Analysis Techniques for Vibratory Data

Kenneth Hrovat

Principal Investigator Microgravity Services (PIMS)

NASA Glenn Research Center (GRC)

Outline

Outline:

- Overview
- Time Domain Analysis
  - Interval statistics
- Frequency Domain Analysis
  - Fourier Transform
    - Discrete Fourier Transform (DFT)
    - Fast Fourier Transform (FFT)
  - Power Spectral Density (PSD)
  - Spectral Averaging
  - Parseval’s Theorem
  - Spectrogram
  - Principal Component Spectral Analysis (PCSA)
- Summary

Overview

Objectives:

- characterize significant traits of the measured data (qualify/quantify)
- compare measured data to history, requirements, or predictions
- summarize measured data

Motivations:

- assist investigators and maintain knowledge base
- provide feedback to those interested in a data set's relativity
- manage large data sets

Approaches:

- time domain analysis
- frequency domain analysis

Time Domain Analysis

Objectives:

- isolate acceleration events with respect to time
- correlate acceleration data with other information
- limit checking against science or vehicle requirement thresholds

Approaches:

- acceleration vs. time → interval statistics

average (AVG)
root-mean-square (RMS)
minimum/maximum (MIN/MAX)

Time Domain Analysis

Acceleration vs. Time

Advantages:

- most precise accounting of the measured data with respect to time
- fundamental approach to quantifying acceleration environment
- “purest” form of the data collected

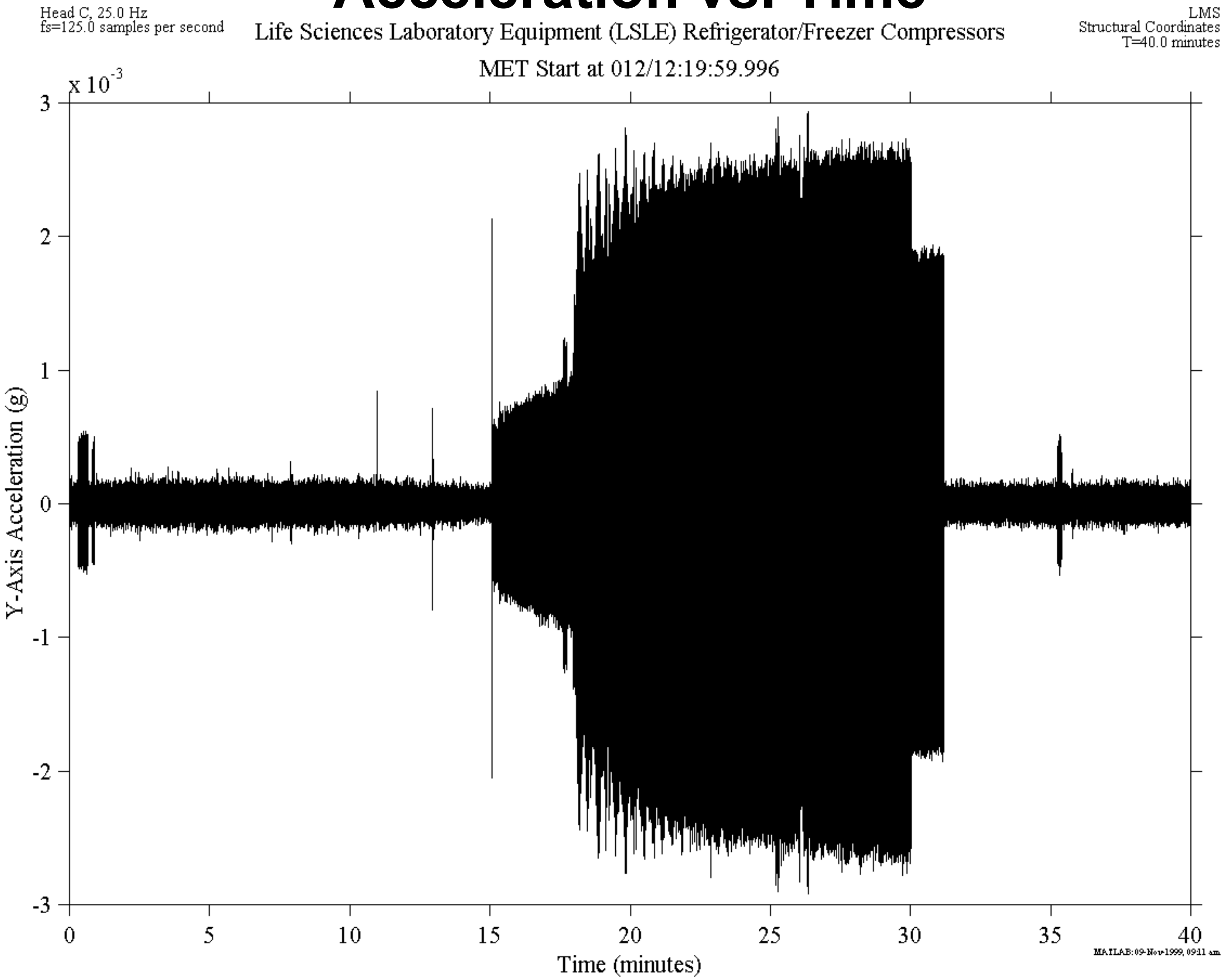
Disadvantages:

- display device (video, printer) constrains resolution for long time spans or high sample rates
- usually not good for qualifying acceleration environment

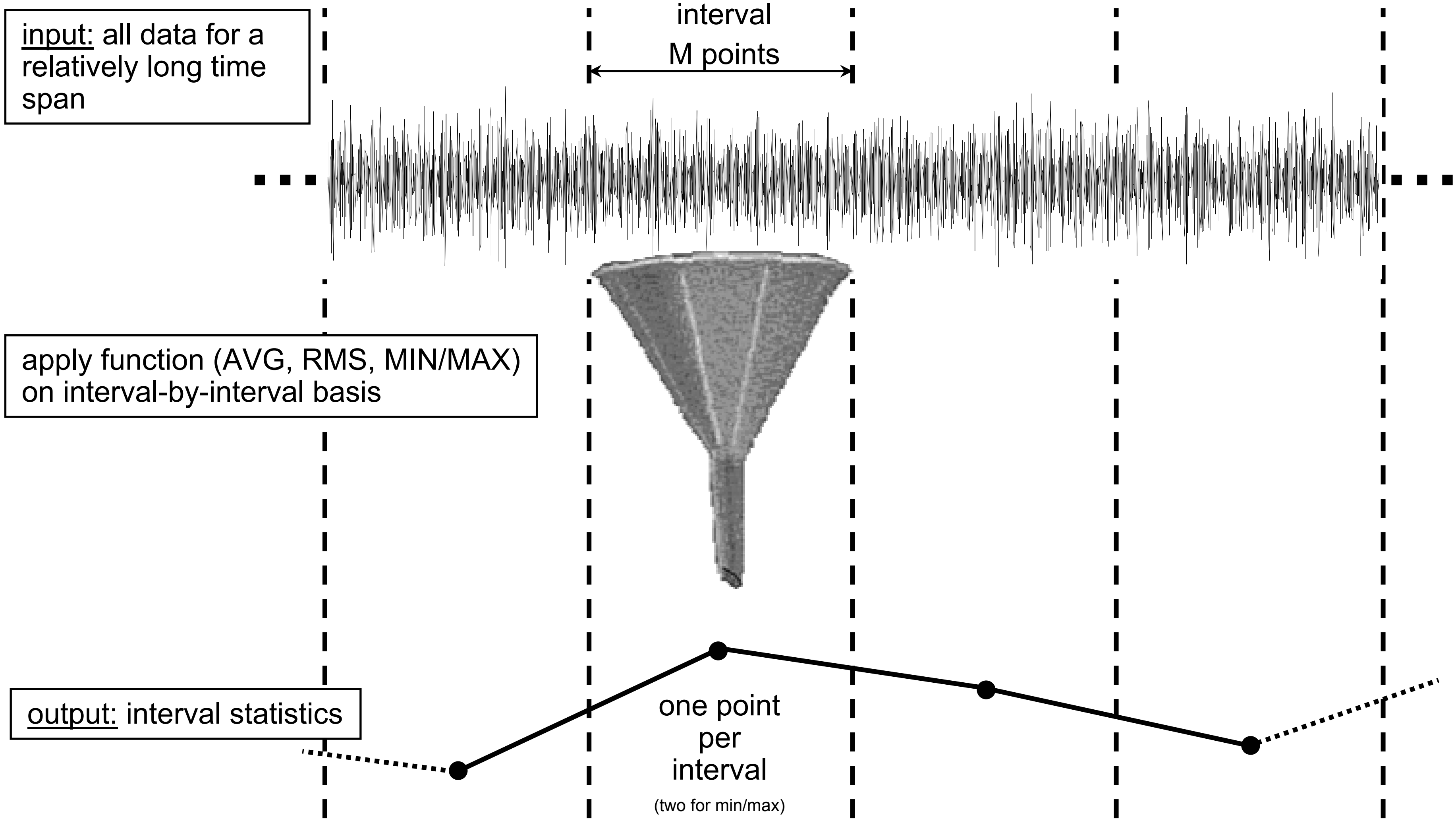
Analysis Techniques for Vibratory Data

Time Domain Analysis

Acceleration vs. Time



Interval Processing



input: all data for a relatively long time span

interval
M points

apply function (AVG, RMS, MIN/MAX) on interval-by-interval basis

output: interval statistics

one point per interval
(two for min/max)

Interval AVG, RMS, MIN/MAX vs. Time

Mathematical Description:

- **AVG**: average (mean) value for each interval

$$x_{AVG}(m) = \frac{1}{M}\sum_{i=1}^{M} x((m-1)M+i); \quad m = 1, 2, ..., \left\lfloor \frac{N}{M} \right\rfloor$$

- **RMS**: root-mean-square value for each interval

$$x_{RMS}(m) = \sqrt{\frac{1}{M}\sum_{i=1}^{M} x((m-1)M+i)^2}; \quad m = 1, 2, ..., \left\lfloor \frac{N}{M} \right\rfloor$$

- N is number of data points that span the entire interval of interest
- M is the number of data points that span a processing interval
- m is the interval index

and $\lfloor\ \rfloor$ is the floor function

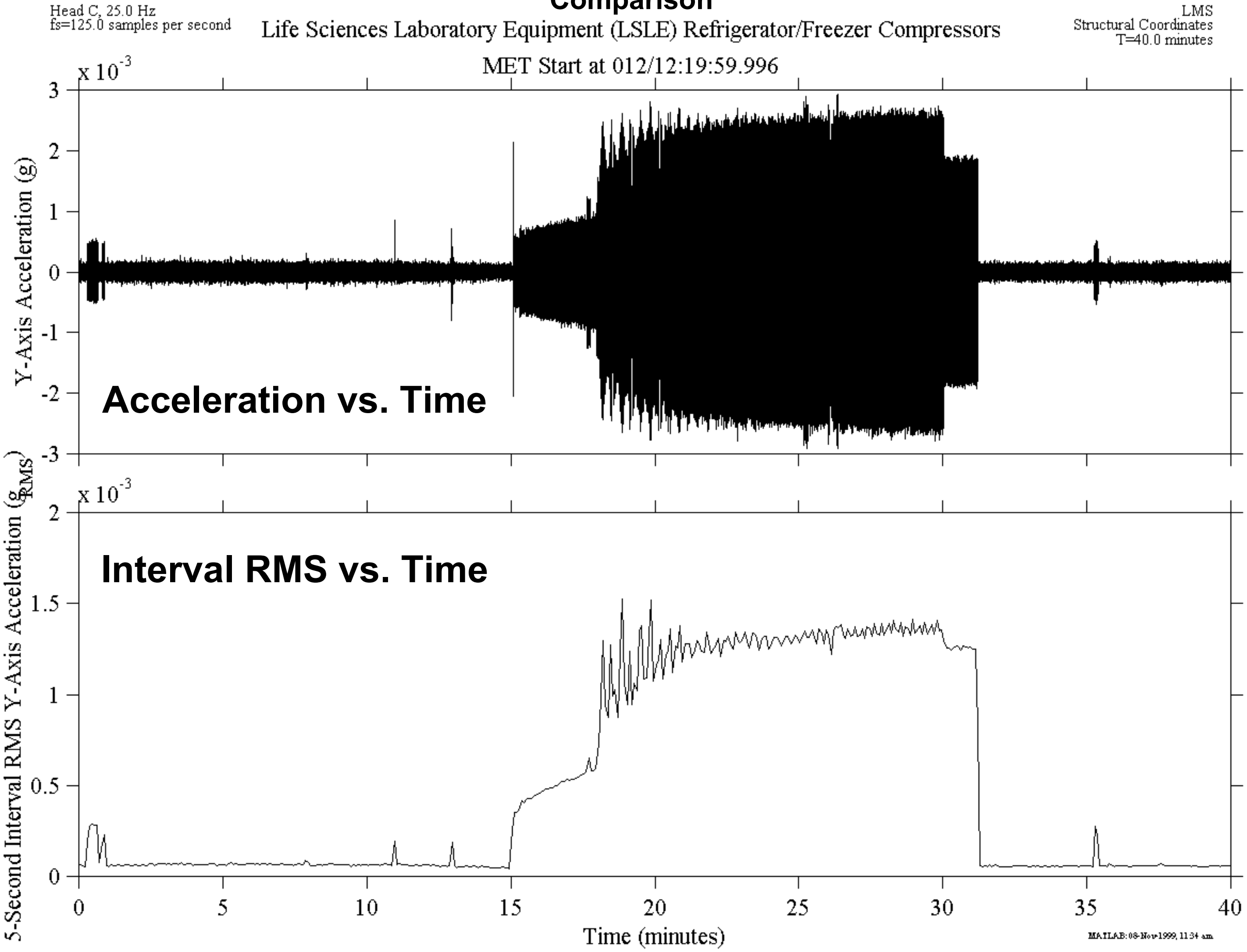
- **MIN/MAX**: both minimum and maximum values are plotted for each interval – a good display approximation for time histories on output devices with insufficient resolution to display all data in time frame of interest

Advantages:	Disadvantages:
• descriptive statistics	not-fully-descriptive statistics
• decimation (compression)	lossy

Analysis Techniques for Vibratory Data

Time Domain Analysis

Comparison

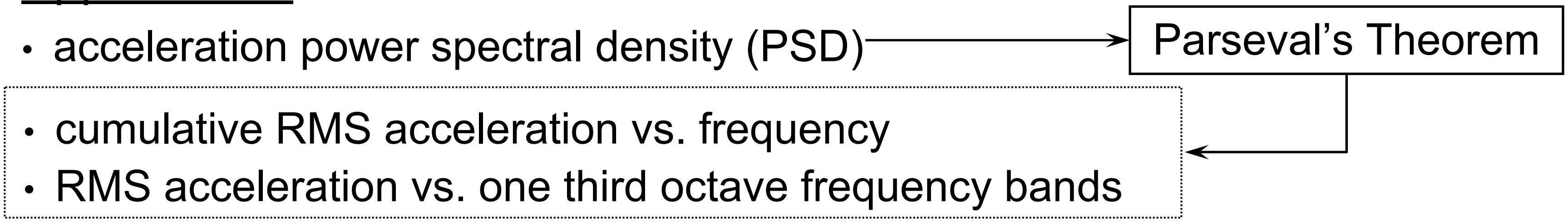


Frequency Domain Analysis

Objectives:

- identify and characterize oscillatory acceleration disturbances
- selectively quantify the contribution of various disturbance sources to the overall measured microgravity environment

Approaches:



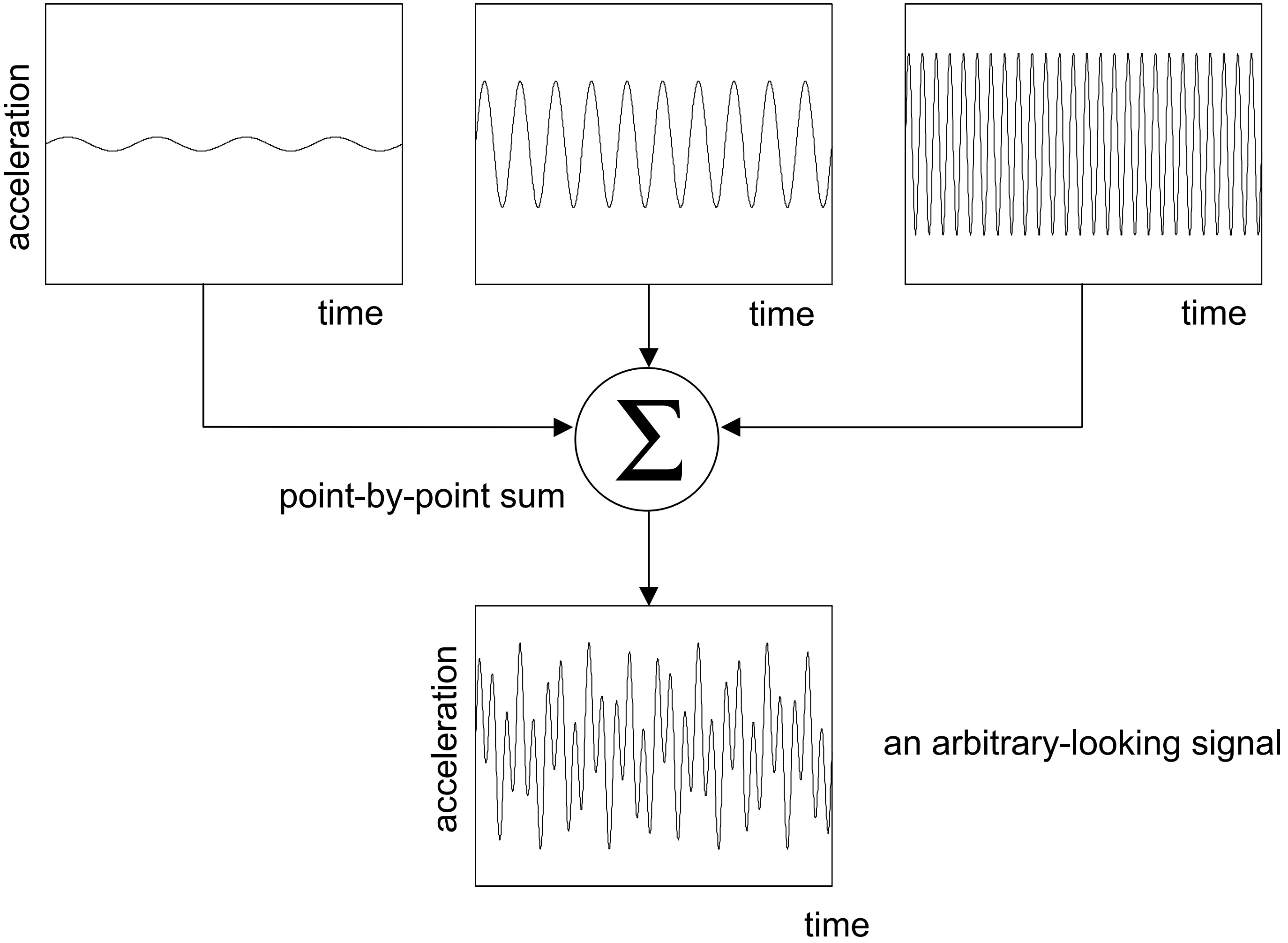
- acceleration power spectral density (PSD)

Parseval's Theorem

- cumulative RMS acceleration vs. frequency
- RMS acceleration vs. one third octave frequency bands
- acceleration spectrogram (PSD vs. *time*)
- principal component spectral analysis (PCSA) vs. frequency

Frequency Domain Analysis

Build Arbitrary-Looking Signal

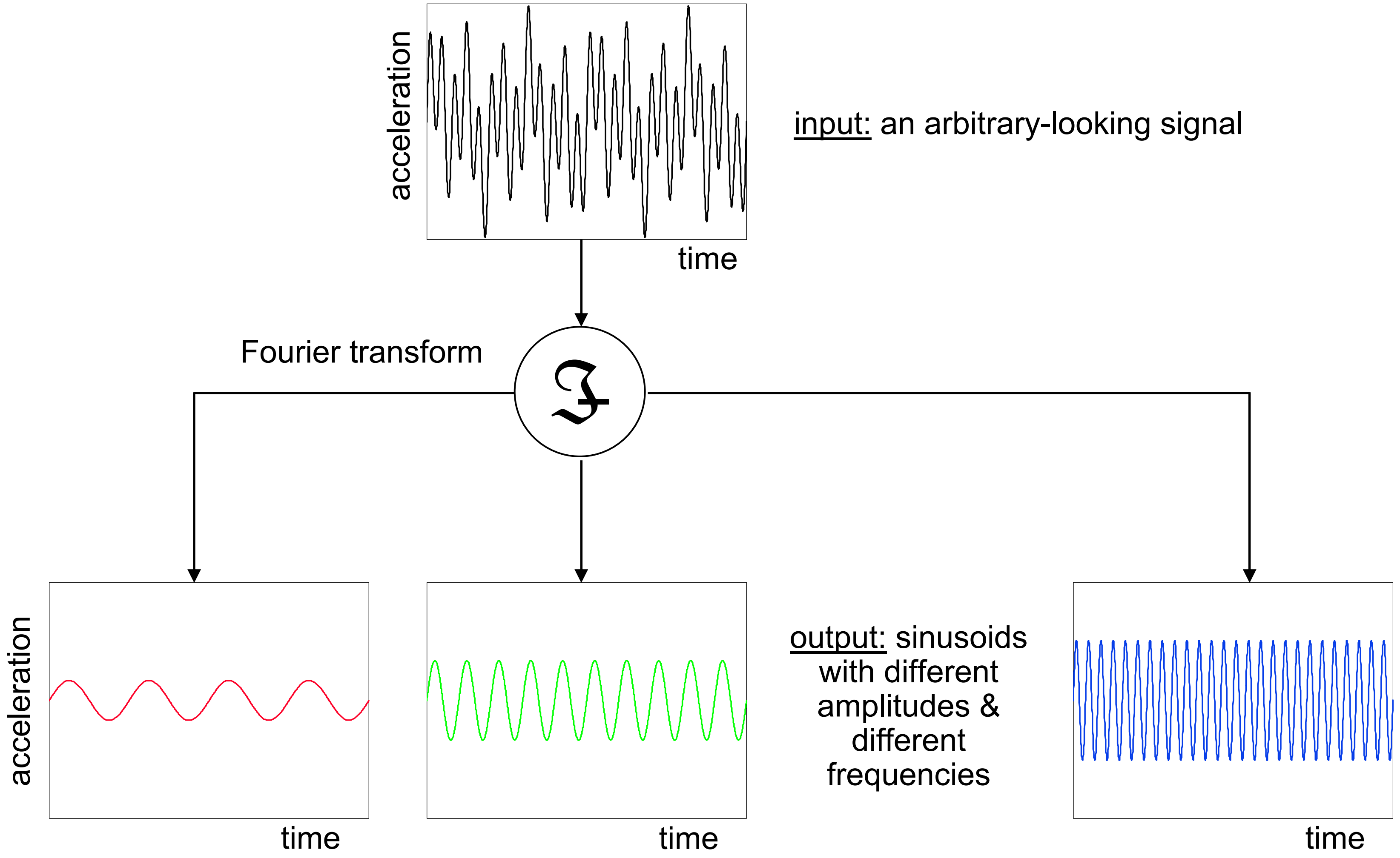


sinusoids with different amplitudes & different frequencies

point-by-point sum

an arbitrary-looking signal

Fourier Transform: Graphical Interpretation

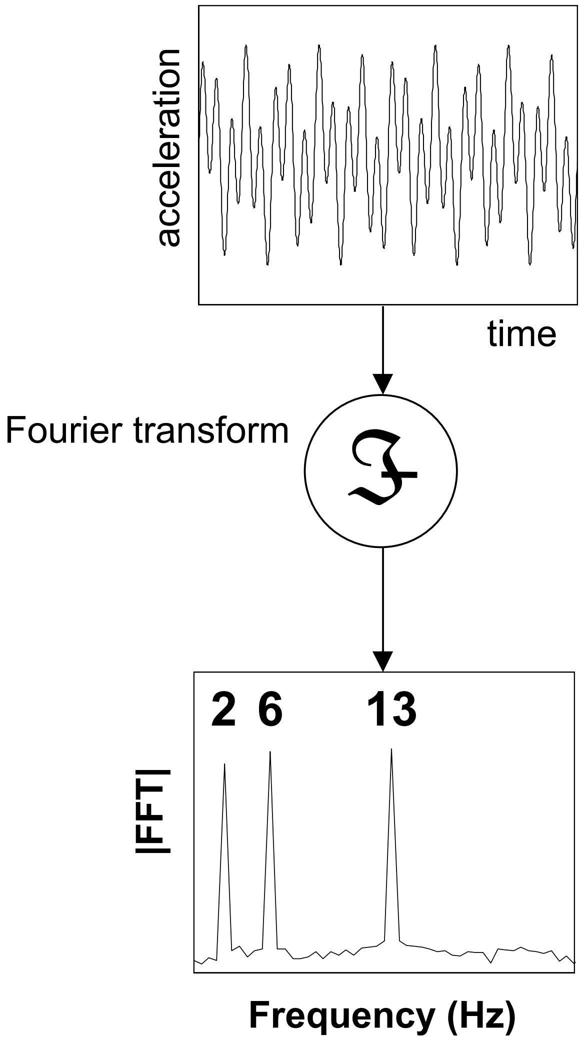


<u>input:</u> an arbitrary-looking signal

Fourier transform

<u>output:</u> sinusoids with different amplitudes & different frequencies

Fourier Transform: Graphical Description



<u>input:</u> an arbitrary-looking signal

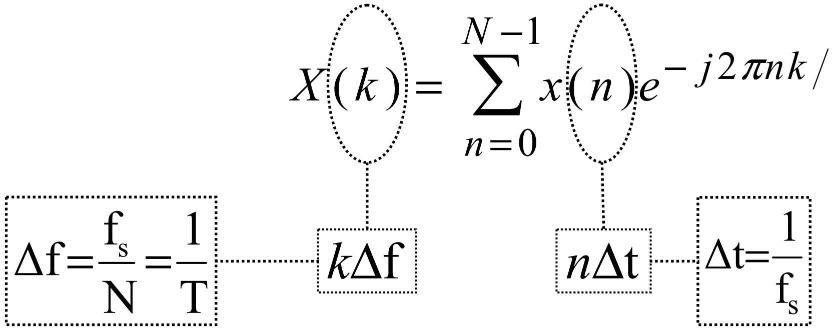
<u>output:</u> sinusoids with different amplitudes & different frequencies

Fourier Transform: Mathematical Description

- **What is it?** It’s a mathematical transform which resolves a time series into the sum of an average component and a series of sinusoids with different amplitudes and frequencies.
- **Why do we use it?** It serves as a basis from which we derive the power spectral density.
- Mathematically, for continuous time series, the Fourier transform is expressed as follows:

$$X(f) = \int_{-\infty}^{+\infty} x(t)e^{-j2\pi f t}dt\,;\ \ j = \sqrt{-1}$$

- For finite-duration, discrete-time signals, we have the discrete Fourier transform (DFT):



$$X(k) = \sum_{n=0}^{N-1} x(n)e^{-j2\pi nk/N}\Delta t \qquad k = 0,1,2,\ldots,(N-1)$$

$$\Delta f = \frac{f_s}{N} = \frac{1}{T} \quad k\Delta f \qquad n\Delta t \quad \Delta t = \frac{1}{f_s}$$

- N is the number of samples in the time series
- T is the span in seconds of the time series
- f_s is the sample rate in samples/second (Hz)
- Δf is the frequency resolution or spacing between consecutive data points (Hz)

- For a power of two number of points, N, a high-speed algorithm that exploits symmetry is used to compute the DFT. This algorithm is called the fast Fourier transform (FFT).

Power Spectral Density (PSD): Mathematical Description

- **What is it?** It’s a function which quantifies the distribution of power in a signal with respect to frequency.
- **Why do we use it?** It is used to identify and quantify vibratory (oscillatory) components of the acceleration environment.
- Mathematically, we calculate the PSD as follows:

$$\underset{k\Delta \mathrm{f}}{P(k)} = \begin{cases} \dfrac{2\left|X(k)\right|^2}{NUf_s} & [g^2/Hz] \text{ for } k = 1,2,\ldots,(N/2)-1 \\ \dfrac{\left|X(k)\right|^2}{NUf_s} & [g^2/Hz] \text{ for } \underset{\text{DC}}{k=0} \text{ and } \underset{\text{Nyquist}}{k=(N/2)} \end{cases}$$

$$U = \frac{1}{N}\sum_{n=0}^{N-1} w(n)^2$$

- X(k) is the “Δt-less” FFT of x(n)
- N is the number of samples in the time series (power of two)
- f_s is the sample rate (samples/second)
- U is window compensation factor
- w(n) is window (weighting) function

- DC is an electrical acronym for **d**irect **c**urrent that has been generalized to mean average value
- Nyquist frequency (f_N) is the highest resolvable frequency & is half the sampling rate (f_N=f_s/2)
- Symmetry in the FFT for real-valued time series, x(n), results in one-sided PSDs; only the DC and Nyquist components are unique – that’s why no factor of 2 for those in the equation
- Caution: some software package PSD routines scale by some combination of f_s, 2, or N

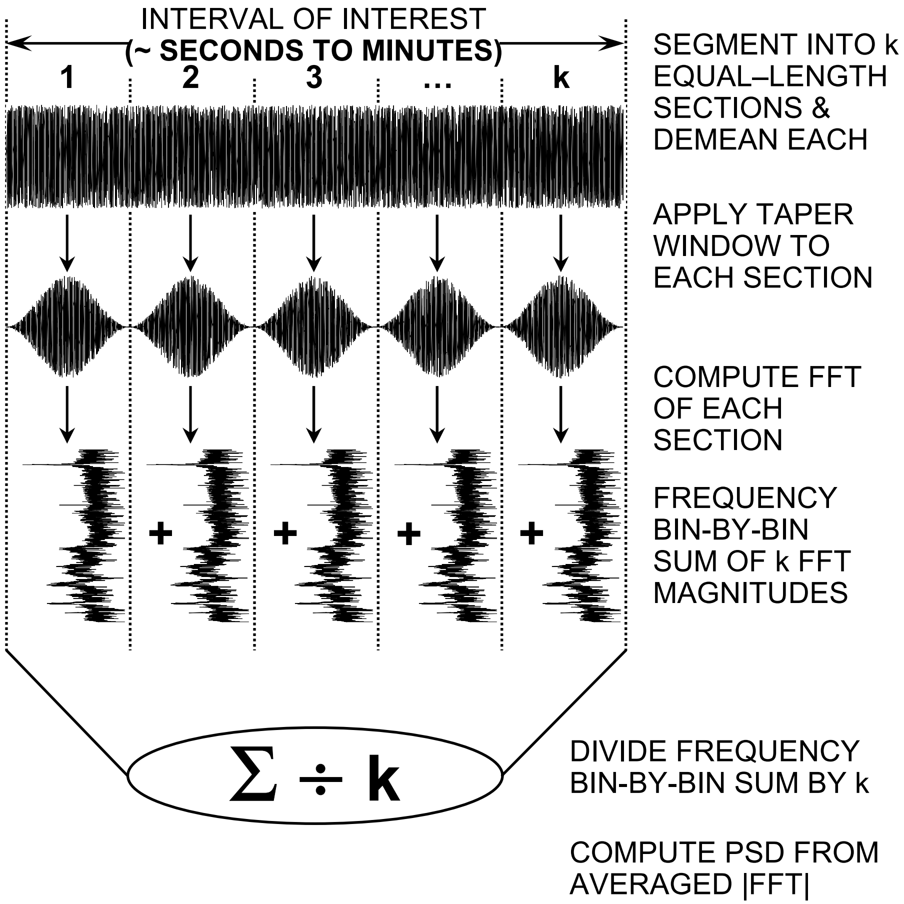
Spectral Averaging

- Assume stationary data
- **Why?** To reduce spectral variance

  The averaging in this process causes the variance of the PSD estimate to be reduced by a factor of k.
- **How?** Welch's (periodogram) method
- **Tradeoff:** Degraded frequency resolution

  As the number of averages (or sections, k) increases, the spectral variance decreases, but this comes at the expense of diminished frequency resolution. This stems from the fact that for a given time series, the more sections you have, the fewer the number of points you get in each section.

Welch's (Periodogram) Method



INTERVAL OF INTEREST

(~ SECONDS TO MINUTES)

SEGMENT INTO k EQUAL–LENGTH SECTIONS & DEMEAN EACH

APPLY TAPER WINDOW TO EACH SECTION

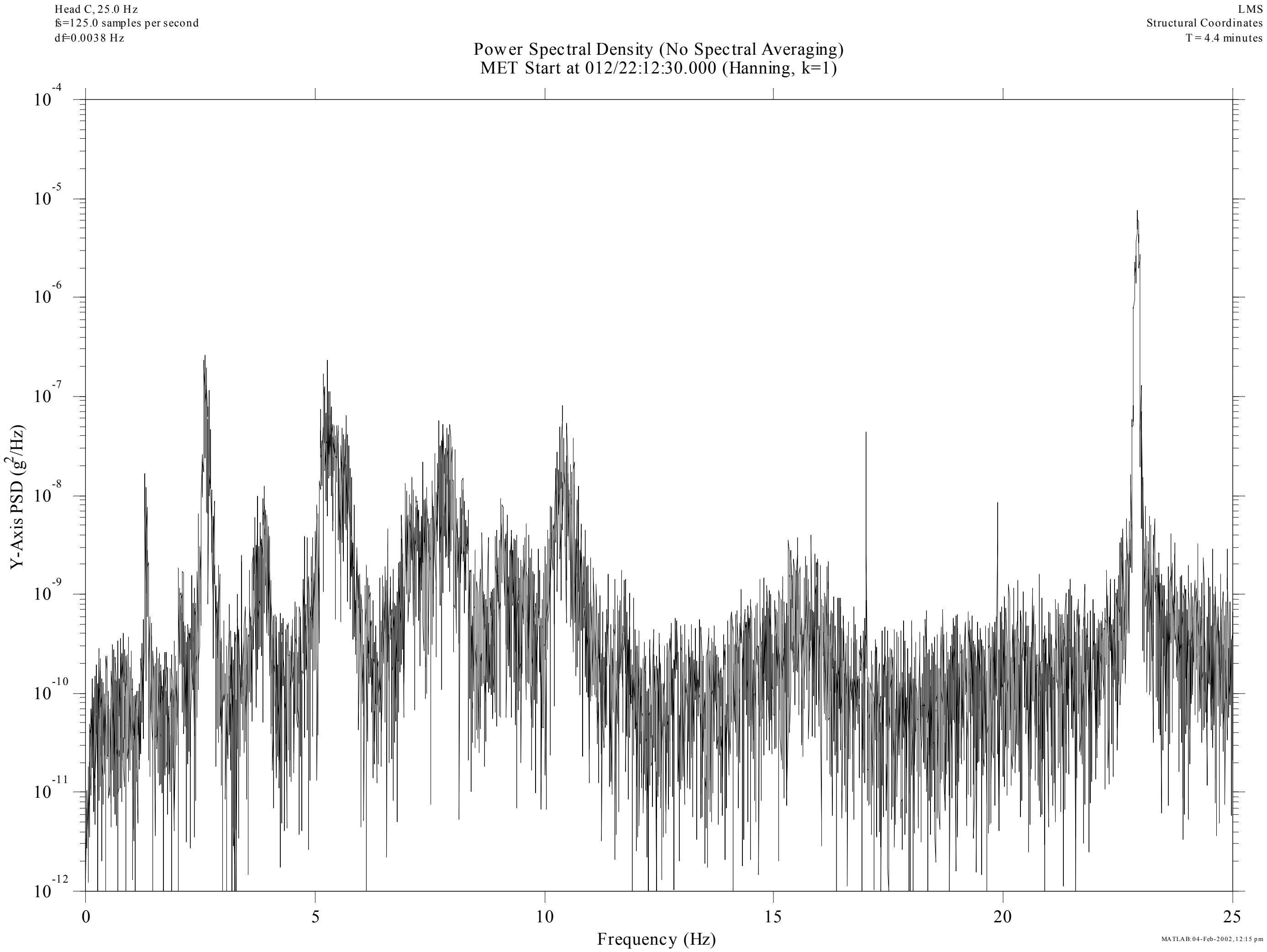
COMPUTE FFT OF EACH SECTION

FREQUENCY BIN-BY-BIN SUM OF k FFT MAGNITUDES

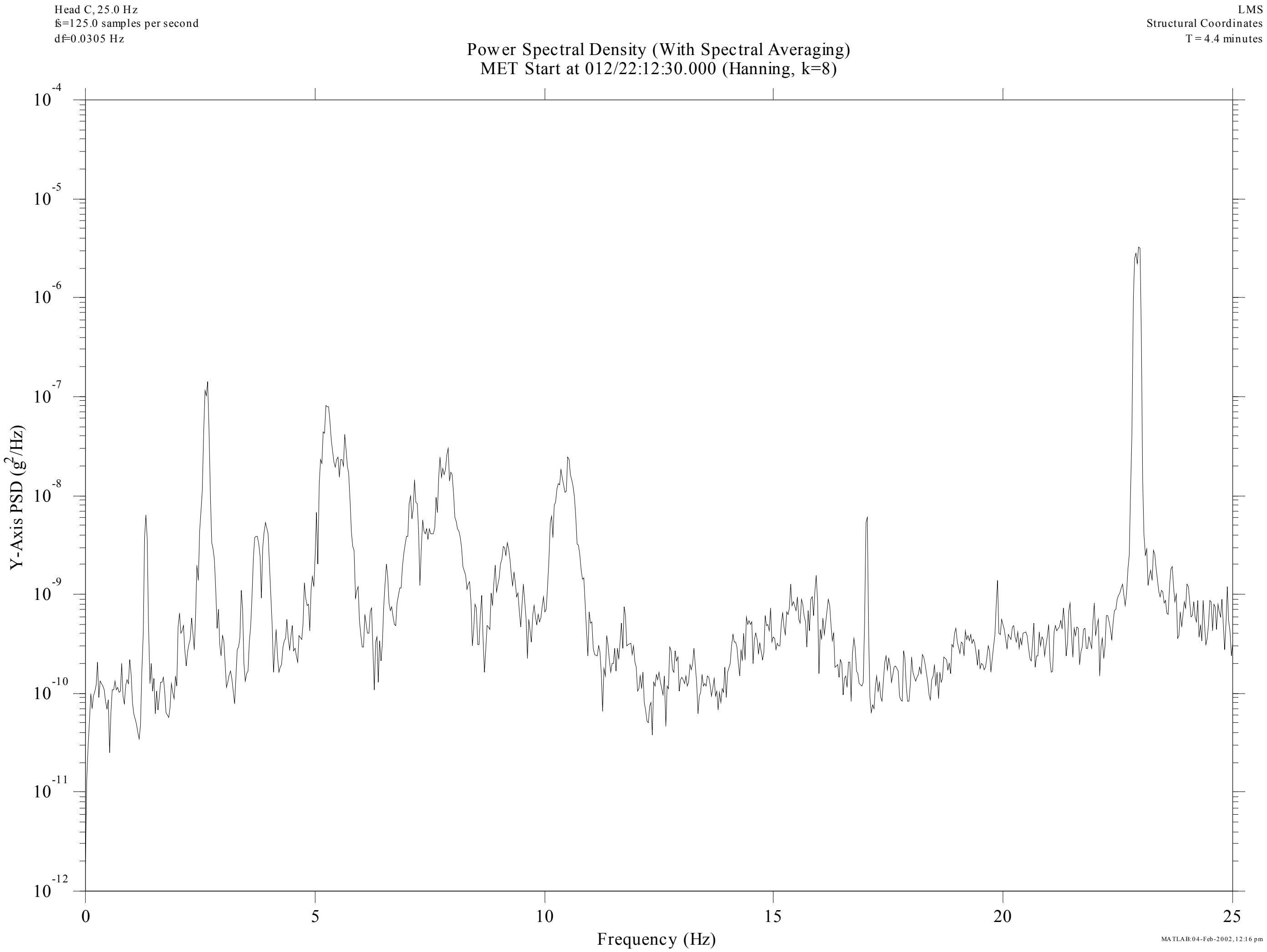
DIVIDE FREQUENCY BIN-BY-BIN SUM BY k

COMPUTE PSD FROM AVERAGED |FFT|

PSD without spectral averaging



PSD with spectral averaging



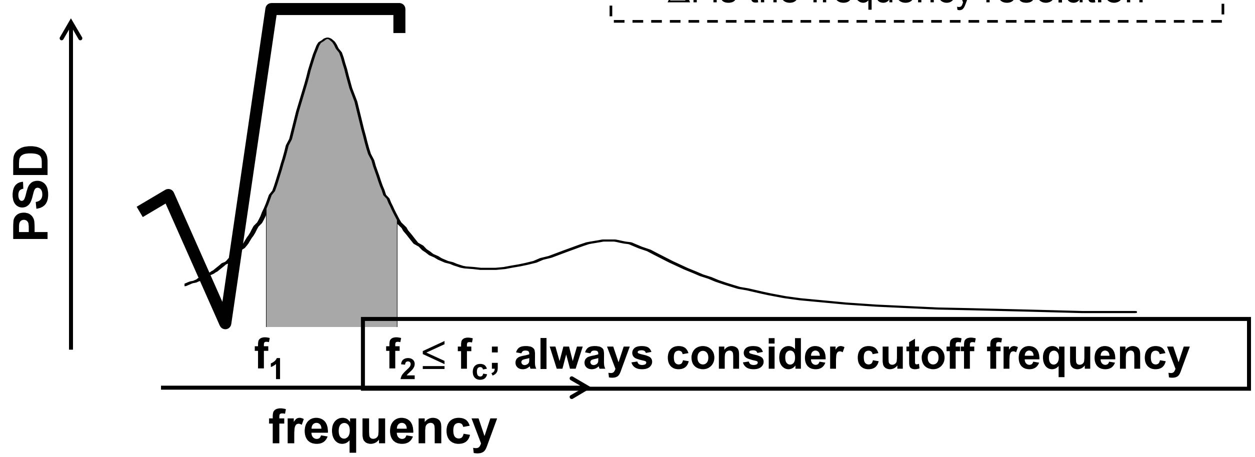
Parseval's Theorem

- **What is it?** It's a relation that states an equivalence between the RMS value of a signal computed in the time domain to that computed in the frequency domain.
- **Why do we use it?** It can be used to attribute a fraction of the total power in a signal to a user-specified band of frequencies by appropriately choosing the limits of integration (summation).
- Mathematically, this theorem can be expressed as:

$$\sqrt{\frac{1}{N}\sum_{n=0}^{N-1}\left|x(n)\right|^2} = \sqrt{\sum_{k=0}^{N/2} P(k)\Delta f}$$

- x(n) is time series
- N is the number of samples in the time series
- P(k) is the PSD of x(n)
- Δf is the frequency resolution

$$\mathrm{RMS}\Big|_{f_1}^{f_2} =$$



$f_2 \leq f_c$; always consider cutoff frequency

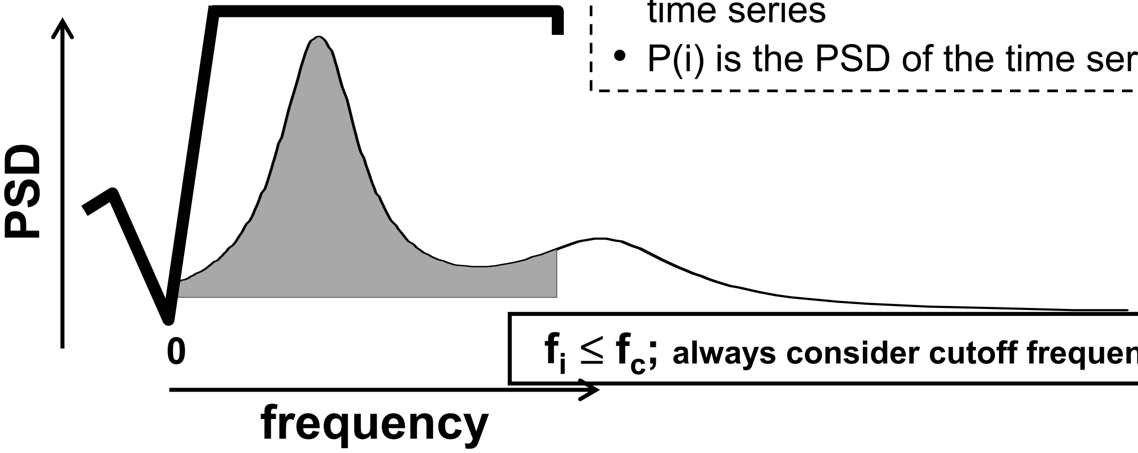
Cumulative RMS vs. Frequency

- **What is it?** It's a plot that quantifies the contributions of spectral components *at and below* a given frequency to the overall RMS acceleration level for the time frame of interest.
- **Why do we use it?** This type of plot highlights, in a quantitative manner, how various portions of the acceleration spectrum contribute to the overall RMS acceleration level.
  - steep slopes indicate relatively strong narrowband disturbances
  - shallow slopes indicate relatively quiet, broadband portions of the spectrum
- Mathematically, we have:

$$a_{\mathrm{RMS}}(k) = \sqrt{\sum_{i=0}^{k} P(i)\Delta f} \qquad k = 0,1,2...,(N/2)$$

- Δf is the frequency resolution
- N is the number of samples in the time series
- P(i) is the PSD of the time series

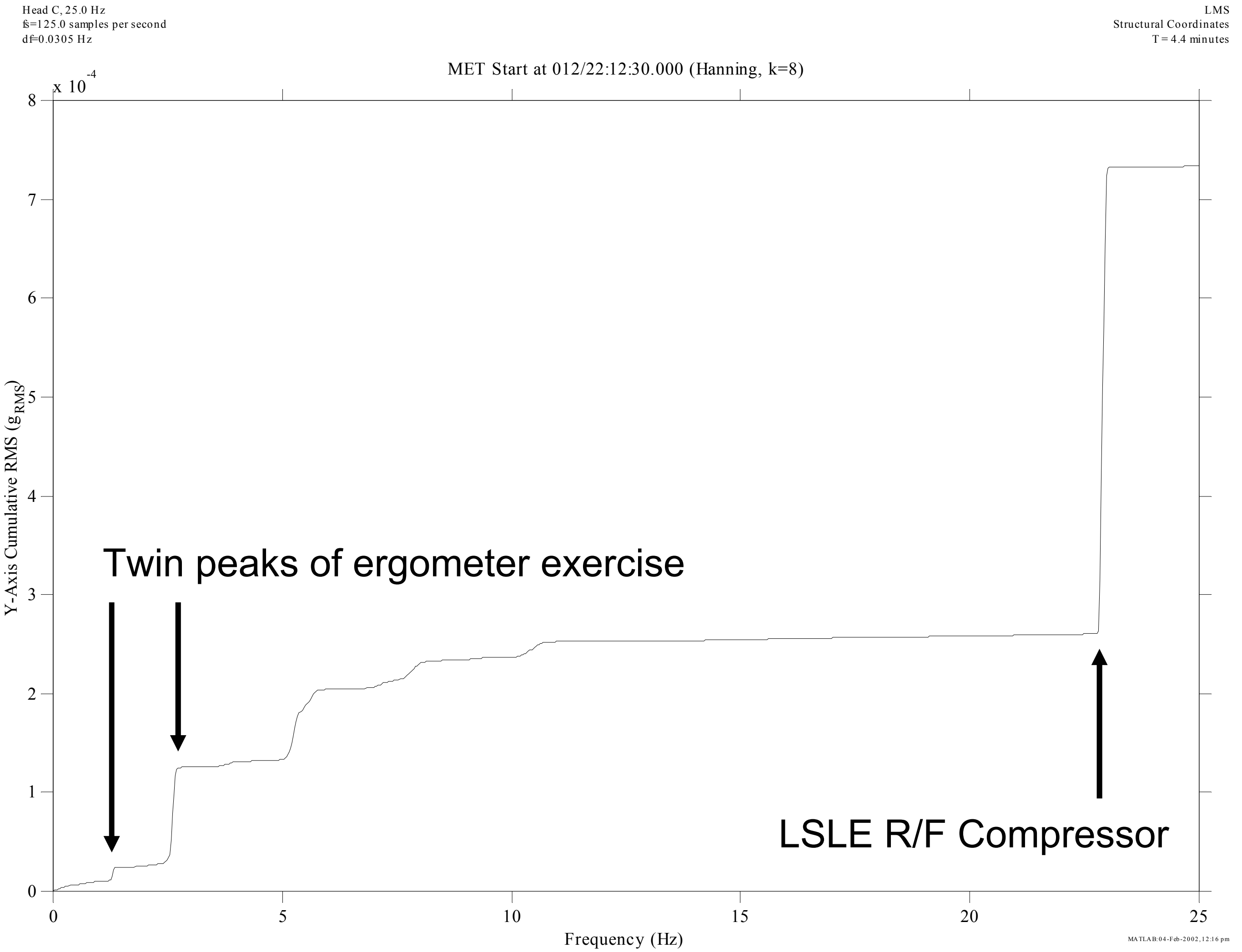
$$\left.\mathrm{RMS}\right|_{0}^{f_i} =$$



$f_i \le f_c$; always consider cutoff frequency

lower limit is clamped to zero, while upper limit slides to right (higher frequenices)

Cumulative RMS vs. Frequency



Twin peaks of ergometer exercise

LSLE R/F Compressor

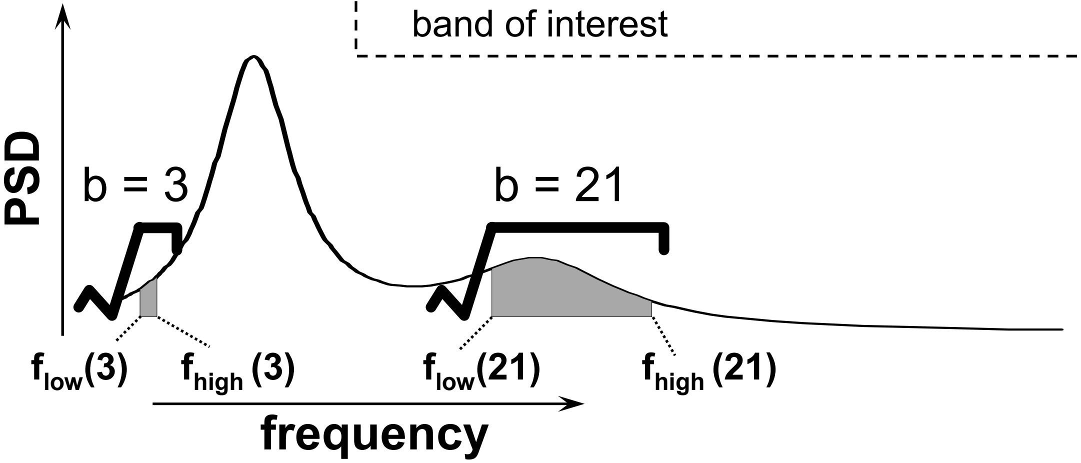
RMS vs. One Third Octave Frequency Bands

- **What is it?** It's a plot that quantifies the spectral content in proportional bandwidth frequency bands for a given time interval of interest.
- **Why do we use it?** The International Space Station vibratory limit requirements are defined in terms of the RMS acceleration level for each of a few dozen one third octave bands between 0.01 & 300 Hz with specified interval of 100 seconds.
- Mathematically, we have:

$$a_{RMS}(b) = \sqrt{\sum_{i=f_{low}(b)}^{f_{high}(b)} P(i)\Delta f} \qquad b = 1,2...,R$$

- $f_{low}(b)$ and $f_{high}(b)$ are frequency indices for the bth one third octave band
- P(i) is the PSD of the time series
- Δf is the frequency resolution
- R corresponds to the highest frequency band of interest

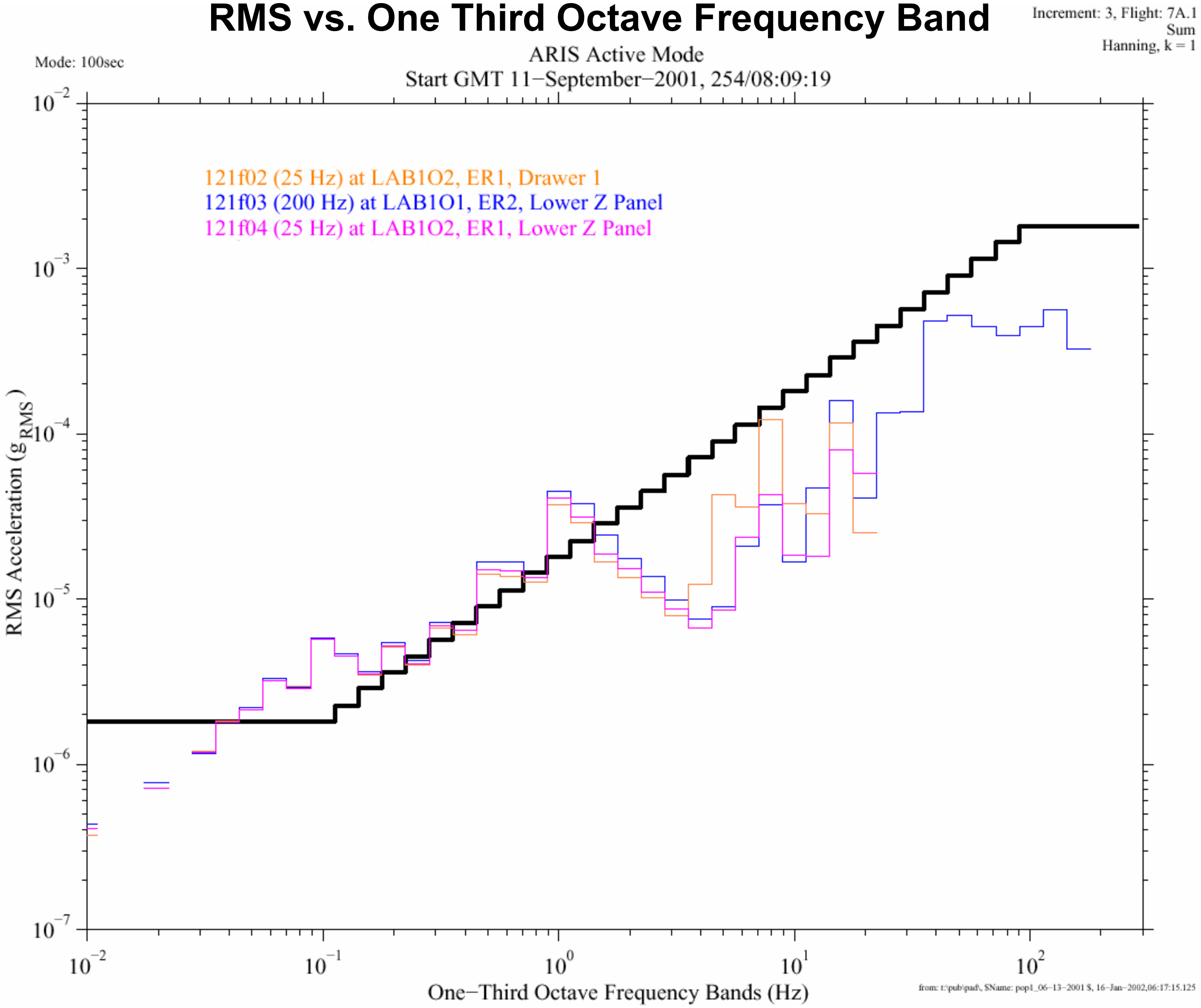
$$\mathrm{RMS}_b \Big|_{f_{low}(b)}^{f_{high}(b)} =$$



Analysis Techniques for Vibratory Data

Frequency Domain Analysis

RMS vs. One Third Octave Frequency Band



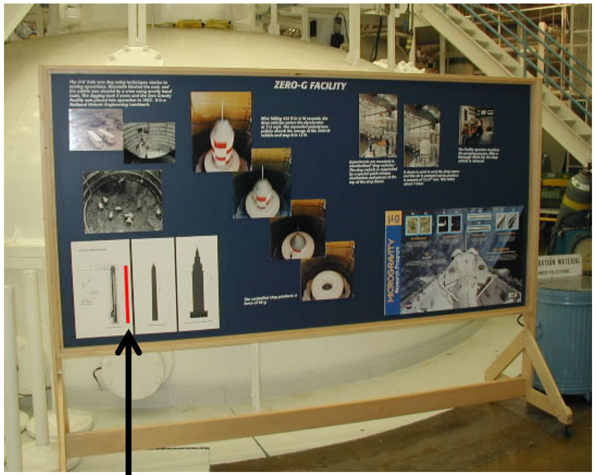
Log scale

Log scale

Frequency Domain Analysis Motivation

Approximate stack height of SAMS/MAMS CDs compiled for 15-year ISS life span is about same length as depth of NASA GRC Zero-G Facility (ZGF)

~475 feet

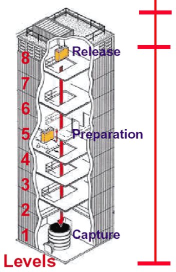


You won’t see this red mark on the poster at ZGF, it was inserted in this figure for comparison.

The CD stack height would fill the ZGF shaft.

Cleveland’s Main Avenue Bridge **~ 92 feet**

NASA GRC 2.2-Second Drop Tower **~ 79 feet**



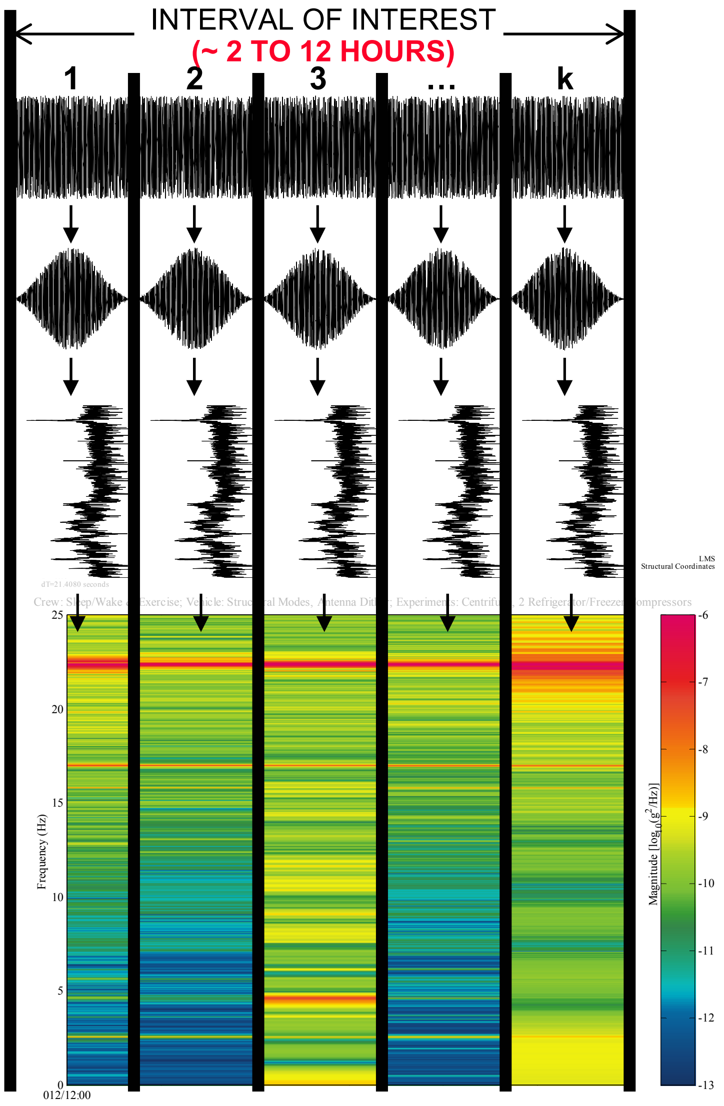
Frequency Domain Analysis

Spectrogram

- **What is it?** A spectrogram is a three-dimensional plot that shows PSD magnitude (represented by color) versus frequency versus time.
- **Why do we use it?**
  - It is a powerful qualitative tool for characterizing long periods of data
  - Identification and characterization of boundaries and structure in the data
    - Determine start/stop time of an activity within temporal resolution, dT (overlap, so dT is not Δt)
    - Track frequency characteristics of various activities within frequency resolution, Δf
- **Things you should NOT do with a spectrogram:**
  - Quantify disturbances in an absolute sense. The cumulative RMS or one-third octave versus frequency plots are better suited for this objective.
  - Rely entirely on it to check for the presence of a disturbance which is either known or expected to be relatively weak (instead, use PSD with proper spectral averaging or PCSA).

defined in later slide

Frequency Domain Analysis



How to Build a Spectrogram

1. SEGMENT INTO k EQUAL–LENGTH SECTIONS AND DEMEAN EACH SECTION

2. APPLY TAPER WINDOW TO EACH SECTION

3. COMPUTE PSD OF EACH SECTION

4. CALCULATE LOG_{10} OF |PSDs| AND MAP NUMERIC VALUES TO COLORS SUCH THAT THE BLUE (BOTTOM) PART OF THE COLOR MAP REPRESENTS SMALLER VALUES THAN THOSE TOWARD THE RED (TOP) PART

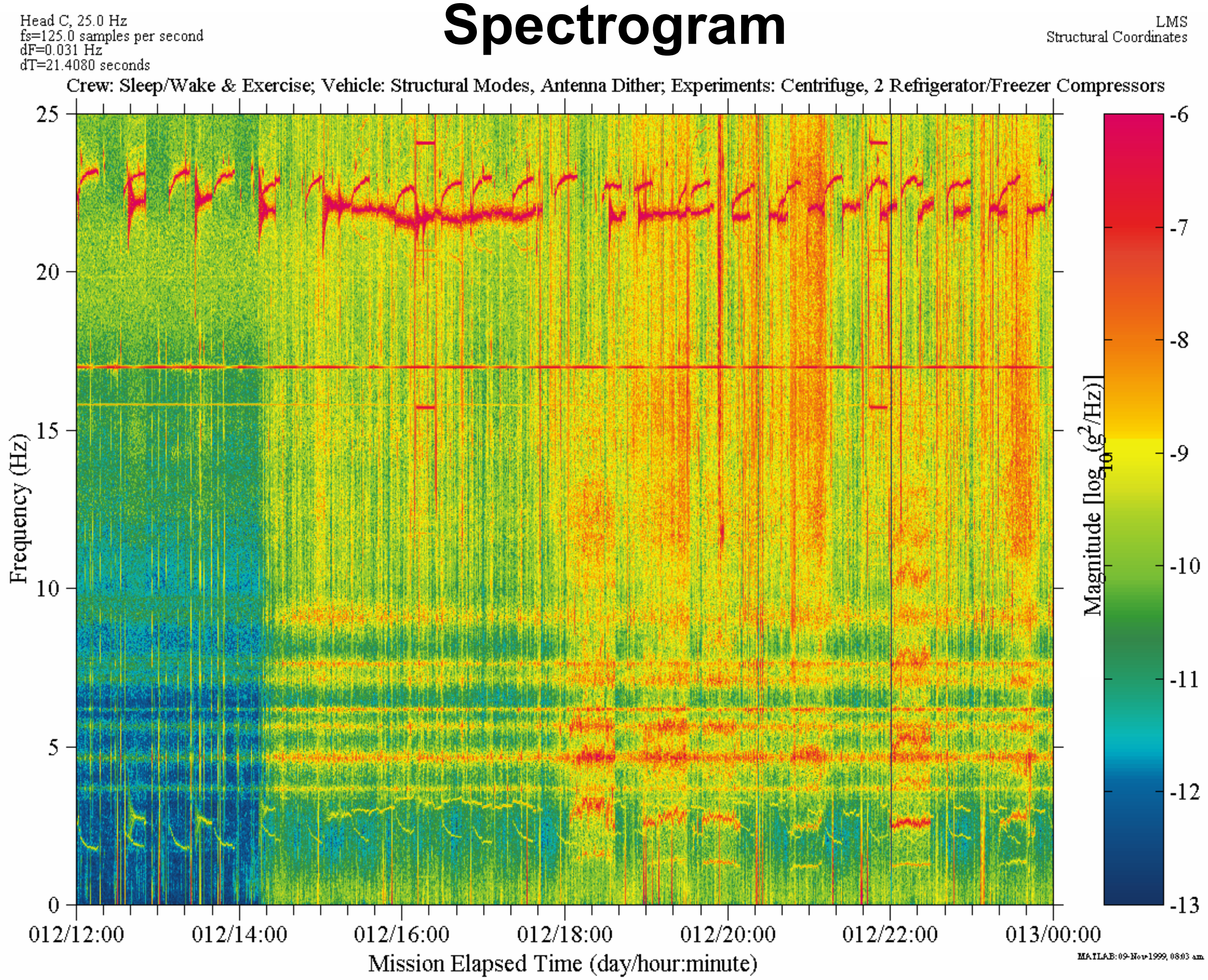
5. DISPLAY EACH OF THE k PSD SECTIONS AS A VERTICAL STRIP OF THE SPECTROGRAM (LIKE WALLPAPERING), SUCH THAT TIME INCREASES FROM LEFT TO RIGHT AND FREQUENCY INCREASES FROM BOTTOM TO TOP

Note: The width of each strip is the temporal resolution and the height of each distinct color patch is the frequency resolution.

Analysis Techniques for Vibratory Data

Frequency Domain Analysis

Spectrogram



Principal Component Spectral Analysis (PCSA)

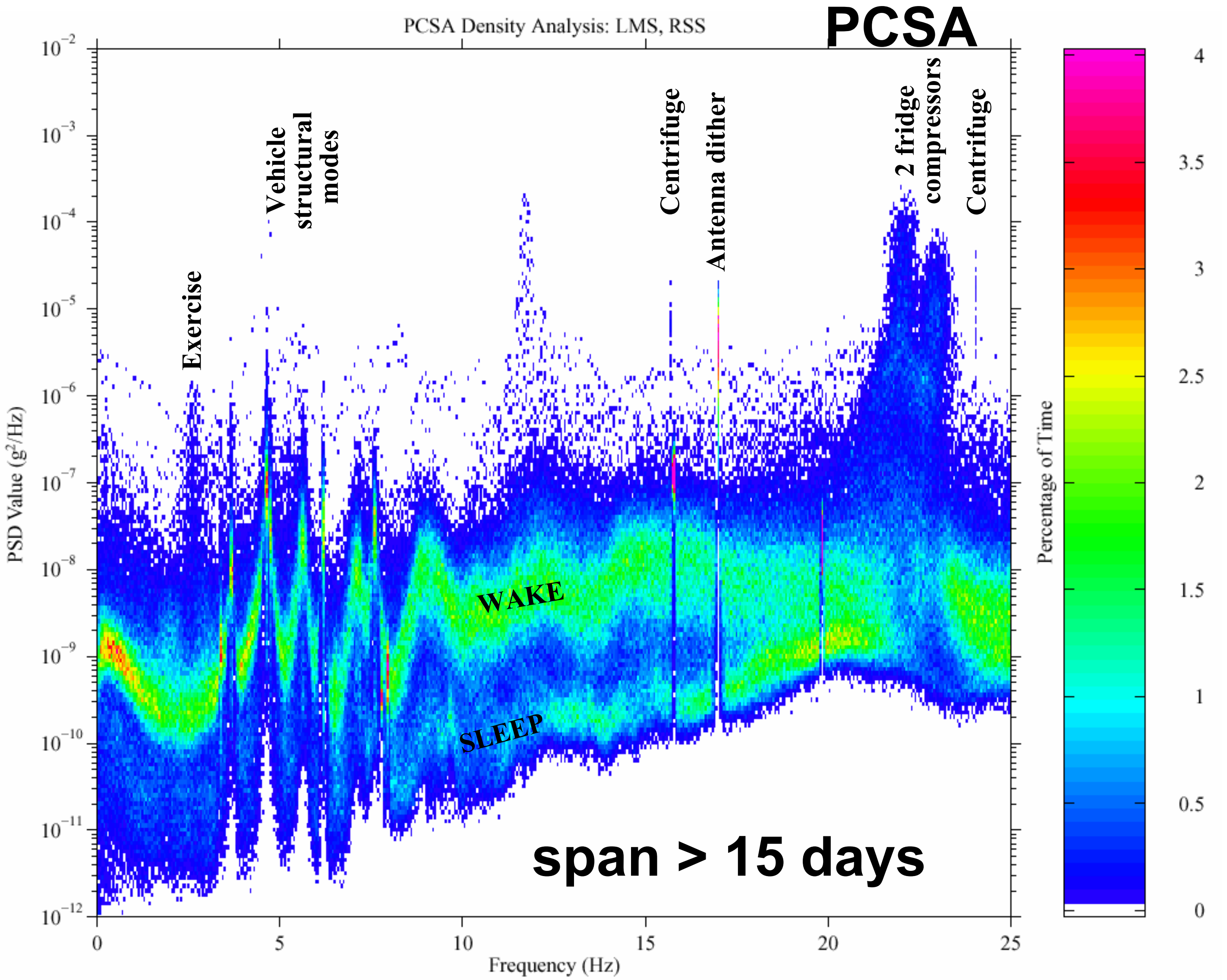
- **What is it?** A frequency domain analysis technique that compiles PSDs in the form of a two-dimensional histogram with frequency-magnitude bins.

- **Why do we use it?** To examine the spectral characteristics of a long period of data.
  - serves to *summarize* magnitude and frequency variations of key spectral contributors
  - better frequency and PSD magnitude resolution relative to a spectrogram

- **Tradeoff:** Poor temporal resolution

Analysis Techniques for Vibratory Data

Frequency Domain Analysis



Time Domain Summary Table

DISPLAY	NOTES
Acceleration vs. Time	• most precise accounting of measured data with respect to time • display device constrains resolution for long time spans or high sample rates
Interval Minimum/Maximum Acceleration vs. Time	• displays upper and lower bounds of peak-to-peak excursions • good display approximation for time histories on output devices with resolution insufficient to display all data in time frame of interest (see notes below though)
Interval Average Acceleration vs. Time	• descriptive statistics • not fully descriptive (“lossy compression”)
Interval Root-Mean-Square (RMS) Acceleration vs. Time	

Frequency Domain Summary Table

DISPLAY	NOTES
Power Spectral Density (PSD) vs. Frequency	• quantifies distribution of power with respect to frequency • windowing (tapering) to suppress spectral leakage • spectral averaging to reduce spectral variance (degraded Δf)
Cumulative RMS Acceleration vs. Frequency	• quantifies RMS contribution at and below a given frequency • quantitatively highlights key spectral contributors
RMS Acceleration vs. One Third Octave Frequency Bands	• quantify RMS contribution over proportional frequency bands • compare measured data to ISS vibratory requirements
Spectrogram (PSD vs. Frequency vs. Time)	• displays power spectral density variations with time • good *qualitative* tool for characterizing long periods • identify structure and boundaries in time and frequency
Principal Component Spectral Analysis (PCSA)	• summarize magnitude and frequency excursions for key spectral contributors over a long period of time • results typically have finer frequency resolution and high PSD magnitude resolution relative to a spectrogram at the expense of terrible temporal resolution