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Understanding and Integrating Resolution, Accuracy and Sampling Rates of Temperature Data Loggers Used in Biological and Ecological Studies

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Abstract

During the 5th Workshop about Temperature-Dependent Sex Determination held in the 38th International Sea Turtles Symposium (16-22 February 2018) in Kobe, Japan, we discussed the uncertainty of temperatures recorded by data logger and their calibration. We report here an extension of this discussion. First, we propose a way to estimate the uncertainty of the average temperature recorded using data loggers considering the accuracy of the data logger (repeatability of measurements), resolution of the data logger (resolution of its indicating device) and period of sampling temperature. Second, a general procedure of calibration is described. Functions to perform the estimates are provided in R package embryo growth freely available.

Keywords: Data logger; Temperature; Resolution; Accuracy; Uncertainty; Sampling period; Calibration

Introduction

Metabolism is the process by which energy and materials are transformed within an organism and exchanged between the organism and its environment [1]. The metabolic rate is the rate at which organisms transform energy and materials and is governed largely by two interacting processes. The first is the Boltzmann factor, which describes the temperature dependence of biochemical processes, and the second is the quarter-power allometric relation, which describes how rates of biological processes scale with body size [2]. Hence, temperature is a key factor in understanding the persistence of organisms within an ecosystem. The range of temperatures within which an organism can survive is termed its thermal niche [2]. For many vertebrates, the thermal niche is relatively wide and centered around 30°C [3]. Thus, when temperature is recorded in the purpose of defining a thermal niche, the accuracy of measurements will not have a major impact on the outcomes of this kind of study.

However, for some physiological processes, thermosensitive changes can occur within a small range of temperatures, and thus the accuracy and resolution of temperature recording instruments become much more important. For example, in turtles egg, incubation temperature during embryogenesis affects various aspects of development [4], including probability of embryo survival [5], sex determination for species with temperature-dependent sex determination [6], and morphology and body size at hatching [7]. In addition, incubation temperature can have long-term effects on the physiology and behavior of hatchlings [8]. Many researchers use data loggers inside the nest cavity to generate temperature records during incubation, to later compare them with various characteristics of hatchlings (e.g., size, performance, sex). However, the uncertainty of data logger measurements can affect the conclusions in some cases. For example, the sex ratio for the leatherback marine turtle shifts from 100% males to 100% females in less than 0.6°C at constant temperatures [9], which can be on the same magnitude as the uncertainty of temperature measurement for many experiments. Indeed, 10 out of 141 published studies on reptile egg incubation reported datalogger accuracy as 0.6 C or higher [10]. However, it is important to note that the term "accuracy" is not well defined in most of these publications.

Thus, as a first step, it is important to recall some important concepts used in metrology [11]. The word "uncertainty" means doubt, and thus in its broadest sense "uncertainty of measurement" means doubt about the validity of the result of a measurement. The uncertainty of measurement is a parameter, associated with the result of a measurement, that characterizes the dispersion of the values that could reasonably be attributed to the measurand. The measurand is a particular quantity subject to measurement. Uncertainty of measurement comprises, in general, many components. Some of these components may be evaluated from the statistical distribution of a series of measurements and can be characterized by experimental standard deviations. The other components, which also can be characterized by standard deviations, are evaluated from assumed probability distributions based on experience or other information.

The accuracy of measurement is the closeness of the agreement between the result of a measurement and a true value of the measurand. It is stressed that the term "precision" should not be used for "accuracy" and that the true value of the measurand is never known.

Repeatability of results of measurements is the closeness of the agreement between the results of successive measurements of the same measurand carried out under the same conditions of measurement. Repeatability may be expressed quantitatively in terms of the dispersion characteristics of the results using multiple of standard deviation or width of confidence interval.

One source of uncertainty of a digital instrument is the resolution of its indicating device. For example, even if the repeated indications were all identical, the uncertainty of the measurement attributable to repeatability would not be zero, for there is a range of input signals to the instrument spanning a known interval that would give the same indication. If the resolution of the indicating device is the value of the stimulus that produces a given indication X can lie with equal probability anywhere in the interval $X - \delta x/2$ to $X + \delta x/2$.

The stimulus is thus described by a rectangular probability distribution of width δx with variance $u^2 = (\delta x)^2/12$, implying a standard uncertainty of $u = 0.29\ \delta x$ for any indication. Repeatability and resolution of indicating device are uncertainty components linked to the dataloggers characteristics. Uncertainty can arise also from the experimental procedure used to obtain measurements. The experimenter can choose different time frequency of reading measurements. The objective of this work is to characterize and propose a standardized method to present uncertainties while working with temperatures recorded during embryo studies.

There are different brands of data loggers available in the market, all of them with different features. Two characteristics which will affect uncertainty of measurement are particularly important when choosing a particular model: accuracy (precision of the material to record temperature) and resolution (how many digits are recorded). In addition, the researcher must define the rate of temperature data recordings during the period when the data logger will be used. In some cases, data loggers may have high resolution but low accuracy, or limited flexibility in the rate of data collection. Ordering a set of data loggers can be a Cornelian dilemma: should the priority be optimization of accuracy, of resolution, or the sampling rate?

An important first step is to clearly conceptualize the difference between resolution and accuracy. Resolution refers to the level of specificity that the data logger will record temperature in its memory. For example, a resolution of 0.5°C indicates that temperatures will be recorded by bins of 0.5°C, even if the electronic chips can read internally the temperature with better resolution. The number of possible temperature records that can be stored during a session is positively related to the available memory but negatively related to the resolution and the range of temperatures that can be recorded. Some data loggers allow the user to choose between several options to optimize eithe the resolution or the memory (Table 1).

For commercially available temperature data loggers, accuracy is represented in the particular logger's technical datasheet as a range (±x°C), with x representing how close an individual recorded data point is from the true value. From a statistical point of view, this statement is too imprecise to be useful, because it is not clear if the ±x indicates a confidence interval, and if it is, there is no information about the underlying distribution and the range. Furthermore, it is not known if the data are censored or truncated [12]. In order to investigate this, we contacted the technical staff of the reseller PROSENSOR (Amanvillers, France) and they defined accuracy as the "maximal uncertainty of the measure". However, this does not provide detail concerning the statistical distribution under consideration. We also contacted the technical support group at Onset Computer (Massachusetts, USA) about their definition of accuracy, to which the leader of the support group stated "I can say that the probability of the logger being within the advertised accuracy is very high. NIST testing can confirm that." (NIST is the U.S. Commerce Department's National Institute of Standards and Technology, which provides calibration services for temperature recording equipment). The statement from Onset Computer confirmed that a statistical distribution underlies what temperature data logger reports but again provided no specifics about the exact distribution. We assume that in both cases, the distributions of values generated by the data loggers were either a Gaussian or a uniform distribution. For modelling purposes, we assume the values generated conform to a uniform rectangular distribution, because it is a more conservative estimate (every allowable value is equally likely) and we cannot rule out data truncation by the data loggers due to limitations of their resolution. For this uniform distribution, the minimum and maximum possible values are defined by the ±x accuracy.

The uncertainty is then a specific measure of the quality of temperature recording by data loggers, considering the accuracy, the resolution and the sampling rate. Data logger uncertainty is then defined by the 95% confidence interval of the average temperature during a certain time, recorded during set sampling period by a data logger with known accuracy and resolution (Table 1).

Furthermore, we propose a standardized method to calibrate data loggers. The experimental procedure used for

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data logger calibration is sometimes described with detail in publications [13,14] but often the published procedure is reported as a simple comparison with a mercury thermometer. Furthermore, even when the experimental procedure was clearly stated, the mathematical method used to correct data logger temperatures when more than 2 control temperatures are used is rarely indicated. Regular calibration testing of data loggers is important because the drift of temperature accuracy can be as large as 0.1°C/year (for UA-001-08, pers. comm. from technical support group at Onset Computer). Our standardized method of calibration uses both a precise experimental procedure and a precise mathematical procedure.

Materials and Methods

Uncertainty of a Measurement

We generated a simulation to measure the impacts of the accuracy, the resolution and the sampling rate on the quality of the average temperature data that are reported in published studies. To do this, we generated 10,000 time series of temperatures gradually changing at a rate chosen in a uniform distribution from -0.002 to +0.002°C per minute with the initial temperature being chosen in a uniform distribution from 25 to 30°C. We then retained only those records of the time series that corresponded to a specified sampling rate (*e.g.*, for a sampling rate of 60 minutes, we retained only temperature data that occurred at the completion of every 60 minutes time bin). To incorporate errors associated with data logger accuracy, we added to each retained temperature a random number obtained from a uniform distribution centered on 0 and with minimum and maximum corresponding to the reported accuracy of each data logger. We truncated the recorded temperatures to mimic the impact of the limitations of the resolution of each data logger (the resolution effect). From a mathematical point of view, the resolution effect can be obtained using this formula:

$$int\left(\left(temperature + resolution/2\right) * \left(1/resolution\right)\right) * resolution$$

With int being the closest allowable value based on the assumed level of resolution. This formula ensures that the truncation effect is well centered in the interval. As an example, assume a dataset has the following temperatures: 30, 30.1, 30.2, 30.3, 30.4, and 30.5°C, with assumed data logger resolution being 0.5°C. Applying this formula, the dataset is converted to what the data logger should report according to its resolution: 30.0, 30.0, 30.0, 30.5, 30.5, and 30.5°C.

Next, the uncertainty is defined as the 95% confidence interval of the difference between the true mean value and the recorded mean value during the relevant interval of time calculated for all the replicates. For the purpose of this test, we have created a function in the R package embryogrowth (version 7.3 and higher) available in CRAN:

```
uncertainty.datalogger (sample. rate,
accuracy, resolution,
max.time = 10 * 24 * 60,
replicates = 1000)
```

With sample.rate being the sample rate in minutes, accuracy being the accuracy of the data logger in °C, resolution being the resolution of the data logger in °C, and max.time being the total time period in minutes over which an average temperature is estimated. This function will generate replicates values of the average temperature for the whole period, and the uncertainty is defined by the range of 95% confidence interval of the difference between true and estimated mean temperature. Optional parameter method is used to control the output estimate as described in the help page of the function that can be displayed using ?uncertainty.datalogger.

Calibration of Data Loggers

For calibration purpose, the data loggers must be checked against at least 3 known temperatures, but better with more, and the recorded temperatures from the data loggers must be compared against temperatures concurrently read from a certified thermometer. A certified thermometer is one that has been certified as being accurate by a national standards laboratory, such as NIST in the U.S. Note that even certified thermometer should be checked for validity periodically, by sending them for testing to a national standards laboratory.

For the comparison at the known temperatures, the data loggers being tested should be immersed in a water bath (be sure the data loggers are waterproof) at the same time as the certified thermometer, preferably with water being stirred the entire time. The data logger should be programmed to record temperatures every minute, with the time of data recording noted by the researcher. At each minute the data logger records a temperature value, the researcher should also record the temperature from the certified thermometer. Begin with the water heated to the maximum anticipated temperature the data loggers will be recording during future research studies, and lastly the minimum anticipated temperature. It may be necessary to add colder water to the stirred bath if the lower end of the anticipated temperature range is below room temperature. The temperatures recorded with the certified mercury thermometer will serve as a reference to correct the temperatures recorded with the data logger. To make this calibration simpler, we have created a function: calibrate.datalogger() in the embryogrowth R package (version 7.3 and higher):

```
calibrate.datalogger (control.temperatures,
read.temperatures,
temperature.series, se.fit)
```

Where control.temperatures are the calibration temperatures, read.temperatures are the temperatures returned for each of the control.temperatures, temperature.series is a series of temperatures to be corrected using the calibration, and se.fit indicates whether standard error of the corrected temperatures

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should be returned. A generalized additive model (parameter gam = TRUE) or a general linear model (parameter gam = FALSE) with Gaussian distribution of error and an identity link is used for this purpose. The help page of the function that can be displayed using calibrate datalogger.

Results

Uncertainty of a Measurement

The uncertainty of measures obtained with two different data logger models were estimated using uncertainty.datalogger() function with 10,000 replicates and average for 10 days.

Table 1: Characteristics of different models of data loggers.

Manufacturer	Model	Range	Accuracy	Resolution	Records	Sample Rate	Battery Replace	Waterproof	Unitary Price	Communication
Maxim Integrated	Thermochron iButton DS1921G-F5#	-40°C to +85°C	±1°C	0.5°C	2048	1min to 115min	No	IP56	$34.00	USB kit $155.00
Maxim Integrated	Thermochron iButton DS1921H-F5#	+15°C to +46°C	±1°C	0.125°C	2048	1min to 255min	No	IP56	$39.00	USB kit $155.00
Maxim Integrated	Thermochron iButton DS1922L-F5#	-40°C to +85°C	±0.5°C	0.0625°C or 0.5°C	4096 or 8192	1s to 273h	No	IP56	$78.95	USB kit $155.00
Maxim Integrated	Thermochron iButton DS1922T-F5#	+20°C to +75°C	±0.5°C	0.0625°C or 0.5°C	4096 or 8192	1s to 273h	No	IP56	$83.95	USB kit $155.00
ONSET	HOBO Pendant® Temperature 8K UA-001-08	-20°C to 70°C	±0.53°C	0.14°C	6500	8s to 18h	Yes	Yes	$52.00	Base UA1 USB $70.00
ONSET	HOBO Pendant® Temperature 64K UA-001-64	-20°C to 70°C	±0.53°C	0.14°C	52000	8s to 18h	Yes	Yes	$67.00	Base UA1 USB $70.00
ONSET	HOBO Water Temperature Pro v2 U22-001	-40°C to 70°C	±0.21°C	0.02°C	42000	8s to 18h	No	Yes	$129.00	Base UA4 USB $124.00
ONSET	HOBO TidbiT MX Temperature 400' Data Logger - MX2203	-20°C to 70°C	±0.2°C	0.01°C	96000	1s to 18h	Yes	Yes	$129.00	Base UA4 USB $124.00
ONSET	HOBO TidbiT MX Temperature 5000' Data Logger - MX2204	-20°C to 70°C	±0.2°C	0.01°C	96000	1s to 18h	No	Yes	$139.00	Bluetooth
Gemini Data Loggers	Tinytag Transit 2	-40°C to 70°C	±0.4°C	0.01°C	8000	1s to 10days	Yes	No	$70.00	USB kit $40.00
Gemini Data Loggers	Tinytag Plus 2 TGP-4017	-40°C to 85°C	±0.4°C	0.01°C	32000	1s to 10days	Yes	IP68	$132.00	USB kit $40.00
Gemini Data Loggers	Tinytag Talk 2 TK-4014	-40°C to 85°C	±0.5°C	0.01°C	16000	1s to 10days	Yes	IP54	$82.00	USB kit $40.00
Omega	OMYL-T10	-30°C to 70°C	±0.4°C	0.01°C	100000	1s to 24h	Yes	IP65	$325.00	USB included
Omega	OMYL-T10E	-30°C to 70°C	±0.4°C	0.01°C	4000000	1s to 24h	Yes	IP65	$370.00	USB included
Dataq	EL-USB-LITE	-10°C to 50°C	±2.5°C	1.0°C	4080	30min (fixed)	Yes	No	$32	USB included

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Dataq	EL-USB-1	-35°C to 80°C	±1.0°C	0.5°C	16382	10s to 12hours	Yes	Yes with case	$59.95	USB included
Dataq	EL-USB-1-LCD	-35°C to 80°C	±0.5°C	0.1°C	16378	10s to 12hours	Yes	IP67	$69.95	USB included
Dataq	EL-USB-1-RCG	-20°C to 60°C	±1.0°C	0.1°C	32000	1s to 12hours	Yes	IP67	$132.00	USB included
Dataq	EL-USB-1-PRO	-40°C to 125°C	±0.4°C	0.1°C	32510	1s to 12hours	Yes	IP67	$149.95	USB included
MadgeTech	EggTemp	0 to 60°C	±0.5°C	0.1°C	32767	2sec to 12hours	Yes	Yes	$189	USB Kit $119
MadgeTech	MicroTemp	-40°C to 85°C	±0.5°C	0.1°C	32767	2sec to 12hours	Yes	Yes	$239	USB Kit $119
MadgeTech	Temp1000IS	-40°C to 80°C	±0.5°C	0.1°C	32767	2sec to 12hours	Yes	No	$239	USB Kit $120
MadgeTech	RHTemp1000	-40°C to 80°C	±0.5°C	0.1°C	16350	1s to 24hours	Yes	No	$429	USB Kit $120
Microdaq	Minnow-T	-30°C to 80°C	±0.3°C	0.01°C	62500	1sec to 1hour	Yes	No	$32	USB included

*The IP is an international standard published by the International Electrotechnical Commission (IEC). It uses a 2-number code, the first one designates dust resistance (0 to 6) and the second one designates water resistance (0 to 8); the higher the number, the more resistant is the product.

The results for iButton DS1921G-F5# (Table 1) were generated using:

uncertainty.datalogger (sample.rate=c(30, 60, 90, 120),

max.time = 10 * 24 * 60,

accuracy=1, resolution=0.5)

The results were shown in Table 2.

Table 2: Uncertainty in °C for iButton DS1921G-F5#.

Sample Rate in minutes	30	60	90	120
Uncertainty in °C	0.1	0.15	0.18	0.21

and For Tinytag Talk 2 TK-4014 (Table 1), the results were generated with:

uncertainty.datalogger (sample.rate=c (30, 60, 90, 120),

max.time = 10 * 24 * 60,

accuracy=0.5, resolution=0.05)

The results were shown in Table 3.

Table 3: Uncertainty in °C for Tinytag Talk 2 TK-4014.

Sample rate in minutes	30	60	90	120
Uncertainty in °C	0.05	0.07	0.09	0.1

The uncertainty returned by this function corresponds to the 95% confidence interval width of the difference between true average temperature and recorded average temperature: the uncertainty of the Tinytag Talk 2 TK-4014 for the average temperature recorded every 60 minutes is around 0.07°C whereas it is only around 0.15°C for the iButton DS1921G-F5#.

It should be noted that the response was not linear and uncertainty increased as the time interval between samples increased (Figure 1). The uncertainty is more dependent on the accuracy and second on the resolution. The measures were obtained with a large range of temperatures and temperature variations, thus the estimated uncertainty can be considered as being dependent only on the data logger characteristics and the sampling rate of temperatures.

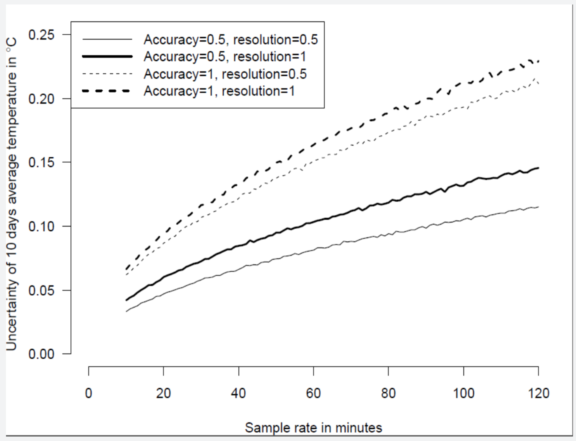

Figure 1: Uncertainty (width of the 95% confidence interval) of the average temperature for 10 days dependent on the accuracy and resolution of the data logger for one measure and the sample rate in minutes.

Calibration of Data Loggers

Water was heated to 40°C in a microwave oven and a UA-001-08 data logger was immersed in the water as well as a certified mercury thermometer. Temperatures were recorded with the data logger and read in thermometer every 5 minutes until water temperature reached air temperature +5°C (Figure 2A). Then the calibration procedure has been run using the function calibrate.datalogger() in R package embryogrowth. The corrected temperature recorded by data logger and the

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temperature recorded using certified mercury thermometer are shown in Figure 2B.

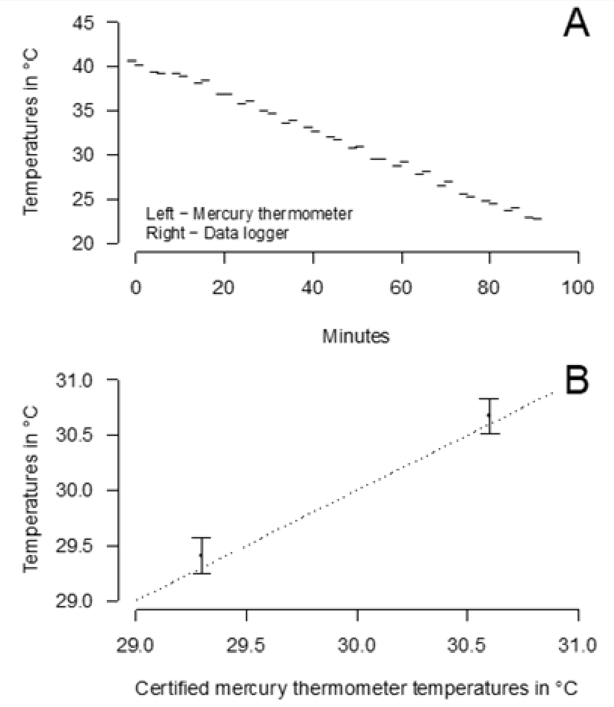

Figure 2:
A. Temperature recorded with certified mercury thermometer, and data logger.
B. Recorded temperatures with data logger calibrated using mercury thermometer temperatures from A.

especially for long period of recording. Both before and after calibrated time series must be included in control. temperatures and read. temperatures parameters in the calibrate.datalogger() function. The standard error obtained for each temperature after calibration is pertinent as it includes corrections for accuracy and resolution characteristics of the data logger but also accuracy and resolution for the calibration thermometer and also temporal drift when before and after calibration temperatures are used.

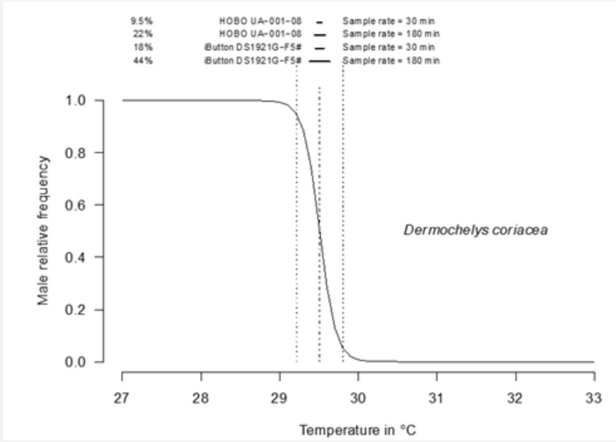

Figure 3: Pattern of temperature-dependent sex determination in the marine turtle *Dermochelys coriacea* (Chevalier et al. 1999). The pivotal temperature is 29.52°C and the range of transitional range of temperature (TRT) is 0.59°C. At the top, the uncertainty of average 10days of temperatures is shown for various situations. The percentages indicate the relative proportion of the TRT as compared to the uncertainty of the 10 days average temperatures.

Discussion

The choice of a sampling rate should depend on the required level of uncertainty for the average temperature considered, on the available memory in the data logger, and the availability and cost of different data loggers. It is particularly useful to define precisely the uncertainty of the measured temperature when the studied phenomenon is highly sensitive to temperature change. For example, the pattern of temperature-dependent sex ratio in the marine turtle *Dermochelys coriacea* shifts from 100% males to 100% females in less than 0.6°C [9,15]. This range of temperatures producing both sexes is called the transitional range of temperatures (TRT). In this case, when the average temperature is studied for 10 days, which correspond to the thermosensitive period of the development (TSP) at high incubation temperatures [16], the ratio between uncertainty of average temperature and TRT can be as high as 24% (Figure 3). In such a case it will be difficult to estimate the real impact of temperature change for this characteristic.

Calibration does not seem to be a critical part of the procedure with our tested data logger: the uncertainty of data logger was on the same order than the uncertainty of certified mercury thermometer and much better than the uncertainty of certified alcohol thermometer. However, we recommend to always calibrate data logger before and after use for an experiment

The correct calibration and adequate uncertainty of data loggers according to the analyzed temperature-dependent phenomenon seem quite logical but they are not always correctly done or at least reported not in publications. When data loggers are used to record temperatures to be analyzed in the context of temperature change due to climate-change, it appears crucial that temperatures are recorded with known uncertainty that is at least smaller than the supposed effect of temperature.

For publication purpose, the function uncertainty. datalogger() can be used to evaluate the uncertainty of one measurement taking into account both accuracy and resolution effect. It can be used also to evaluate the uncertainty of series of measurements done during H hours at a h sampling rate.

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