# Outlier Detection for the Evaluation of the Measurement Uncertainty of Environmental Acoustic Noise

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***Abstract*— The difference between a measurable value and a threshold does not involve a straightforward comparison of values, given that such a measurement result has to be expressed in a manner consistent with the principle of the ISO Guide to the Expression of Uncertainty in Measurement (GUM). In the other words, the uncertainty of the measured value has to be taken into account. Such matters are highly relevant to the area of the measurement of relative levels of environmental noise from the perspective of providing an adequate estimate of the indetermination associated with such measurements. Here it is necessary to account for the uncertainty that appears around particular noise events. The intention of the first phase of this study is to eliminate outliers that occur when measuring signals in real time. Then the second phase will determine the uncertainty associated with the measurement of purified signals.**

***Index Terms*— Digital signal processing, environmental acoustic measurements, measurement uncertainty, real-time systems, statistical analysis.**

## I. Introduction

THE MANAGEMENT of the result of a comparison between a measured value and a threshold is a very relevant issue today [1]. An increasing number of decision-making processes are based on the outcomes of these comparisons, which may have implications not only from an economic point of view, but also on environmental and/or social matters. The problem stems from the comparison between a measured quantity and a threshold value [3]–[5], which is not possible through a simple mathematical comparison between the two values, given that it must take into account the uncertainty associated with the measurement [6]–[11]. The task of establishing the decision-making rules to test the compliance of a product to specifications, taking into account the uncertainty of the measurement, relies on [1], [12], and [13]. Both show that the higher the uncertainty of measurement, the smaller the degree of compliance, but neither shows how to assess the level of confidence in the outcome of the comparison, therefore resulting in heightened levels of risk that a wrong decision is being made [1].

For all these reasons, a considered uncertainty statement has to accompany any measurement findings. Only in this way would the comparison between a measurement and a corresponding reference value make sense, and be in accord with the current technical international standard [1]. Any measurement certification has to adhere to this standard.

In the case of environmental acoustic noise measurements, exceeding thresholds may cause health risks for the public, and then, it becomes essential to find the relationship between measurement uncertainty and acceptable social risk. Thus, in the last decade, the issue of the quantification of the residual doubt associated with the measurement of environmental noise had surfaced as a key issue. In addition to the referenced standard, a consistent package of Ente Nazionale Italiano di Unificazione standards is devoted to uncertainty in acoustics [14], [15]. However, an adequate technical and procedural reference standard has not yet been available. Even the uncertainty of a noise measurement, in certain cases, may be greater than the reference threshold stated by the standard for that source.

In order to quantitatively describe the environmental noise, which appears very often as a random floating sound signal, some parameters expressed in decibels (dB) referred to a $p_{\mathrm{rif}} = 20\ \mu$Pa pressure are used.

1) The equivalent level $L_{\mathrm{eq}}$, which indicates the level of a continuous stationary noise having the same acoustic energy content of the floating noise under measurement

$$L_{\mathrm{eq}} = 10\log\frac{1}{T}\int_T \left[\frac{p(t)}{p_{\mathrm{rif}}}\right]^2 dt.$$

2) Quantile levels $L_q$ representing the sound levels overcome by a given fraction of the observation time. For instance, L90 specifies the sound level that has been overcome for 90% of the observation time and L50 is the median of the statistical distribution, i.e., there is an equal probability of picking a value greater than L50 or one lower than L50.

Scientists and experts of this field focused their attention on this subject, identifying the possible sources of uncertainty and trying to develop models that include all the quantities contributing to the determination of the uncertainty in the measurement of acoustic pressure levels. These quantities include the uncertainty due to the characteristics of measurement instrumentation (phonometer or multichannel analyzers), the error deriving from the positioning of the instrumentation and the uncertainty to be associated with the intrinsic variability of the phenomenon under observation.

Manuscript received July 21, 2015; revised September 14, 2015; accepted September 23, 2015. Date of publication November 4, 2015; date of current version January 4, 2016. The Associate Editor coordinating the review process was Dr. Kurt Barbe.

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Digital Object Identifier 10.1109/TIM.2015.2491038

The latter uncertainty source is of particular practical and scientific interest, since the contribution to the uncertainty due to the occurrence of particular sound events (spot events) has to be considered in order to determine the measurement uncertainty adequately. As a matter of fact, these spot events significantly disturb the value of the progressive equivalent level yielded by the measurement task. For instance, a spot event within a measurement in an urban environment with heavy vehicle traffic might be the result of the transiting of a particularly heavy vehicle or of an ambulance. For these reasons, it is interesting to analyze the change of equivalent levels caused by subsequent measurements performed on a given environmental acoustic phenomenon and with the same instrument placed in the same position with the same procedure. This kind of analysis does not depend on the above-mentioned inevitable instrumental, methodological, and operating uncertainties and takes into account only the variability of the acoustic phenomenon.

This paper is an extended version of [16]. The eventual aim of the research described in this paper is the realization of an advanced system for the environmental acoustic monitoring and for the real-time assessment of uncertainty associated with measured levels. In particular, this paper addresses the issues of the identification of the outliers occurring in the time history of an environmental noise signal due to the spot event, following a histogram-based statistical approach, in order to allow the determination of the uncertainty associated with the measurement of the filtered signal.

## II. Review of the State of the Art

In this section, some principal research topics in the area of the characterization of environmental noise measurements are highlighted. In particular, the techniques available in the literature for the identification of unwanted sounds will be explored.

The onset of one or more acoustic events during a measurement may cause a significant alteration of the equivalent noise level and then it might induce the analyst not to consider that particular event or to arbitrarily extend the measurement time so as to reach a new stable reading of the equivalent noise level. However, it is not entirely appropriate to allow operator's subjectivity in the identification and elimination of acoustic events, which may only be apparently believed not to be characteristic of the sources under examination. This indeterminacy is then intrinsic to the variability of the measurand (i.e., the quantity under measurement) rather than due to strictly metrological issues.

In the literature, there are several works about this theme. Kim [17] uses some acoustic patterns to improve the detection of unwanted sound in several fields such as traffic noise monitoring. He observes that there is a remarkable difference between a pattern of traffic noise and one from unwanted sound, like the one, for example, between vehicle horn sound and special purposed vehicle sirens, which have a sound pressure similar to the one of unwanted acoustic patterns but their frequency waveforms are of a distinctive periodic type. Thus, the author transformed various transmitted sound signals via microphones into frequency bands, then compared them with sound pressure of accident sounds that were saved in a database, where they are classified according to their frequency content. The author states that, with a database of various acoustic patterns and an image detection system, which today can operate at an accuracy rate of about 90%, the detection rates of unwanted traffic sounds will be increased of at least 2%–3%.

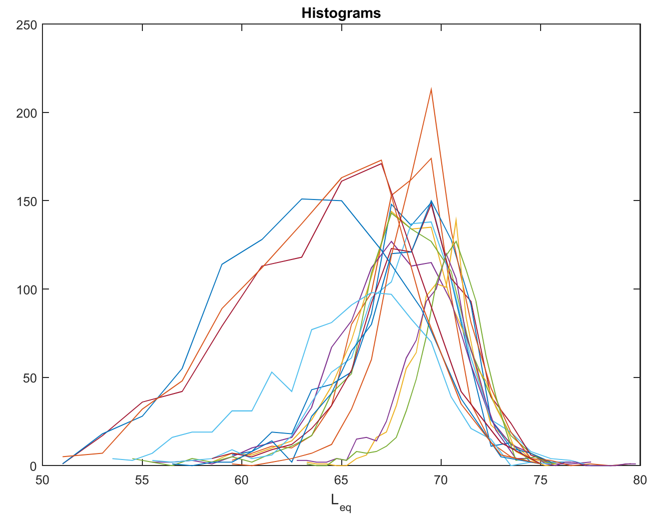


Fig. 1. Comparison between histograms of the 16 $L_{\mathrm{eq}}$ acquisitions.

Schröder *et al.* [18] focus their attention on part-based models (PBMs) for the detection of emergency siren sounds in traffic noise. In particular, starting from hidden Markov models that are flexible in time but rigid in the spectral dimension, they propose PBMs, widely used in computer vision, in order to detect the sound of sirens. The authors show that, for clean condition training, clean test samples could be classified with higher accuracies than all other approaches.

In [19], the eigenface method is used to model the sound frequency distribution features. Using this approach, the frequency spectrum of different kinds of vehicle sounds produced under similar working conditions is classified and identified.

Moschioni *et al.* [20] compare methods based on the coherence and expert system techniques based on the intensity in order to identify the contribution of single sources to global sound levels. Furthermore, a new solution adopting directional sound measurement and consequently implementing both coherence and intensity approaches is proposed.

The methods based on the retrieval of acoustic patterns from a database and their matching with the acquired sound equivalent level may have limitations in their sensitivity, due to the possible incompleteness of the database. The aim of this paper is to start the development of a method for the elimination of outliers that occur when measuring signals in real time and for the determination of the uncertainty associated with the measurement of purified signals.

## III. Proposal for Outlier Detection

During the first phase of the work, the attention was focused on the determination of uncertainty in environmental noise measurements according to the variability of the measurand,

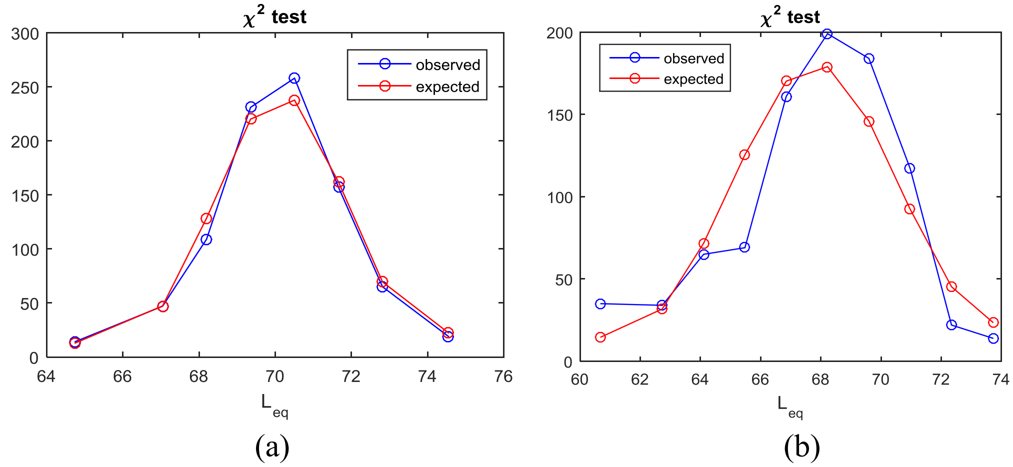


Fig. 2. Comparison between observed distribution and expected Gaussian distribution in: (a) sequence no. 10; (b) sequence no. 1.

starting from a series of measurements. The proposed procedure involves two steps.

1) In the first stage, acquired noise levels in a time interval are processed in order to remove outliers.
2) Then the remaining measured values are used for providing the test results in terms of mean value and standard deviation.

In the literature, there are several methods for outliers detection with very diverse features, performance, and application fields. Although, in general, an outlier is a data point significantly different from others, it is possible to read different definitions: Efron and Tibshirani [29] propose the definition: an outlier is an observation (or a subset of observations) which appears to be inconsistent with the remainder of that set of data. Chandola *et al.* [22] define outliers in wireless sensor networks (WSNs) as those measurements that significantly deviate from the normal pattern of sensed data. Potential sources of outliers in data collected by WSNs include noise, errors, and actual events [30].

Since the first phase of this work is the outlier detection in an acquired signal of environmental noise, among the techniques that could be chosen, the attention was turned to those designed in the context of the networks of sensors and particular attention has been focused on nonparametric approach, which assumes no prior distribution [23]. The authors, after a statistical analysis of the acquired signal, which is the result of a measurement session conducted near a motorway, considered this hypothesis particularly fit for this phenomenon of traffic noise. In particular, in order to verify whether a distribution fixed in advance cannot be attributed to acoustic measurements from traffic noise, sequences of 16 acquisitions carried out during one day are considered with the phonometer (Larson Davis 831, class 1) placed on the side of a motorway and span a time interval from 9 A.M. to 12 P.M. Each acquisition block covers a 15-min interval with equivalent noise levels measured every 1 s. These data do not include unwanted acoustic events in order to observe and verify the background noise.

To statistically characterize the distribution of data, the simulation environment MATLAB was used: for each measure, the histograms of the equivalent noise levels are determined in the first step (Fig. 1) and then the $\chi^2$ tests (Fig. 2) are applied on these noise level sequences, in order to verify if a Gaussian model can be hypothesized for the originating population.

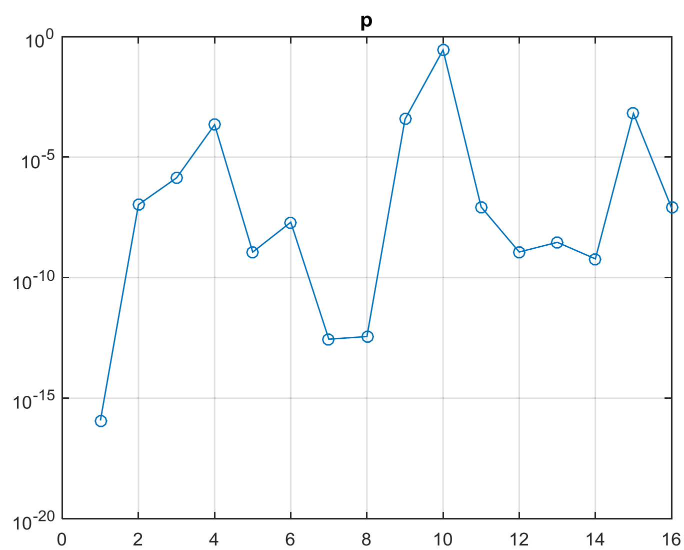


Fig. 3. Levels of statistical significance $p$ of all 16 acquisitions.

For the $\chi^2$ tests, the significance level $\alpha$ has been changed between 0 and 1, $\alpha$ being the probability of rejecting the null hypothesis when it is true. As a result, for all reasonable values of $\alpha$, all sequences except the tenth turned out not to be Gaussian [Fig. 2(a) and (b)].

For each test, the level of statistical significance $p$ was also determined. Chosen an expected statistical distribution (Gaussian in the present case), the $p$-value is the probability of observing the given sample or one which is in worse agreement with the expected distribution, given that the null hypothesis is true. Then, the smaller the $p$-value, the worse the agreement with the expected distribution.

From Fig. 3, it is easy to see that only the tenth sequence of data can be considered Gaussian, since the $p$-value is close to 1.

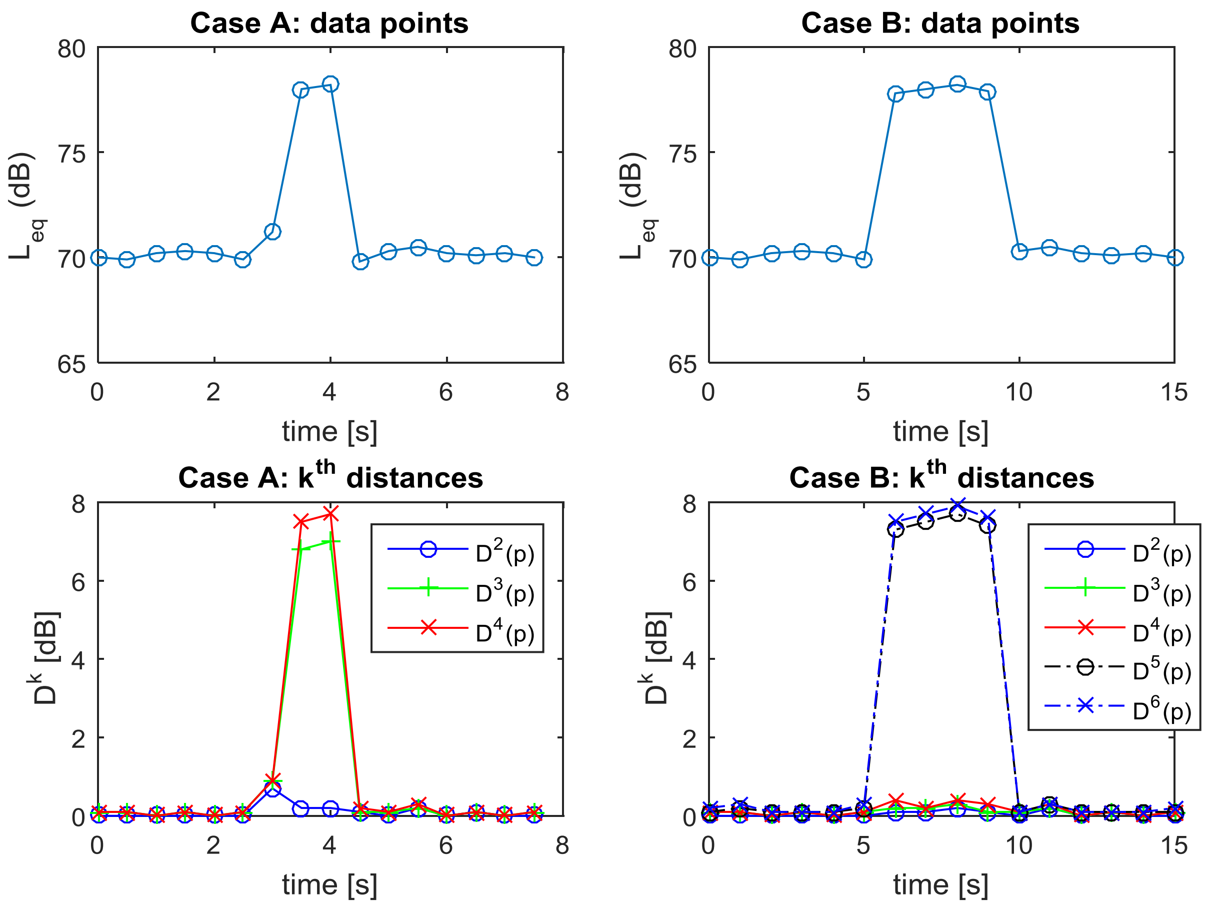


Fig. 4. Examples of outlier detection for different $k$ values.

About the networks of sensors and in particular the nonparametric approach, which assumes no prior distribution, a distance measure is defined between a new test instance and the statistical model, and a threshold on this distance is used in determining whether the observation is an outlier. One of the most widely used approach in this category is the histogram [24]. This model involves counting the frequency of occurrence of different data instances (thereby estimating the probability of occurrence of a data instance) and compares the test instance with each of the categories in the histogram and tests whether it belongs to one of them.

In the case of sensors that generate a significant amount of data, outlier detection is critical to identify and store only the really useful pieces of information. In this context, in order to optimize communication costs, instead of collecting all the data in one central location for processing, with the model histogram information are collected on the distribution of the data, and, using the hints to filter out unnecessary data, potential outliers are identified.

With reference to environmental noise, the outlier detection purifies the measured signal from any abnormal contributions in order to analyze, in the second phase of this work, the determination of the measurement uncertainty on the signal produced by the measuring activity.

The outlier detection is based on the distance between two neighboring data points: the distance can be compared with a fixed threshold or with all the other data points.

For a data point $x$, defined the distance as the absolute difference between two data points, all the other data points can be sorted according to their distances to $x$ in an ascending order. Suppose the sorted list is $x_1, x_2, \ldots, x_k, \ldots$ and $|x_1 - x| \leq |x_2 - x| \leq \cdots \leq |x_k - x| \leq \cdots$

Let $D^k(x) = |x_k - x|$ represent the distance between data point $x$ and its $k$th nearest neighbor ($x_k$). An outlier is defined in the literature in two different ways [24].

*Definition 1:* A data point $x$ is called an $O(d, k)$ outlier if $D^k(x) \geq d$.

*Definition 2:* A data point $x$ is called an $O(n, k)$ if there are no more than $n - 1$ other data points $y$, such that $D^k(y) > D^k(x)$.

Between these two definitions of outlier, the first one was chosen, because it is more inherent in the object of this paper: if they had chosen the second one, a minimum of $n - 1$ points would never been considered, in particular the $n - 1$ points with the greatest distance. Even though this approach would not significantly affect average and standard deviation of the sample, removing some points reduce the ability to describe the process.

The choice of $k$ parameter in Definition 1 is related to the event duration compared with the period of observation. In the algorithm for the outlier detection, the value that is assigned to the $k$ parameter is very important, because it determines the accuracy of the algorithm. In Fig. 4, there are four graphs that illustrate, for two different outliers (cases A and B), how the

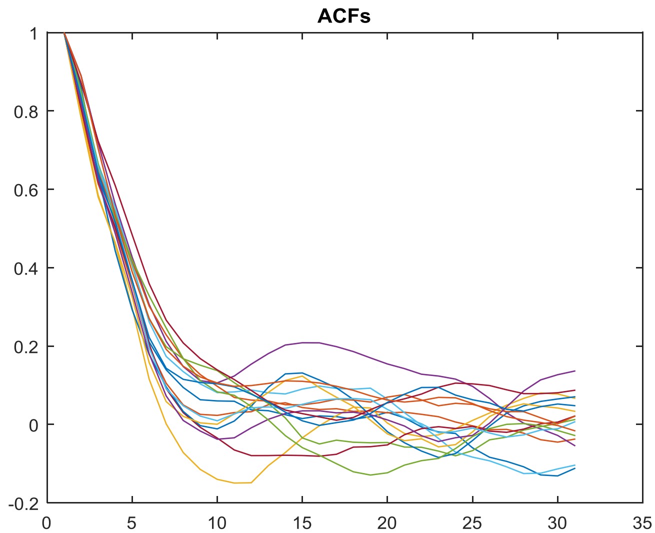


Fig. 5. Autocorrelation functions for all 16 acquisitions ($L_{eq}$ measured every 1 s).

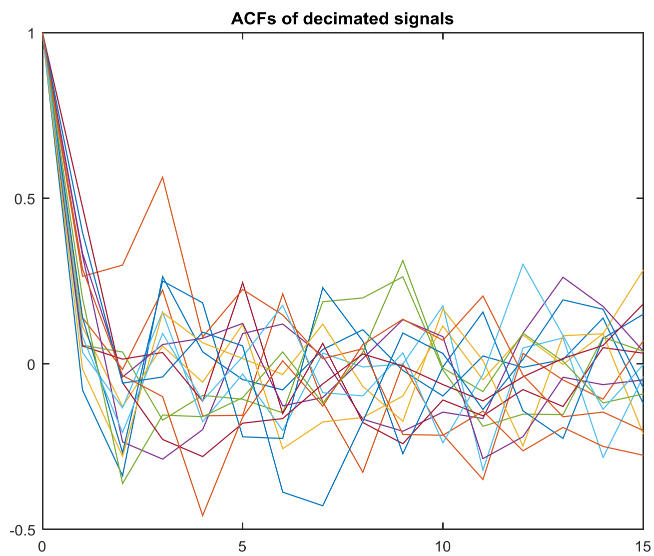


Fig. 6. Autocorrelation functions for all 16 acquisitions ($L_{eq}$ measured every 30 s).

sensitivity of the algorithm changes when the parameter $k$ changes.

For each case, the top part of Fig. 4 shows the sequence of data points and the bottom part of Fig. 4 shows the corresponding trends of $k$th distances. In case A, the event consists of two data points. It is clear that the outlier can be detected only if $k \geq 3$ is chosen with a proper threshold $d$. In case B, the event consists of four data points. For the same threshold value $d$ of the previous example, the outlier can be detected only for $k \geq 5$.

To establish a criterion of choice of the parameter $k$, in order to give the user the possibility to decide whether to delete an event or not, the authors propose to consider an event such as outlier or as an element characterizing the acoustic phenomenon according mainly to its duration; so the autocorrelation function has been studied for each measurement carried out. As a result, the value at which the autocorrelation becomes negligible is considered a valid reference value. For instance, from Fig. 5, in which the

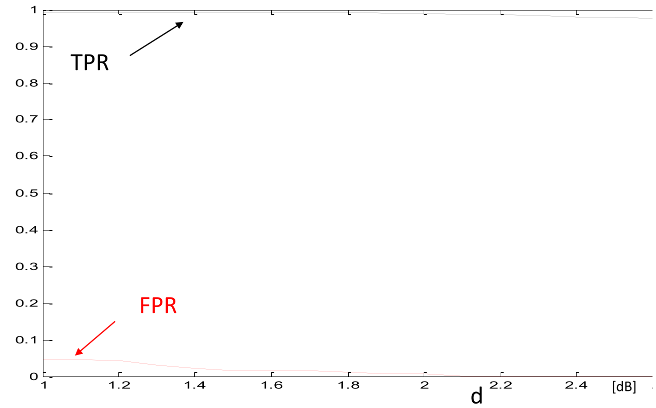


Fig. 7. FPR and TPR versus the threshold $d$.

TABLE I

CONTRIBUTION OF OUTLIER REMOVAL ON MEAN AND STANDARD DEVIATION

| # example | mean value (dB) | | standard deviation (dB) | |
|---|---|---|---|---|
| | before algorithm | after algorithm | before algorithm | after algorithm |
| I | 64.4 | 64.3 | 1.9 | 1.6 |
| II | 64.9 | 64.9 | 1.7 | 1.7 |
| III | 65.4 | 65.1 | 2.1 | 1.6 |
| IV | 66.0 | 65.1 | 5.2 | 1.5 |
| V | 66.5 | 65.4 | 5.4 | 1.4 |

autocorrelation function of all the 16 acquisitions is shown, it is clear that, since the measurement time is equal to 1 s, the events that characterize the phenomenon under observation have an average persistence time of the order of about 10 s: so to characterize a spot event as outlier to be deleted, the user has to choose a value of $k < 10$. The $k$ parameter depends on the measurement period as well.

In [16], the data are measured every 30 s and outliers were identified for $k = 1$, since the phenomenon duration is comparable with the measurement period. Fig. 6 reports the autocorrelation function for the 16 sequences with a measurement period of 30 s. In this case, the persistence time turns out to be close to one and this can motivate a choice of $k = 1$, as was done in [13].

## IV. Experimental Results

In order to experimentally validate the proposed approach, tests were performed on acquired data blocks. Each acquisition block covers a 15-min interval with equivalent noise levels measured every 30 s. The set of 16 acquisitions has been subdivided into two subsets collected during the 24 h of a whole day. The first subset is composed of 11 nonconsecutive

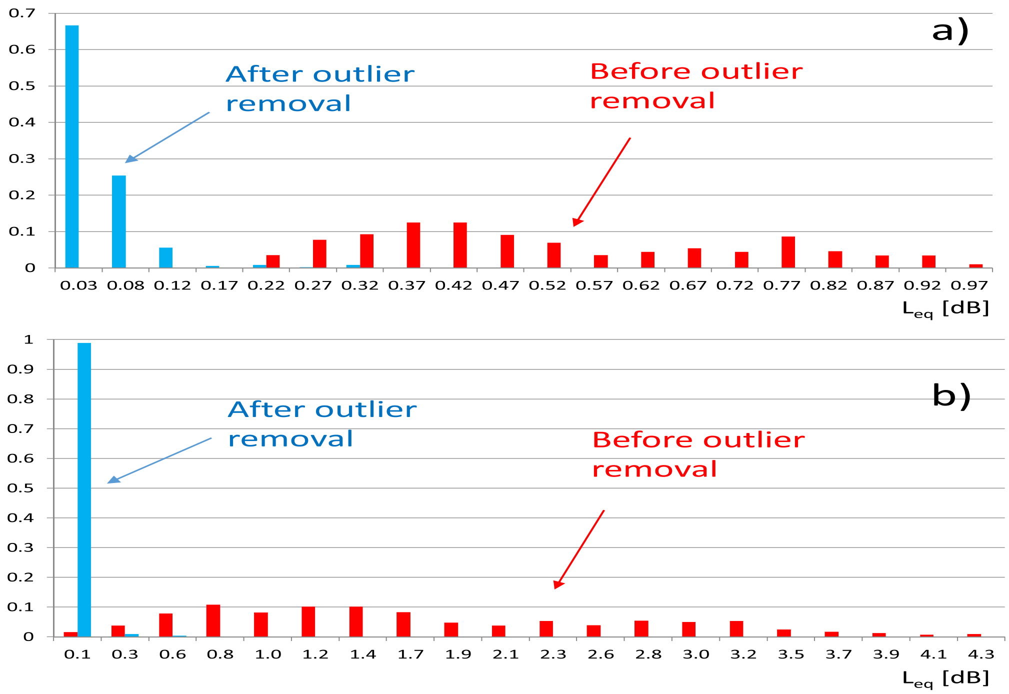


Fig. 8. Normalized histograms of the (a) mean differences and (b) standard deviations of the differences.

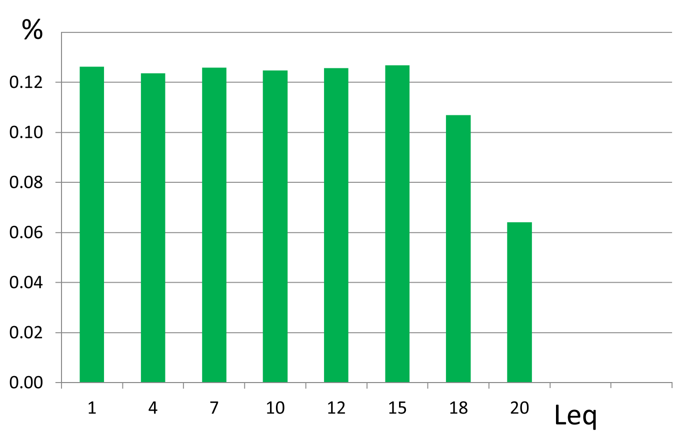


Fig. 9. Normalized histogram of the superimposed outliers.

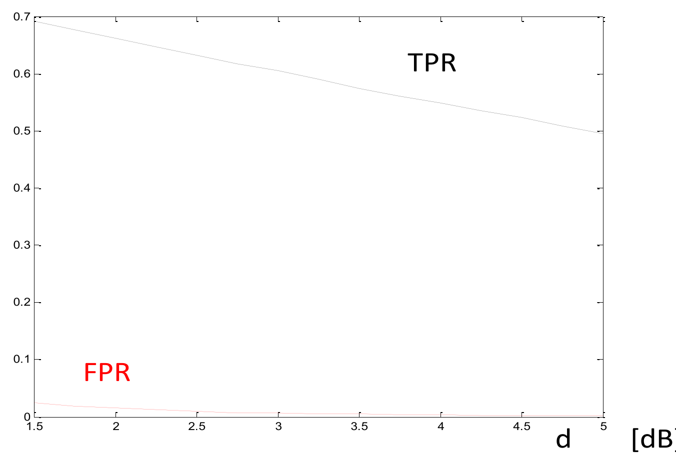


Fig. 10. FPR and TPR versus the threshold $d$ for the second series of tests.

acquisition blocks that have been used in the tuning of the algorithm. The remaining five nonconsecutive blocks have been used for the test phase, whose results will be reported in the following.

The $D^k(x)$ has been evaluated with $k = 1$ for each one of the tuning acquisition blocks in order to have indications for the minimum value of the threshold $d$. Then outliers have been superimposed onto the test acquisition blocks and the percentages of false positives (FP) and true positives (TP) have been evaluated for different values of the threshold $d$. In Fig. 7, the trends of the FP ratio (FPR) and TP ratio (TPR) are shown versus the threshold $d$. In these tests, the threshold $d$ has been chosen to be equal to 2 because in correspondence with this value there is the best tradeoff between TPR (100%) and FPR (0.04%).

The performance of the so setup procedure is evaluated, considering the signal with superimposed outliers and the equivalent levels measured on the sequences: 1) before the superimposition of the outliers; 2) after the superimposition of the outliers; and 3) after the elimination of the detected outliers. The results are compared in order to quantify the removing capability of the procedure. In detail, the differences between the data in 1) and 2) have been compared with the differences between the data in 1) and 3). For each one of these two sets of differences, the mean and the standard deviation have been evaluated. The normalized histograms of the two sets of mean differences are reported in Fig. 8(a), while the normalized histograms of the two sets of standard deviations of the differences are reported in Fig. 8(b). As can be seen, the difference between the $L_{eq}$ after the outlier removal is

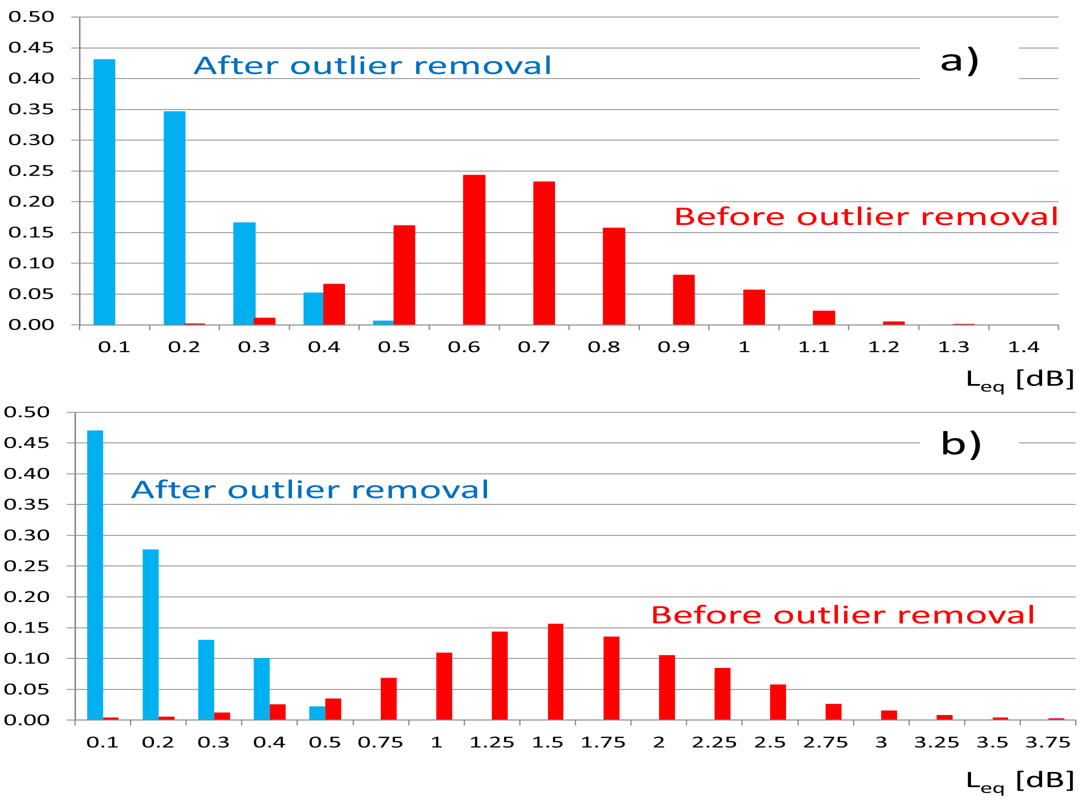


Fig. 11. Normalized histograms for the second series of tests of the (a) mean differences and (b) standard deviations of the differences.

close to zero for about 70% of the data, with a worst case value of 0.37 dB. Without the removal algorithm, the $L_{\mathrm{eq}}$ may be overestimated up to 1 dB. The analysis of the standard deviations shows that the removal algorithm yields a residual value of the standard deviation of 0.1 dB, which contributes to the overall uncertainty, while there was an overestimation of the standard deviation before the removal up to 4 dB. It is evident that the correction has a greater influence on the standard deviation than on the mean value.

Eventually Table I reports a summary of the results of a series of tests performed with different kinds of outliers:

1) example I: one outlier with a small value (a few decibel above the mean);
2) example II: no outlier;
3) example III: two small outliers;
4) example IV: one bigger outlier;
5) example V: one small outlier and one big outlier, where the smaller one is <5 dB, and the bigger is > 10 dB above the mean.

Only in example II the algorithm finds one outlier instead of two, while in all the other cases, the number of detected outliers is equal to the expected number. From Table I, it can be stated that the outlier removal algorithm has a minor influence on the mean value and standard deviation in the case of one outlier with a small value (example I) and two small outliers (example III). However, it has a significant influence on the standard deviation in the case of one large outlier (example IV) and one big outlier (example V).

A second series of tests has been carried out with different parameters of the algorithm. The 11 sequences of data points have been collected, with a measurement time of 5 s. Outliers have been added onto these sequences at random time positions and with random amplitudes. The amplitudes of the imposed outliers follow the distribution described in Fig. 9 as normalized occurrence histograms.

For the tests, the value of $k = 11$ was chosen in order to stress the algorithm. The percentages of FP and TP have been evaluated for different values of the threshold $d$. In Fig. 10, the trends of the FPR and TPR are shown versus the threshold $d$. In these tests, the threshold $d$ has been chosen to be equal to 3.5 corresponding to a TPR of 58% and an FPR of 0.5%.

For each one of these two sets of differences, the mean and the standard deviation have been evaluated. The normalized histograms of the two sets of mean differences are reported in Fig. 11(a), while the normalized histograms of the two sets of standard deviations of the differences are reported in Fig. 11(b). From the analysis of Fig. 11, one can observe that in this case, the difference between the $L_{\mathrm{eq}}$ after the removal is close to zero for almost 45% of data, in 95% of the cases, the difference is less than 0.3 dB, and in the worst case, there is an overestimation of about 0.5 dB. Vice versa without the removal algorithm, there is an average overestimation of about 0.7 dB, and in the worst case, it reaches more than 1.2 dB. The analysis of the values of the standard deviation shows that the overestimation of about 3 dB is reduced by the algorithm down to 0.5 dB. The latter value contributes to the measurement uncertainty.

## V. Conclusion

This paper has presented a contribution to a wider research activity aiming to evaluate the uncertainty associated with the measurement of relative levels of environmental noise. The specific focus of this paper has been the study and estimation of the influence of the occurrence of spot events on the measurement uncertainty. An algorithm has been implemented and experimentally verified with real field data. The results show that the outlier detection and subsequent removal allow a significant reduction of the systematic bias and of the contribution to the uncertainty of environmental acoustic noise measurement. In particular, these tests have highlighted that for a measurement time of 1 s and $k = 1$, the residual uncertainty of the algorithm is about 0.1 dB and for a measurement time of 5 s and $k = 11$, the residual uncertainty of the algorithm is about 0.5 dB. These results can be deemed definitely acceptable. This proves that the outlier detection and removal are tasks of utmost importance for these kinds of measurements. These results represent a basis for future research work aiming to analytically evaluate the uncertainty in environmental acoustic noise measurements that takes into account the occurrence of outliers as a source of uncertainty.

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