way it is possible to evaluate the residual error probability consequent to any choice of the guard level.
- The fraction of measurements that are discarded for any guard level is computed as the ratio between the number of examples for which the output of the winning neuron is above the guard level and the total number of measurements in the session. In this way it is possible to obtain a family of curves showing the fraction of discarded measurements as a function both of the noise peak amplitude and of the guard level.
- The operation is repeated for all the neurons that can be considered as representing each identified cluster (usually a good choice is to use the central neuron of each cluster).
- The guard level is finally chosen as the most suitable compromise between the affordable error probability and the affordable discard rate, referring to the worst case found.

An example of the two mentioned graphs, as obtained for the developed sensor, and the relevant choice of the guard level are shown in Fig. 2: the curves are a least-squares approximation of the experimental ones.

IV. Neural Network Training

A. Training Set Generation

The main problem to be tackled here is that the network is required to give a TOF resolution of a fraction of a microsecond: the actual TOF of the echoes in the training set has, therefore, to be known within a few tens of nanoseconds. This, in turn, requires distance d, air temperature θ and relative

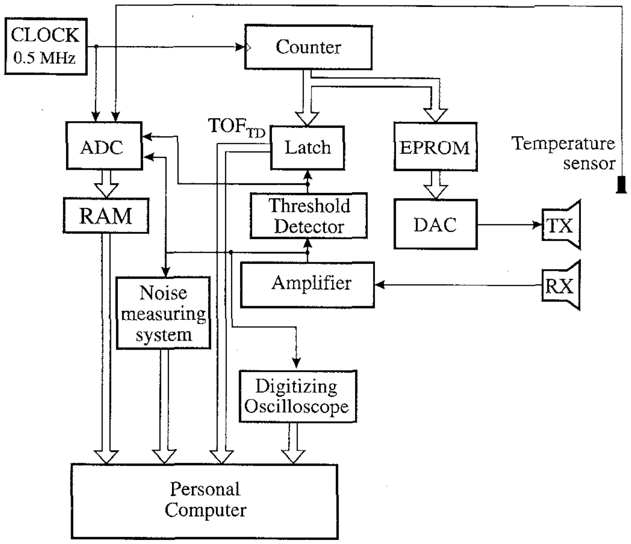

Fig. 3. Arrangement used to generate the training set for the neural network.

humidity RH to be known with very little uncertainty, which is not an easy task. The authors avoided this problem by using the arrangement shown in Fig. 3.

A digitizing oscilloscope, with the same number of bits as the ADC employed in the sensor, was used to acquire echoes from a target located at a fixed distance of about 0.5 m in a sealed ambient with temperature controlled to within 0.01°C. Under such conditions the TOF is stable within 50 ns. The oscilloscope was triggered at a suitable fixed delay after the transmission of the US pulse: it then acquired one thousand samples of the echo at the sampling frequency of 2.5 MHz; the reference TOF was determined as the mean value of the time location of the highest peak of one thousand echoes.

The sensor hardware was simulated by searching each acquired echo for the time it crosses the threshold and by subsampling it five times, synchronously with the sensor clock: finally the aforementioned one hundred samples at 500 kHz are taken for each echo. The echoes were then labeled with the time difference between the reference TOF, computed as described above, and their own threshold crossing time TOF_{TD} (Fig. 3): such differences were the values the network was trained to estimate.

Although this was a faithful simulation of the sensor behavior, all the available examples would have referred to the same TOF, and furthermore the TOF differences fed into the network would all have been multiples of 2 μs: thus the neural network could not have extracted the amount of knowledge necessary to successfully interpolate at the desired level. Since varying the measured distance of the small necessary TOF skew is quite a difficult operation, such echoes were created artificially: before simulating the sensor behavior, the echoes acquired with the oscilloscope were time-shifted by multiples of the initial 0.4 μs sampling interval, while the relevant target difference was computed from the reference TOF, time-shifted by the same amount.

Ten thousand echoes per measurement session were recorded while artificially generating acoustic noise in the sealed ambient. The training set was generated by extracting one to two thousand echoes from these records so that all the target values were well represented in the set.

TABLE I
EXPECTED AND ACTUAL DISCARD RATES FOR DIFFERENT VALUES OF THE NOISE PEAK AMPLITUDE

Noise peak amplitudes	10%	15%	22%	32%	42%
Estimated worst-case discard rates	2%	5%	15%	44%	70%
Actual discard rates	0.1%	1%	13%	38%	56%

B. Training Strategies

The echoes that each neuron in the CL must recognize are very similar, due to the amplitude-noise to phase-noise transformation. This suggests that averaging all the echoes pertaining to each class and presetting the weights of the relevant neuron to such a value should make the training easier.

This, in fact, greatly speeded up the training phase: a negligible improvement was obtained by performing a post-training with the conventional LVQ rule. This strategy has a further advantage in that only the neurons corresponding to classes that are actually present are generated, thus avoiding ineffective neuron redundancy.

The training of the MLP's was performed in a conventional way, with a Levenberg–Marquardt algorithm, which insured a very fast convergence. Topologies were tested with four to eight neurons in the hidden layer; a seven-hidden-neuron network was adopted, which still gave the best results with a low complexity.

V. EXPERIMENTAL RESULTS

The training procedure and the subsequent tests were carried out in the presence of different levels of artificially induced acoustic noise: after the receiving transducer, the noise peak amplitude was in the range of about 10% to about 40% of the echo peak amplitude.

The guard level was set, as shown in Fig. 2, to obtain a 10^{-4} residual error probability. The expected discard rate is also shown in the figure as a function of the noise peak amplitude. The typical rms TOF dispersion, obtained in sessions of ten thousand measurements with the TD alone, was of about 17 μs; after the CL processing the figure was cut down to about 0.9 μs, and after the MLP interpolation was reduced to about 0.36 μs. The CL thus provides a reduction of the TOF dispersion by about twenty times with respect to the results of the TD alone, while the MLP's further cut the dispersion by 60%. Almost the same results were obtained for all the tested noise peak amplitudes: the price paid, however, was the increase of the discard rate with the noise increase, as shown in Table I, which was, however, well below the estimated worst-case values (see Fig. 2), as expected.

The reduction provided by the neural network makes the TOF contribution to the distance uncertainty negligible, with respect to the other sources discussed in Section II, unless a

TABLE II
STANDARD UNCERTAINTY CONTRIBUTIONS

	Measured distance $d = 0.5$ m			Measured distance $d = 0.2$ m		
	TD	CL	MLP	TD	CL	MLP
$c_{T_F}^2 u^2(T_F)$ $\times 10^{-6}$m^2	9.4	0.03	0.004	9.4	0.03	0.004
$c_\theta^2 u^2(\theta)$ $\times 10^{-6}$m^2	0.068			0.01		
$c_{RH}^2 u^2(RH)$ $\times 10^{-6}$m^2	0.13			0.021		
$u_c^2(d)$ $\times 10^{-6}$m^2	9.6	0.23	0.2	9.4	0.061	0.035
$u_c(d)$ mm	**3.1**	**0.48**	**0.45**	**3.1**	**0.25**	**0.19**

very accurate measurement of both temperature and humidity is performed.

Table II is obtained from (2) and shows the distance standard uncertainty, $u_c(d)$, for two distances of 0.2 m and 0.5 m, when the temperature is measured with a standard uncertainty $u(\theta) \approx 0.29°$C (which corresponds to the 0.5°C uncertainty of the temperature sensor); and the relative humidity is within the typical range of 30–90% RH [which corresponds to a standard uncertainty $u(RH) \approx 17\%$ RH].

It appears that, after the neural post-processing, the contribution of the relative humidity predominates, and the TOF contribution becomes negligible at the larger distance. Under these conditions, the developed sensor provides an accuracy of better than 0.5 mm over a 0.5 m measured distance. However, it is important to remark that, whenever differential measurements are performed in steady temperature and relative humidity conditions, the neural network cuts the distance standard uncertainty down to the level of 60 μm, without requiring the measurement results to be filtered or smoothed.

VI. CONCLUSIONS

Post-processing ultrasonic echoes using neural networks is an effective solution to improve the measurement accuracy of ultrasonic distance sensors when low-frequency pulses are employed. A competitive layer trained with a learning vector quantization method (i.e., in a supervised manner) is able to reduce the standard uncertainty of the time-of-flight measurement to 0.9 μs, which corresponds to a distance standard uncertainty of about 150 μm. A second-level multilayer perceptron, which adds a negligible computational complexity, further reduces the distance standard uncertainty to 60 μm.

The neural post-processing therefore makes the problem of the TOF uncertainty minor: the uncertainty contribution of the relative humidity is, in fact, likely to become the dominant effect, provided the usual compensation of the temperature effect is performed.

The first-level competitive layer can be conveniently designed and trained by exploiting the *a priori* knowledge of the processed echoes both to choose the neuron number and to preset their weights. If this is done, training the network can be almost effortless. The performance of the sensor is guaranteed by the presence of a "guard" neuron that guards against gross errors in highly noisy conditions, at the disadvantage of only a measurement discard rate that increases with noise.

The implemented two-level approach allowed a very low computational complexity to be obtained. As a consequence, the strict necessity of employing special fast and costly digital signal processors is removed, while a throughput of 100 measurements per second is still possible. An embedded noise-measuring circuit allows one to know *a priori* the expected measurement discard rate.

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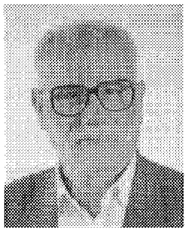
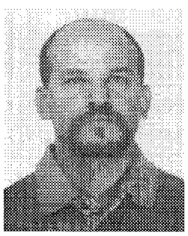
Alessio Carullo was born in Italy in 1966. He received the degree in electronic engineering in 1992 from Politecnico di Torino, Torino, Italy.

In 1993, he developed a new ultrasonic distance sensor for automotive applications with a grant of CRF (Centro Ricerche FIAT). At present, he is a Doctorate student in Electronic Instrumentation. His main fields of interest are the development and characterization of intelligent instrumentation and the development of new sensors for environmental quantities. Currently, he is working at the development of a new ultrasound-based humidity sensor.



Franco Ferraris was born in Italy in 1945. He received the degree in electrical engineering from Politecnico di Torino, Torino, Italy, in 1969.

Until 1989, he was associated professor of Electronic Measurements at the Dipartimento di Automatica e Informatica of the Politecnico di Torino. In 1990, he became full professor of Electronic Measurements at the Dipartimento Elettrico, Elettronico e Sistemistico of the University of Catania, Catania, Italy. Since 1991, he has been with the Dipartimento di Elettronica of the Politecnico di Torino. His fields of interest include automatic controls and system theory, biomedical measurements, intelligent measurement systems and intelligent sensors. Lately, his research work mainly concerned the measurement system modeling, the design and development of measurement instrumentation for mechanical and electrical quantities and the design and metrological characterization of sensors of angular velocity and linear acceleration.



Salvatore Graziani (S'93–M'95) received the Doctorate degree in automatic controls in 1994.

He is a researcher at the Dipartimento Elettrico, Elettronico e Sistemistico of the University of Catania, Catania, Italy. His main fields of interest are the intelligent instrumentation, the use of fuzzy logic and neural networks in measurement systems and the control and system aspects of seismology.

Ugo Grimaldi was born in Italy in 1964. He received the degree in electronic engineering in 1989 from Politecnico di Torino, Torino, Italy, and the Doctorate in Metrology in 1993.

In 1993, he took part in a European research project on the development of new atomic frequency standards: he worked at the PTB (Physikalisch-Technische Bundesanstalt), Germany, and at the Observatoire Cantonal, Neuchâtel, Switzerland. His main research fields are the design and the development of intelligent instrumentation, the design and the metrological characterization of sensors for mechanical, electrical, and environmental quantities. At present, he is working at the development of new automotive sensors of distance and angular velocity on a post-doctorate grant.

Marco Parvis was born in Italy in 1958. He received the degree in electrical engineering in 1982 from the Politecnico di Torino, Torino, Italy, and the Doctorate in Metrology in 1987.

He worked as a research assistant of Electronic Measurements at the Dipartimento di Automatic e Informatica of the Politecnico di Torino until 1990, and at the Dipartimento di Elettronica of the Politecnico di Torino until 1994. Since 1994, he has been with the Seconda Facoltà di Ingegneria of the Politecnico di Torino. His main fields of interest are intelligent instrumentation, application of signal processing to measurement, biomedical and chemical measurements. At present, he is working at the development of new sensors for mechanical and chemical quantities, to the characterization of Hall-effect current sensors and to the development of low-cost versatile power measuring systems.