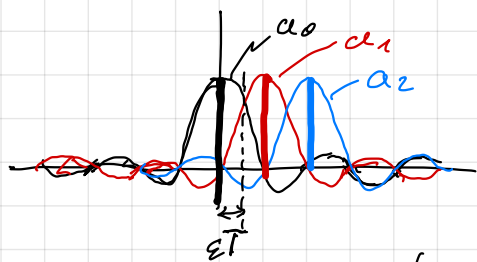


Wireless Receivers

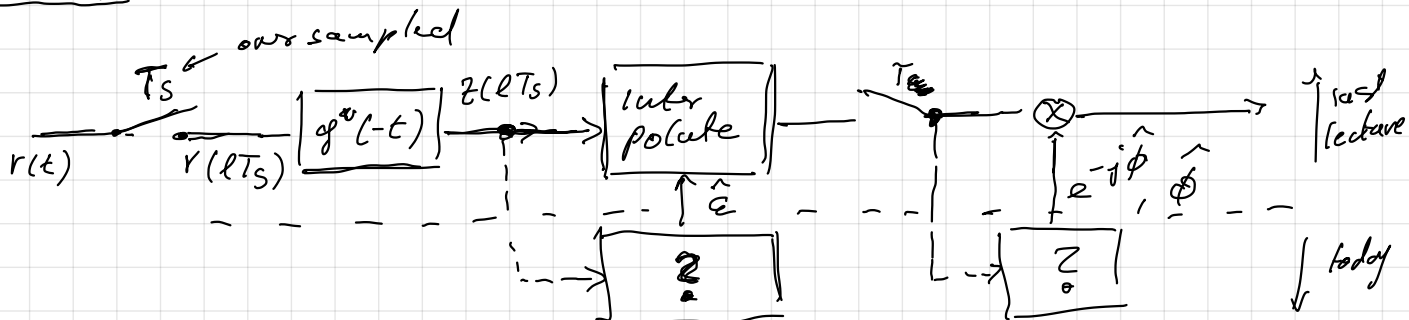
10/3/20

Parameter Estimation



$0 \leq \epsilon T \leq 1$ Sampling-time offset ϵT_s

Receiver:



How to get to $\hat{\epsilon}$ and $\hat{\phi}$?

Receiver Parameter Estimation

Formulate the ML condition

we have: $\underline{r} = [\dots, r(-2T_s), r(-T_s), r(0), r(T_s), r(2T_s), \dots]$ (oursampled samples)

Unknowns: transmitted symbols $\underline{a} = [\dots, a[-2], a[-1], a[0], a[1], a[2], \dots]$

Time offset: ϵ

Phase offset: ϕ

$$\{\hat{\underline{a}}, \hat{\underline{\epsilon}}, \hat{\phi}\} = \arg \max_{\underline{a}, \underline{\epsilon}, \phi} Pr(\underline{r} | \underline{a}, \epsilon, \phi)$$

Blind estimation: data is unknown

a) Joint estimation: search over all options

b) Estimate parameters one-by-one

→ marginalize over the others = take the average over the others

• Timing $\hat{\epsilon}$: $Pr(\underline{r} | \epsilon) = \int \sum_{\underline{a}} Pr(\underline{a}) Pr(\underline{r} | \epsilon, \underline{a}, \phi) p(\phi) d\phi$

uniform uniform

$-\pi \dots +\pi$ $-\pi \dots +\pi$

- Phase $Pr(\underline{r}|\phi) = \int \sum_{\underline{a}} Pr(\underline{a}) Pr(\underline{r}|\phi, \underline{a}) p(\underline{a}) d\underline{a}$

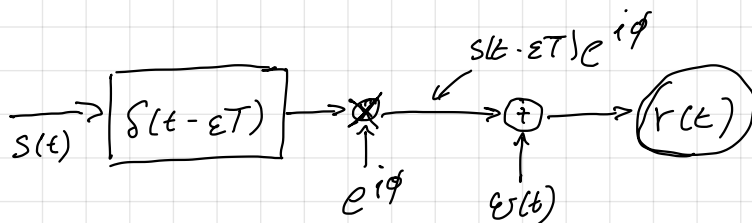
3) Estimation one after another
 $\hookrightarrow$ for each parameter assume we know the ones we estimated before perfectly

- Timing $\underline{\varepsilon}$: $\hat{\underline{\varepsilon}} = \arg \max_{\underline{\varepsilon}} Pr(\underline{r}|\underline{\varepsilon})$

- Phase ϕ : $\hat{\phi} = \arg \max_{\phi} Pr(\underline{r}|\underline{\varepsilon}=\hat{\underline{\varepsilon}}, \phi)$

- Data $\underline{a}$: $\hat{\underline{a}} = \arg \max_{\underline{a}} Pr(\underline{r}|\underline{\varepsilon}=\hat{\underline{\varepsilon}}, \phi=\hat{\phi}, \underline{a})$

ML criterion for AWGN channel $\rightarrow$ Goal is to define $Pr(\underline{r} | \dots)$



$$r(t): \mathcal{CN}(\underbrace{s(t-\epsilon T)}_{\text{Tx Sequence incl. phase offset}} e^{j\phi}, \sigma^2) \sim e^{-\frac{|r(t) - s(t-\epsilon T)e^{j\phi}|^2}{2\sigma^2}}$$

$\mathcal{CN}(0, \sigma^2) \sim e^{-\frac{|w(t)|^2}{2\sigma^2}}$

Ref RX signal (no noise) + given ϵ, ϕ
 $s(t-\epsilon T) e^{j\phi}$

Instead of comparing to the delayed ref sequence $s(t-\epsilon T)e^{j\phi}$ we compare $s(t)e^{j\phi}$ to an "un-delayed" RX sequence/samples $r(t+\epsilon T)$ and write $\underline{r}(t+\epsilon T)$ as a function of $\underline{r}(t)$ [$\underline{r}(tT_s)$]

Consider $p_r(\underline{r} | r^{ref})$

For one sample: $p(r | r^{ref}) = \exp(-|r - r^{ref}|^2)$ $\sum_n |r_n - r_n^{ref}|^2$

for multiple samples: $p(\underline{r} | \underline{r}^{ref}) = \prod_n p(r_n | r_n^{ref}) = \exp(-\|\underline{r} - \underline{r}^{ref}\|^2)$

$$= \exp(-\cancel{\|\underline{r}\|^2} + 2\text{Re}\{(\underline{r}^{ref})^H \underline{r}\} - \|\underline{r}^{ref}\|^2)$$

Note: $\|\underline{r}\|^2$ is indep. of the parameters we try

has no impact on finding the maximizing parameters

$$\mathcal{L}(\underline{r} | r^{ref}) \sim \exp(2\text{Re}\{(\underline{r}^{ref})^H \underline{r}\} - \|\underline{r}^{ref}\|^2)$$

$r(t+\epsilon T) \leftrightarrow$

Compare the "corrected" sampled sequence $r(t+\epsilon T)$ with sampled TX output (w/o time delay)

$$r(t) \rightarrow \underline{r}(t+\epsilon T) = \underline{z}_e(\epsilon) \quad \text{with} \quad r^{ref} \rightarrow s(t) = \sum_k a_k g(t-kT) e^{j\phi} \Big|_{t=\epsilon T}$$

$$\mathcal{L}(\underline{z}_e(\epsilon) | \underline{a}_e e^{j\phi}) = \exp(+2\text{Re}\{\underline{a}_e^H e^{-j\phi} \underline{z}_e\} - \|\underline{a}_e\|^2)$$

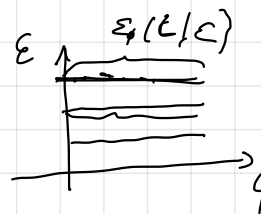
$$\mathcal{L}(\underline{z} | \underline{a} e^{j\phi}) = \exp(+2\text{Re}\{\underline{a}^H e^{-j\phi} \underline{z}\} - \|\underline{a}\|^2)$$

$$= \exp \left(\sum_{l=-L}^{+L} \left[2 \operatorname{Re} \{ \alpha_l^* z_l(\varepsilon) e^{-j\phi} \} \right] - \sum_{l=-L}^{+L} |a_l|^2 \right)$$

~~for large L~~
→ const.

$$= \exp \left(\sum_{l=-L}^{+L} 2 \operatorname{Re} \{ \alpha_l^* z_l(\varepsilon) e^{-j\phi} \} \right)$$

↑ derived from our Rx samples @ $r(LT_s)$



Blind estimation average over all possible $\underline{a}$, or α_l $l=-L \dots L$

$$\mathbb{E}_{\underline{a}} \{ L(\underline{z} | \underline{a} e^{j\phi}) \} \rightarrow \underline{a} \text{ is in the exponent}$$

$$\underline{\mathbb{E}}_{\underline{a}} \{ f(\underline{a}) \} \neq f(\underline{\mathbb{E}}_{\underline{a}} \{ \underline{a} \})$$



Workaround: Taylor expansion

$$\exp \{ 2 \operatorname{Re} \{ \sum \alpha_l^* z_l(\varepsilon) e^{-j\phi} \} \} = 1 + \underbrace{2 \operatorname{Re} \{ \sum \alpha_l^* z_l(\varepsilon) e^{-j\phi} \}}_{\text{①} \rightarrow 0} + \underbrace{\left(\operatorname{Re} \{ \sum \alpha_l^* z_l(\varepsilon) e^{-j\phi} \} \right)^2}_{\text{②}}$$

$$\text{① } \mathbb{E}_{\underline{a}, \phi} \{ 2 \operatorname{Re} \{ \sum \alpha_l^* z_l(\varepsilon) e^{-j\phi} \} \} = \operatorname{Re} \left\{ \mathbb{E}_{\underline{a}, \phi} \left\{ \underbrace{\sum \alpha_l^* z_l(\varepsilon) e^{-j\phi}}_{\text{②}} \right\} \right\}$$

$$\text{②} = \left(\frac{1}{2} \sum_l \alpha_l^* z_l(\varepsilon) e^{-j\phi} + \frac{1}{2} \sum_l \alpha_l z_l^*(\varepsilon) e^{+j\phi} \right)^2 \leftarrow \text{remove the } \operatorname{Re} \{ \dots \}$$

$$= \sum_l \left(|a_l|^2 |z_l(\varepsilon)|^2 + \frac{1}{2} \operatorname{Re} \{ a_l^2 (z_l(\varepsilon))^2 e^{j2\phi} \} \right)$$

Average $\underline{\mathbb{E}}_{\underline{a}}$

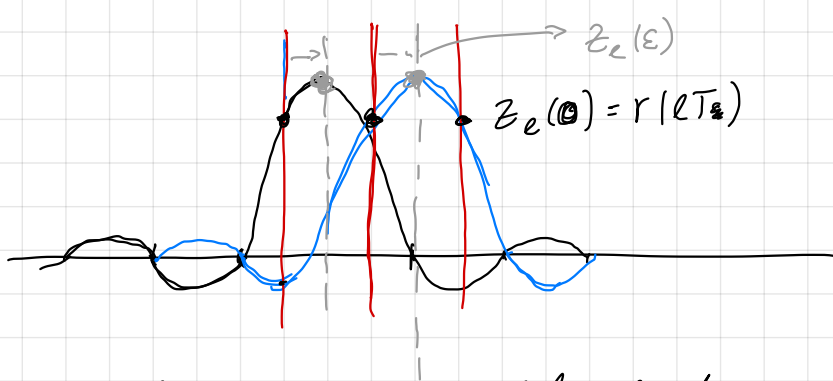
$$= \mathbb{E}_{\phi} \left\{ \underbrace{\sum_l \underbrace{\mathbb{E}_{\underline{a}} \{ |a_l|^2 \}}_{\rightarrow \text{const.}} |z_l(\varepsilon)|^2}_{\rightarrow \text{const.}} + \frac{1}{2} \operatorname{Re} \left\{ \underbrace{\mathbb{E}_{\underline{a}} \{ a_l^2 \}}_{\text{const.}} (z_l(\varepsilon))^2 e^{j2\phi} \right\} \right\}$$

Average over $\phi \in [0, 2\pi]$ → eliminates the 2nd term

$$L(\varepsilon) \sim \sum |z_l(\varepsilon)|^2 \quad \text{with } z_l(\varepsilon) = r(LT_s + \varepsilon T)$$

↑ write as a fct. of $r(LT_s)$

$$\hat{\varepsilon} = \arg \max_{\varepsilon} \sum |z_l(\varepsilon)|^2$$



$$L(\epsilon) \sim \sum |z_e(\epsilon)|^2$$

with $z_e(\epsilon) = r(lTs + \epsilon)$ ✗

we only have $r(lTs)$

write $z_e(\epsilon)$ as a fct. of the samples I have $r(lTs)$

How to construct $z_e(\epsilon)$ from $r(lTs)$

Interpolate: band-limited signal

1) write as Fourier series, evaluate at $lTs + \epsilon$

$$|z_e(\epsilon)|^2 = \sum_{n=-\infty}^{\infty} \underbrace{c_n}_{\text{offset}} \underbrace{e^{j2\pi n \epsilon}}_{\text{Fourier coeffs centered around the lth symbol}}$$

2) Get $c_n^{(l)}$ from our samples $r(pTs)$ around $r(lTs)$

the symbol l $lTs, lTs + Ts, lTs + 2Ts, lTs + 3Ts, \dots, lTs + (M-1)Ts$

M -fold our sampling

$$c_n^{(l)} = \sum_{p=0}^{M-1} |r(lTs + pTs)|^2 e^{-j \frac{2\pi}{M} np}$$

3) Substitute into $L(\epsilon) \sim \sum_{\epsilon} |z_e(\epsilon)|^2 = \sum_{\epsilon} \underbrace{\sum_l}_{\text{over all samples}} \underbrace{\sum_{p=0}^{M-1}}_{\text{over all samples}} |r(lTs + pTs)|^2 e^{-j \frac{2\pi}{M} np} e^{j2\pi n \epsilon}$

Note: $r(t)$ is band limited to $\pm \frac{1}{2T}$

$\Rightarrow |r(t)|^2$ is bandlimited too, but to $\frac{1}{T}$

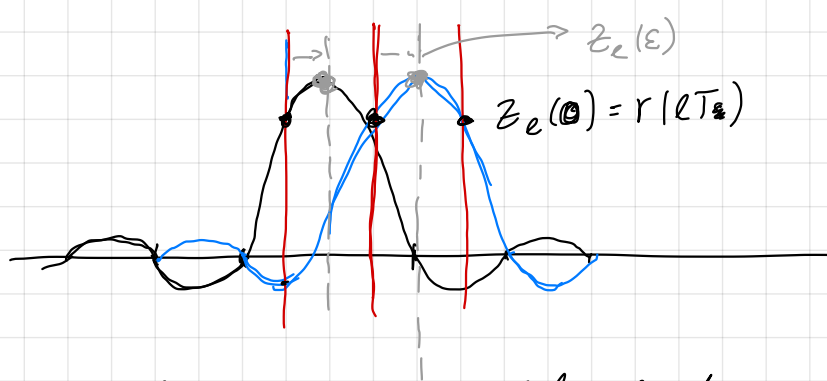
need values $\rightarrow$ only c_{-1}, c_1 and $c_0 \neq$

$$L(\epsilon) \sim c_0 + \underbrace{c_{-1} e^{-2\pi j \epsilon} + c_1 e^{-2\pi j \epsilon}}_{\text{conjug. conj pairs}} = c_0 + 2 \operatorname{Re} \left\{ c_1 e^{-2\pi j \epsilon} \right\}$$

should be real for $\omega \neq$

$$c_1 = \sum_{\epsilon} \sum_p |r(lTs + pTs)|^2 e^{-j \frac{2\pi}{M} p} = \text{FT of squared rx samples}$$

$$\underline{\underline{\epsilon}} = \arg(c_1) \frac{1}{2\pi}$$



$$\underline{LCE} \sim \sum |z_e(\epsilon)|^2$$

with $z_e(\epsilon) = r(lT_s + \epsilon)$ ✗

we only have $r(lT_s)$

write $z_e(\epsilon)$ as a fct. of the samples I have $r(lT_s)$

How to construct $z_e(\epsilon)$ from $r(lT_s)$

Interpolate: band-limited signal

1) write as Fourier Series, evaluate at $lT + \epsilon$

$$|z_e(lT + \epsilon)|^2 = \sum_{n=-\infty}^{\infty} \underbrace{c_n}_{\text{offset}} e^{j2\pi n \epsilon} \cdot e^{j2\pi n \frac{l}{M} T}$$

N T-spaced samples
M-fold oversampled

2) Get c_n from our samples $r(pT_s)$

$$c_n = \sum_{p=0}^{M-1} |r(pT_s)|^2 e^{-j\frac{2\pi}{M} np}$$

3) Substitute into

$$z_e(\epsilon) = \sum_n c_n e^{j2\pi n \epsilon} e^{j2\pi \frac{n}{M} l T}$$

$$\sum_l z_e(\epsilon) = \sum_l \sum_n c_n e^{j2\pi n \epsilon} e^{j2\pi \frac{n}{M} l T}$$

$\neq 0$ except $n = \pm N$
 $n = 0$

$$\Rightarrow \sum_l z_e(t) = \sum_l (c_{-N} e^{j2\pi N \epsilon} + c_0 + c_N e^{-j2\pi N \epsilon})$$

$$c_0 + c_{-N} e^{-j2\pi N \epsilon} + c_N e^{-j2\pi N \epsilon} = c_0 + 2 \operatorname{Re} \left\{ c_N e^{-j2\pi N \epsilon} \right\}$$

conjug. conj. pairs

must
should be real for var

$$c_N = \sum_p |r(pT_s)|^2 e^{-j\frac{2\pi}{M} p}$$

for M=4:
1; -j; -1; j

$$\underline{\underline{\epsilon}} = \arg(c_N) \frac{1}{2\pi}$$

Phase Estimation $\rightarrow$ Assume that $\varepsilon = \hat{\varepsilon}$
 Timing is already corrected
Data aided: know data $\underline{a}^{(0)}$ known

$$L(\phi) = L(\underline{z} | \underline{a} = \underline{a}^{(0)}, \varepsilon = \hat{\varepsilon}, \phi) = \exp \left(\operatorname{Re} \left\{ \sum_l \underline{a}_l^{(0)*} z_l(\hat{\varepsilon}) e^{j\phi} \right\} \right) \rightarrow \max$$

$\rightarrow$ Real valued

$$\hat{\phi} = \arg \left(\sum_l \underline{a}_l^{(0)*} z_l(\hat{\varepsilon}) \right) \quad \checkmark \quad \text{Ambiguity of } \pm \pi$$

Non-data aided: not knowing $\underline{a}$

Problem: $L(\phi)$ depends on $\underline{a}$ or a_l

PSK: 

Idea: Remove dependency on $a_l \leftarrow$ single symbol

- Assumption: PSK-modulation $z_l(\hat{\varepsilon}) = a_l e^{j\phi}$ $a_l = c$ $\overset{\text{data}}{\downarrow}$
 $j2\pi \frac{1}{Q} d_l$
- Note: $(a_l)^Q = \left(e^{j2\pi \frac{1}{Q} d_l} \right)^Q = e^{j2\pi d_l}$ $d_l = \text{int.}$
 $\equiv 1$ regardless of d_l

Consider modified RX-signal $\left[z_l(\hat{\varepsilon}) \right]^Q = \underbrace{a_l^Q}_1 e^{jQ\phi}$

$$L(\phi) = \operatorname{Re} \left\{ \sum_l \underline{(a_l^{(0)})^Q} \underline{(z_l(\hat{\varepsilon}))^Q} e^{-j\phi} \right\}$$

$$\hat{\phi} = \arg \left(\sum_l (z_l(\hat{\varepsilon}))^Q \right) \frac{1}{Q} \quad \text{Ambiguity of } \pm \frac{\pi}{Q}$$

$\pm \pi$

