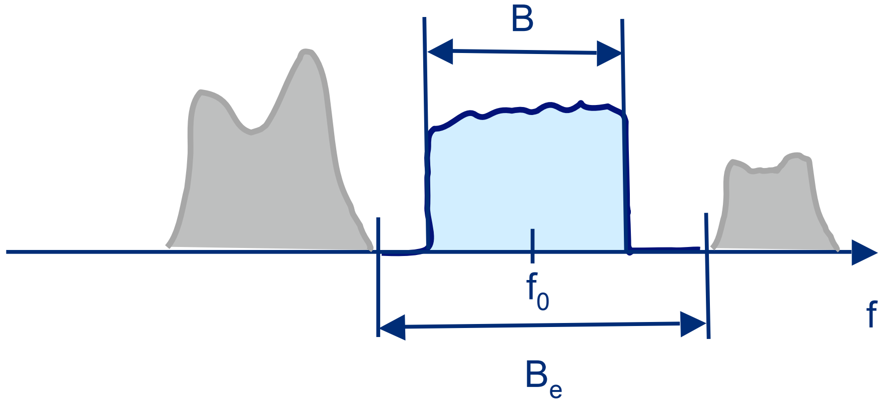
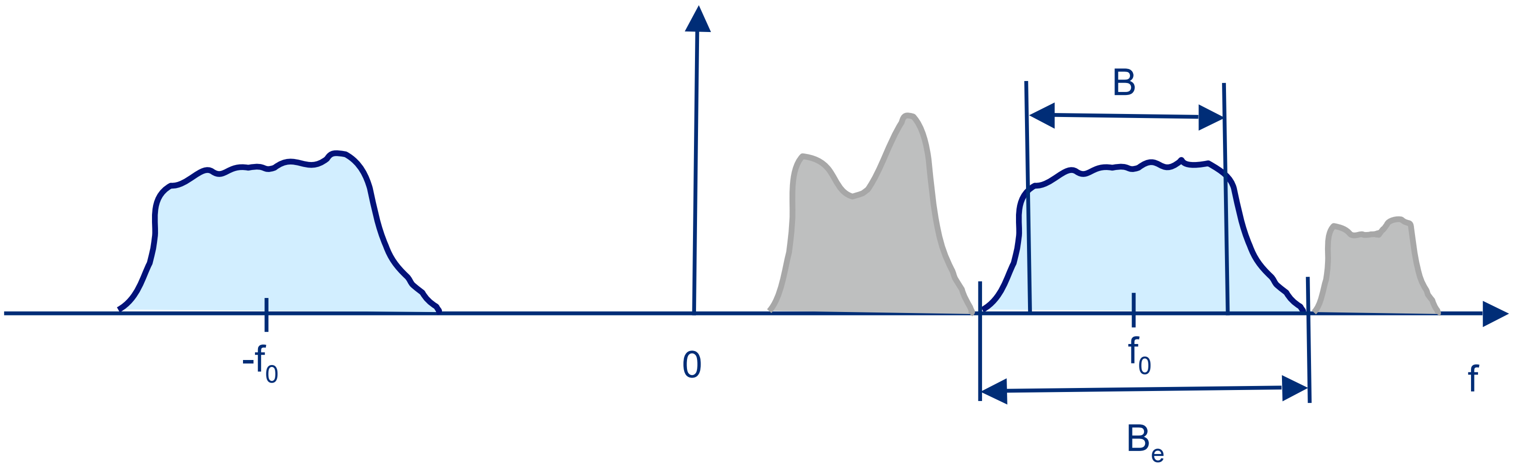
Cyclostationary Feature Detection

Robust Energy Detector



- Suppose the primary signals left perfect guard bands
- Assume secondary users used all of B_e
- We can use the estimates in the guard bands to estimate the noise/interference in the primary band, and gain robustness to interference uncertainty

Motivation for Feature Detection



- Real life does not have perfect guard bands
- But primary signal has non-random components (features) that if detected can be used to discriminate w.r.t. noise. These features are:
  - Double sided (sinewave carrier)
  - Data rate (symbol period)
  - Modulation type

Questions to be answered …

- What transformation extracts signal features?
- How do we implement feature detectors?
- How do we detect features?
- What is the performance advantage over the energy detector?
- What are the feature detector limitations?

Detecting Periodic Signal Features

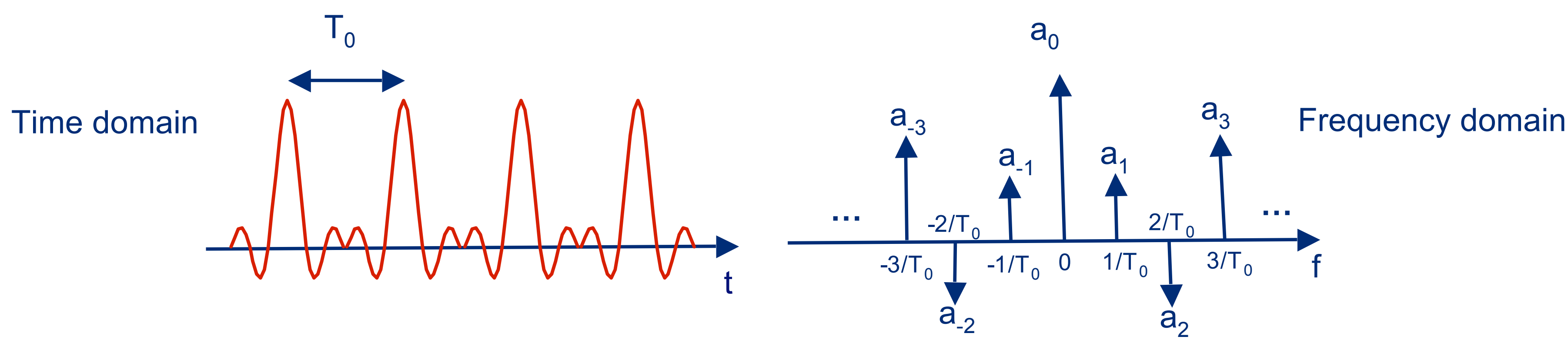
1st order periodicity signal with period T_0: $x(t) = x(t+T_0)$

Periodic signals can be represented using Fourier series coefficients:

$$x(t) = \sum_{k=-\infty}^{\infty} a_k e^{jkw_0 t}$$ with fundamental frequency $$w_0 = \frac{2\pi}{T_0}$$

Fourier coeff. $$a_k = \frac{1}{T_0}\int_{T_0} x(t) e^{-jkw_0 t} dt$$ obtained by projecting onto complex sinewave basis $\boldsymbol{e^{-jkw_0 t}}$

Fourier series expansion extracts features of the periodic signal



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Some Observations

Periodic signals are deterministic, so by applying Fourier series analysis they can be represented as a sum of sinewaves that are easy to detect

Modulated signals are not truly periodic, cannot apply Fourier analysis directly

Modulated signals have built-in periodic signals that can be extracted and analyzed using Fourier analysis

Double Sideband Modulation

Let x(t) be amplitude modulated signal at some carrier f_0

$$x(t) = a(t)\cos(2\pi f_0 t)$$

Carrier f_0 is a built-in periodicity that can be detected

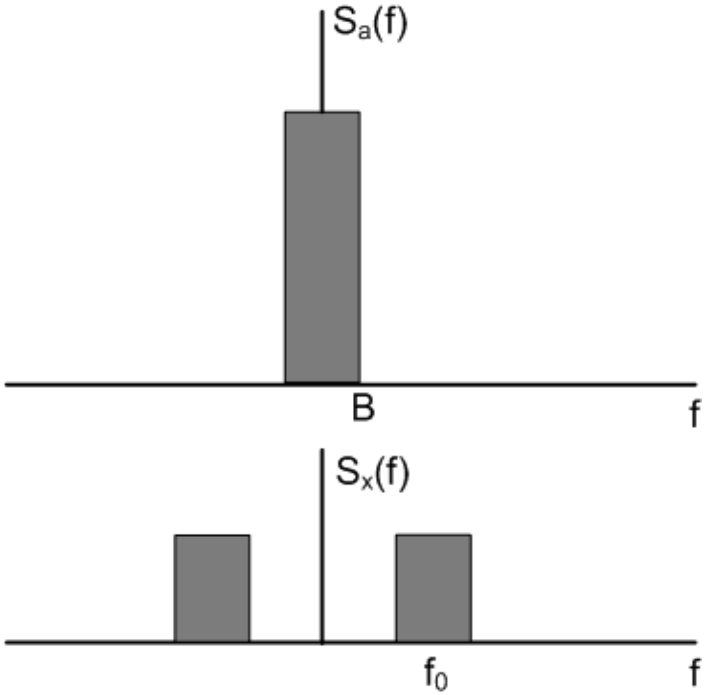
a(t) is random data that is characterized statistically:

mean, variance, autocorrelation function, and power spectrum density are sufficient to specify wide-sense stationary process

$$m_a = E\{a(t)\} = 0 \qquad R_a(\tau) = E\left\{a(t)a(t-\tau)^*\right\}$$

$$S_a(f) = F(R_a(\tau))$$

$$S_x(f) = \frac{1}{4}S_a(f+f_0) + \frac{1}{4}S_a(f-f_0)$$



Spectrum of x(t) does not contain any sinewave components

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Extracting Features corresponding to a Sinewave Carrier

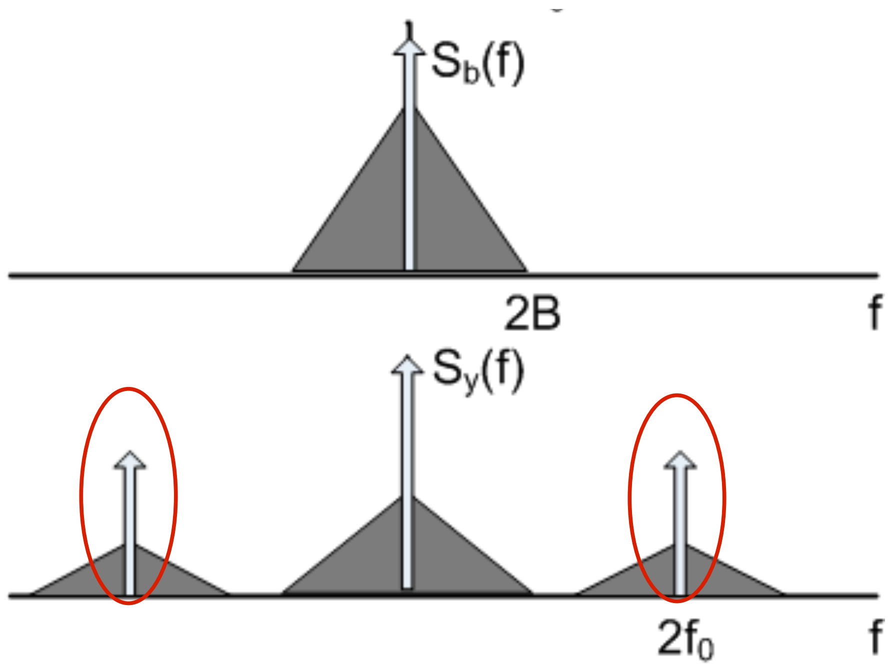
Quadratic transformation of x(t) produces spectral lines at 0, $\pm 2f_0$

$$y(t) = x(t)^2 = a(t)^2 \cos^2(2\pi f_0 t)$$

$$y(t) = \frac{1}{2}\left[b(t) + b(t)\cos(2\pi(2f_0)t)\right]$$

$$b(t) = a(t)^2 = K + c(t)$$

$$K = E\{a^2(t)\} > 0$$



Note that squared signal has positive mean,
so PSD of y(t) has sinewave component at $2f_0$
with amplitude proportional to the mean of $a^2(t)$

$$S_y(f) = \frac{1}{4}\left[K\delta(f) + S_c(f) + K\delta(f \pm 2f_0) + + \frac{1}{4}S_c(f \pm 2f_0\right]$$

Pulse-shaped Modulated signal with Symbol Period T_0

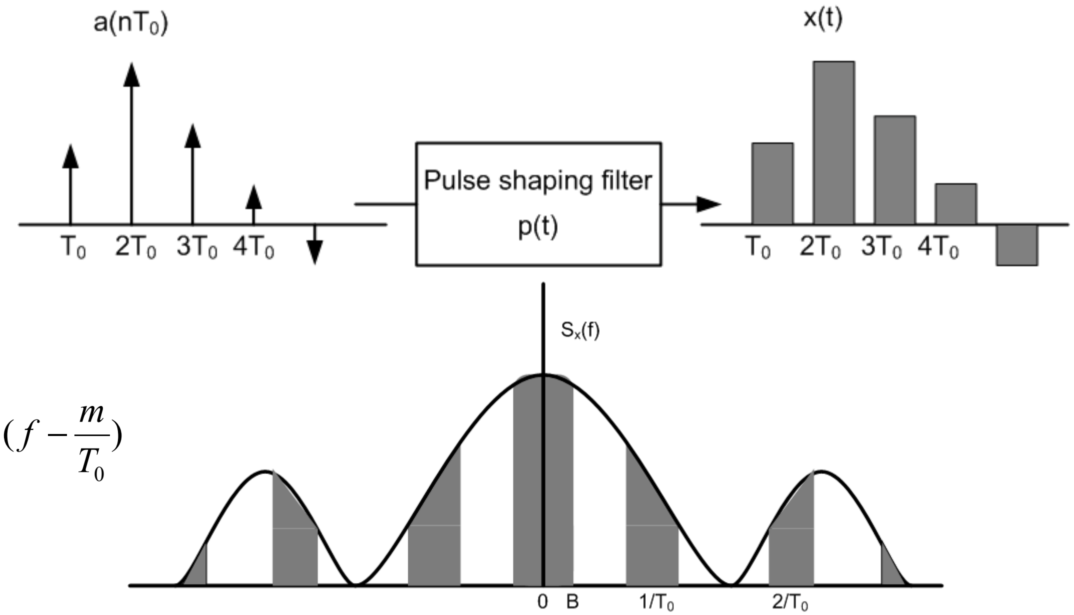
Lets consider baseband pulse-shaped modulated signal x(t), with symbol rate T_0

$$x(t) = \sum_n a(nT_0)\, p(t - nT_0)$$

Symbol period T_0 is a built-in periodicity that can be detected

$a(nT_0)$ is zero mean data

p(t) is low pass filter confined to $(-T_0/2, T_0/2)$



$$S_x(f) = \frac{1}{T_0} |P(f)|^2 \sum_m S_a(f - \frac{m}{T_0})$$

Extracting Features corresponding to Symbol Period T_0

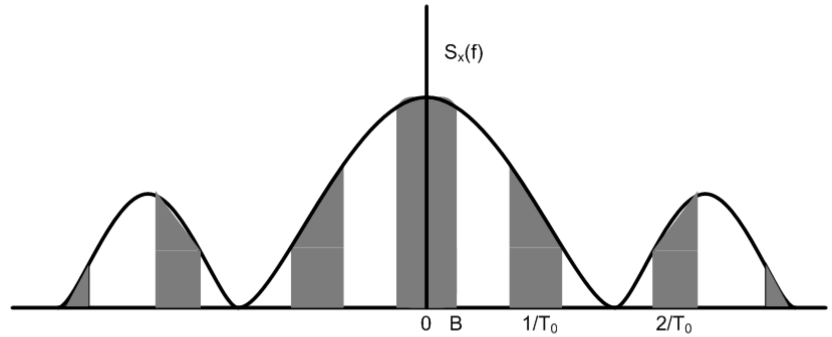
Quadratic transformation of x(t) produces spectral lines at m/T_0

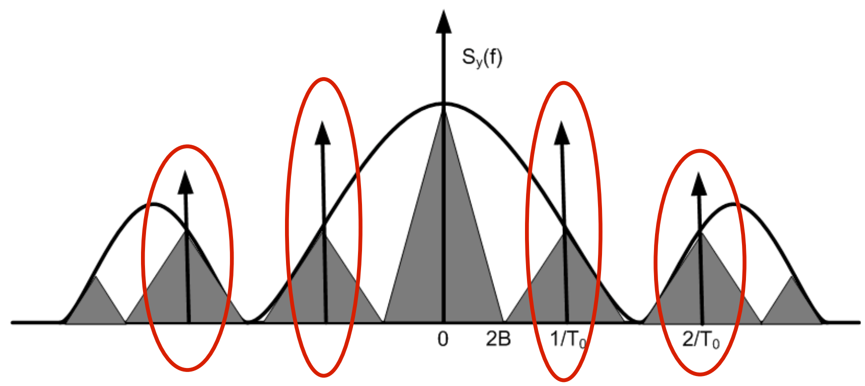
$$y(t) = x(t)^2 = \sum_n b(nT_0)q(t - nT_0)$$

$$q(t) = p(t)^2$$

$$b(nT_0) = a(nT_0)^2 = K + c(nT_0)$$

$$K = E\{a(nT_0)^2\} > 0$$





Note that squared signal has positive mean, so PSD of y(t) has sinewaves at m/T_0 with amplitude proportional to $p^2(t)$

$$S_y(f) = \frac{1}{T_0}|Q(f)|^2 \sum_m \{\underline{K\delta(f - \frac{m}{T_0})} + S_c(f - \frac{m}{T_0})\}$$

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Review: Stationary Processes

So far we treated modulated signals as wide-sense stationary (WSS) processes.

Noise is a typical WSS process.

WSS processes have time invariant autocorrelation function:

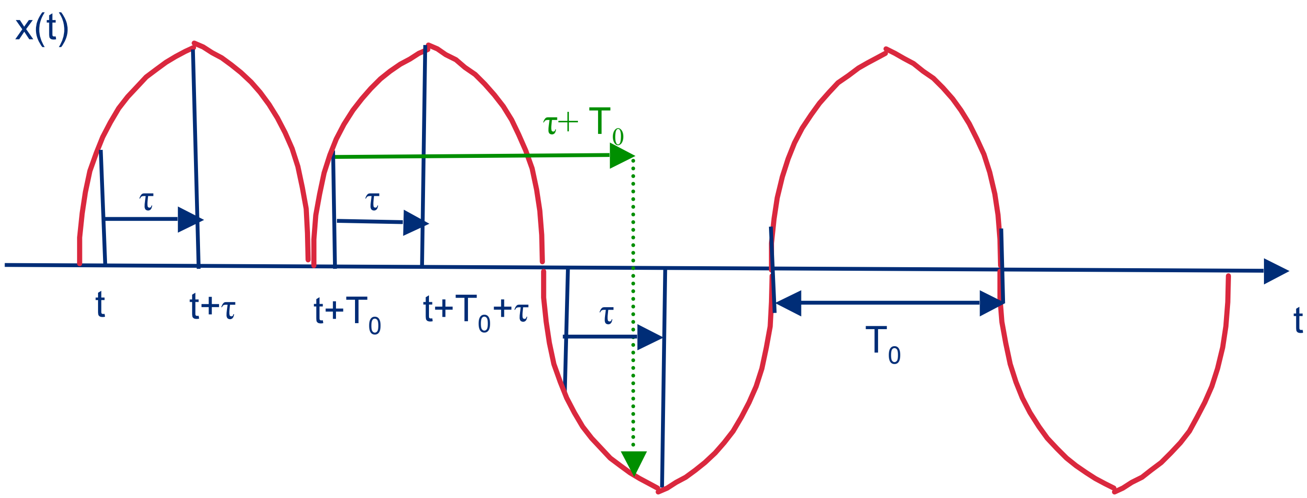
$$R_x(t,\tau) = E\left\{ x(t) x(t-\tau)^* \right] \quad \Rightarrow \quad R_x(t,\tau) = R_x(\tau) \quad \forall t$$

Wiener relationship relates autocorrelation and power spectrum density:

$$S_x(f) = F\{R_x(\tau)\} = \int_{-\infty}^{\infty} R_x(\tau) e^{-j2\pi f\tau} d\tau$$

When analyzing WSS processes it is sufficient to know either *R* (τ) or *S(f)* (case of radiometer)

Modulated signals are Cyclostationary Processes



Modulated signals are cyclostationary processes.

Definition: Cyclostationary process has periodic autocorrelation function

$$R_x(t,\tau) = R_x(t+T_0,\tau)$$

Periodic in t not in τ

Cycle Autocorrelation

Since autocorrelation function is periodic, it can be represented by Fourier coeff.

$$R_x^{\alpha}(\tau) = \lim_{T \to \infty} \frac{1}{T} \int_T x(t + \frac{\tau}{2}) x(t - \frac{\tau}{2})^* e^{-j2\pi\alpha t} dt$$ **cycle autocorrelation**

If cyclostationary with period T then cycle autocorrelation has component at α=1/T

Autocorrelation function is also quadratic transform thus feature of modulated signals that are function of symbol rate, carrier, etc. can be detected

Spectral Correlation Function

Cycle autocorrelation is time domain transform,
what is its frequency domain equivalent?

Wiener relationship can be established for cyclostationary processes too:

$$S_x^\alpha(f) = F\{R_x^\alpha(\tau)\} = \int_{-\infty}^{\infty} R_x^\alpha(\tau) e^{-j2\pi f\tau} d\tau$$

$$S_x^\alpha(f) = \lim_{\Delta t \to \infty} \lim_{T \to \infty} \frac{1}{\Delta t} \frac{1}{T} \int_{-\Delta t/2}^{\Delta t/2} X_T(t, f + \frac{\alpha}{2}) X_T^*(t, f - \frac{\alpha}{2}) dt$$

Spectral correlation function

$$X_T(t, f) = \int_{t-T/2}^{t+T/2} x(u) e^{-j2\pi f u} du$$

is spectral component of x(t) at frequency f with bandwidth 1/T

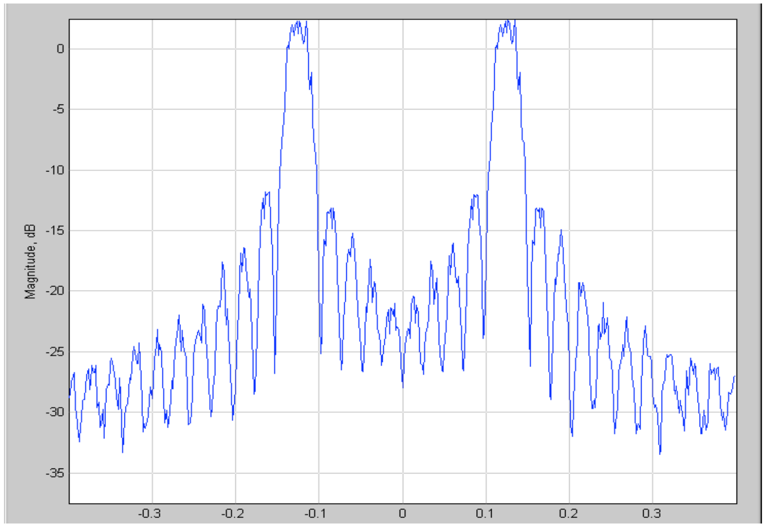
S_x^α is a two dimensional complex transform on a support set (f, α)

Spectral correlation function can be used for feature detection

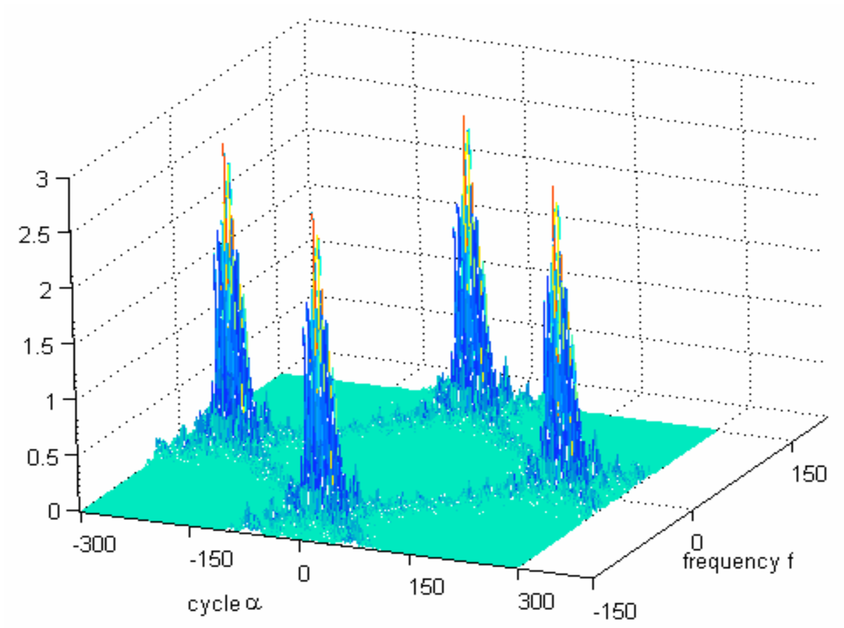
Example of Spectral Correlation Function

BPSK modulated signal:

– carrier at 125 MHz, bandwidth 20 MHz, square root raised cosine pulse shape with roll-off=0.25, sampling frequency 0.8 GHz



Power Spectrum Density



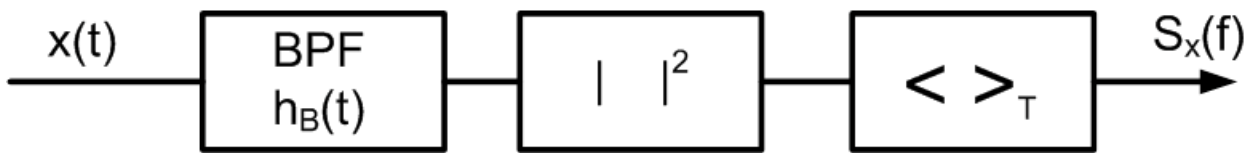
Spectrum Correlation Function

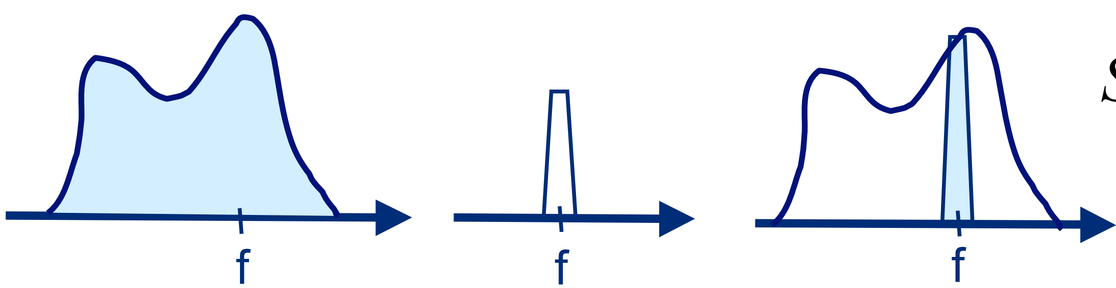
Measuring Power Spectrum Density

Spectrum analyzer approach for power spectrum density measurement

Localize power at some frequency by passing the signal through a narrow bandpass filter $h_B(t)$ centered at frequency f.

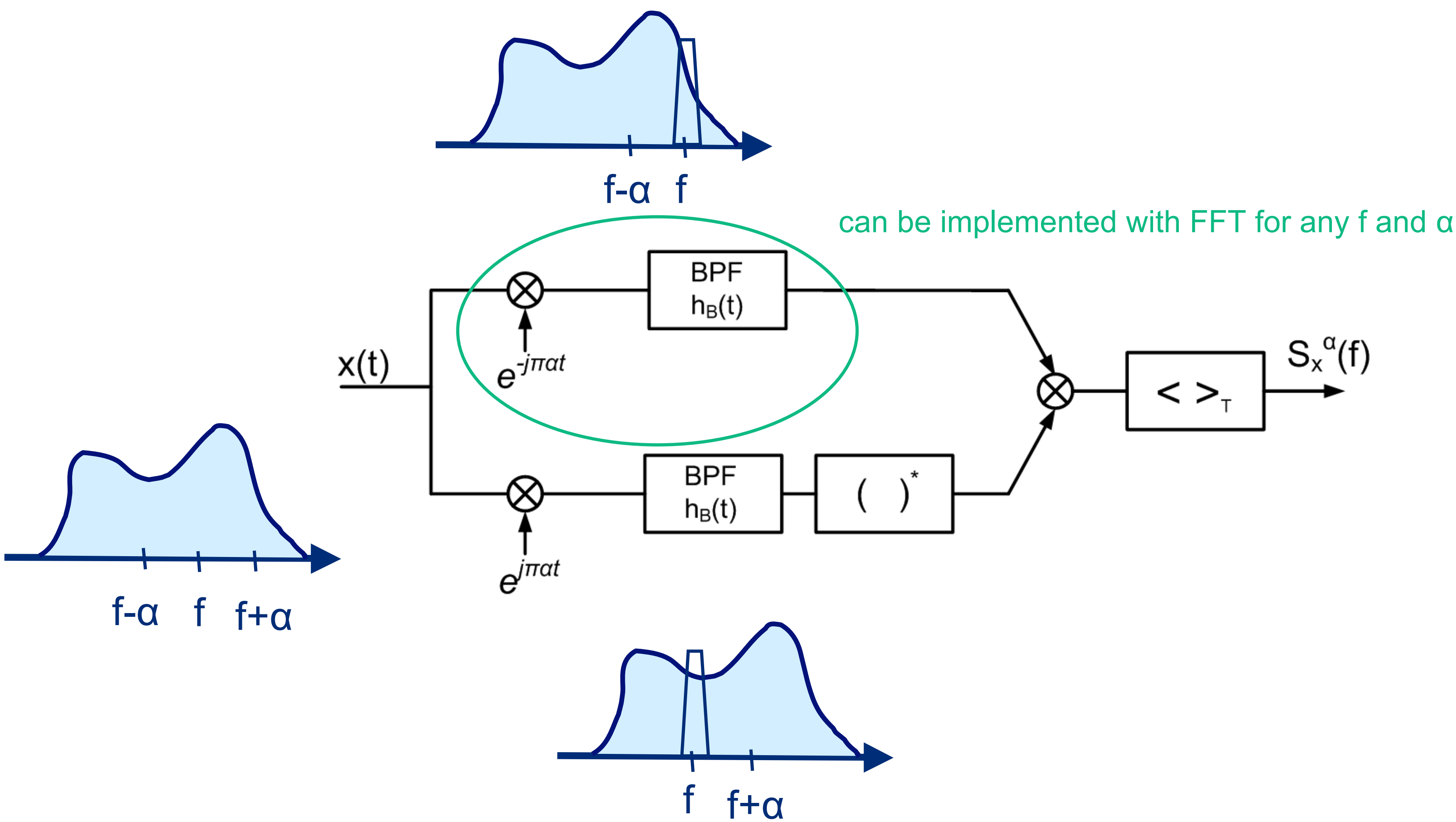
Average the magnitude of the output over period T, i.e. $< \; >_T$.





$$S_x(f) = \lim_{B \to 0} \frac{1}{B} \left\langle \left| h_B(t) \otimes x(t) \right|^2 \right\rangle_T$$

Measuring Spectral Correlation



$$S_x^{\alpha}(f) = \lim_{B \to 0} \frac{1}{B} \left\langle \left[h_B(t) \otimes x(t) e^{-j\pi\alpha t} \right] \cdot \left[h_B(t) \otimes x(t) e^{j\pi\alpha t} \right]^{*} \right\rangle_T$$

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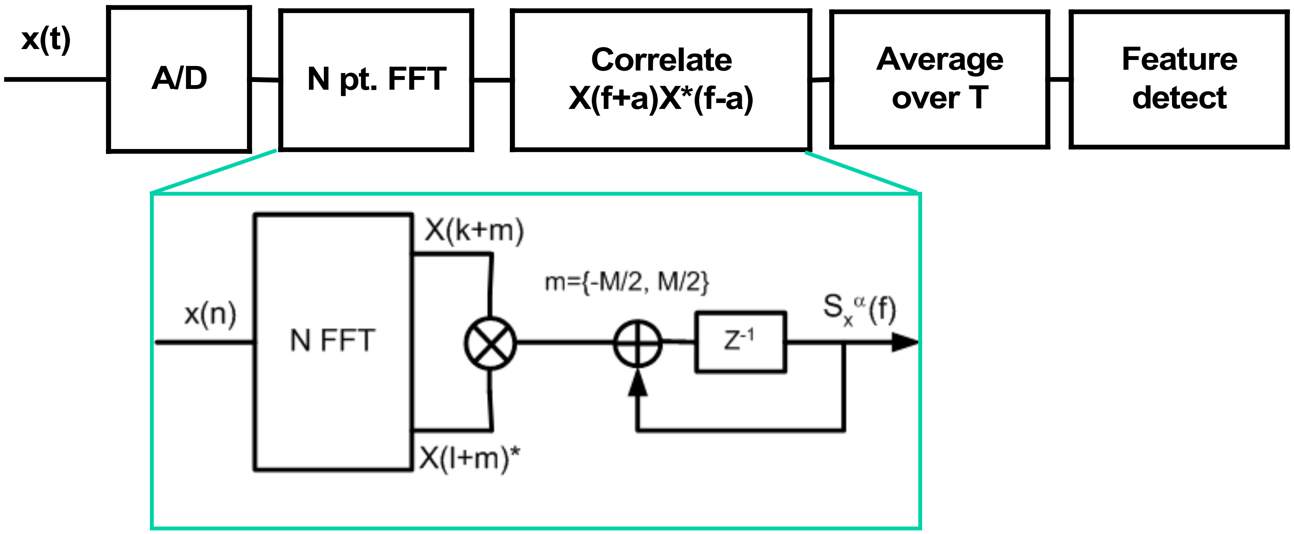
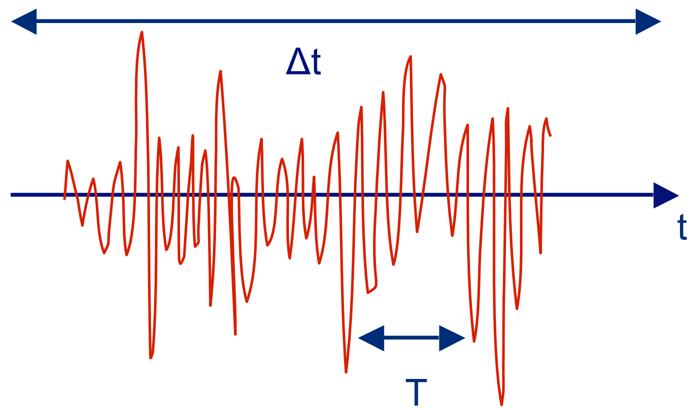
Implementation using FFT



Complexity is increased with respect to energy detector

Number of complex multipliers scales as $\sim O(N^2 + N \log N)$

Sampling, Frequency, and Cycle Resolution

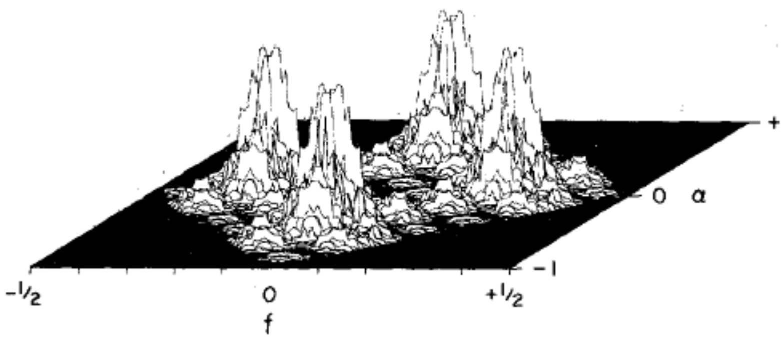


$$S_x^{\alpha}(f) = \lim_{\Delta t \to \infty} \lim_{T \to \infty} \frac{1}{\Delta t} \frac{1}{T} \int_{-\Delta t/2}^{\Delta t/2} X_T(t, f + \frac{\alpha}{2}) X_T^*(t, f - \frac{\alpha}{2}) dt$$

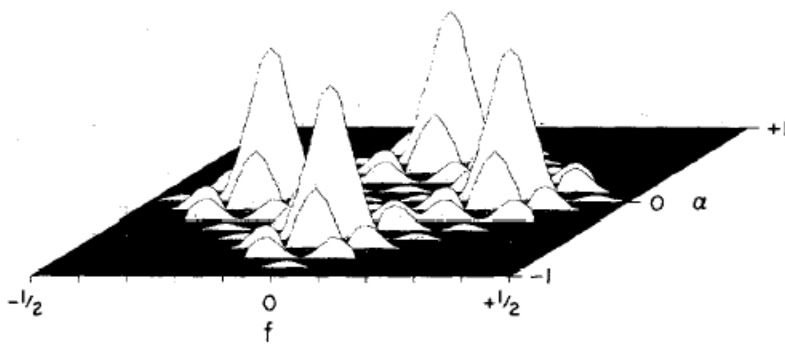
Sampling:	In order to detect features at cycle α must sample at $F_s > 2\max\{\alpha, B\}$, and support set for $S_x^{\alpha}(f)$ is $-F_s/2 <$ f, $\alpha < F_s/2$
Frequency resolution:	In order to resolve features need to have sufficient resolution in f and α Spectral resolution in f can be increased by $T=1/\Delta f$
Cycle resolution:	Cycle resolution depends on the total observation interval $\Delta\alpha = 1/\Delta t$ Increase the resolution in α by smoothing and $\Delta t >> 1/\Delta f = T$

Example: Cycle Resolution Improvement

BPSK at carrier



Δt= 4 T



Δt= 1024T

Gardner 1986: Measurement of spectral correlation

Can we use Cyclostationary detectors for Sensing?

- If processing signals and noise like wide-sense stationary processes then radiometer is the optimal non-coherent detector

- If processing signals like cyclostationary processes then (at increased complexity) features like double sideband, data rates, and modulation type can be detected

- What is the optimal feature detector for cyclostationary signals in noise?

- Noise is not cyclostationary process, can cyclostationary detectors benefit from that information?

- What are the limitations?

Model

Hypothesis testing: Is the primary signal out there?

$$H_0: \quad y(n) = w(n)$$

$$H_1: \quad y(n) = x(n) + w(n)$$

x(n) is primary user signal with known modulation and $S_x^{\alpha}(f)$

w(n) is noise with zero mean and unknown power N_0 that could vary over time

mean power $\mu_{N_0} = E(N_0)$

variance $\sigma_{N_0}^2 = E(N_0^2) - E(N_0)^2$

and $\rho_{N_0} = \dfrac{\sigma_{N_0}^2}{\mu_{N_0}^2}$

Assume very low SNR at the detector

Maximum likelihood detector of noise power is: $\tilde{N}_0 = \dfrac{1}{N}\sum_{k=1}^{N} y^2(n)$

Cyclostationary Detection

Spectral correlation function of *y(n)*:

$$H_0: \qquad S_y^{\alpha}(f) = S_w^{\alpha}(f)$$

$$H_1: \qquad S_y^{\alpha}(f) = S_x^{\alpha}(f) + S_w^{\alpha}(f)$$

Noise is not cyclostationary process thus $S_w^{\alpha}(f)=0$ for $\alpha \neq 0$.

What is the sufficient statistics for optimal Maximum Likelihood detector?

For fixed number of samples N compute estimate of SCF:

$$\tilde{S}_y^{\alpha}(f) = \frac{1}{N}\frac{1}{T}\sum_{n=0}^{N} Y_T(n, f+\frac{\alpha}{2}) Y_T^{*}(n, f-\frac{\alpha}{2})$$

$$Y_T(n,f) = \int_{n-T/2}^{n+T/2} y(u) e^{-j2\pi f u} du$$ T pt. FFT around nth sample

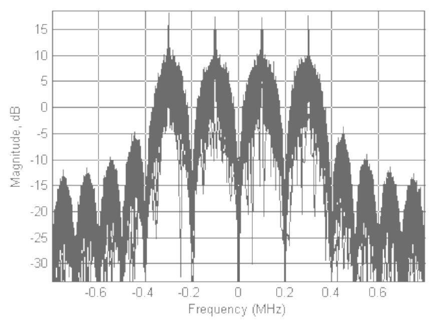
Energy vs. Feature Detection

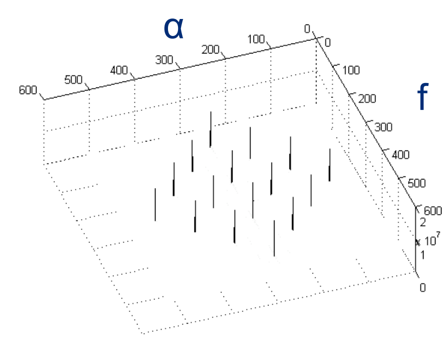
Frequency modulation $x(n) = \sum_{k=-\infty}^{\infty} \cos(2\pi(f_c - f(n))n)h(n - kT_b)$ $\qquad f(n) = \sum_{m=1}^{M} \delta_m(n) f_m$

Spectrum density

Spectral correlation

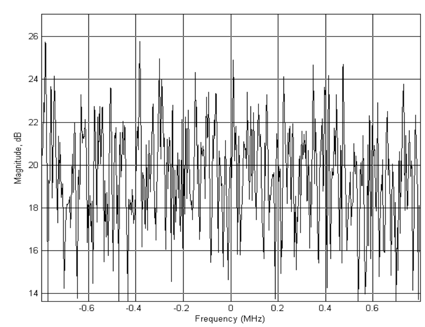
High SNR

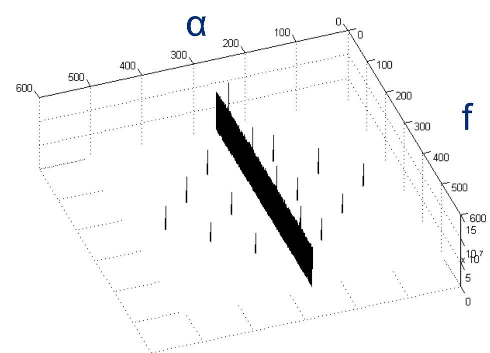




peaks at $\alpha = kf_m$

Low SNR





Energy detector operates on SCF for α=0 thus noise uncertainty limits the detection

Feature detector operates on SCF where α≠0, where noise has no components

Optimal Cyclostationary Detectors

Multi-cycle detector:

$$z_{mc}(N) = \sum_{\alpha} \int_{-\frac{f_s}{2}}^{\frac{f_s}{2}} S_x^{\alpha}(f)^* \tilde{S}_y^{\alpha}(f) df$$

Single-cycle detector:

$$z_{sc}(N) = \int_{-\frac{f_s}{2}}^{\frac{f_s}{2}} S_x^{\alpha}(f)^* \tilde{S}_y^{\alpha}(f) df$$

Cyclostationary detector is also non-coherent detector due to quadratic transformation

But coherently detects features thus has a processing gain w.r.t. energy detector

Performance of Cyclostationary Detector

Single cycle detector case : $z_{sc}(N) = \int_{-\frac{f_s}{2}}^{\frac{f_s}{2}} S_x^{\alpha}(f)^* \tilde{S}_y^{\alpha}(f) df$

Performance of the detector is measured in terms of output SNR, as P_{md} and P_{fa} are mathematically intractable to compute.

Output SNR is related to deflection coefficient: $d = \frac{E(z_{sc} \mid H_1) - E(z_{sc} \mid H_0)}{\sqrt{Var(z_{sc} \mid H_0)}}$

Energy detector: $d(0) \sim \frac{d_0(0) SNR_{in} \sqrt{N}}{\sqrt{1 + \rho_N (1 + \frac{3}{2} N)}}$

$$d_0(\alpha) \approx \left[\int_{-\infty}^{\infty} \left| S_x^{\alpha}(f) \right|^2 df \right]^{1/2}$$

Feature detector: $d(\alpha) \sim \frac{d_0(\alpha) SNR_{in} \sqrt{N}}{\sqrt{1 + \rho_N}}$

When noise variance perfectly known ($\rho_N = 0$), detectors perform comparably
When noise variance unknown ($\rho_N \neq 0$), feature outperforms energy detector

Special case: No excess bandwidth

Amplitude modulated signal:

$$x(t) = \sum_n a(nT_0)\,p(t - nT_0)$$

where $a(nT_0)$ is data with PSD $S_a(f)$

$p(t)$ is pulse shaping filter with $P(f)$

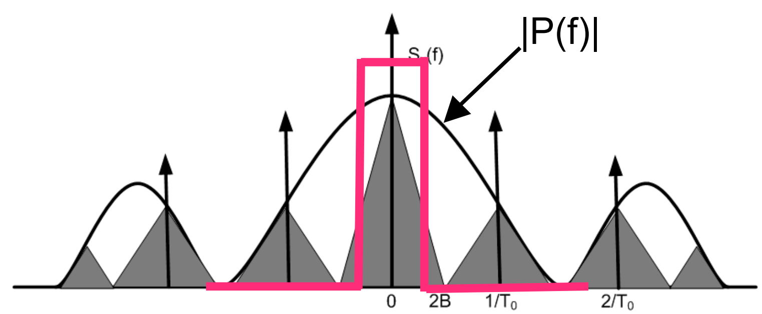
$$S_x^{\alpha}(f) = \frac{1}{T_0} P\left(f + \frac{\alpha}{2}\right) P^*\left(f - \frac{\alpha}{2}\right) S_a\left(f + \frac{\alpha}{2}\right)$$

for $\alpha = k/T_0$

If the pulse shape is sinc function:

$$P(f) = \begin{cases} 1 & \text{for } -1/2T_0 \le f < 1/2T_0 \\ 0 & elsewhere \end{cases}$$

$$\left| S_x^{\pm k/T_0}(f) \right| = 0$$



If there is no spectral redundancy, i.e. excess bandwidth, then feature corresponding to data rate cannot be detected

Special case: Quadrature/Single Sideband Modulation

$$x(t) = a(t)\cos(2\pi f_0 t) + b(t)\sin(2\pi f_0 t)$$

If a(t) and b(t) are uncorrelated and have equal power spectral density

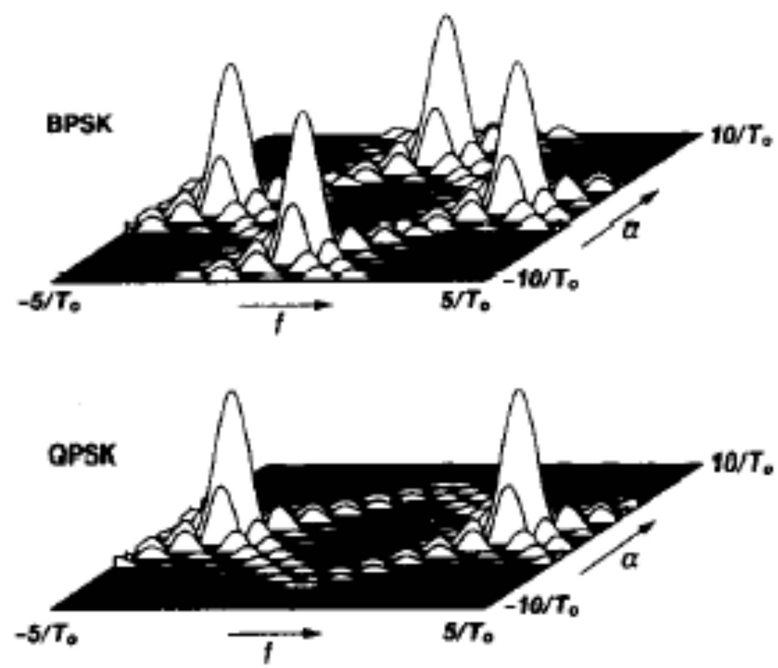
$$S_a(f) = S_b(f)$$

$$R_{ab}(\tau) = E\{a(t)b^*(t+\tau)\} = 0$$

$$S_{ab}(f) = F\{R_{ab}(\tau)\} = 0$$

$$S_x^{\pm 2f_0}(f) = \frac{1}{4}\left(S_a(f) - S_b(f)\right) \pm \frac{1}{2} jS_{ab}(f)$$

Under balancing conditions: $S_x^{\pm 2f_0}(f) = 0$



Features related to sinewave carriers cannot be detected for quadrature modulation

Distortions due to …

Time delay:

$$h(t) = \delta(t - t_0) \qquad z(t) = x(t - t_0)$$

$$H(f) = e^{-j2\pi f t_0} \quad \Rightarrow \quad S_z(f) = S_x(f)$$

$$S_z^{\alpha}(f) = S_x^{\alpha}(f) e^{-j2\pi\alpha t_0}$$

Variable timing offset or jitter can attenuate features while averaging SCF

Filtering:

$$z(t) = h(t) \otimes x(t) = \sum_{u=-\infty}^{\infty} h(u) x(t - u)$$

$$H(f) = \sum_{t=-\infty}^{\infty} h(t) e^{-j2\pi f t} \quad \Rightarrow \quad S_z(f) = \left|H(f)\right|^2 S_x(f)$$

$$S_z^{\alpha}(f) = H(f + \frac{\alpha}{2}) H(f - \frac{\alpha}{2})^* S_x^{\alpha}(f)$$

H(f) can attenuate or even null some features, but spectrum redundancy helps

Further Issues with Feature Detectors

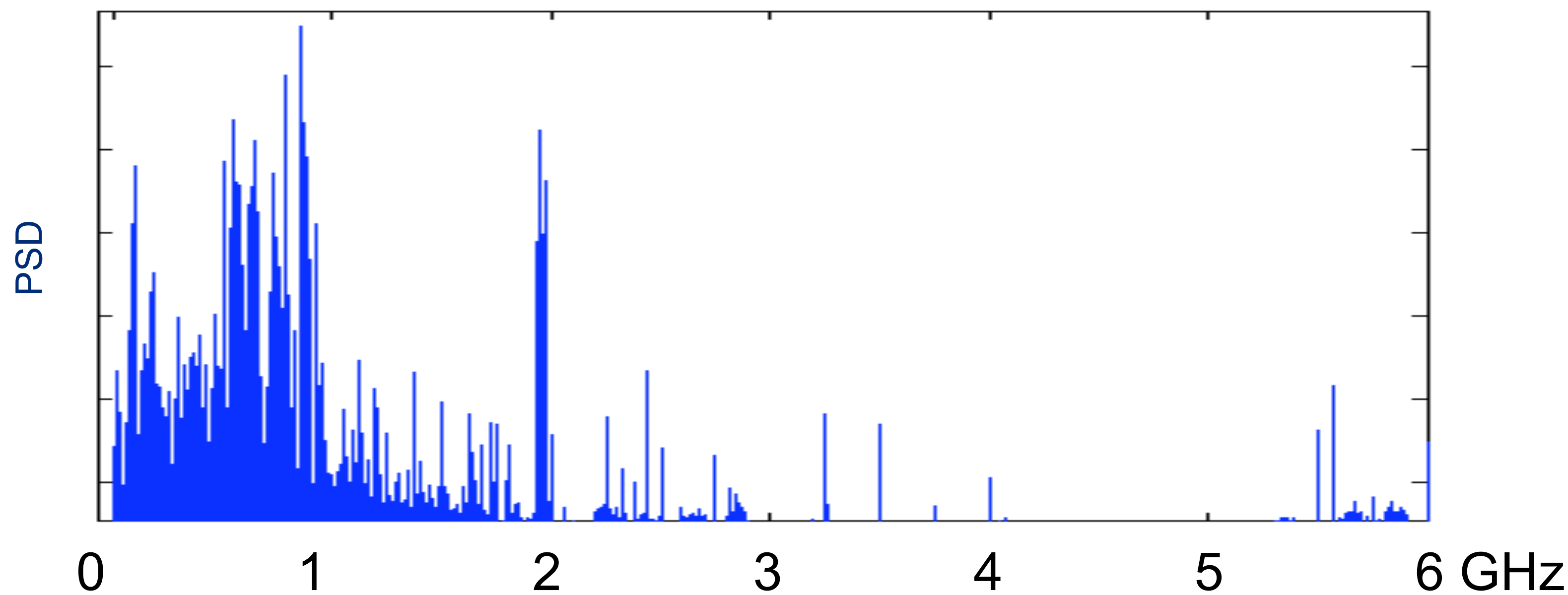
- Strong signals in adjacent bands
  - Spectral redundancy that contributes to correlation might be corrupted by correlation of adjacent blockers
- Interference from secondary
  - Should not have features that can be confused for the primary
- Receiver nonlinearity is also modeled as quadratic transformation
  - Strong signal features get aliased in weak signal feature space
- Cyclostationary noise sources in RF receivers due to mixing with local oscillators
- Coherence time of the channel response limits the averaging time for SCF estimate

What we learned about Feature Detectors

- What transformation extracts signal features?
  - Spectral correlation function - 2D transform (α,f)
- How do we implement feature detectors?
  - FFT cross products for all offsets with windowed averaging
- How do we detect features?
  - Coherent detection in feature space
- What is the performance advantage over the energy detector?
  - Robustness to noise/interference uncertainty
- What are the feature detector limitations?
  - Spectral leakage of strong signals, non-linearities, …

Implementation Issues

Spectrum Utilization



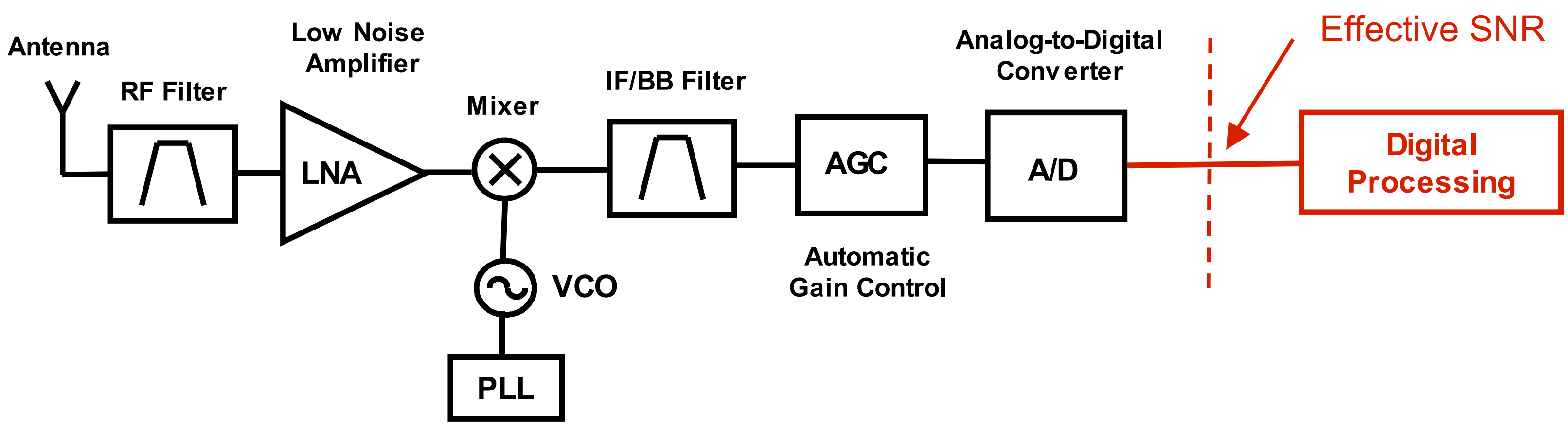
Freq (GHz)	0~1	1~2	2~3	3~4	4~5	5~6
Utilization(%)	54.4	35.1	7.6	0.25	0.128	4.6

Measurements show that there is wide range of spectrum utilizations across 6 GHz of spectrum

Three regimes of spectrum utilization

- Regime 1: No scarcity
  - Bands where spectrum utilization is below 5%
  - No temporal and spatial variations
  - Early stage of cognitive radio network deployment
- Regime 2: Medium scarcity
  - Bands where spectrum utilization is below 20%
  - Small temporal and spatial variations
  - More than one cognitive radio network deployment
- Regime 3: Significant scarcity
  - Bands where spectrum utilization is above 20%
  - Significant temporal and spatial variations
  - Multiple competing cognitive radio networks

Radio Front-end Architecture Overview

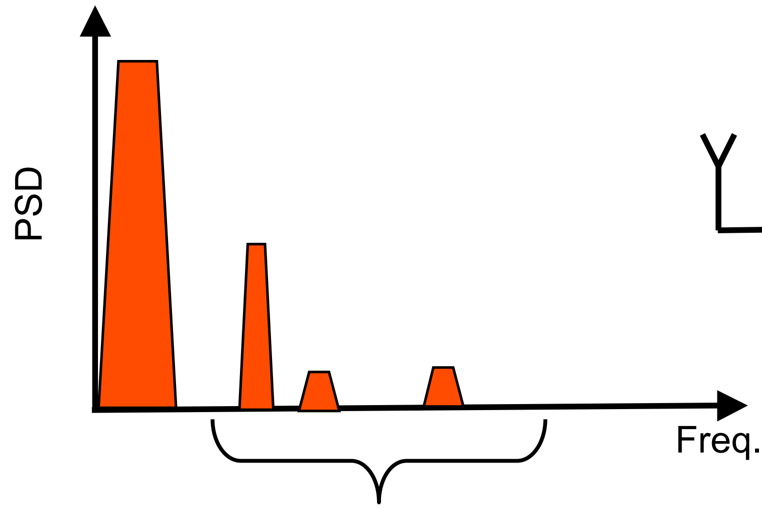


So far, we have looked at the digital signal processing algorithms, and evaluated their performance with respect to input (effective) SNR.

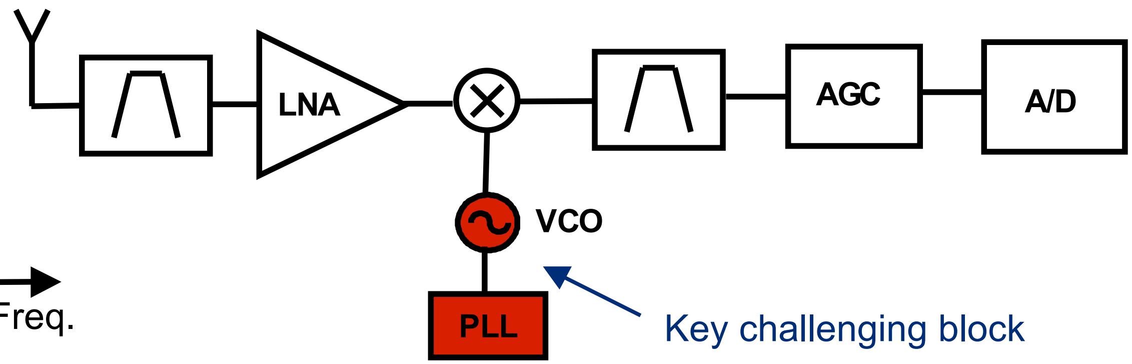
But, effective SNR is also determined by the performance front-end circuits, so the adequate specs are needed.

What is the right architecture and what are the important (challenging) circuit blocks for three regimes of spectrum utilization?

No Spectrum Scarcity Regime



Search one NARROW frequency band at the time



- Wideband antenna and RF filter to cover wide spectrum opportunities (e.g. 1 GHz)
- Wideband tuning VCO challenges: tuning range over band of interest, small settling time, small phase noise:
  - state of the art: 1GHz tuning range, 100 usec settling time, -85 dBc/Hz at a 10 kHz
- Narrow band BB filter – channel select
- A/D low speed and moderate resolution

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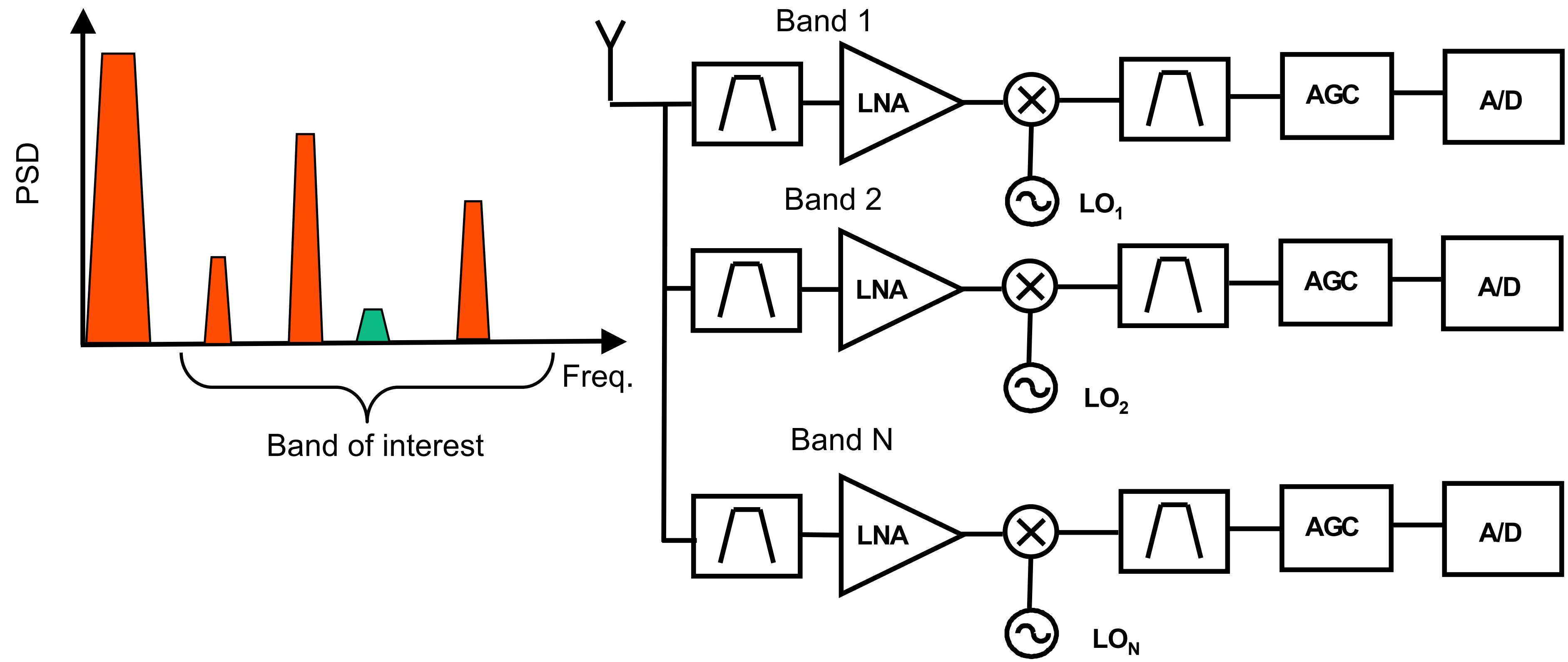
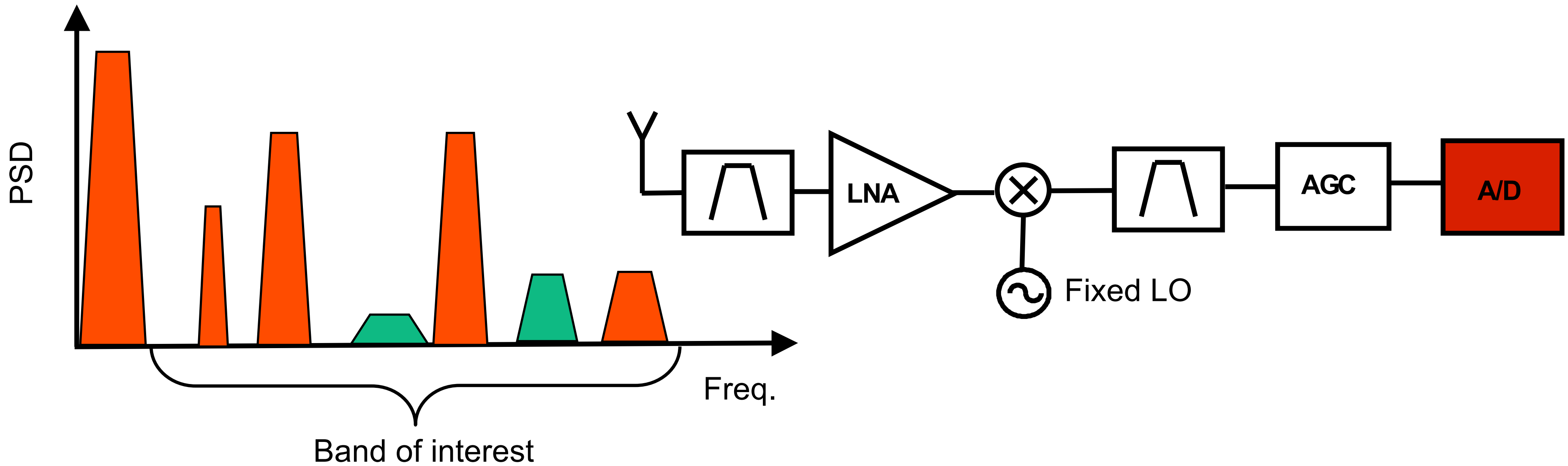
Moderate Spectrum Scarcity Regime



- Search over multiple frequency bands at one time, or selectively pick the targeted band based on temporal changes
- Increased number of components, but still relaxed Local Oscillator (LO) and A/D requirements

Significant Spectrum Scarcity Regime



- Search wide frequency band continuously for instantaneous spectrum sensing
- Frequency sweeping not suitable as the sensing measurements become stale
- However, A/D speed increases to sample wider bands
- Large signals in-band present large dynamic range signal
- A/D resolution increases as AGC cannot accommodate both small and large signals

Wideband Circuits

- Antennas
  - Ultra-wideband (UWB) antennas for 0-1 GHz and 3-10 GHz have already been designed, and can be used for sensing purposes
- LNAs
  - State-of-the-art UWB LNAs achieve 20 dB gain, low noise figure ~ 3 dB, and low power consumption ~ 10mW
  - Noise figure uncertainty in the order of 2 dB and varies with frequency
- Mixers
  - Linearity and power are the design main challenges
  - Non-linearities can cause mixing down of signals out-of-band into the band of interest

A/D Requirements

- Speed Criteria (sampling frequency)
  - Based on the Nyquist criterion minimum is signal bandwidth
    - Regimes 1&2: determined by channel select filter (~ 100 MHz)
    - Regime 3: determined by total sensing bandwidth (~ 1-7 GHz)
- Resolution Criteria (number of bits)
  - Determined by dynamic range of the signal
    - For example, if band of interest covers WiFi:
      - Maximum received signal near WiFi Access Point (-20 dBm)
      - Minimum received signal equal to sensitivity of WiFi Rx (-100 dBm)
      - Dynamic range (DR) is approximately 80 dB
  - Required number of bits is N ~ ((DR) -1.76)/6.02
    - For DR=80dB more than 12 bit A/D is needed
  - Input SNR should not be degraded by more than x dB

A/D Figure of Merits

- Effective number of bits is obtained from measured SNR:

$$ENOB = (SNR(dB) - 1.76) / 6.02$$

- Spurious free dynamic range (SFDR) is the ratio of the single tone signal amplitude to the largest non-signal component within the spectrum of interest

- Universal figure of merit is the product of effective number of quantization levels and sampling rate

$$M = 2^{ENOB} F_{samp}$$

- If dissipated power is taken into account

$$F = \frac{2^{ENOB} F_{samp}}{P_{diss}}$$

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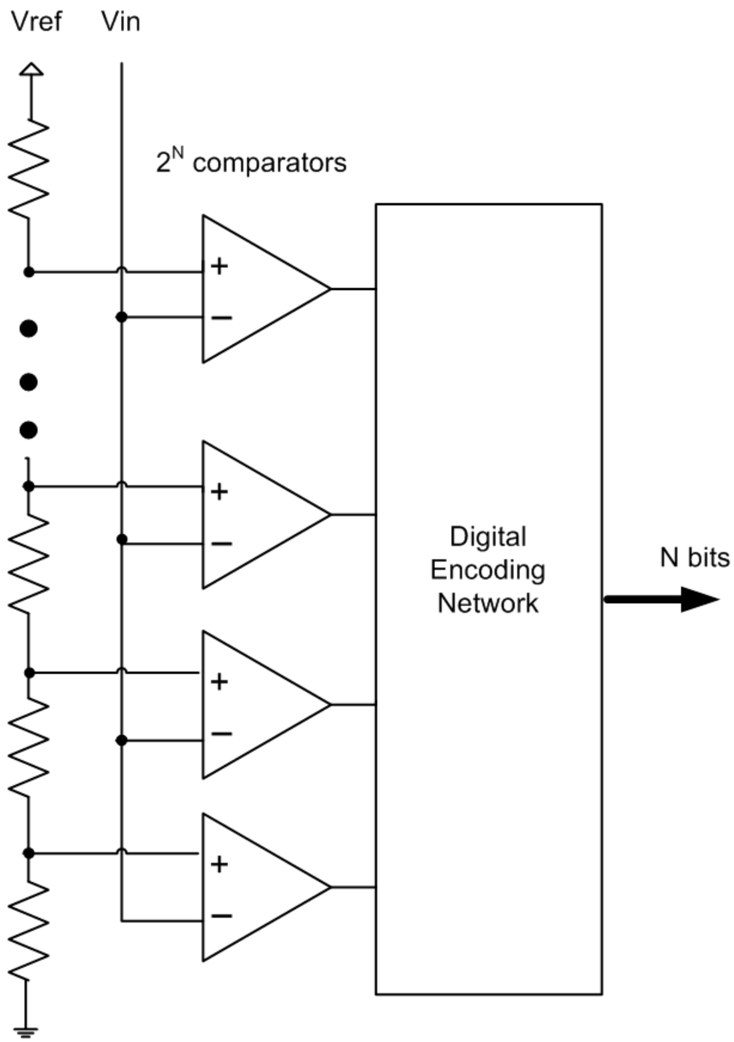
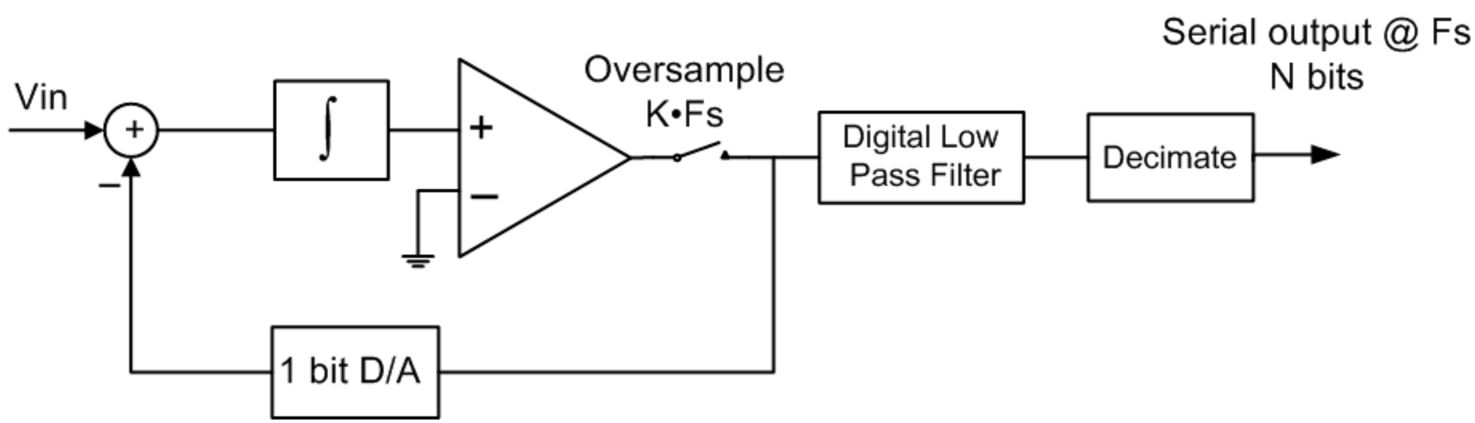
High speed A/D – Flash architecture



- Fastest architecture
- Power and area increase ***exponentially*** with number of bits
- Feasible up to 8 bits of resolution

High Resolution A/D – Sigma delta conversion



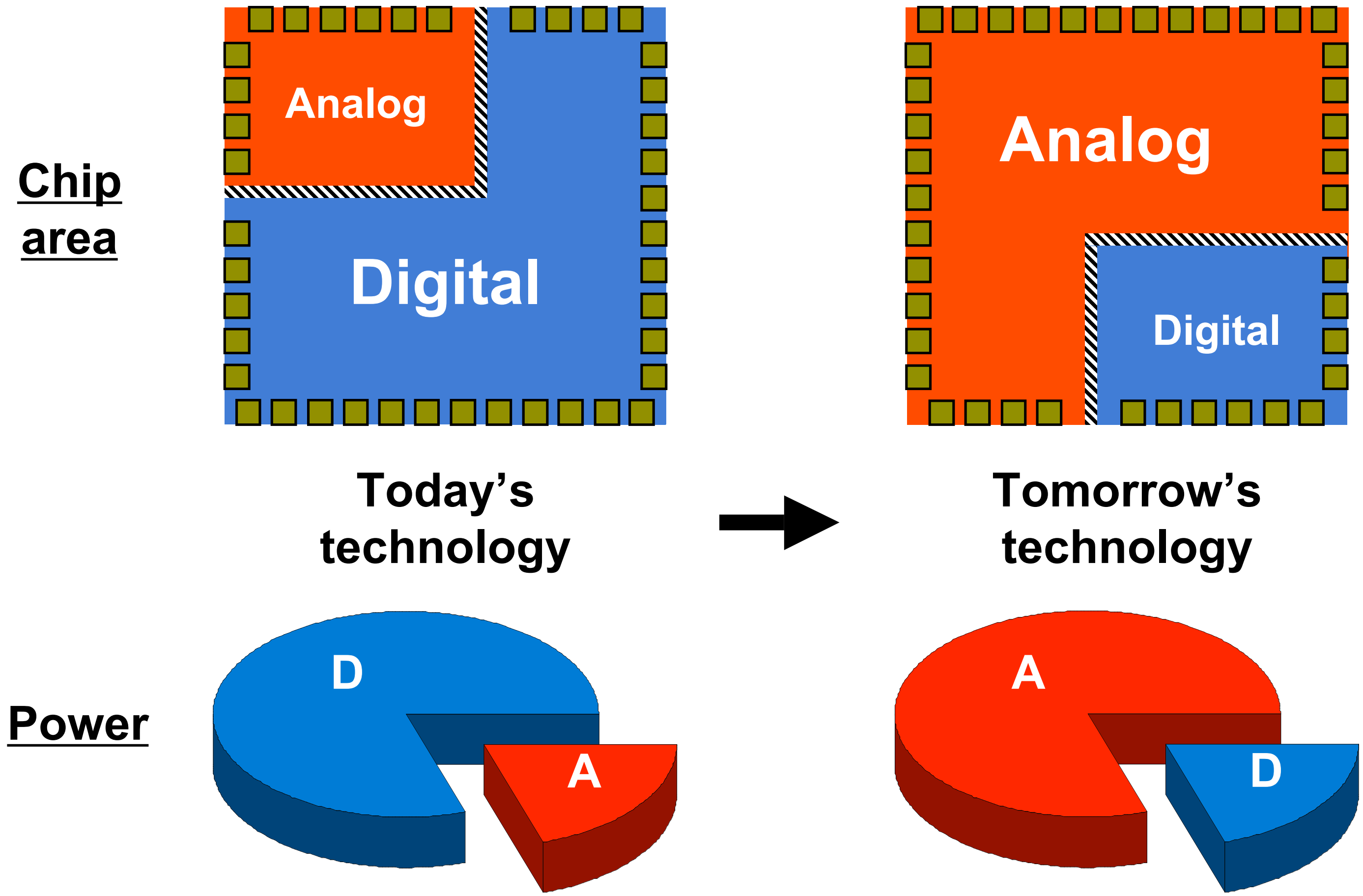
- Trading speed for resolution, plus additional latency
- Can achieve resolution up to 24 bits, but speed ~ 2 MHz
- Digital filter removes components at or above the Nyquist frequency, data decimator removes over-sampled data

State-of-the-art A/D converters

Resolution	Speed	ENOB	Power (W)	Cost ($)	Manufacturer
8	1.5 Gs/s	7.5	1.9	500	National
10	2.2 Gs/s	7.7	4.2	1,000	Atmel
12	400 Ms/s	10.4	8.5	200	Analog Dev.

Cannot afford in consumer mobile devices, maybe in dedicated infrastructure

Impact of CMOS Scaling



Cost dominated by analog!

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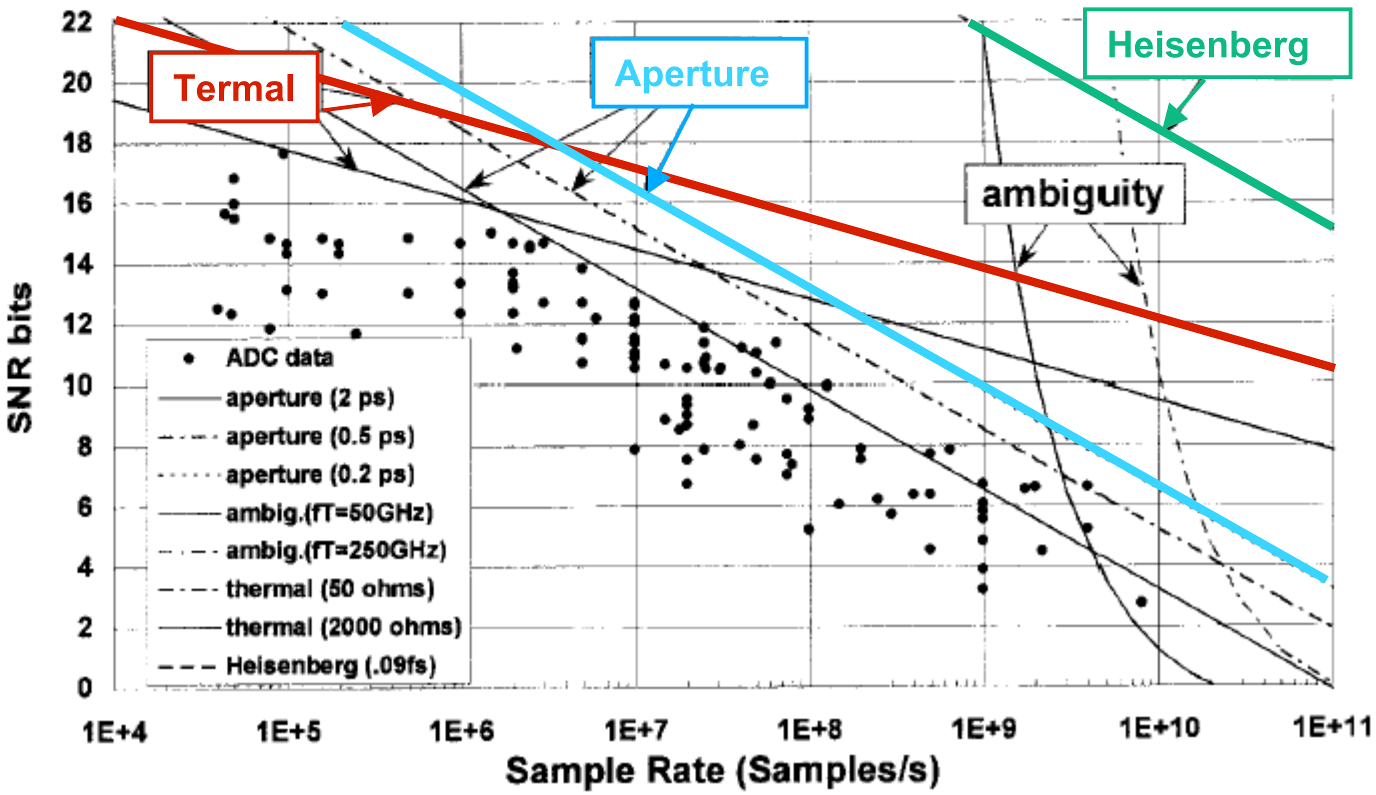
Fundamental A/D Limitations

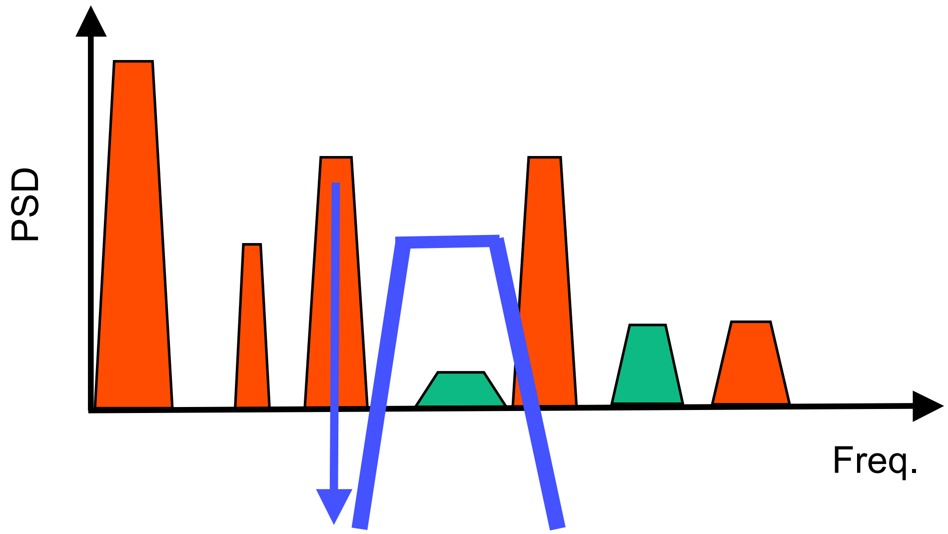


- Thermal noise, aperture uncertainty and comparator ambiguity are setting the fundamental limits on resolution and speed

How to reduce requirement on A/D resolution?

- Spectrum sensing requires sampling of weak signals
  - Quantization noise must not limit sensing
- Strong primary user signals are of no interest to detect
  - Strong signals are typically narrowband
- At every location and time, different strong primaries fall in-band
  - Need a band-pass filter to attenuate narrowband signal, but center frequency must be tuned over wide band
- Dynamic range reduction through filtering in:
  - Frequency, time, space …..

Frequency domain filtering



Challenging specifications:

1. High center frequency
2. Narrow band
3. Large out of band rejection
4. Tuning ability

External components not favorable, on chip CMOS integration leads reduced cost and power

Sharp roll-off RF filters need high Q, leads to high power consumption and large circuitry area to accommodate the passive elements (inductors and capacitors).

Non-ideal filters cause signal leakage across the bands and degrade weak signal sensing performance

Novel technologies for filtering like RF MEMs suffer from insertion loss, hard to design for high frequencies and require time to tune to the desired band

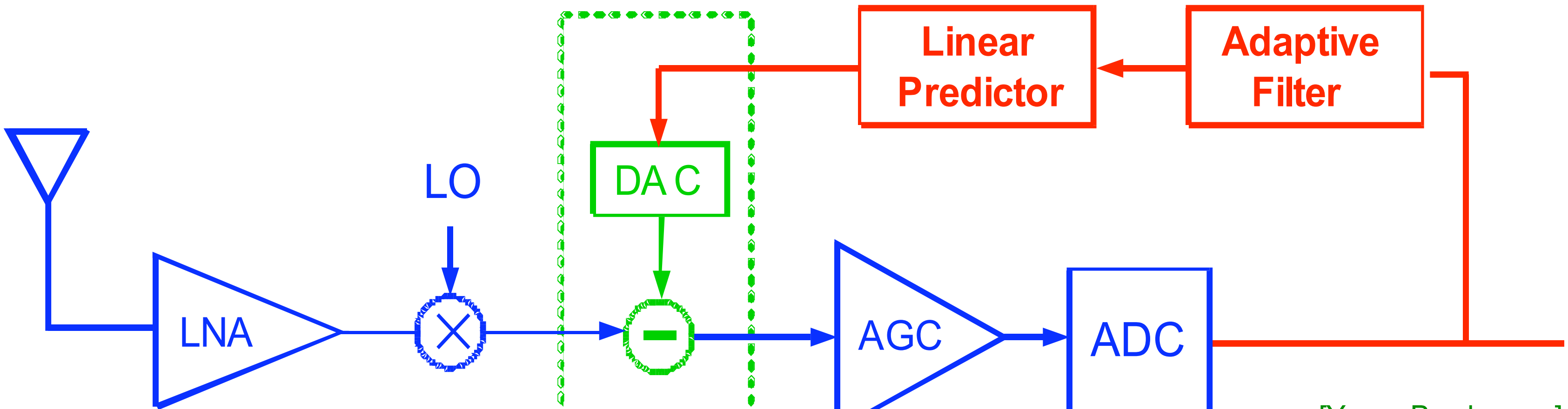
Time domain processing

- Provide strong signal cancellation through subtraction in time domain
  - It is sufficient to attenuate signal, not perfectly cancel
- Mixed signal approach that uses digital signal processing to reduce the requirements on analog circuits
  - Novel radio architectures, new circuits around A/D
  - Flexibility offered by adaptive digital signal processing
- Multiuser detection algorithms are based on the same principles:

"If the interfering signal is very strong, it is then possible to decode it, reconstruct it and subtract from the received waveform …"

Feedback Approach

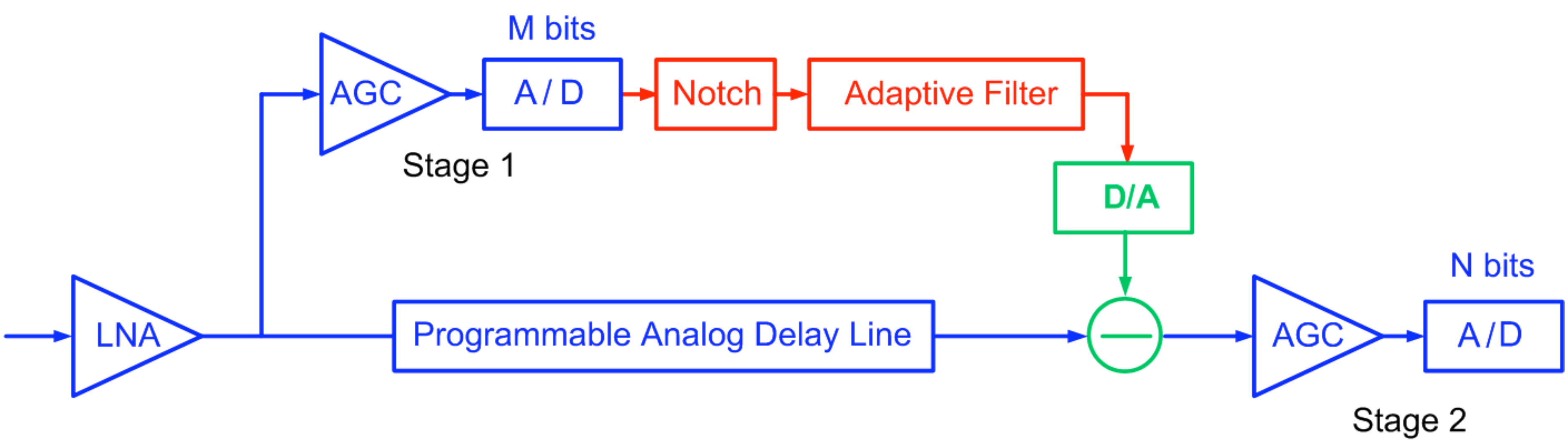
- **Closed loop feedback around AGC and ADC**
- **Digital Prediction Loop**
  - Adaptive Filter: Separate interference from desired signal
  - Linear Predictor: Predict future interference in real time
- **Analog Forwarding Path**
  - Analog Subtraction: Dynamically cancel interference in the time domain
  - DAC: Reconstruct estimated interference



[Yang, Brodersen]

Feedforward Approach

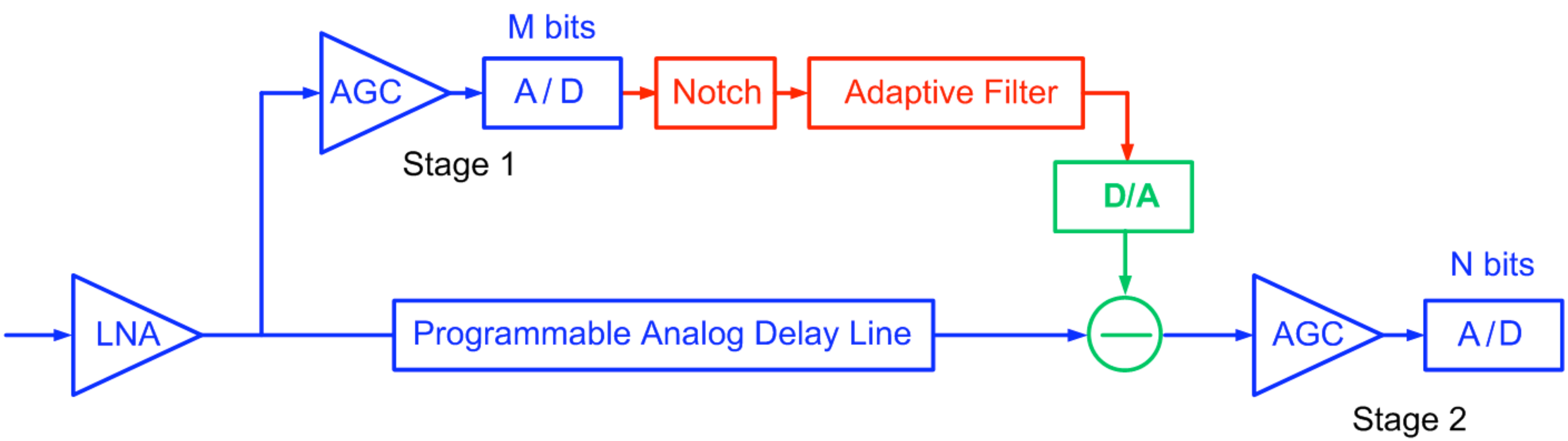
- **Feed forward architecture with 2 stage low resolution A/D conversion to achieve overall high resolution $2^M+2^N \ll 2^{M+N}$**
  - **Stage 1 A/D:** M bits sufficient to sample interference
  - **Stage 2 A/D:** N bits resolve desired signal after interference subtraction



[Yang, Brodersen]

Feedforward Approach

- **Digital Prediction Loop**
  - Notch Filter: Prevent cancellation of desired signal
  - Adaptive Filter: Estimate the strong interference signal
- **Analog Forwarding Path**
  - Analog Subtraction: linear over wideband of interest
  - Programmable delay line: compensate for the delay through Stage 1 A/D, digital processing path, and D/A reconstruction to align the signal for subtraction



Issues with time domain cancellation

- Quite novel approach, still in a research phase …

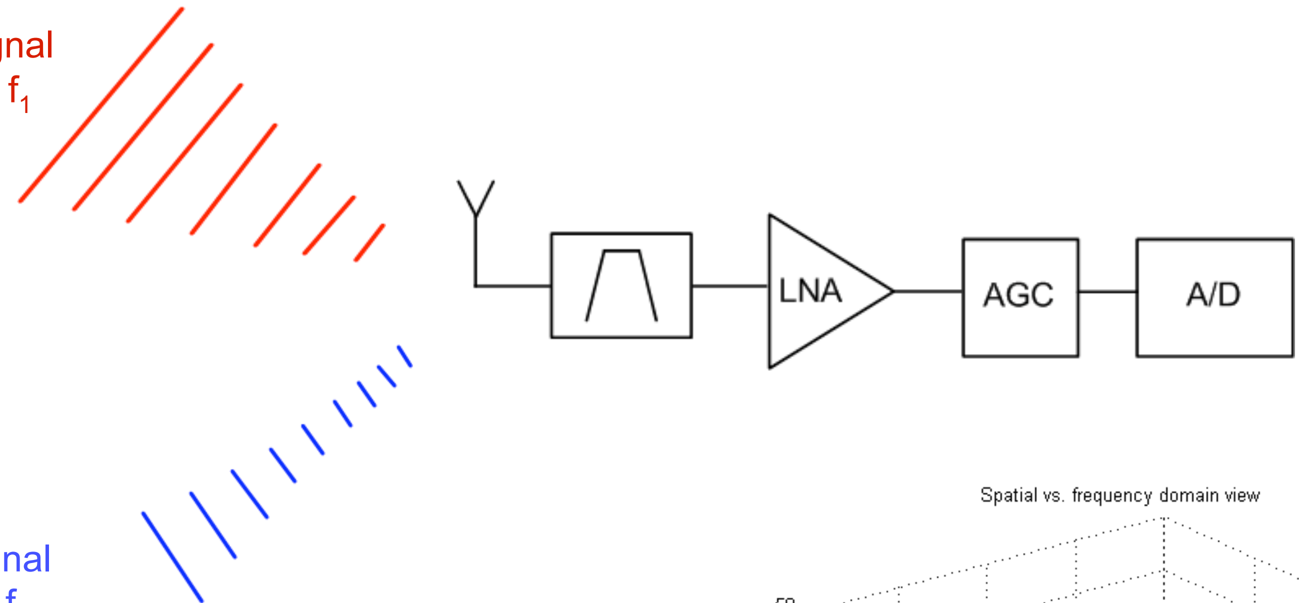
- Adaptive filter estimation error limits the performance of the interference cancellation due to:
  - Time varying interference, quantization, and prediction errors

- Analog subtraction
  - Critical timing constraints and phase accuracy

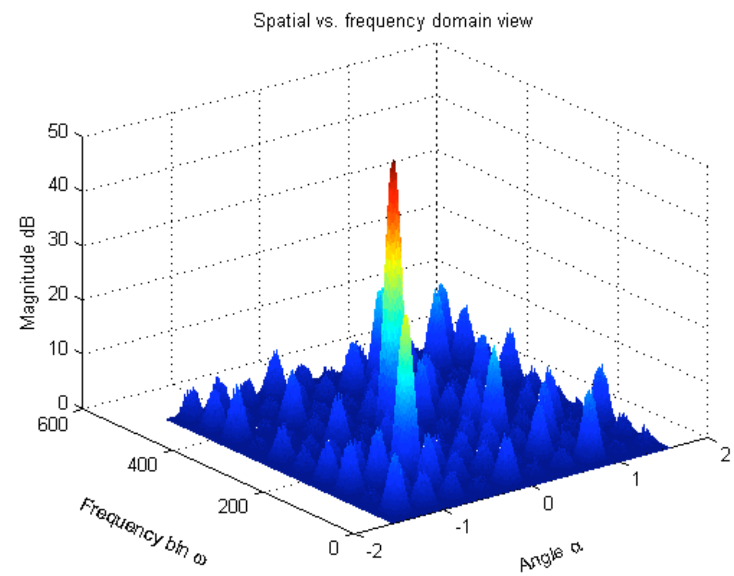
- Circuit non-linearities might further corrupt sensing of desired bands

Why Spatial Domain?

Primary User signal
at frequency f_1



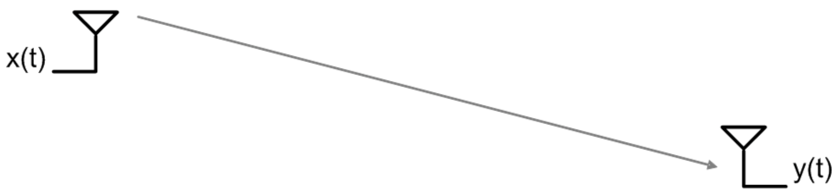
Primary User signal
at frequency f_2



- Strong primary users are at distinct frequencies, but they also come from distinct spatial directions

How can we resolve spatial dimension?

Single receive antenna



Received signal is delayed copy of transmitted signal

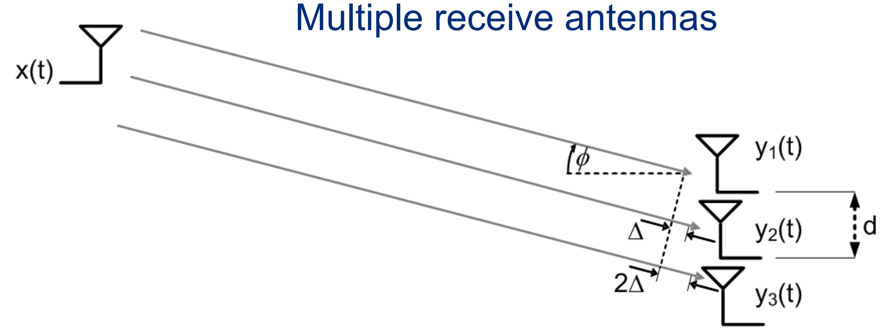
$$y(t) = A\,x(t - \hat{o})$$

where A is the path gain and τ is the path delay.

Narrowband baseband equivalent channel model:

$$y(t) = \alpha \cdot x(t) \qquad \alpha = Ae^{-j2\pi f_c \tau}$$

Multiple receive antennas



Received signal on each antenna is also delayed copy, and delays are function of incident angle

$$\begin{pmatrix} y_1(t) \\ y_2(t) \\ y_3(t) \end{pmatrix} = \alpha \cdot \begin{pmatrix} 1 \\ e^{-j2\pi\Delta} \\ e^{-j4\pi\Delta} \end{pmatrix} \cdot x(t)$$

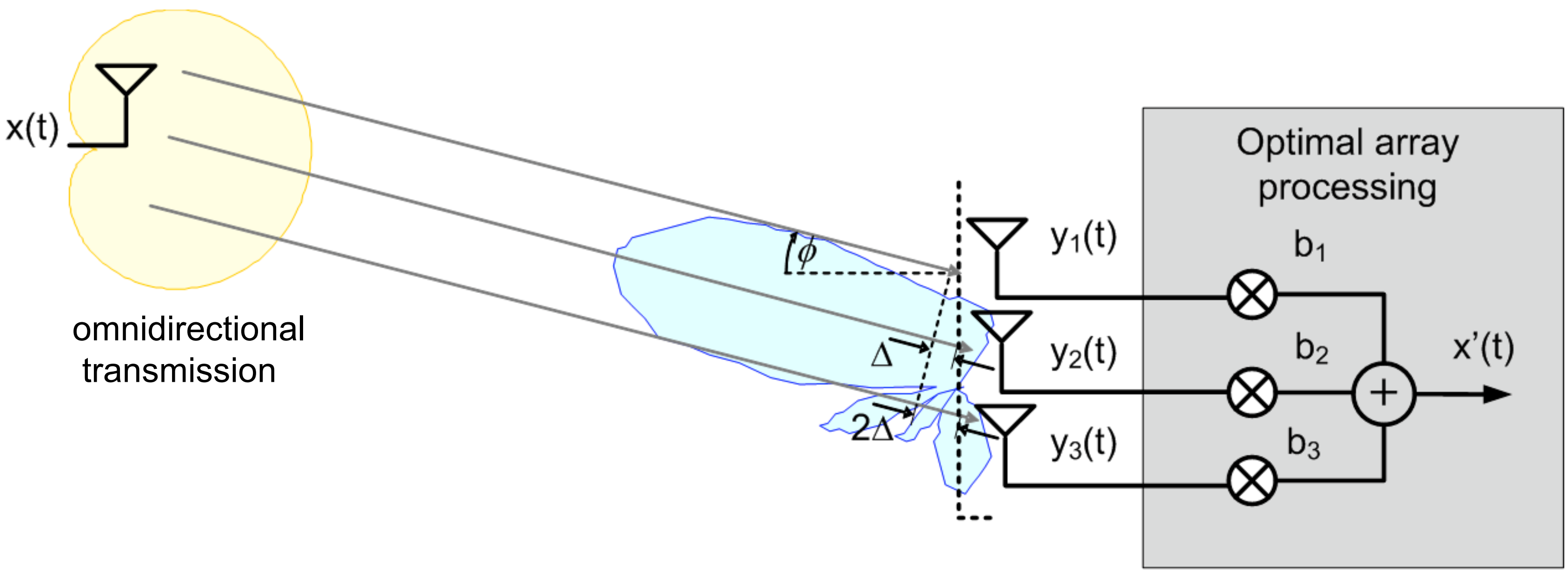
where $\Delta = d / \lambda \cdot \sin(\phi)$

Channel model expressed in vector form:

$$\underline{y}(t) = \alpha \cdot \underline{e}(\phi) \cdot x(t)$$

$\underline{e}(\phi)$ is antenna array spatial signature in direction ϕ

Receive Beamforming



Projecting received signal onto direction ϕ is equivalent to creating a beam that maximizes the received signal strength

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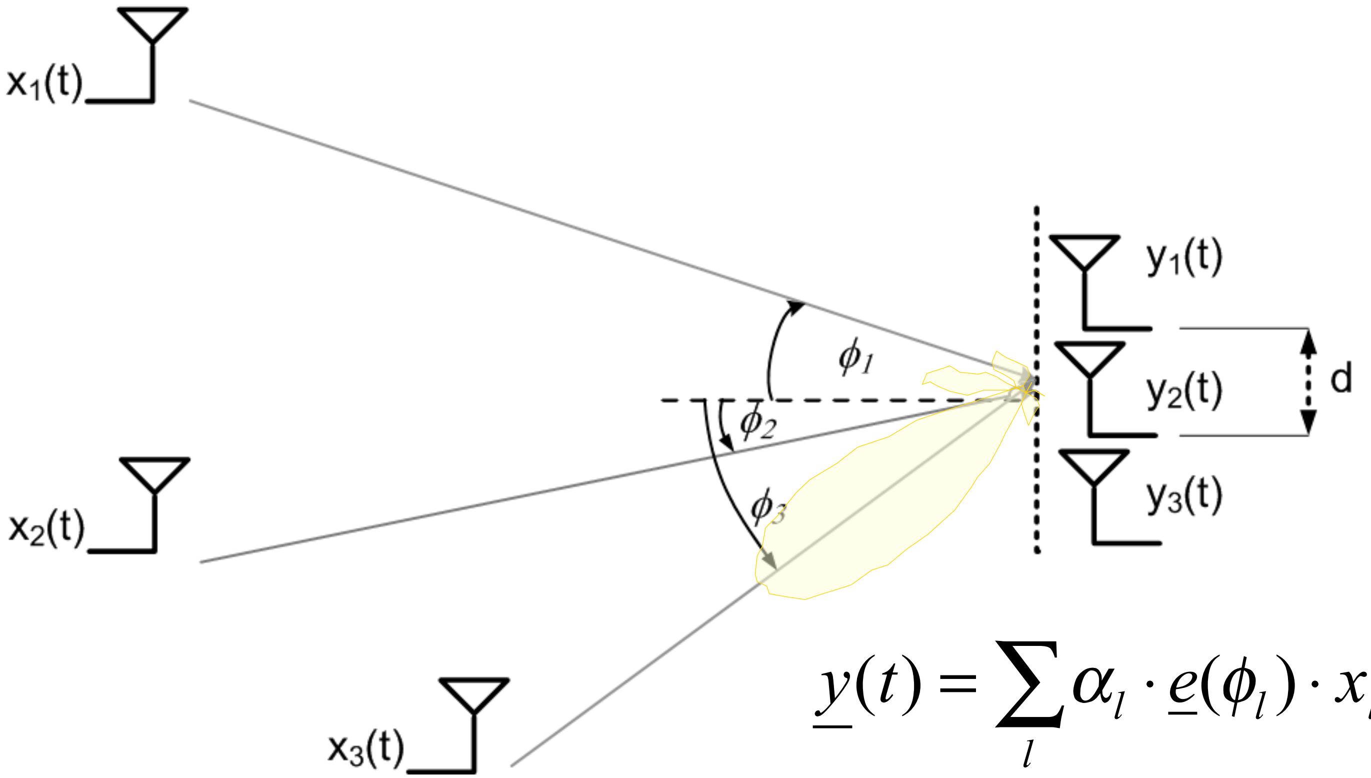
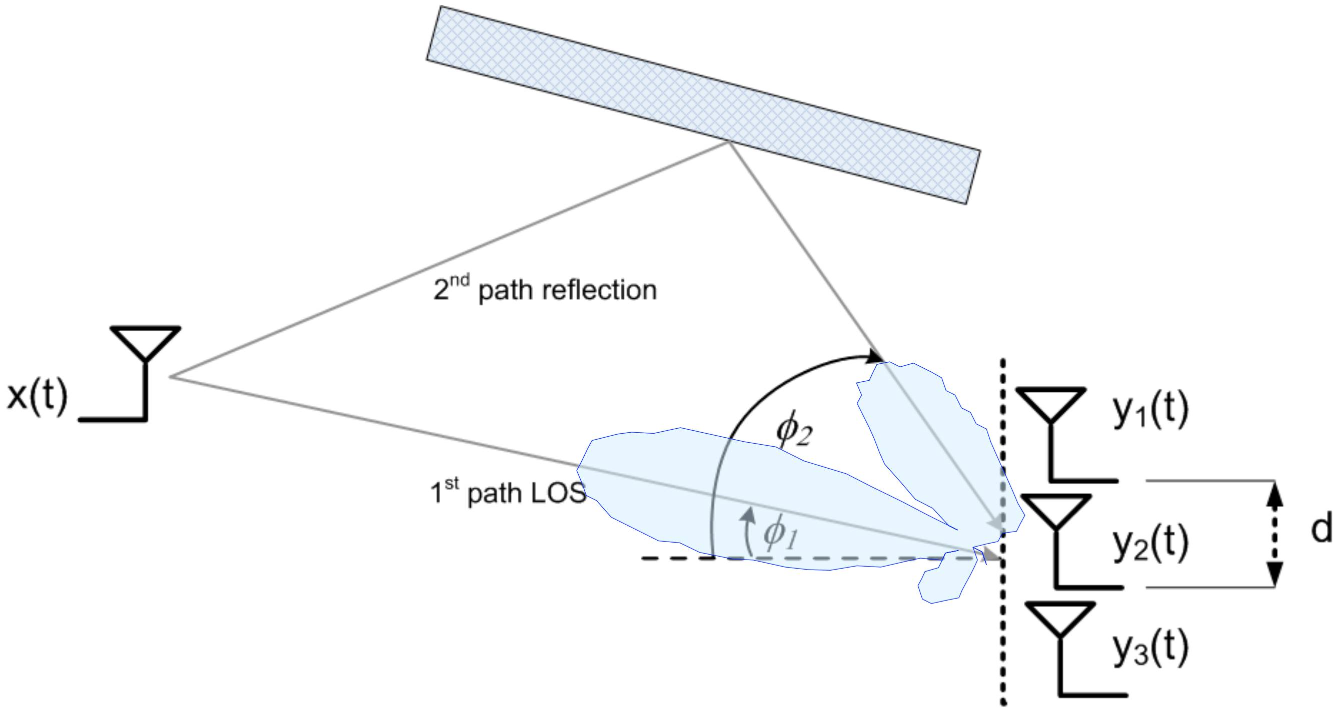
Multiple User Channels



$$\underline{y}(t) = \sum_l \alpha_l \cdot \underline{e}(\phi_l) \cdot x_l(t)$$

Multiple users with different incident angles can be resolved through linear processing, i.e. projection onto their spatial signatures

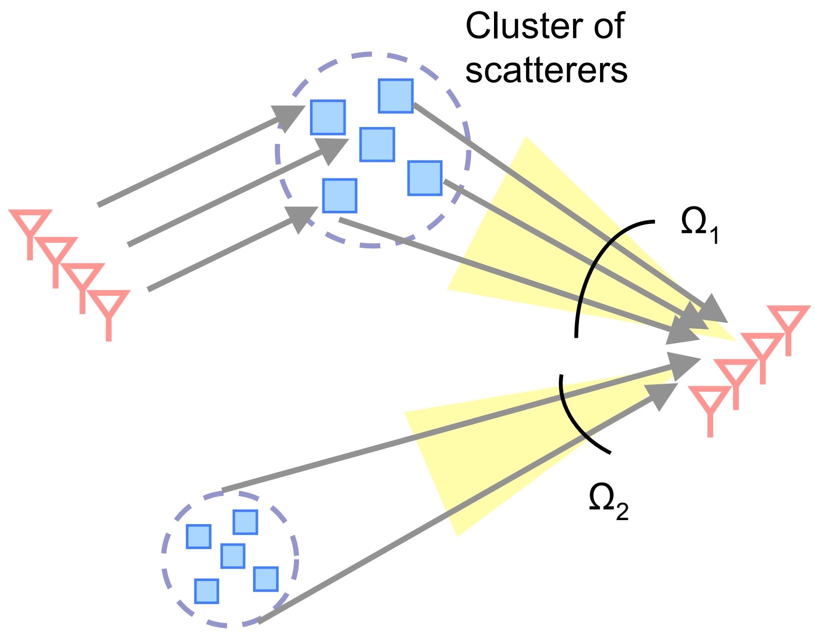
Multipath Channel



$$\underline{y}(t) = \sum_{l} \alpha_l \cdot \underline{e}(\phi_l) \cdot x(t)$$

Multipath channel can also be resolved into paths with distinct angles of arrivals

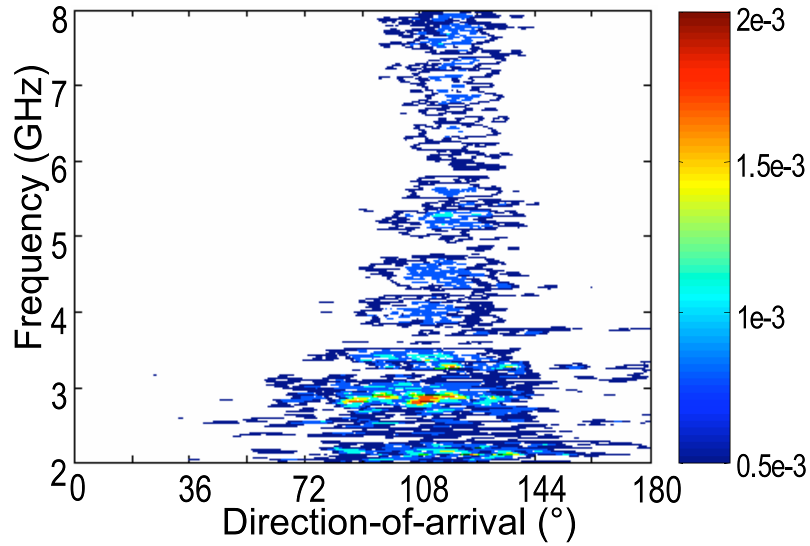
Channel Modeling in Angular Domain



- Recent modeling approach of multiple antenna channels has adopted clustered model fully described with:
  - Number of clusters
  - Angular spread of each cluster

[Poon, Tse, Brodersen]

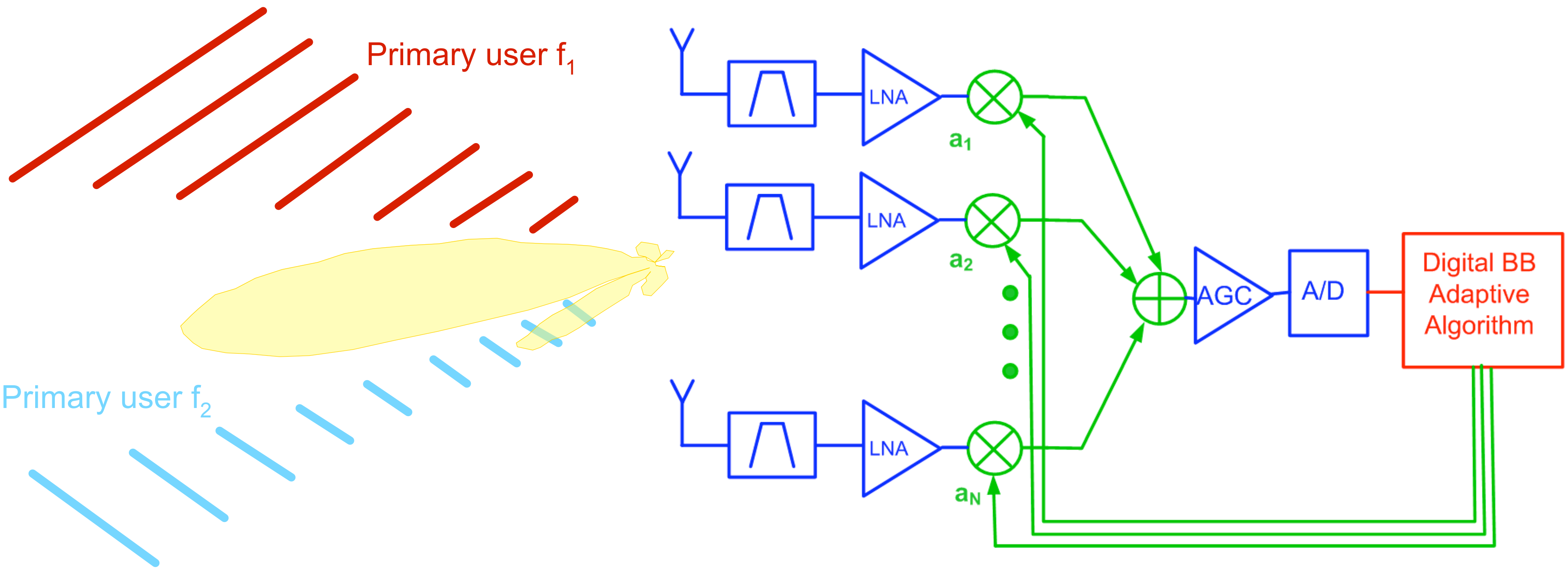
Measurements of Physical Environments



Intel data from A.S.Y. Poon

		Frequency (GHz)	No. of Clusters	Cluster Angle (°)
Outdoor	Cost 259	2.15	4	7.5
Indoor	USC UWB	0–3	2–5	37
	Intel UWB	2–8	1–4	11–17
	Spencer00’	7	3–5	25.5
	Cost 259	24	3–5	18.5

Spatial Filtering Approach



- Enhance receiver front-end with RF phased antenna array
- Combine antenna outputs in analog domain prior to A/D for reduced dynamic range
- Perform digital baseband processing to identify strong signal frequencies and directions
- Create beam that suppress strong signals, potentially enhance sensitivity in CR direction

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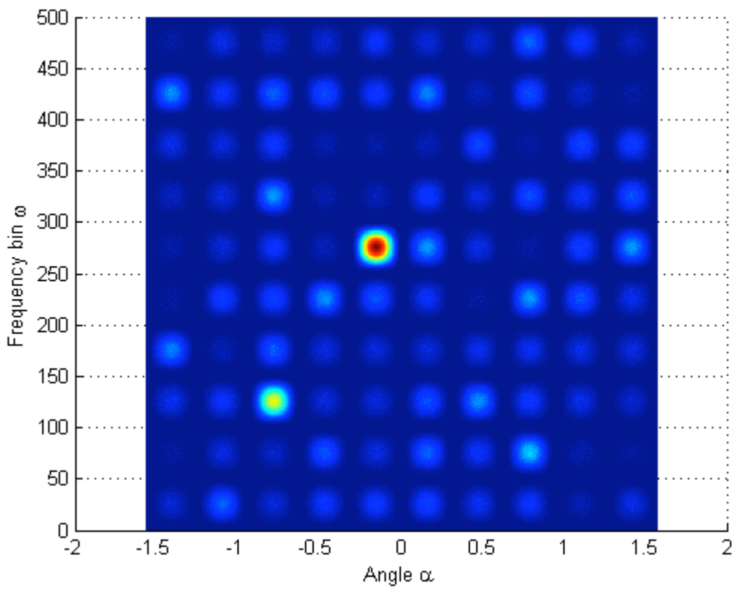
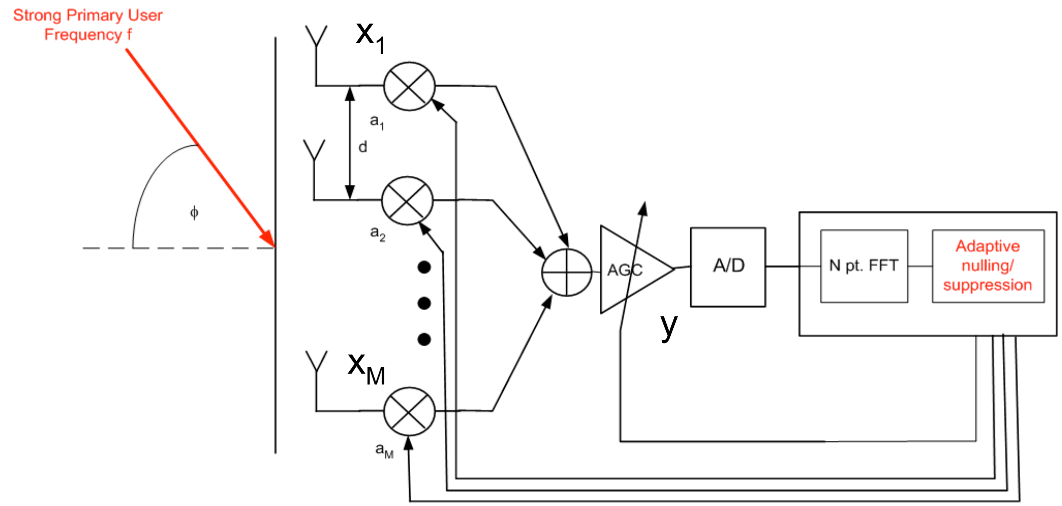
Interference Suppression

Spectrum map
Spatial vs. frequency view





Goal:
Equalize the Spectrum map

1. Frequency analysis through wideband FFT enabled by high speed A/D
2. Spatial analysis through beam sweeping
3. Beam coefficient set to reduce the dynamic range

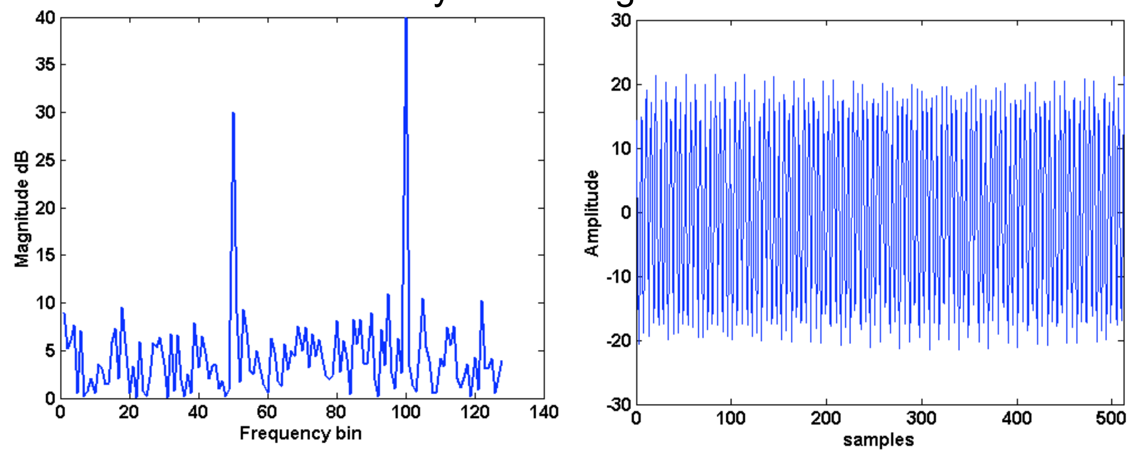
An Example

- FFT N=128 points
- 4 antennas, 8 sweeps
- Avg. SNR= 10 dB per sub-carrier
- 2 strong PUs

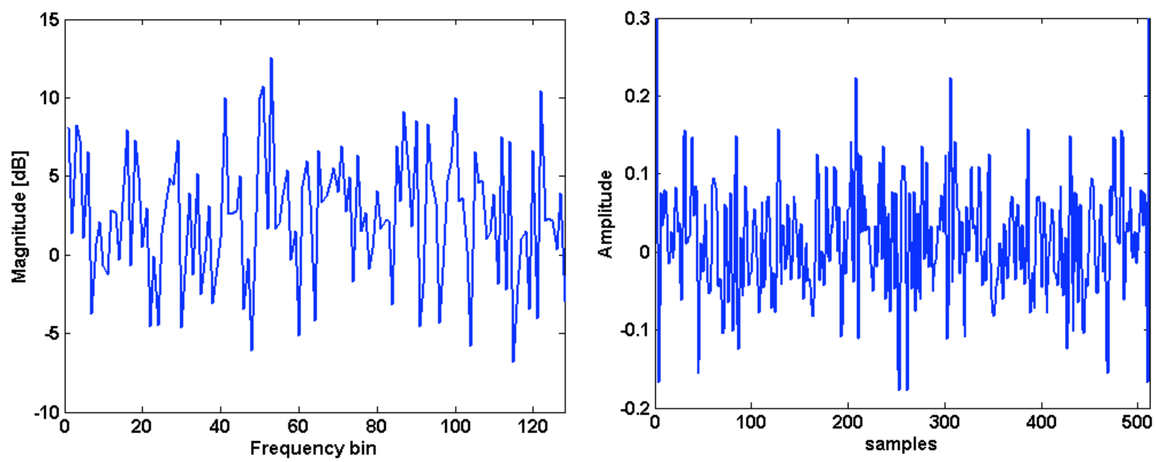
  α_1=45° P_1=40dB k=100 bin

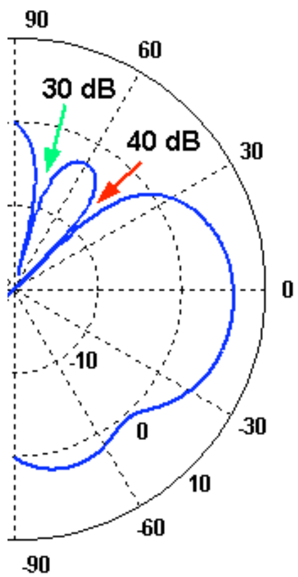
  α_2=70° P_2=30dB k=50 bin
- Other signals random DoA
- Constraint: max power=10 dB

Before dynamic range reduction



After dynamic range reduction

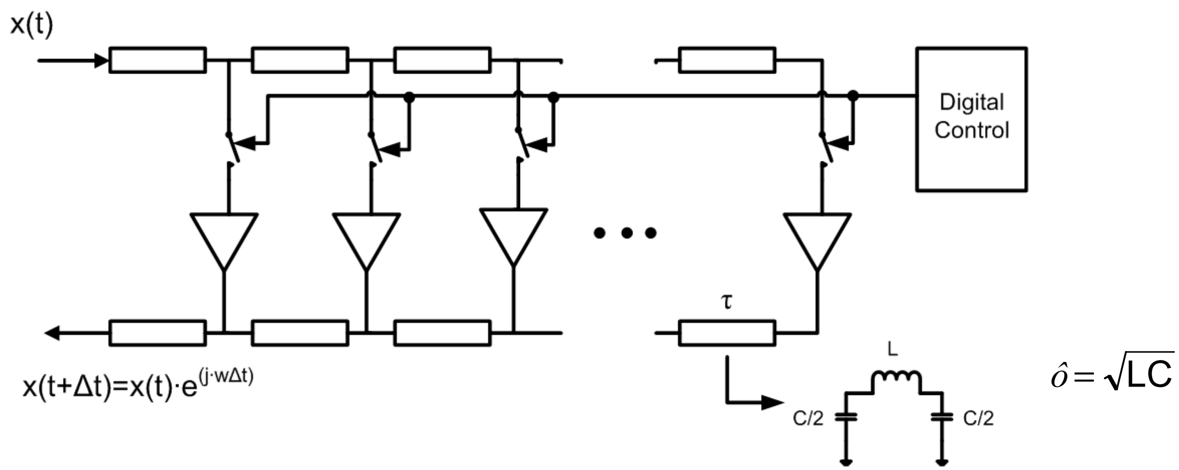




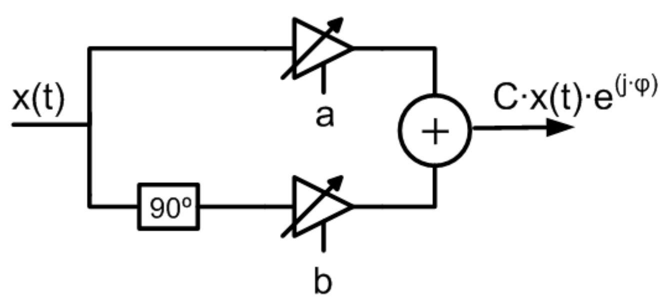
Beam that reduces dynamic range

Implementation Advantages of RF Phase Shifters

- Easy to implement and no intrinsic delay, as opposed to active cancellation with strict timing constraints
- Switched delay lines: provides phase shifts through actual time delays



- Vector modulators: variable attenuators on in-phase and quadrature signals



Summary

- Different spectrum utilization regimes require different radio architecture designs:
  - Frequency sweeping one band at the time
  - Parallel sensing of several narrow bands
  - Simultaneously sensing over wide band
- New challenges arise in wideband circuit designs to accommodate large dynamic range signals so that sensing of weak signals is not corrupted
- The most critical component in spectrum sensing over wide bands is high speed A/D converter with challenging resolution requirements
- Approaches to relax the dynamic range requirements must involve filtering of strong primary signals in time, space, or frequency:
  - Active cancellation, phased antenna arrays, and tunable analog filters

Technical Take-home Points

- Fundamentally new constraint: Non-interference to Primary
- Long-range/High-power use is possible
- As spectrum vacancies fill up, need wideband architectures
- Low Primary SNR is the "typical case"
- Key challenges:
  - Fading
    - Needs within system cooperation
  - In-band Secondary Interference
    - Needs Sensing-MAC in addition to Data-MAC
    - Better detectors (coherent and feature) buy some freedom
  - Out-of-band Blocking signals

Policy Food for Thought

- Gains are possible by opportunism (not just part 15 style)
- Competes/Complements UWB style easements
- Need for System vs. Device regulation:
  - Regulation is needed to set the P_{HI} and primary protection margin
  - Devices work collectively to avoid interfering
  - Different systems are all contributing to interference
    - Power control heterogeneity – how to divide up the protection margin?
    - Predictability buys performance
  - How to certify a possibly open system?
  - “IEEE” vs. FCC rules
    - Sensing-MAC
    - No chameleons

Far Reaching Policy Comments

- Implications of cooperation:
  - Cooperation means infrastructure (ad-hoc or dedicated)
  - Non-Frequency specific sensing infrastructure
  - Needs to be incentivized properly
    - Gradual deployment possible
    - Primaries must not have the right to exclude
    - "Free rider" problems unclear (harmless piggy backer, parasite, competitor)
- Other non-sensing infrastructures for opportunism:
  - Beacons, location based spectrum databases, explicit denials, …
- Opportunism sets the stage for efficient markets
  - Grows demand to the point of scarcity
  - Encourages commoditification of spectrum

For more info including bibliography please visit:

www.eecs.berkeley.edu/~sahai