A Beamforming Method for Blind Calibration of Time-Interleaved A/D Converters

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> Joint work with Steve Huang September 30, 2005





• Motivation

- Problem Formulation
- Blind Calibration Method
- Convergence
- Simulations and Conclusions





- Applications requiring ADCs operating at high data rates ⇒ Time-interleaved ADCs.
- Constituent ADCs have gain, offset, timing mismatches that need to be estimated and corrected in the digital domain.
- Correction achieved by digital filter banks operating on ADCs outputs (Johansson and Lowenborg, 2002; Prendergast et al. 2004). Requires 10 to 20 % excess samples.
- Timing offset estimation can be performed either with test signals or blindly. Blind methods do not lower ADC throughput and can adjust to changes online.





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Problem Formulation

- If $x_c(t)$ is a CT bandlimited signal with bandwidth B, can be recovered from its samples $x(n) = x_c(nT_s)$ if $f_s = 1/T_s > f_N = B/\pi$.
- Instead of using a single fast ADC, we employ N slow ADCs operating at f_s/N .



• Due to timing offsets, quantization errors and thermal noise, output of *i*-th ADC

$$z_i(m) = x_i(m) + v_i(m)$$

for $1 \le i \le N$, where $v_i(m) \sim N(0, N_0/2)$ WGN and

$$x_i(m) = x_c(mT_i + ((i-1) + \delta_{i-1})T_s)$$

where $T_i = NT_s$ = sampling period of slow ADCs, $\delta_{i-1}T_s$ = timing offset of *i*-th ADC measured wrt 1st ADC

• If $F_i(e^{j\omega}) = e^{j\omega(i-1+\delta_{i-1})}$, analysis filter bank model for N = 4:



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• For N = 4, let

$$\mathbf{X}_{I}(e^{j\omega}) = \begin{bmatrix} X_{1}(e^{j\omega}) & X_{2}(e^{j\omega}) & X_{3}(e^{j\omega}) & X_{4}(e^{j\omega}) \end{bmatrix}^{T}$$
$$\mathbf{X}_{A}(e^{j\omega}) = \begin{bmatrix} X(e^{j\frac{\omega}{4}}) & X(e^{j(\frac{\omega}{4}-\frac{\pi}{2})}) & X(e^{j(\frac{\omega}{4}-\pi)}) & X(e^{j(\frac{\omega}{4}-3\frac{\pi}{2})}) \end{bmatrix}^{T}$$

= DTFT of exact ADC outputs, and vector of alias components of fast sampled sequence, and

$$oldsymbol{\delta} = \left[egin{array}{cccc} \delta_1 & \delta_2 & \delta_3 \end{array}
ight]^T$$

= vector of timing mismatches.



• We have

$$\mathbf{X}_{I}(e^{j\omega}) = \frac{1}{4} \mathbf{M}(e^{j\omega}, \boldsymbol{\delta}) \mathbf{X}_{A}(e^{j\omega}) ,$$

where

$$\mathbf{M}(e^{j\omega}, \boldsymbol{\delta}) = \mathbf{D}(e^{j\omega}, \boldsymbol{\delta}) \mathbf{V}(\boldsymbol{\delta})$$
$$\mathbf{D}(e^{j\omega}, \boldsymbol{\delta}) \stackrel{\triangle}{=} \operatorname{diag} \left\{ e^{j\frac{\omega}{4}(i-1+\delta_{i-1})}, 1 \le i \le 4 \right\}$$

and

$$\mathbf{V}(\boldsymbol{\delta}) = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & u_1 & u_1^2 & u_1^3 \\ 1 & u_2 & u_2^2 & u_2^3 \\ 1 & u_3 & u_3^2 & u_3^3 \end{bmatrix}$$

= Vandermonde matrix with

$$u_i = e^{-j\frac{\pi}{2}(i+\delta_i)}$$

• By inverting $\mathbf{V}(\boldsymbol{\delta})$, we can find synthesis filters $G_i(e^{j\omega})$ such that

$$X(e^{j\omega}) = \sum_{i=1}^{N} G_i(e^{j\omega}) X_i(e^{j\omega})$$

For small δ_i 's, filters G_i admit a closed-form 1st-order Farrow representation.

• Synthesis filter bank for N = 4:





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Blind Calibration

• Let N = 4, if $\alpha = (f_s - f_N)/f_s = \%$ of excess samples, the alias matrix is *rank deficient* for $|\omega| < 4\alpha\pi$:

$$\mathbf{X}_{I}(e^{j\omega}) = \frac{1}{4} \mathbf{M}_{R}(e^{j\omega}, \boldsymbol{\delta}) \begin{bmatrix} X(e^{j(\frac{\omega}{4} + \frac{\pi}{2})}) \\ X(e^{j\frac{\omega}{4}}) \\ X(e^{j(\frac{\omega}{4} - \frac{\pi}{2})}) \end{bmatrix}$$

with $\mathbf{M}_{R}(e^{j\omega}, \boldsymbol{\delta}) = \mathbf{D}(e^{j\omega}, \boldsymbol{\delta})\mathbf{V}_{R}(\boldsymbol{\delta})$, where

$$\mathbf{V}_R(oldsymbol{\delta}) = egin{bmatrix} 1 & 1 & 1 \ u_1^{-1} & 1 & u_1 \ u_2^{-1} & 1 & u_2 \ u_3^{-1} & 1 & u_3 \end{bmatrix}$$

is a 4×3 reduced Vandermonde matrix.





• Can find a nulling filter bank $\mathbf{H}(e^{j\omega}, \boldsymbol{\delta})$ such that

$$\mathbf{H}(e^{j\omega},\boldsymbol{\delta})\mathbf{X}_{I}(e^{j\omega})=0$$

for $|\omega| < 4\alpha\pi$.

• Structure of nulling filter bank:

$$\mathbf{H}(e^{j\omega},\boldsymbol{\delta}) = \mathbf{c}^T(\boldsymbol{\delta})\mathbf{D}^{-1}(e^{j\omega},\boldsymbol{\delta})$$

for $|\omega| < 4\alpha\pi$, =0 otherwise, where

$$\mathbf{c}^T(oldsymbol{\delta}) = \left[egin{array}{ccc} c_1(oldsymbol{\delta}) & c_2(oldsymbol{\delta}) & c_3(oldsymbol{\delta}) & c_4(oldsymbol{\delta}) \end{array}
ight]$$

satisfies

$$\mathbf{c}^T(\boldsymbol{\delta})\mathbf{V}_R(\boldsymbol{\delta}) = 0$$
 .

• Set $c_1 = 1$. Then, for small δ_i s:

$$egin{aligned} c_2(oldsymbol{\delta}) &pprox & -1+rac{\pi}{4}(\delta_2+\delta_3-\delta_1) \ c_3(oldsymbol{\delta}) &pprox & 1-rac{\pi}{2}(\delta_3-\delta_1) \ c_4(oldsymbol{\delta}) &pprox & -1+rac{\pi}{4}(-\delta_2+\delta_3-\delta_1) \end{aligned}$$

Applied Math. Seminar



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• Consider the 1st-order Farrow approximation

$$K_{i}(e^{j\omega}, \delta_{i-1}) = e^{-j\omega(i-1+\delta_{i-1})/4} H_{\rm LP}(e^{j\omega})$$

$$\approx K_{i0}(e^{j\omega}) + \delta_{i-1} K_{i1}(e^{j\omega}),$$

where $H_{\rm LP}(e^{j\omega})$ = ideal lowpass filter of bandwidth $4\alpha\pi$.

• Let

$$a_i(m) \stackrel{\triangle}{=} k_{i0}(m) * z_i(m) \quad , \quad b_i(m) \stackrel{\triangle}{=} k_{i1}(m) * z_i(m)$$

Consider the adaptive null-steering structure



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Applied Math. Seminar

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• Consider the objective function

$$J(\hat{\delta}) = E[e^2(m, \hat{\delta})]/2$$

where

$$e(m, \hat{\delta}) = \sum_{i=1}^{4} c_i(\hat{\delta})(a_i(m) + b_i(m)\hat{\delta}_i)$$

= nulling filter output.

• We have

$$\nabla_{\hat{\delta}} e(m, \hat{\delta}) \approx \begin{bmatrix} -b_2(m) \\ b_3(m) \\ -b_4(m) \end{bmatrix} + \frac{\pi}{4} \begin{bmatrix} -a_2(m) - a_4(m) + 2a_3(m) \\ a_2(m) - a_4(m) \\ a_2(m) + a_4(m) - 2a_3(m) \end{bmatrix}$$



• $\hat{\delta}(m)$ obtained by *stochastic gradient algorithm*

$$\hat{\boldsymbol{\delta}}(m+1) = \hat{\boldsymbol{\delta}}(m) - \mu e(m, \hat{\boldsymbol{\delta}}(m)) \nabla_{\hat{\boldsymbol{\delta}}} e(m, \hat{\boldsymbol{\delta}}(m))$$

where $\mu = \text{step size}$, with initial condition

$$\hat{\boldsymbol{\delta}}(0) = \mathbf{0}$$
 .

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Convergence

- Use ODE/stochastic averaging method. Assume μ small, $x_c(t)$ zero-mean WSS.
- Write adaptive algorithm as

$$\hat{\boldsymbol{\delta}}(m+1) = \hat{\boldsymbol{\delta}}(m) + \mu \mathbf{T}(\hat{\boldsymbol{\delta}}(m), \mathbf{y}(m))$$

where $\mathbf{y}(m) = [\mathbf{a}^T(m)\mathbf{b}^T(m)]^T$. Due to the stochastic gradient structure of the algorithm,

$$t(\hat{\boldsymbol{\delta}}) = E[T(\hat{\boldsymbol{\delta}}, \mathbf{y}(m))] = -\nabla_{\hat{\boldsymbol{\delta}}} J(\hat{\boldsymbol{\delta}}) ,$$

so $J(\boldsymbol{\delta})$ = Lyapunov function for ODE

$$rac{d\hat{oldsymbol{\delta}}}{dt} = t(\hat{oldsymbol{\delta}})(t) \; ,$$

so ODE trajectories converge to a minimum of $J(\hat{\delta})$.



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Convergence (cont'd)

• For small δ and $\hat{\delta}$

$$J(\hat{\delta}) \approx \frac{1}{2} \{ \left[(\delta_2 - \delta_1 - \delta_3) - (\hat{\delta}_2 - \hat{\delta}_1 - \hat{\delta}_3) \right]^2 A \\ + \left[\left((\delta_1 - \delta_3) - (\hat{\delta}_1 - \hat{\delta}_3) \right)^2 + (\delta_2 - \hat{\delta}_2)^2 \right] B + |\mathbf{c}(\hat{\delta})|^2 C \}$$

with

$$A = \frac{1}{2\pi} \int_{-\alpha\pi}^{\alpha\pi} \omega^2 S_x(e^{j\omega}) d\omega$$
$$\frac{B}{2} = \frac{1}{2\pi} \int_{\frac{\pi}{2} - \alpha\pi}^{\frac{\pi}{2} + \alpha\pi} \omega^2 S_x(e^{j\omega}) d\omega$$
$$C = 2\alpha N_0$$

where we neglect cubic terms.



Convergence (cont'd)

- For noiseless case, unique minimum of J for small offset and offset estimates is δ̂ = δ if A > 0 and B > 0, so x(n) must have power in band [-απ, απ] and [±π/2 − απ, ±π/2 + απ].
- Ensures that as $m \to \infty$

 $\hat{\pmb{\delta}}(m) \sim N(\pmb{\delta}, \mu P)$

where P = positive definite matrix.



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Bandlimited WGN input



Simulation parameters

- Signal bandwidth: $[-0.75\pi, 0.75\pi]$
- $\delta_1 = 0.02, \, \delta_2 = 0.01, \, \delta_3 = -0.01.$
- $\mu = 2 \, 10^{-4}$.
- design $\alpha = 0.225$.



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Multitone sinusoidal input



Simulation parameters

• Input frequencies: 0.1π , 0.45π , 0.75π .

•
$$\delta_1 = 0.02, \, \delta_2 = 0.01,$$

•
$$\mu = 10^{-3}$$

• design
$$\alpha = 0.15$$
.



Calibrated ADC output



Uncalibrated ADC, 70dB SNR

Calibrated ADC, 70dB SNR





- Blind calibration of time-interleaved ADCs presented, requires 10 to 20 % oversampling and intermittent excitation of certain frequency bands.
- Simulated for up to 16 channels, but 2 or 4 channels primary interest for today's ADC technology.
- Postprocessing of analog circuits with mismatched components source of interesting adaptive signal processing problems.



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Thank you!!

