Ocean Instrumentation, Course 13.998
Lecture on Instrumentation Specifications
Jim Irish, WHOI, 10 Feb 2005

I. Sensor/Instrument Specification Definitions:

Range – is the maximum and minimum value range over which a sensor works well. Often sensors will work well outside this range, but require special or additional calibration. e.g. salinity sensors deployed in salinity of a few PPT in an estuary which is below where the PSU scale is defined (2 PSU). However, generally if you try to operate a sensor outside its range, it will not work (give a constant output at the max, significantly change sensitivity or give erratic results) or be damaged e.g. a 130 m pressure sensor deployed at 200 m depth.

Accuracy – how well the sensor measures the environment in an absolute sense. That is how good the data is when compared with a recognized standard. e.g. a temperature sensor accurate to 0.001º C is expected to agree within 0.001º C with a temperature standard such as a triple-point-of-water cell or the temperature measured by a PRT standardized in recognized calibration standards or by another sensor with the same accuracy calibrated properly. This is what you want to compare results with other observations.

Resolution – the ability of a sensor to see small differences in readings. e.g. a temperature sensor may have a resolution of 0.000,01º C, but only be accurate to 0.001º C. That is you can believe the size of relative small <u>changes</u> in temperature, which are smaller than the accuracy of the sensor. Resolution in often controlled by the quantization in digitizing the signal – e.g. one bit is equal to 0.0005º C. This is not a function of the sensor, but the sampling process.

Repeatability – This is the ability of a sensor to repeat a measurement when put back in the same environment. It is often directly related to accuracy, but a sensor can be inaccurate, yet be repeatable in making observations.

Drift – This is the low frequency change in a sensor with time. It is often associated with electronic aging of components or reference standards in the sensor. Drift generally decreases with the age of a sensor as the component parts mature. A smoothly drifting sensor can be corrected for drift. e.g. Sea Bird temperature sensors that are drifting about 1 mºC/yr (and have been smoothly changing for several years) allow one to correct for the drift and get more accurate readings. Drift is also caused by biofouling that can't be properly corrected for, but we often try.

Hysteresis – A linear up and down input to a sensor, results in an output that lags the input e.g. you get one curve on increasing pressure and another on decreasing. Many pressure sensors have this problem, for better ones it can be ignored. It is often seen in a CTD when the pressure reading on deck after recovery is different from the reading before it is deployed. It is not a problem with the response time of the sensor, but is an inherent property of some sensors that is undesirable. In a CTD it also may be a temperature sensitivity problem.

Stability – is another way of stating drift. That is, with a given input you always get the same output. Drift, short and long term stability are really ways of expressing a sensor's noise as a function of frequency. Sometimes this is expressed as guaranteed accuracy over a certain time period. Drift is often a problem with pressure sensors under high pressure. All sensors drift with time – hence the standardization of PRTs in triple-point-of-water and gallium melt cells.

Response time – a simple estimate of the frequency response of a sensor assuming an exponential behavior. We will discuss in more detail below.

Refer to Sea Bird temperature specification sheets:

Self heating – to measure the resistance in the thermistor to measure temperature, we need to put current through it. Current flowing through a resistor causes dissipation of heat in the thermistor, which causes it to warm up, or self-heating. This is especially important in temperature measurement. If the water velocity changes, the amount of advective cooling will change, and the temperature sensed will change as a function of velocity – anemometer effect.

Settling time – the time for the sensor to reach a stable output once it is turned on. Therefore, if you are conserving power by turning off the sensors between measurements, you need to turn on the power and wait a certain time for the sensor to reach a stable output.

Voltage required – the voltage supply range over which the sensor has a stable output. Too low a voltage and the sensor doesn't work properly, too high and something burns out.

Current drawn – what the sensor draws at each voltage. Generally this varies inversely with voltage (the sensor draws a nearly constant power - current times voltage). Therefore, you need to supply a known voltage and current. If you do this from a battery, beware that the voltage decreases as the battery discharges, and the current rises. Also, the amount of power you can get out of a battery changes with the amount of current drawn. Therefore, when you calculate power requirements, you need to know the current over the full voltage range to get power and battery requirements. We will discuss this in more detail later in a lab.

Output – a voltage range e.g. 0 to 5 volts for an input range of 0 to 30º C, or a frequency modulated sine wave, or a square wave of frequency range 6 to 12 kHz, etc.

Fit of calibrations to equation – thermistors are log devices, so fit as an inverse polynomials of log of sensor output (frequency), which change from K to Celsius by the 273.15

Sensor Noise Estimation: - Besides digitizing noise, there is another limitation in a measurement due to the inherent noise in a sensor itself. Today we have the technology to reduce the digitizing interval or digitizing noise to below the sensor noise, so the limiting factor in a measurement is generally the physics of the sensor itself. Ideally, one would put the sensor in a noise free environment and measure the spectra of the sensor's output to get the sensor noise. However, this would only work if the sensor's noise was not related to signal level, and if you could find a noise free environment.

Consider the case where several sensors are measuring the same geophysical signal, s(t), and that in addition to this signal each sensor sees its own inherent noise, $n_i(t)$. Therefore, the signal that we record from sensor i is,

$$x_i(t) = s(t) + n_i(t)$$

The cross-covariance function then becomes

$$\begin{aligned} R_{xixj}(\tau) &= \{x_i(t)\ x_j(t-\tau)\} \\ &= \{[s(t) + n_i(t)][s(t-\tau) + n_j t-\tau)]\} \\ &= \{s(t)\ s(t-\tau)\} + \{s(t)\ n_j t-\tau)\} + \\ &\qquad \{n_i(t)\ s(t-\tau)\} + \{n_i(t)\ n_j(t-\tau)\} \end{aligned}$$

where { } is the expected value of the quantity or the integral of the quantity in brackets over all time divided by the integral of time. Assuming that the signal and the noise are uncorrelated, e.g. {n(t) s(t)} = 0 and that the noise between the sensors as also uncorrelated $\{n_i(t)\ n_i(t)\} = 0$, then

$$R_{xixj}(t) = \{s(t)\ s(t-\tau)\} + \delta_{ij}(n_i(t)\ n_j(t-\tau)\}$$

Transforming, the cross spectrum is

$$C_{ij} = \int_{-\infty}^{\infty} R_{ij}(t)\ e^{-\iota\omega\tau}\ d\tau = S(\omega) + \delta_{ij}N_{ij}$$

where S is the transform of the signal and N is the transform of the noise. For the case of only two sensors, 1 and 2,

$$C_{11}(\omega) = S(\omega) + N_{11}(\omega)$$

$$C_{12}(\omega) = S(\omega)$$

$$C_{22}(\omega) = S(\omega) + N_{22}(\omega)$$

The co-spectrun extracts the signal from the noise of the sensors and can be used to improve the signal to noise when it is poor with only one sensor.

If we define N as the sum of the two noises,

$$\begin{aligned} N(\omega) &= N_{11}(\omega) + N_{22}(\omega) \\ &= [C_{11}(\omega) - S(\omega)] + [C_{22}(\omega) - S(\omega)] \\ &= C_{11}(\omega) + C_{22}(\omega) - 2\ C_{12}(\omega) \end{aligned}$$

Consider the difference between the two signals,

$$d(t) = x_1(t) - x_2(t),$$

then the auto-covariance of this difference function is

$$\begin{aligned} R(\tau) &= \{d(t)\ d(t-\tau)\} \\ &= \{[x_1(t) - x_2(t)]\ [x_1(t-\tau) - x_2(t-\tau)]\} \\ &= \{x_1(t)\ x_1(t-\tau)\} - \{x_1(t)\ x_2(t-\tau)\} \\ &\quad - \{x_2(t)\ x_1(t-\tau)\} + \{x_2(t)\ x_2(t-\tau)\} \end{aligned}$$

Again assuming that the cross terms are zero as above, and transforming, the spectrum of the difference is

$$\begin{aligned} D(\omega) &= S(\omega) + N_{11}(\omega) - S(\omega) - S(\omega) + S(\omega) + N_{22}(\omega) \\ &= N_{11}(\omega) + N_{22}(\omega) = N(\omega) \end{aligned}$$

Therefore the difference of two signals measuring the same geophysical signal and different uncorrelated noises is just the sum of the noises in the two sensors. The noise also contains any calibration errors, etc. in our normalization of the sensor’s data. It is obvious that the same exercise can be carried out with three sensors, and cross spectral techniques used separate the three individual sensor noise spectra. It should be clear that this noise spectra is the limiting quantity in any spectral measuring process i.e. we can not get any better than our sensors.

An example of this is seen in spectra on the following page. Several temperature spectra are shown from moored temperature sensors in various locations on the west coast of the US. The record taken in the Strait of Juan De Fuca shows a spectrum which tends to level out at high frequencies, and this level is above he digitizing noise level discussed above. Since this mooring had dual sensors at that depth, a cross spectrum and a spectrum of the difference could be taken and the sum of the noise levels of the sensors estimated. It was then assumed that the instrument noise of both sensors contributed equally to the results, so the noise spectrum was divided by 2 and is shown to be the cause of the spectrum leveling out. This noise cannot be reduced without changing sensors to ones with lower noise level. In this case we need not have sampled as often. A 30 cph (3 minute) sample would match the sampling interval and sensor noise to the environmental signal. This reduced sample rate will have the effect of reducing the required data storage space, or allow the experiment to be lengthened.

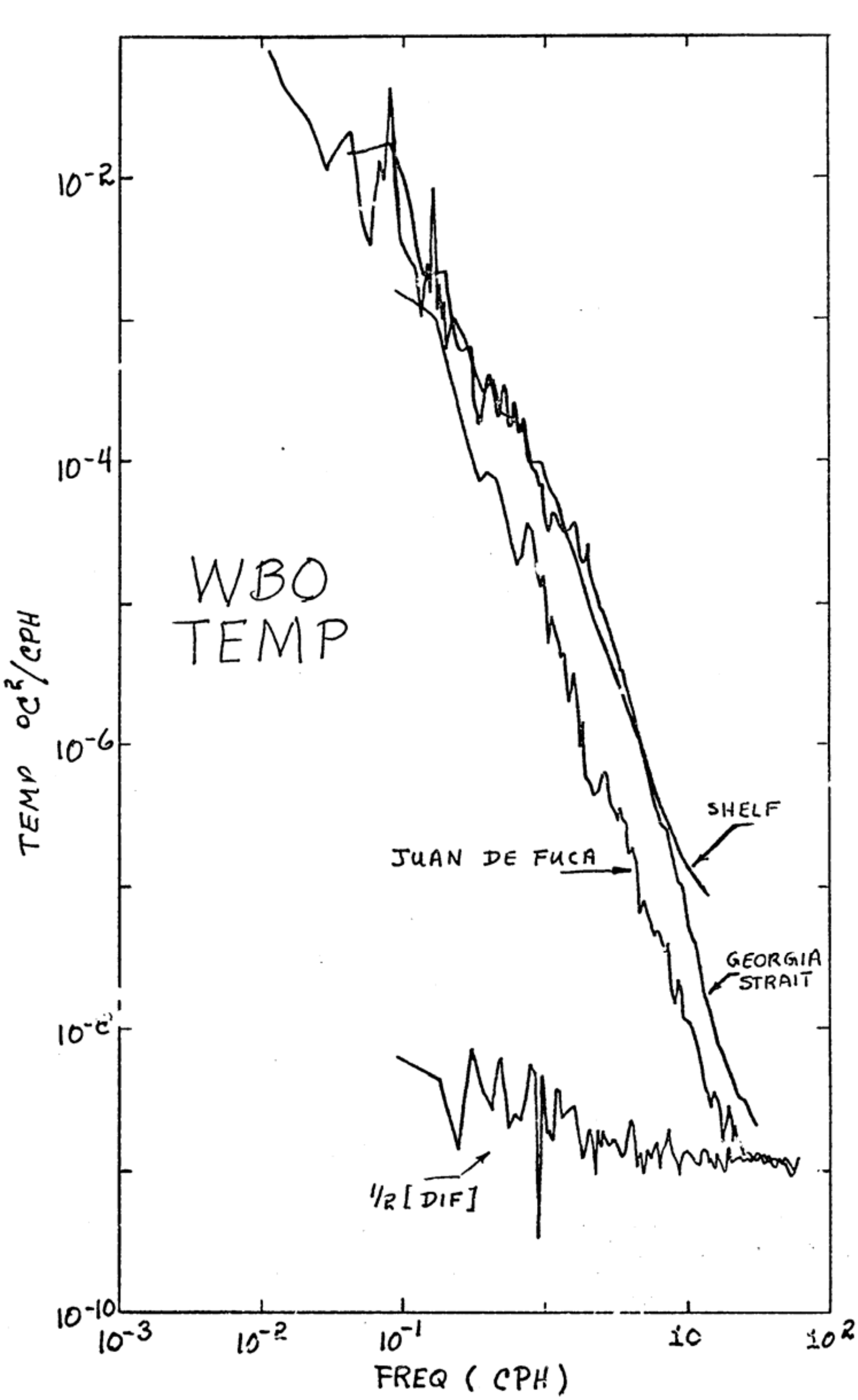
Another way to get the sensor noise is to put in no signal and look at the output. It is nearly impossible to do this. However, consider the example below where a temperature sensor was put into the bottom of a fjord with a sill and where there is almost no temperature signal. The sensor levels off at the noise of the sensor (considering that most sensor noises are somewhat white, or have equal energy at all frequencies.

Examples are:

Mike Gregg’s microstructure sensor in British Columbia Fjord.

Flowerbed test of pressure sensors –

Crossspectral of San Clemente pressure – implying signal related noise. That is noise increases with increasing signal.



Moored temperature spectra from the Pacific Northwest, with the power spectra of the record in the Strait of Juan De Fuca and one half the difference spectra representing the sensor noise illustrates the noise limitation of these sensors at high frequencies.

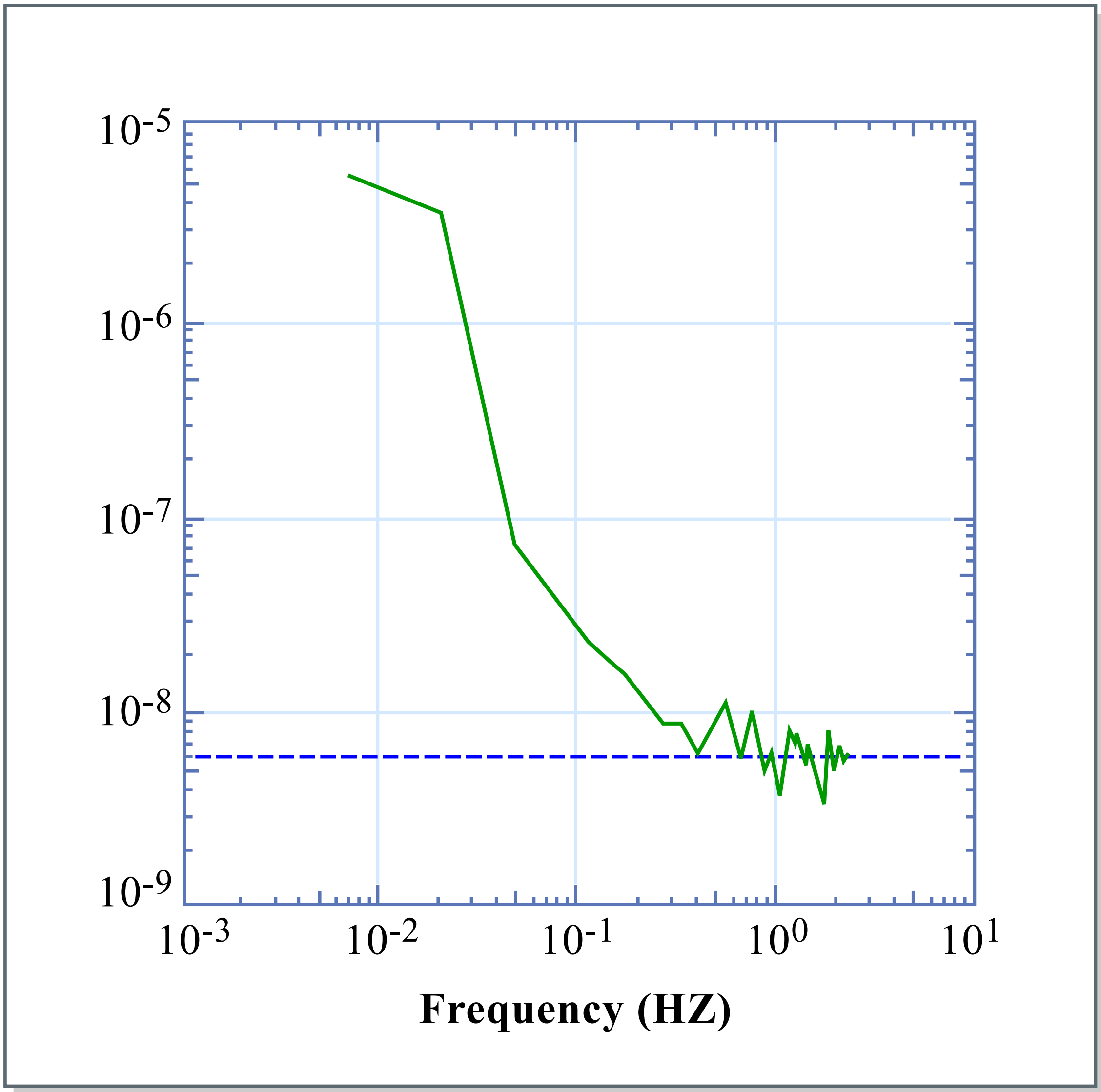
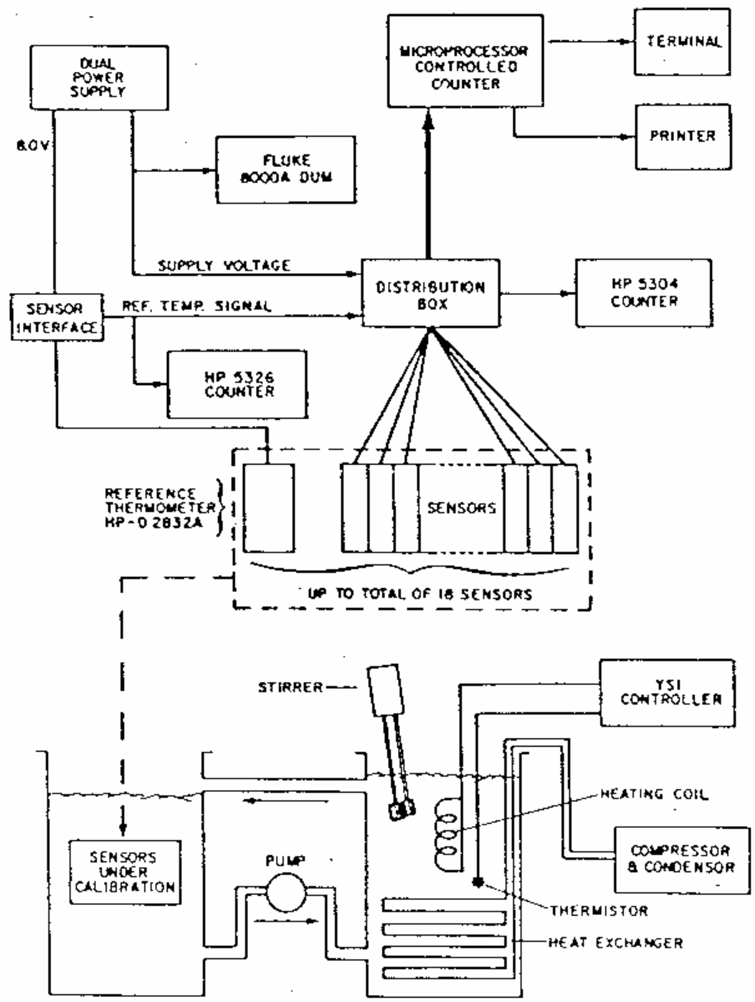


Figure by MIT OCW.

Noise spectrum of a Sea Bird SBE-03-01 temperature spectrum made by the APL/UW Microstructure Structure Recorder in a fjord below the sill depth where little environmental signal exists, so the sensor noise dominates at higher frequencies (>0.5 Hz)

Static Calibrations: Sensors must be calibrated against some standard in order that the results can be relied upon and compared to other observations – have a known accuracy. For example, take the case of a temperature sensor on the CTD system used for vertically profiling the water column. It is calibrated in a temperature controlled water bath. The temperature of this bath is cooled by a water-cooling heat exchanger that constantly removed heat from the tank. A temperature controller measures the temperature of the bath with a thermistor, and puts heat into the water by an immersion heater to maintain the desired temperature. The water in the tank is will mixed by a stirring motor. This whole procedure is illustrated below for a typical temperature calibration setup (similar to what we will use in lab later in class).

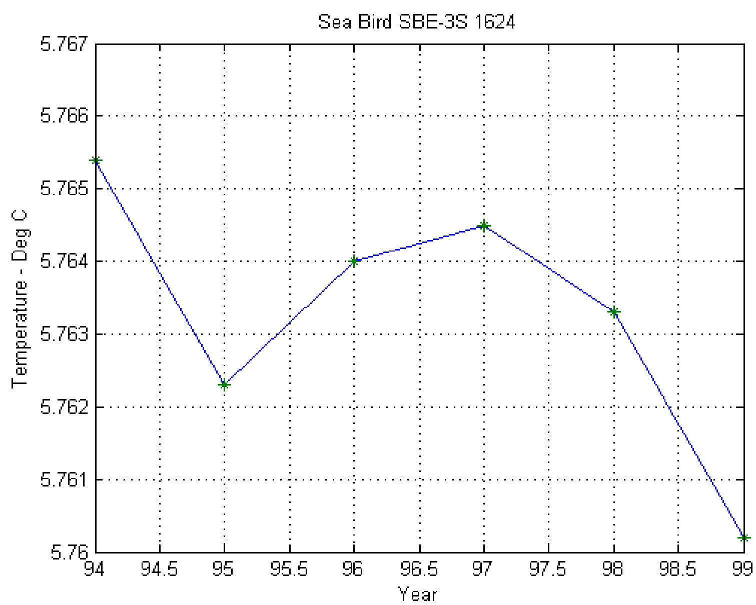


The temperature sensor or sensors to be calibrated are placed in this well mixed tank, and allowed to come to thermal equilibrium. A reference thermometer (e.g. PRT) is placed with the sensors under calibration, and the readings from the reference thermometer and sensors being calibrated are recorded.

The reference thermometer is regularly sent back the National Institute of Standards and Technology for calibration. This reference thermometer is generally a platinum resistance thermometer (PRT), and with repeated calibrations accumulates a history on how it changes with time. In order to check its operation before each calibration, the reference thermometer is generally "standardized" in a triple-point-of-water cell to check one point in absolute temperature and a Gallium melt cell to check a second point. The triple point is defined in terms of the temperature where gas, water and ice phase all exist as 0.010,00 °C ±0.000,01 °C. The Gallium melt cell (29.7646°C) provides an upper point for oceanographic range of temperatures. The PRT (which is linear) is used to interpolate between these two points based on its calibration. We will discuss the temperature standards later, currently the IPT90, when we discuss water properties, and temperature measurement.

The actual temperature of the water is then calculated and plotted versus the output from each sensor. When a number of points at different temperatures have been taken, plotted, and appear consistent, the results are then fit to the functional form of the sensor. If the sensor were linear, then a least squares linear fit is done on the actual temperature and the sensor output, and the derived coefficients can then be used to normalize any data collected with the sensor. The least squares fitting removes some of the random statistical error associated with a single calibration point, and gives a smoothed, consistent summary of the calibration results. It is obvious that other functional forms can be used to fit the data. It is best to study the sensor's physical behavior, and choose a functional form that best represents the type of sensor being used, rather than just expand the calibration in a power series. As an example, the Sea Bird Electronics temperature sensor as shown on the calibration sheet returned from a calibration at Sea Bird.

Calibration History: – determine long-term stability/drift of sensor. Consider SBE-3S Serial Number 1624 – plot with input of 7,000 Hz.
First Calibrated 21-Apr-94 – residuals ~ 0.2 mºC
Calibrated 12-Oct-95 – residuals ~0.2mºC – change from last calib. –0.41mºC or 0.28mºC/yr.
Calibrated 24-Sept-96 – residuals ~0.2mºC – change from last calib. +1.80mºC or 1.89mºC/yr
Calibrated 20-Dec-97 – residuals ~0.2mºC – change from last calib. +1.00mºC or 0.80mºC/yr
Calibrated 3-Sept-98 – residuals ~0.2mºC – change from last calib. –1.27mºC or 1.80mºC/yr
Calibrated 6-Nov-99 – residuals ~0.2mºC – change from last calib. –3.69mºC or 3.14mºC/yr



Output of Sea Bird Temperature Sensor 1624 from yearly calibrations in deg C.

Paroscientific pressure sensor – calibration as function of temperature

Calibrate several pressure sensors on same manafold so any small systematic calibration error will be removed when take difference in observations to get pressure gradients.

Biofouling on conductivity sensors – major cause of drift observed in time. Reduced by putting poison cells (tributyltin) on sensors to discourage growth. Works reasonably well in higher latitudes away from coastal waters for about year – but still get drift.

SEA-BIRD ELECTRONICS, INC.

1808 136th Place N.E., Bellevue, Washington 98005 USA

Phone: (206) 643 - 9866 Fax: (206) 643 - 9954 Internet: seabird@seabird.com

SENSOR SERIAL NUMBER = 1629
CALIBRATION DATE: 27-Sep-96s

TEMPERATURE CALIBRATION DATA
ITS-90 TEMPERATURE SCALE

ITS-90 COEFFICIENTS

g = 4.83406520e-03
h = 6.77564998e-04
i = 3.26730215e-05
j = 3.25482938e-06
f_0 = 1000.000

IPTS-68 COEFFICIENTS

a = 3.68160997e-03
b = 5.90725810e-04
c = 1.47974337e-05
d = 3.25638963e-06
f_0 = 6254.902

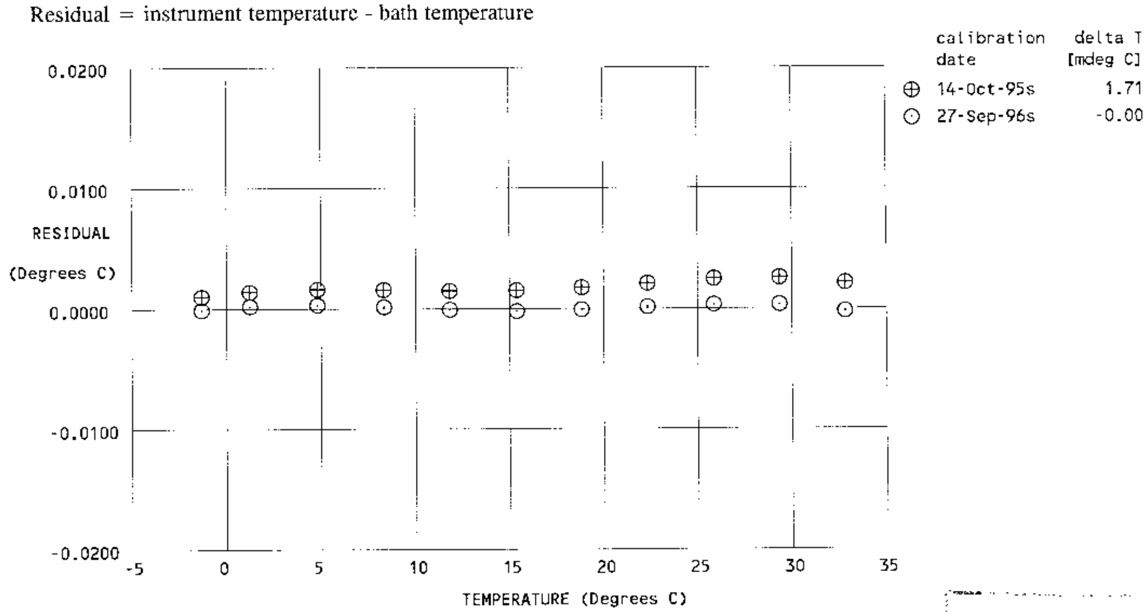
BATH TEMP (ITS-90 °C)	INSTRUMENT FREQ (Hz)	INST TEMP (ITS-90 °C)	RESIDUAL (ITS-90 °C)
-1.5292	6254.902	-1.5293	-0.00018
1.0319	6630.528	1.0320	0.00013
4.6052	7181.545	4.6054	0.00024
8.1109	7753.409	8.1110	0.00008
11.6142	8356.639	11.6141	-0.00014
15.1741	9002.974	15.1738	-0.00028
18.6371	9664.780	18.6370	-0.00015
22.1382	10367.650	22.1383	0.00007
25.6657	11110.829	25.6659	0.00026
29.1370	11877.103	29.1373	0.00026
32.6116	12679.260	32.6113	-0.00028

Temperature ITS-90 $= 1/\{g + h[\ell n(f_0/f)] + i[\ell n^2(f_0/f)] + j[\ell n^3(f_0/f)]\} - 273.15$ (°C)

Temperature IPTS-68 $= 1/\{a + b[\ell n(f_0/f)] + c[\ell n^2(f_0/f)] + d[\ell n^3(f_0/f)]\} - 273.15$ (°C)

Following the recommendation of JPOTS: T_{68} is assumed to be 1.00024 * T_{90} (-2 to 35 °C).

Residual = instrument temperature - bath temperature



Dynamic Calibrations or Frequency Response: A sensor is a filter that affects the frequency content of the data that passes through it. It is up to the experimentalist to make sure that these filtering effects are understood and do not affect the results that he is trying to obtain.

To measure the frequency response function, L(ω), of a sensor, one could input an impulse, measure the response, transform it to obtain the frequency response function. An impulse is a good input since it contains all frequencies. To see this, consider the gate function

$$\delta(t) \approx 1/\tau\ \Pi(t/\tau) \supset \mathrm{Sinc}(f\tau) = \mathrm{Sin}(\pi f\tau)/\pi f\tau$$

as τ -> 0, the gate function goes to an impulse. The first zero crossing of the SINC function occurs at $f = 1/\tau$, where the Sin goes to zero. This is also observed to be the inverse of the length of the gate function, τ. So as τ goes to zero, the zero crossing moves to higher and higher frequency and the Sinc function broadens. See graph below for three different width gate functions and associated Sinc function. In the limit of a delta function, the Sinc function goes to constant function of frequency. The transform of the impulse, is a nonzero constant so contains equal energy at all frequencies!

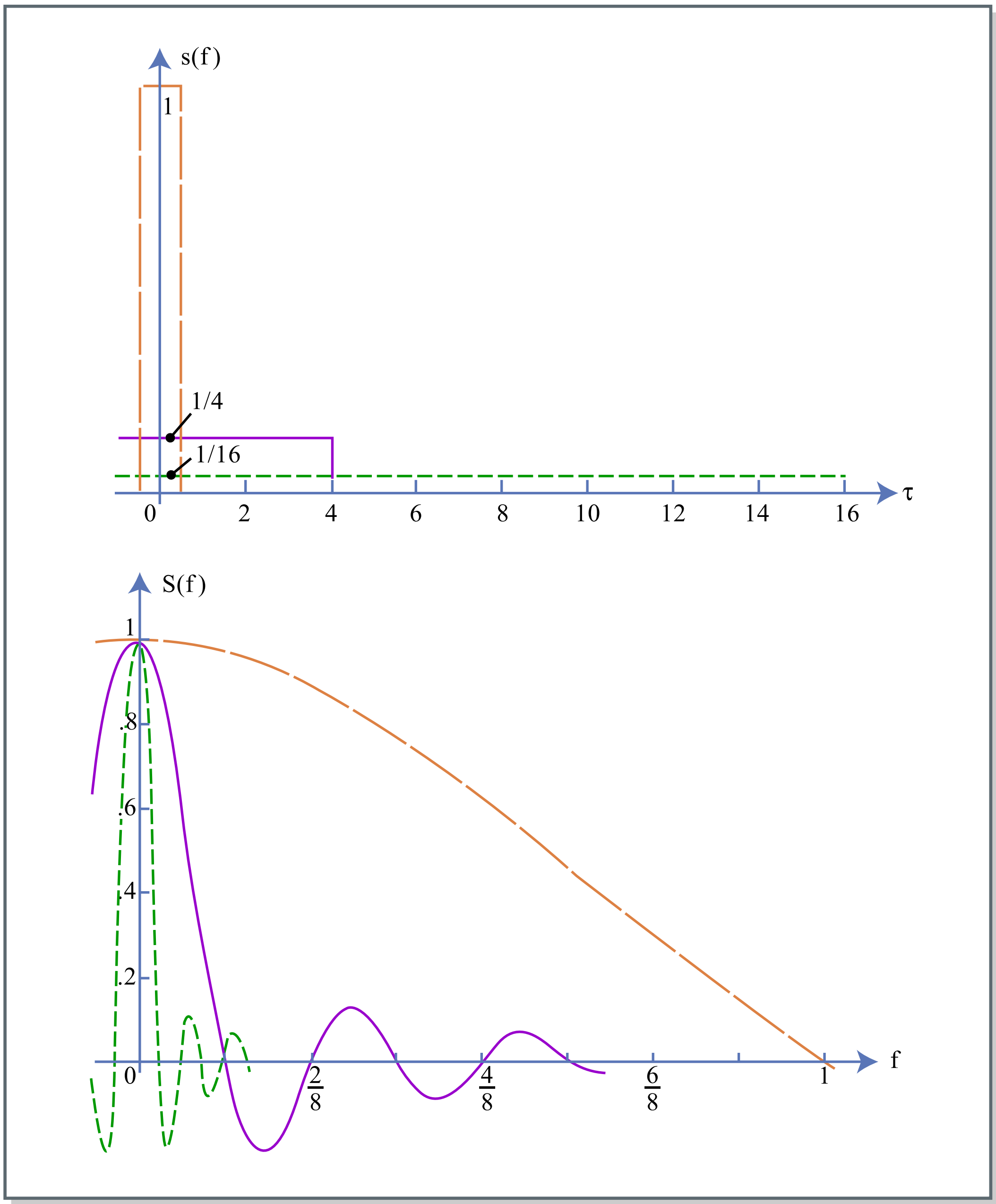


Figure by MIT OCW.

The gate function with varying widths (16, 4, 1) on top, and the associated transform (Sinc function) on the bottom, showing that the Sinc gets broader as the gate gets narrower.

If we are considering a temperature sensor, it is difficult to input a true impulse, because it is an infinitely short and infinitely high pulse. For turbulence sensors you can create a plume of hot water and move the sensor through that to get a response function estimate. However, for sensors with slow response times, consider the case of the step function.

$$x(t) = 1 \text{ for } t > 0$$

$$x(t) = 0 \text{ for } t < 0.$$

This is easy to make, just plunge the sensor quickly from warm air into cold water or between a warm and cold-water bath in a time much faster than the response time of the sensor. In this case we have a scaled step function where we can write

$$T(t) = T_{air} \text{ for } t < 0$$

$$T(t) = T_{water} \text{ for } t > 0$$

Now the derivative of the step function is an impulse which has an amplitude, A, equal to the change in temperature, $T_{air} - T_{water}$. We assume that the time for the sensor to move through the interface is short compared with the response time of the sensor, so relative to the sensor's response time, the change in temperature does look like a true step. Thus, we have a known input or forcing function. If the sample interval, δt, is small compared with the response time of the sensor, then we can resolve the sensor's response which looks a bit more like a slow ramp, rather than a step. Hence, with a known input, and a measure of the output as a function to time, y(t), we can calculate the response function. From the definition of the convolution product we have

$$y(t) = T(t) * l(t)$$

$$y(t) = T(t) * L(\omega)$$

and transforming into frequency space, the convolution theorem allows us to replace the convolution product in time space with a multiplication in frequency space. Therefore, we can divide the transforms to get the frequency response function,

$$L(\omega) = \frac{y(t)}{T(t)} = \frac{\text{output}}{\text{input}}$$

Note that we want the impulse narrow so that it contains energy at all frequencies. If our step were indeed a true impulse, then its transform would be just 1 and the response would be the transform of the output, y(t). However, our step function, and hence our first difference, has an amplitude, A. Note that to accurately measure any phase shifts, knowing when the impulse or step was applied is of critical importance (when t=0).

Moored Wein Bridge Oscillator Temperature Sensor: A plastic thermal mass added to the sensing element of the sensor to "prefilter" the data and eliminate unwanted high frequency fluctuations. The time constant of this mass (the time for the temperature to diffuse through the material and the center reach 1/e of the final temperature) was supposed to be about 2 minutes to act as a prefilter to prevent aliasing with a 2-minute sample interval. The mass was added to prevent aliasing, but it could also "contaminate" the results by filtering out high frequency fluctuations of interest. Also, as part of an internal waves experiment, it was desired to measure the high frequency portion of the spectrum where any sensor frequency response effects would be important. Therefore, the response was estimated by the method discussed above.

The sensor was held in air above the well-stirred calibration tank with cold water, and at time zero plunged into the tank and the output recorded. This produced the step response shown in the top panel on the following page. The change in temperature was 15.5° C, and measured by allowing the sensor to reach equilibrium, making a temperature reading and subtracting it from the initial reading. The output was digitized to an equivalent 1 m°C with a δt of 5.489 seconds. The data was normalized to temperature in ºC, and the first difference taken to obtain the graph at the bottom of the following page, which is an estimation of the impulse response, where the impulse was input at t = 0 (with an accuracy of ±1 second). Note that the sensor response lagged the impulse considerably, and reaches a peak value 50 to 60 seconds after the impulse (or step). If you took the time constant from the plot for when the value reached 1/e of the final value (~14.2ºC), you would get a time constant of about 105 seconds.

This signal was then transformed, and scaled by the magnitude of the step (i.e. 15.5°C) to get the frequency response function also shown on the top of the following page. The sensor's spectral response is about 1 (or 0 db where db = 20 log A_{out}/A_{in}) at low frequency as the sensor follows low frequency temperature changes well. The discrete points in the transform are shown by the stars, and the response of a simple exponential filter with a time constant of 90 seconds is shown as the solid line for comparison.

The single exponential filter has an impulse response,

$$l(t) = 1/\tau\ e^{-t/\tau} \text{ or a}$$

$$\text{step response} = (1 - e^{-t/\tau})$$

where τ is the <u>time constant</u> of the filter. When an instrument's response is specified as a time constant, they are assuming an exponential behavior of the sensor. Note that for a temperature sensor this is a function of the water velocity past the sensor that will decrease the boundary layer thickness and increases the heat transfer as the velocity increases and result in a lower time constant. In the tank test we used a well stirred tank, which was about 0.5 m/s velocity flushing. The exponential filter has a frequency response of

$$L(\omega) = (1 + i\ 2\pi f\tau)^{-1}$$

$$\text{Gain}^2 = |L(\omega)|^2 = [1 + (2\pi f\tau)^2]^{-1}$$

$$\text{Phase} = -\text{atan}(2\pi f\tau)$$

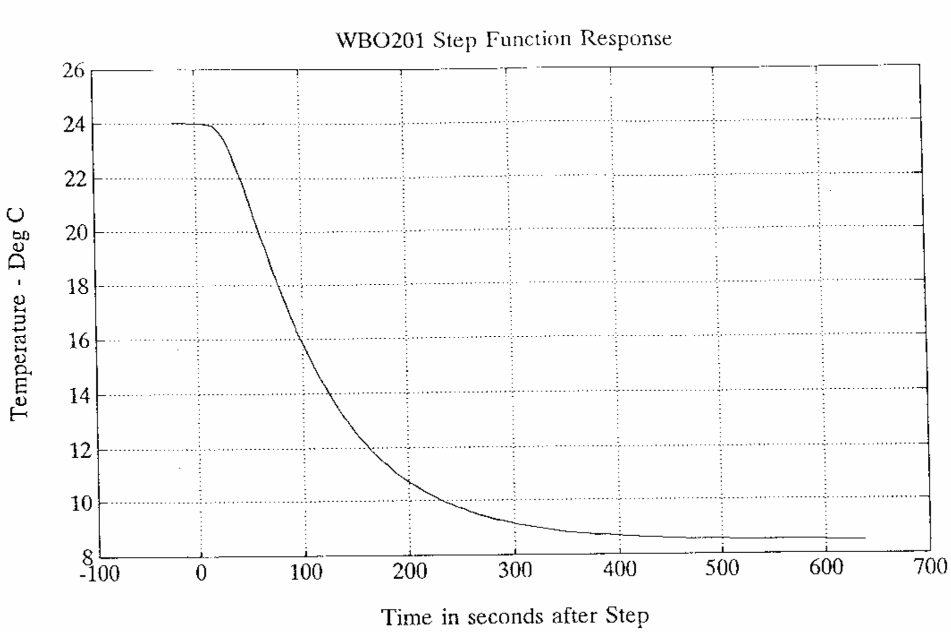
Out to the Nyquist frequency (15 cph), the measured frequency response is well fit by this simple 90-second exponential filter, and this result was used to correct the spectra for the response of the sensor. Note that we have plotted the amplitude response only (really power as we expressed the filter response in db) and have not considered the phase shift. Thus, the prefilter was adequate and attenuated high frequencies at the Nyquist by almost one decade, and suppressed higher frequencies to a greater extent.

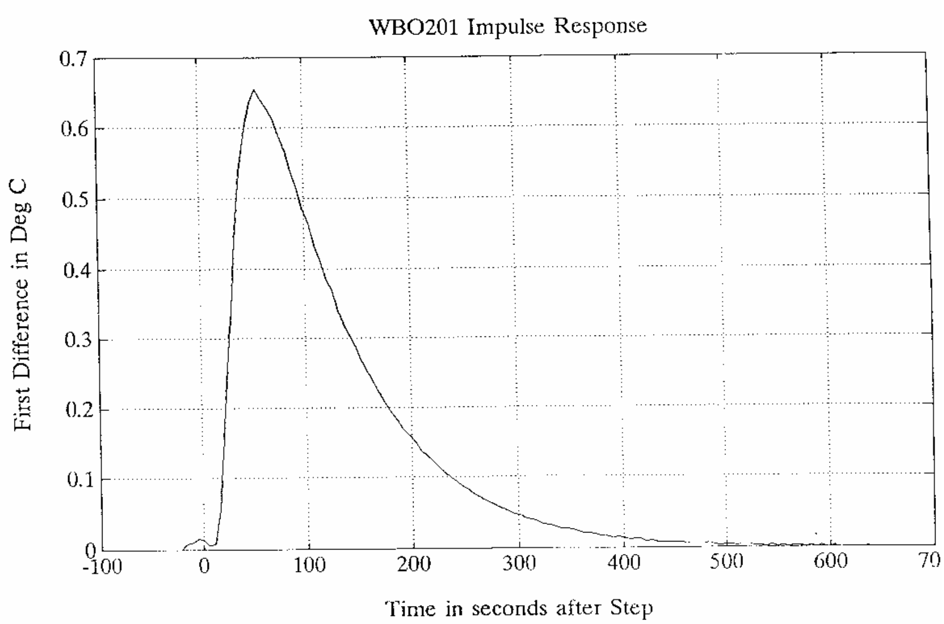
For a paper on fine structure and internal waves in the ocean, Levine and Irish (1981) wanted to get accurate spectra out to the Nyquist frequency, and used this response function to correct moored spectra near the Nyquist frequency for sensor response effects and obtain an estimate of the true frequency dependence.

Other types of input that are/have been used to estimate the frequency response can be:

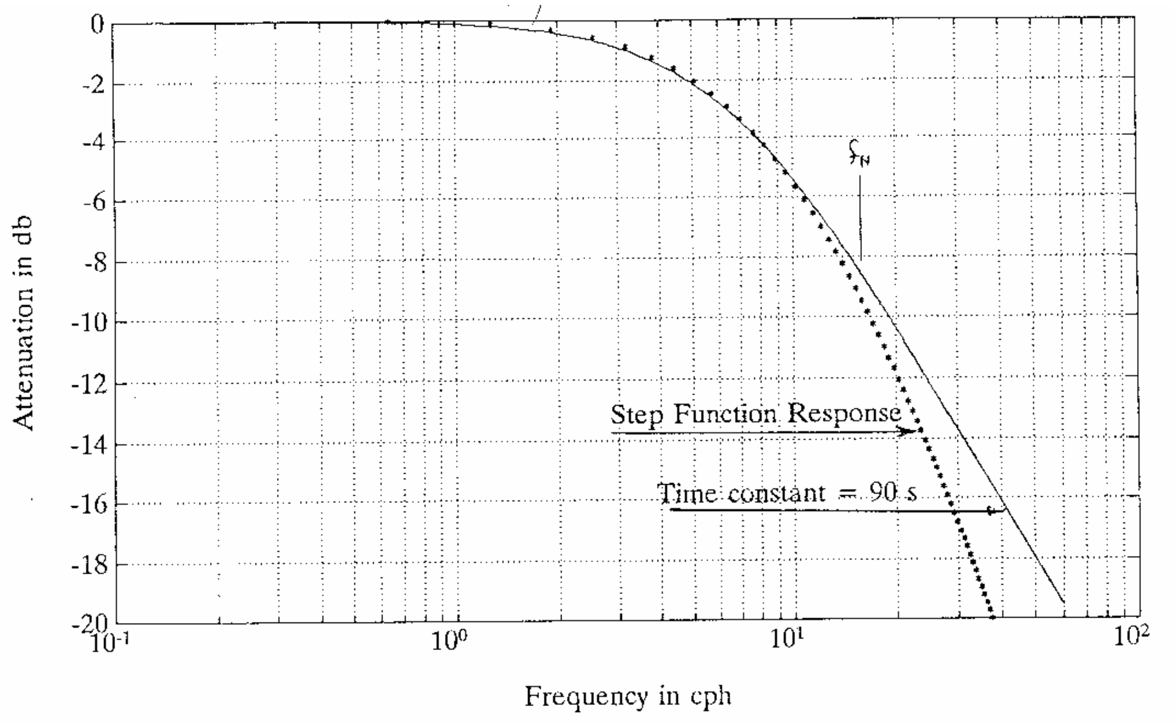
Plume tank - thermal plume of hot water to make an “impulse”

Vertical stratified tank – step function in temprature and/or salinity.





The step function response (top) and corresponding estimate of the impulse response (bottom) for WBOT S/N 201 with thermal mass added.



Frequency response function measured for WBOT 201.

Properly Sampling the Environment: Lets summarize the needs to be considered in properly sampling the environment as discussed above:

1. Suppress unwanted high frequencies by such techniques as prefiltering. (e.g. Placing a thermal mass on a temperature sensor to filter out high frequency fluctuations before digitizing. One could average a frequency over the sample interval, which is the same as applying a "boxcar" filter to the data before digitizing.) Also, the sensor could be sampled at a high rate to resolve high frequencies and the storage system average the data to suppress high frequency fluctuations, or you could resolve the higher frequency (if enough storage space were available, and then take care of things in post-processing.) Example of the Paroscientific pressure sensor over its entire pressure range – needed to convert to pressure then average pressure to remove the waves. Averaging frequency on a non-linear output would bias the mean value from the actual.

2. Sample at least twice the highest frequency present after any prefiltereing to prevent aliasing. (Normally one would sample several times the highest frequency desired after taking the proper steps to prefilter the data.)

3. Sample long enough to give the required

   a. resolution in frequency - $\delta f = 1/T$ (This is also the lowest frequency, and is often dictated by data storage or battery capacity as well as ship schedules and funding.)

   b. confidence in spectral results - necessary. (Note that the confidence limits for the cross-spectrum or the coherence are different than the auto-spectrum, and fairly complicated.) There is a trade off in resolution and confidence - generally we can not get the resolution and confidence that we would like.

4. Know the calibration and frequency response of the sensor to

   a. make sure that the uncertainty in the absolute calibration of the sensor is appropriate i.e. compare results between instruments, and calculate derived quantities.

   b. be sure that there are no sensor response effects in the frequency region of interest or if so, that

   c. corrections for sensor response are made.

5. Know the digitizing effects of the recording system so that any effects it puts into the data are negligible. It is easy to reduce the digitizing noise to below the sensor noise, however again too much below means that you are recording too many bits and wasting data storage space.

6. Understand what statistics are needed, and what type of processing needs to be done, so

   a. The experiment can be designed to give the required data and

   b. Analysis techniques can be tailored to reducing the data.

   c. Remove trends (unresolved low frequencies) as non-stationarities, e.g. tides on surface wave spectra.

Warning: You really need to know what is out there to design a properly sampled experiment. There can be aliasing due to improper sampling in space and/or time.

"Window on the real world"

bounded on low frequency side by 1/T
bounded on the high frequench side by $F_n = 1/(2\delta t)$
bounded on the bottom by digitizing effects – LCN = $\delta x^2/12/F_n$
further bouned on the bottom by the sensor noise
data quality estimate by SNR between sensor noise and signal.

If time:

Paroscientific pressure sensor noise level
plume tank metal film temperature sensor frequency response