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Z.L. Warsza¹, M.J. Korczyński²

¹*Technical University, Kielce-Radom, Poland* ²*Technical University, Lodz, Poland*

IMPROVING OF THE TYPE A UNCERTAINTY EVALUATION BY REFINING THE COLLECTED DATA FROM PERIODICAL AND NON-PERIODICAL INFLUENCES

A new approach to improving the type A uncertainty evaluation by cleaning of the collected data from unwanted influences which appears as non-periodical and periodical components identified in the data is presented in the paper. The approach refers to regularly in time sampled data. The non-periodical components are equivalent to trends while the periodical components are a type of disturbances of unknown a priori period. The cleaning process comply with the main stream of ISO GUM recommendation and can be recognized as good practice in uncertainty evaluation as the elimination of the influence like identified drift and periodic components are resulting in better approximation of the type A uncertainty. The proposed approach is discussed in the paper and the numerical result is presented as well

Keywords: the measurement process, the type A uncertainty, the systematic component.

1. Introduction

A graphical model of the measuring process and proposed type A measurement uncertainty evaluation upgrading, of the collected data are presented in Fig. 1. Let assume, that the measurand is characterized by only one value, which is subjected to disturbances while it is passing through the tested object and measurement channel.



Fig. 1. Model of the measurement process and upgraded evaluation of the uncertainty type A nd measurement result estimator \overline{x} of the regularly sampled measurand x

Disturbances arise internally in the measurement process depend on different physical phenomena and come from outside effecting jointly with imperfection and aging of elements of the measurement channel. The dispersion of collected values is the set of measurand realizations. Upgraded evaluation of the measuring process data handling includes two stages. The collected data are passing first through the stage 1, in which corrections of known influences are applied as well as "outliers" are identified and treated for example by the procedure described in [9]. Then data are passing through the second stage. In the stage 2, data sampled regularly or collected in known time spacing are processed by clean procedure from linear or non-linear nonperiodical trend and also from periodical components identified in collected data. This is the cleaning data procedure proposed by authors before any further data handling and uncertainty evaluation. The above model seems to be more appropriate and the data after cleaning better represent the true value of measurand, so also the calculation of uncertainties by applying GUM recommendation gives better results, then without cleaning.

Furtherer evaluation of the measurement uncertainty used for the set of cleaned data is similar to actual GUM recommendations and is as follows: when the sample of n observations q_i was corrected from identified components then the new mean value $\overline{x} \equiv \overline{q}$ is calculated, as the best estimate of the whole population of trials (collected data – observations) of the measured value, x. The standard deviation $s(\overline{q})$ of that mean is the standard uncertainty, $u_A(x)$. The evaluation is based on the statistical method and is one of two basic component of combined standard uncertainty expressed by formula: $u_c(x) = \sqrt{u_A^2(x) + u_B^2(x)}$. The coverage interval, according to GUM, is calculated as expanded uncertainty expressed as a product of coverage factor and combined uncertainty: $U_p(x) = k_p u_c(x)$.

The strictly theoretical background for application of the A method for uncertainty calculation for cleaned data requires:

• observations q_i do not carry any recognizable systematic component;

• results q_i after cleaning are uncorrelated (statistically independent) and are of the equal weight;

• results q_i are randomly distributed and the statistical parameters of collected data are estimate of the population with needed level of confidence;

• mean value $\overline{x} \cong \overline{q}$ of the sample could be accepted as the proper result of measurements, its standard deviation $s(\overline{q}) \cong u_A$ is calculable as for Normal distribution and it is the pure statistical component of accuracy.

Procedure of the uncertainty $u_A(x)$ evaluation according to actual ISO GUM [1] method A recommendation is for corrected values of observations: $q_1, q_2, q_3, ..., q_n$, where: -n – number of observations and the is recommending below equations numbered from (1) to (4), as followings:

mean value:

$$\overline{\mathbf{x}} \equiv \overline{\mathbf{q}} = \frac{1}{n} \sum_{i=1}^{n} q_i \; ; \tag{1}$$

variance of the sample

$$s^{2}(q_{i}) = \frac{1}{n-1} \sum_{i=1}^{n} (q_{i} - \overline{q})^{2};$$
 (2)

experimental standard deviation:

$$s(\overline{q}) = \sqrt{s^2(q_i)}; \qquad (3)$$

standard uncertainty of type A:

$$u_{A}(x) = s(\overline{q}) = \frac{s(q_{i})}{\sqrt{n}} = \sqrt{\frac{1}{n(n-1)} \sum_{i=1}^{n} (q_{i} - \overline{q})^{2}}$$
. (4)

The literature [2-7], dealing with uncertainty evaluation, relates mainly to the above GUM [1] approach. The Monte Carlo based method, MCM, presented for example in [6] and in GUM Supplement 1 do not refers to data cleaning as proposed here, so any data handling before MCM is applied are not forbidden, so it is allowed if appropriate or even welcome if improves the final result of uncertainty evaluation. Considerations in GUM [1] and in related literature, refers only for the sample of limited number of independent trials and not correlation of data is required.

There are still many areas in measurement science, research and technology to which today's GUM recommendation cannot be applied due its limitations. GUM do not treat uncertainty calculation properly if:

• the set of raw observations is not the sample of the pure random population.

• the set of raw observations is of not the normal distribution

• and also

• the method does not take into consideration the order and relations between samples, do not refers to:

- time variable samples, or;

 sample of which elements are influenced by ambient conditions, which require stochastic stationary and non stationary processes modelling as more adequate to the real world and;

• the GUM method does not refers to the evaluation of uncertainties of dynamic parameters and parameters obtained as a result of digital signal processing (DSP) for different algorithms.

Measurement data handling by removing all a priori "known" systematic components from raw observations still do not guarantee to get the sample free of unknown disturbing the data regular components. Theses components should be also eliminated, but identification of all of them might not be possible. The identification and removing such elements from the set of data can be recognized as "cleaning of data" or signal filtering as the data are similar to set of digital values of recorded signals. If an additional information is known, e.g. procedure: how observations x_i of the constant value x of the measured quantity are collected, i.e. regularly sampled as series in time or space or by other known way, then some of undesirable components as outliers, trend or harmonics in relation to the length of the sample, could be cleaned up. It can be done only partly by the input filtration, more - by algorithms including identification of the components. For regularly sampled observations the stage 2 of data cleaning as presented in Fig. 1 is propose to added to good practice of GUM recommendation. The Least Square Method for components identification was applied for examples presented in [11]. It is worth to say clearly, that enough properly "cleaned" observations additionally may be also statistically dependent, i.e. they could be autocorrelated, especially if they have been collected in relatively too short periods between trials. Also Normal distribution may not be the best distribution for the real measurement data. The mean value of the sample of such observations is not always the most likelihood parameter of their distribution and other unbiased estimators should be used, as the midrange of rectangular distributions and median (MED) of Laplace double-exponential ones [3, 10]. The last two problems were explained and discussed in [12]. The methods of achieving the best possible values of the uncertainties: $u_B(x)$ and $U_p(x)$

are presented in [10].

These problems are very important as new generation of instruments and measurement systems can be build in which calculation of uncertainty of measurement can be incorporated as one their function [8].

2. Detection and discrimination of systematic components from regularly sampled measurements

As it is pointed out in previous chapter after correction of sample observations from known systematic disturbances some unknown components of the regular, systematic nature may still remain. Is uncertainty, u_A , is calculated for such data, still contaminated by systematic nature of effects, the obtained value is too high, as not only random dispersion of measurement results is present. Such raw measurement data shouldn't be treated as random stationary process, i.e. should not be characterized by statistical parameters only. The "cleaning" task is to investigate, in collected data, a priori unknown such effects as no periodical trend and as periodical interference components. This is possible only if the collected data are regularly sampled or time interval between sampled data is known.

The proposed cleaning process should be preceded by elimination of outliers, the data which are inconsistence to other collected data. That problem was deeply analyzed by Pavese and Ichim [9] and the specific procedure of elimination of outliers proposed.

As time dependent trend seems to be identified applying mathematical rules including LSM method for optimalisation, the constant value which may be incorporated in measurement data will remain unknown until the instrument calibration process will take place. However the constant may be time dependent due to instrument ageing, but such constant value wouldn't influencing uncertainty uA . That constant value practically do not varies if observations are performed in relatively short time, but may be time dependent during the life of instrument or full time of testing of the particular object due to variation of measuring conditions and aging of its and instrumentation parameters [2]. The measuring circuit might require also the extraordinary internal calibration. The electrical drift of the instrument may be corrected by self calibration procedure, by manual or automatic internal calibration, but it not covers the correction of the trend of entrance signal to the instrument. For sensors special stand is needed. If the instrument self-calibration is not available in situ, the constant value of its non-recognizable trend must be treated as a estimated additional component of the uncertainty, $u_B(x)$.

There are few methods to identify and to remove from raw measurement data the trend and other interfering components. One of the simplest – the Least Square Method (LSM) was applied as it is shown in the Example described below.

Example: The 4 1/2 digit digital voltmeter of was used to collect measurement data of the parameter of some process. The data was sampled uniformly in time and n = 121 results in (V) are as follows:

Table 1

1,2200	1,2080	1,2186	1,2263	1,2497	1,2725	1,2981	1,2731	1,2500
1,2286	1,2181	1,2183	1,2162	1,2247	1,2253	1,2108	1,2409	1,2529
1,2696	1,2577	1,2397	1,2300	1,2341	1,2562	1,2449	1,2378	1,2203
1,1920	1,2056	1,2092	1,2198	1,2227	1,2210	1,2134	1,2064	1,2138
1,2154	1,2220	1,2352	1,2479	1,2385	1,2277	1,2206	1,2320	1,2466
1,2679	1,2412	1,2279	1,1897	1,2123	1,2291	1,2498	1,2450	1,2343
1,2356	1,2420	1,2239	1,2101	1,2057	1,2044	1,2011	1,1940	1,1941
1,1836	1,1956	1,2002	1,2159	1,2142	1,1963	1,1840	1,1726	1,1657
1,1553	1,1726	1,1932	1,2146	1,1983	1,1904	1,1736	1,1874	1,2003
1,1950	1,1911	1,1754	1,1594	1,1748	1,1799	1,1817	1,1816	1,1907
1,1937	1,1982	1,1956	1,1977	1,1868	1,1684	1,1455	1,1648	1,2019
1,2126	1,2086	1,1885	1,1760	1,1729	1,1706	1,1692	1,1921	1,2036
1,2229	1,1996	1,1810	1,1609	1,1314	1,0975	1,0704	1,0845	1,0954
1,1146	1,1172	1,1148	1,1263					

Rough results of observations of the Example

The task was to calculate the average value from the 121 trails of collected readings of the voltage and to estimate the uncertainty as its standard deviation after the identification and elimination of earlier unknown systematic effects (like linear or other no periodical trend and periodic components). There is no available information regarding corrections which could be applied to measurement results in the beginning of calculations. Uncertainty u_B is not in the scope of interest in this numerical example.

Solution:

The raw data values v_i (in order of collection) are presented in Fig. 2, a. The declining trend of that data is observed. The trend and oscillation were discovered in the collected data as it is presented in Fig. 2, a. Physical analysis of the measurement process should confirm that such systematic components could exist in the raw sample. For comparison on Fig. 2, b are given raw observations and their values after each of two steps of elimination: firstly trend and secondly oscillation. Additionally in Fig. 3 it is shown how sets of observations ordered by values change by these two steps of data cleaning. Ideal shape of such curve for Normal distribution is very near to the integral probability curve (Laplace) turned by 90⁰.



Fig. 2. Sets of measurement data: a) deviations of raw measurement data from mean value in order of the regular sampling and identified systematic components incorporated in data, b) Sets of measurement data after cleaning from trend and oscillation

Mean values and uncertainties, u_A of all three sets of measurement data are given in Table 2.

Deviations Δv_i of raw data from the mean value $\overline{x} \equiv \overline{q}$ are seen on the Fig. 2, a and curve 1 in Fig 4 is connecting points of their histogram intervals (j – from j=1 to j=8 represents number of intervals). On axis "y" are given the empirical occurrences $w_j = n_j / n$,

where n_j – number of data in the interval j, n – number of all collected data. The width of intervals are calculated using as follows

h =
$$\frac{\max(\Delta v_i) - \min(\Delta v_i)}{m} = \frac{0.228}{8} = 0.0285$$
, (5)

where m = 8 – number of intervals.



Fig. 3. Raw measurement data and after each step of cleaning ordered by values

Even from the first glimpsed to the curve 2 of Fig 4, it obvious that histogram is non symmetric and do not seems to have a Normal distribution shape. Despite of that the mean value \overline{V} and standard deviation $s(v_i)$ were calculated using formulas: (1) and (3), which are suggested by GUM [1]. These results will be compared to the similar results after each cleaning process of the data as it is quoted in Tab. 2.

Table 2

		Data cleaned from:			
Measurement data	Raw data V _i	trend q _i	trend and single oscillation q _i		
2	$\chi^2 = 52.28 >$	$\chi^2 = 3.83 <$	$\chi^2 = 3.25 <$		
χ^2 criterion for normal distribution	$>\chi^2_{5,\ 0.05} = 11.1$	$<\chi^2_{5,\ 0.05} = 11.1$	$<\chi^2_{5,\ 0.05} = 11.1$		
owion	negative result	positive results			
Mean value	$\bar{v} = 1.2029$	q =1.2028	$\overline{q} = 1.20262$		
Standard deviation	$s(v_i) = 0.03953$	$s(q_i) = 0.02409$	$s(q_i) = 0.02407$		
Uncertainty u _A	0.003593	0.002190	0.002188		
Ratio of standard deviations	$\frac{\overline{s(v_i)}}{s(q'_i)} = \frac{0.039}{0.024}$	$\frac{953}{409} \approx 1.6407$	$\frac{s(v_i)}{s(q)} \approx 1.6420$		
Result of measurements	$x = 1.2029 \pm 0.0036$		$x = 1.2026 \pm 0.0022$		

The parameters of colleted measurement data sample of raw observations

Assuming "zero" value of the trend is on mean value and applying the LSM method to trend line we obtain:

$$y(i) = (-7.82E-06)i^2 + (7.82E-05)i + 0,033.$$
 (6)

The data $\Delta q'_i$ deviations of the sample corrected by elimination increments of the nonlinear trend in relation to its mean value are presented in Fig. 2b. Their mean value is the same as before but range is now smaller, it is changed from 0,228 to 0,143. The new histogram for corrected data $\Delta q'_i$ is presented by curve 2 in Fig. 4. The Normal distribution can be expected, but it is appropriate to test the thesis of compliances using criterion χ^2 and in which χ^2 is expressed by:

$$\chi^{2} = n \sum_{j=1}^{n_{P}} \frac{\left(w_{j} - p_{j}\right)^{2}}{p_{j}}, \qquad (7)$$

where p_i – is a probability of interval j according to Normal distribution.

Let assume the significance level of a test $\alpha = 0,05$. For such level no more then 5 % discrepancy between experimental and theoretical could appear. From table of $\chi^2_{v,\alpha}$ distribution, is that: $\chi^2_{5,0,05} = 11,1$ as in our Example the degree of freedom is 5 ($v = n_p - 2 - 1 = 5$) and it is the first index of $\chi^2_{v,\alpha}$ and the second α is significance level of a test. Numerical calculated value form experimental data χ^2 equals:

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$$\chi^2 = 121 \sum_{j=1}^{8} \frac{\left(w_j - p_j\right)^2}{p_j} = 3,83.$$
 (8)

After clearing out the linear trend from the set of measurement data, the distribution χ^2 test allows us to conclude that the collected data belong to the Normal distribution. The following requirements is satisfied: $\chi^2 = 3,83 < \chi^2_{5,0,05} = 11,1$. Test gave positive result, so hypothesis about this type of distribution was proved.

Periodical component – see Fig 2a, is detected using also the LSM method. It has quite small amplitude but is influencing on the calculated value of uncertainty u_A . Curve 3 of histogram obtained for data after two steps of cleaning is given also on Fig 4. Range of that data is practically the same about 0,143 and the mean value is also practically not changed as the whole number of sinusoid period is in the length of data.



Fig. 4. Distributions of the measurement data deviations from the mean value

Steps of calculations of parameters for raw data and corrected data were performed according to formulas as stated before and are presented in Tab. 2. In practice, as the two significant digits of the u_A uncertainty are enough in the most cases to describe result of measurements, so the proposed here data cleaning by identification of one or two components seems to be quite sufficient in that numerical example. Some numerical intermediate results presented in table have more digits, but it is done deliberately for better presentation how cleaning can be effective.

Conclusion: The measurement data cleaning is resulting in lowering experimental standard deviation by 64.00% after trend elimination and by 64.08% for trend and periodical component elimination. So, the cleaning process is resulting in lowering the standard u_A uncertainty on the same ratio. No further periodical component is observed in corrected data. But to check the correctness of that statement the harmonic analysis for all collected data was applied. The amplitudes of harmonics are calculated as fraction of standard uncertainty of $s(q_i)$ – see Fig 5. On x axis is an order of harmonic components of analyzed data. The graph represents typical character for process of the low frequency noise. It proves the earlier expectations about no predominant harmonic observation.

Based on cleaned measurement data, it is possible

to calculate others parameters like expanded uncertainty based on t-Student distribution for small number of observations n. This approach is well developed in GUM recommendations [1] and was treated widely in literature.

3. Verification of cleaning method

To verify the proposed cleaning of measurement data procedures the authors also use the simulation method. It is based on adding known systematic components to the sample of collected random measurement data and next application of the proposed cleaning procedure. Such verification is presented in Example 2 given in [11]. The original collected data were classified as sample from the population of probability distribution function uniformly distributed, and the linear and periodical component were added to that data. The parameters of the both added components were not known a priori for the person, who applied the cleaning procedure. This procedure was just the same as presented in Example of this paper.

If the set of measurement data is contaminated by periodical character, then the mean value is slightly changed due to it, unless not complete number of periods are in the collected set. Such situation is very likely in practice, and then it is worth to remove such periodical component, what was elaborated by authors and results of some numerical example are presented above. The basic parameters of such periodical signal were identified, i.e.: amplitude, frequency and phase

shift. The LSM was applied as the criterion for their optimization.



Fig. 5. Frequency spectrum of measurement data deviations after cleaning. (frequencies of harmonics are related to of the reciprocal of the period of all measurement data collecting time)

4. Summary and final conclusions

This paper propose upgrading of the procedure recommended by guide ISO GUM for evaluation of the uncertainty by type A method in the case of regularly sampled data measurements. This is done by "cleaning" the raw measurement data from unknown systematic components, which is based on identification and removing from set of data the trends of linear and periodical characters. The rule after data cleaning is such that the standard uncertainty lowers. It was proved by many elaborated examples of which one for normal distribution is presented as Example. Example for uniform distribution is quoted in [11]. In that Example the precision of the periodic component identifications by LSM method was also tested and its result was enough satisfied for uncertainty u_A estimations. Calculations of the uncertainty \boldsymbol{u}_A in the case when nearer measurement observations are correlated, and standard uncertainty as accuracy measure of other then the mean value estimators of random population (e.g. midrange - for uniform distribution, median - for double exponential one) are also described for complarisonnino \$1 0ases in practice it is enough to remove from raw data the linear trend component and the main harmonic function only. That should satisfied accuracy commonly applied in uncertainty uA evaluation and could be added to GUM recommendations in the way as and summarised on Fig. 6 (data cleaning operations described in this paper are shown over the dotted line). Without application of the cleaning process of unknown systematic components they could influencing twice on final measure of result accuracy, i.e.: on u_A value and second time in the estimation of u_B uncertainty components.

It is very important in the measurement practice to be sure that identified regular components in the raw sample are really become from undesirable interference signals and they are not just the result of random dispersion of observations in this particular sample. It is recommended to check them in few samples collected in nearly similar circumstances and compare them by the properly choose criterion. Or on other way by recording the sample as long as possible and then to test if it is stationary, e.g. by dividing it to parts and compare if regular components identified in these parts are similar.

This paper do not draw out all aspects of investigation of trends and other disturbances in raw measurement results and "data cleaning" by application signal filtration method [2, 3, 9] – but is contributing to the such wide problem. It is obvious that one publication do not refers all.

This cleaning approach is an early stage of data handling before investigation the influence of their autocorrelation and choosing the adequate probability distribution as next stages proposed to of the procedure of the uncertainty of type A evaluation are presented in [12], while the improvement procedures the uncertainty of type B and overall uncertainty u_C in [10]. All these proposals may be included in activity of developing the GUM recommendations on expression of the uncertainty in measurement [7], but before that they also need some task of standardization.



Fig. 6. Scheme of upgraded procedure of uncertainty u_A calculations

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Рецензент: д-р техн. наук, проф. И.П. Захаров, Харьковский национальный университет радиоэлектроники, Харьков.

ПІДВИЩЕННЯ ЯКОСТІ ОЦІНЮВАННЯ НЕВИЗНАЧЕНОСТІ ЗА ТИПОМ А ШЛЯХОМ ФІЛЬТРАЦЇ НАКОПИЧЕНИХ ДАНИХ ВІД ПЕРІОДИЧНИХ ТА НЕПЕРІОДИЧНИХ ВПЛИВІВ

Варша З.Л., Корчинскі М.Й.

Представлено новий підхід до підвищення якості оцінювання невизначеності за типом А шляхом фільтрації накопичених даних від небажаних впливів, що з'являються в даних у вигляді неперіодичних та періодичних складових. Підхід призначений для постійних в часі вибіркових даних. Неперіодичні складові еквівалентні, на відміну від періодичних, типу завад з невідомим апріорно періодом. Процес фільтрації відповідає загальним рекомендаціям ISO GUM і може бути визнаний гарною практикою в оцінюванні невизначеностей як виключення впливів випадкових та періодичних складових, отриманих при кращій апроксимації невизначеності за типом А. Запропонований підхід обговорено в друкованих виданнях, і числові дані вважаються задовільними.

Ключові слова: процес вимірювання, невизначеність за типом А, періодичні і неперіодичні впливи.

ПОВЫШЕНИЕ КАЧЕСТВА ОЦЕНИВАНИЯ НЕОПРЕДЕЛЕННОСТИ ПО ТИПУ А ПУТЕМ ФИЛЬТРАЦИИ НАКОПЛЕННЫХ ДАННЫХ ОТ ПЕРИОДИЧЕСКИХ И НЕПЕРИОДИЧЕСКИХ ВОЗДЕЙСТВИЙ

Варша З.Л., Корчински М.И.

Представлен новый подход к повышению качества оценивания неопределенности по типу А путем фильтрации накопленных данных от нежелательных воздействий, появляющихся в данных в виде непериодических и периодических составляющих. Подход предназначен для постоянных во времени выборочных данных. Непериодические составляющие эквивалентны, в отличие от периодических, типу помех с неизвестным априорно периодом. Процесс фильтрации соответствует основным рекомендациям ISO GUM и может быть признан хорошей практикой в оценивании неопределенности как исключение воздействий случайных и периодических составляющих, полученных при лучшей аппроксимации неопределенности по типу А. Предлагаемый подход обсужден в печати, и числовые данные прияты как удовлятия, неопределенность по типу А, периодические и непериодические воздействия.