Direct Design of Orthogonal Filter Banks and Wavelets

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Outline

- Introduction
- Early and recent work
- Constrained linear updates and a convex QP formulation for least-squares design of conjugate quadrature (CQ) filters
- Constrained linear updates and an second-order cone programming formulation for minimax design of CQ filters
- Experimental results

1. Introduction

• Two-channel FIR filter bank



$$\hat{X}(z) = \frac{1}{2} [F_0(z)H_0(z) + F_1(z)H_1(z)]X(z) + \frac{1}{2} [F_0(z)H_0(-z) + F_1(z)H_1(-z)]X(-z)$$

• Perfect reconstruction (PR) conditions

$$F_0(z)H_0(z) + F_1(z)H_1(z) = 2z^{-l}$$
$$F_0(z)H_0(-z) + F_1(z)H_1(-z) = 0$$

• A conjugate quadrature (CQ) filter bank assumes

$$H_1(z) = -z^{-(N-1)}H_0(-z^{-1}), \ F_0(z) = z^{-(N-1)}H_0(z^{-1}), \ F_1(z) = z^{-(N-1)}H_1(z^{-1})$$

 \Rightarrow the 2nd PR condition is automatically satisfied

(no aliasing) and the 1st PR condition becomes

$$H_0(z)H_0(z^{-1}) + H_0(-z)H_0(-z^{-1}) = 2$$
 (PS)

which is called the *power* symmetric (PS) condition

because it implies

$$\left|H_0\left(e^{j(\pi/2-\theta)}\right)\right|^2 + \left|H_0\left(e^{j(\pi/2+\theta)}\right)\right|^2 = 1 \quad \text{for any} \quad \theta$$

2. Early and Recent Work

- Representative early and recent work include
 - Smith and Barnwell (1984)
 - Mintzer (1985)
 - Vaidyanathan and Nguyen (1987)
 - Rioul and Duhamel (1994)
 - Lawton and Michelli (1997)
 - Tuqan and Vaidyanathan (1998)
 - Dumitrescu and Popeea (2000)
 - Tay (2005, 2006)

- The most common design technique:
- A half-band filter P(z) is a zero-phase FIR filter satisfying

$$P(z) + P(-z) = 2$$

• Let $P(z) = H_0(z)H_0(z^{-1})$, then the PS condition

$$H_0(z)H_0(z^{-1}) + H_0(-z)H_0(-z^{-1}) = 2$$

becomes

$$P(z) + P(-z) = 2$$

So P(z) is a half-band filer and it is *nonnegative*:

$$P(e^{j\omega}) = H_0(e^{j\omega})H_0(e^{-j\omega}) = \left|H_0(e^{j\omega})\right|^2 \ge 0 \qquad (P)$$

Design steps:

(a) Design a lowpass half-band FIR filter P(z) with nonnegativity property $P(e^{j\omega}) \ge 0$

(b) Perform a spectral decomposition $P(z) = H_0(z)H_0(z^{-1})$

• Vanishing moment (VM): the number of VMs equals to

the number of zeros of H₀ at $\omega = \pi$:

$$\frac{d^{l}H_{0}(e^{j\omega})}{d\omega^{l}}\bigg|_{\omega=\pi} = (-j)^{l} \sum_{n=0}^{N-1} (-1)^{n} n^{l} h_{n} = 0, \text{ for } l = 0, 1, ..., L-1$$

3. Least-Squares Design of CQ Filters

Problem Formulation

• Let

$$H_0(z) = \sum_{n=0}^{N-1} h_n z^{-n}$$
 with *N* even, and $h = [h_0 \ h_1 \dots h_{N-1}]^T$

• A direct approach: minimizing a least squares type

objective function subject to the PS constraint:

minimize
_h

$$\int_{\omega_a}^{\pi} \left| H_0(e^{j\omega}) \right|^2 d\omega$$
subject to: $H_0(z)H_0(z^{-1}) + H_0(-z)H_0(-z^{-1}) = 2$

• The objective function is a positive definite quadratic form:

$$\int_{\omega_a}^{\pi} \left| H_0(e^{j\omega}) \right|^2 d\omega = h^T Q h$$

with *Q* a symmetric positive definite Toeplitz matrix:

$$Q = \text{toeplitz}\left(\left[\pi - \omega_a \quad -\sin \omega_a \quad \cdots \quad \frac{-1}{N-1}\sin[(N-1)\omega_a]\right]\right)$$

• The constraint is the PS condition:

$$H_0(z)H_0(z^{-1}) + H_0(-z)H_0(-z^{-1}) = 2$$
 (PS)

that is equivalent to N/2 second-order equality

constraints:

$$\sum_{n=0}^{N-1-2m} h_n \cdot h_{n+2m} = \delta(m) \text{ for } m = 0, 1, \dots, (N-2)/2$$

with $\delta(m) = 1$ for m = 0 and $\delta(m) = 0$ for $m \neq 0$.

• The design problem now becomes a *polynomial optimization problem* (POP):

$$\underset{h}{\text{minimize}} \quad h^T Q h = \left\| Q^{1/2} h \right\|^2$$

subject to:
$$\sum_{n=0}^{N-1-2m} h_n \cdot h_{n+2m} = \delta(m) \quad \text{for } 0 \le m \le (N-2)/2$$

• The POP can be modified to include VM requirement:

minimize
h^TQh =
$$\|Q^{1/2}h\|^2$$

subject to: $\sum_{n=0}^{N-1-2m} h_n \cdot h_{n+2m} = \delta(m)$ for $0 \le m \le (N-2)/2$
 $\sum_{n=0}^{N-1} (-1)^n n^l h_n = 0$ for $l = 0, 1, ..., L-1$

- Features of these problems:
 - All polynomials are of second-order.
 - The objective function is convex
 - Nonconvex problems because of the N/2

second-order equality constraints (the PS conditions).

- Examples of the PS constraints
- 1. $N = 4 \implies 2$ constraints:

$$h_0^2 + h_1^2 + h_2^2 + h_3^2 = 1$$
$$h_0 \cdot h_2 + h_1 \cdot h_3 = 0$$

2. $N = 20 \Rightarrow 10$ constraints:

$$h_{0}^{2} + h_{1}^{2} + \dots + h_{19}^{2} = 1$$
 (20 terms)

$$h_{0} \cdot h_{2} + h_{1} \cdot h_{3} + \dots + h_{17} \cdot h_{19} = 0$$
 (18 terms)

$$h_{0} \cdot h_{4} + h_{1} \cdot h_{5} + \dots + h_{15} \cdot h_{19} = 0$$
 (16 terms)

$$h_{0} \cdot h_{6} + h_{1} \cdot h_{7} + \dots + h_{13} \cdot h_{19} = 0$$
 (14 terms)

$$\vdots$$

$$\vdots$$

$$h_{0} \cdot h_{16} + h_{1} \cdot h_{17} + h_{2} \cdot h_{18} + h_{3} \cdot h_{19} = 0$$
 (4 terms)

$$h_{0} \cdot h_{18} + h_{1} \cdot h_{19} = 0$$
 (2 terms)

Constrained Linear Updates

- In the *k*th iteration of the algorithm we update filter coefficients from $h^{(k)}$ to $h^{(k+1)} = h^{(k)} + d$ to achieve two things:
 - to reduce the filter's stopband energy h^TQh
 - to better approximate constraints

$$\sum_{n=0}^{N-1-2m} h_n \cdot h_{n+2m} = \delta(m), \ 0 \le m \le N/2 - 1$$

- The stopband energy at $h^{(k+1)}$ is equal to $\left\|Q^{1/2}(d+h^{(k)})\right\|^2$
- The constraints at $h^{(k+1)}$ becomes

$$\sum_{n} h_{n}^{(k)} h_{n+2m}^{(k)} + \sum_{n} h_{n}^{(k)} d_{n+2m} + \sum_{n} d_{n} h_{n+2m}^{(k)} + \sum_{n} d_{n} d_{n+2m} = \delta(m)$$

 Imposing constraints on the smallness of increment vector d:

$$|d_i| \le \beta$$
 for $i = 1, 2, ..., N$

the 2nd-order constraints can be linearized:



• This leads to a set of (N-2)/2 linear equations:

$$\sum_{n} h_{n}^{(k)} d_{n+2m} + \sum_{n} d_{n} h_{n+2m}^{(k)} = \delta(m) - s^{(k)}(m) \equiv u^{(k)}(m)$$

which can be expressed as

$$C^{(k)}d = u^{(k)}$$

• The smallness constraint on *d* is given by

$$|d_i| \le \beta$$
 for $1 \le i \le n \iff Ad \le b$

• The linear constraint on VMs is given by

$$\sum_{n=0}^{N-1} (-1)^n n^l (d_n + h_n^{(k)}) = 0 \quad \text{for } 0 \le l \le L - 1 \quad \Leftrightarrow \quad Dd = v^{(k)}$$

<u>A Quadratic Programming (QP) Formulation</u>

• Summarizing, the solution strategy is to *iteratively* update the filter coefficients from $h^{(k)}$ to $h^{(k+1)} = h^{(k)} + d^{(k)}$ with $d^{(k)}$

obtained by solving the QP problem

minimize
$$\left\|Q^{1/2}(d+h^{(k)})\right\|^2$$

subject to: $Ad \leq b$

$$\begin{bmatrix} C^{(k)} \\ D \end{bmatrix} d = \begin{bmatrix} u^{(k)} \\ v^{(k)} \end{bmatrix}$$

4. Minimax Design of CQ Filters

Problem Formulation

• The formulation in this case is changed to

subject to:
$$\begin{split} \min_{h} \max_{\substack{\omega_{a} \leq \omega \leq \pi}} & \left| H_{0}(e^{j\omega}) \right| \\ \sum_{n=0}^{N-1-2m} h_{n} \cdot h_{n+2m} = \delta(m) \quad \text{for } 0 \leq m \leq (N-2)/2 \\ & \sum_{n=0}^{N-1} (-1)^{n} n^{l} h_{n} = 0 \quad \text{for } l = 0, 1, \dots, L-1 \end{split}$$

Constrained Linear Updates

• Like in the least squares design, the constrained linear update gives

$$\underset{d}{\text{minimize maximize}} \quad \left| H_0(e^{j\omega}) \right|$$

subject to:
$$Ad \leq b$$

$$\begin{bmatrix} C^{(k)} \\ D \end{bmatrix} d = \begin{bmatrix} u^{(k)} \\ v^{(k)} \end{bmatrix}$$

• Dealing with the objective function, we write

$$H_0(e^{j\omega}) = \sum_{n=0}^{N-1} h_n e^{-jn\omega} = h^T c(\omega) - jh^T s(\omega)$$

$$c(\omega) = \begin{bmatrix} 1 & \cos \omega & \cdots & \cos(N-1)\omega \end{bmatrix}^T$$
, $s(\omega) = \begin{bmatrix} 0 & \sin \omega & \cdots & \sin(N-1)\omega \end{bmatrix}^T$

hence

$$\left|H_{0}(e^{j\omega})\right| = \sqrt{\left(h^{T}c(\omega)\right)^{2} + \left(h^{T}s(\omega)\right)^{2}} = \left\|\begin{bmatrix}c(\omega)^{T}\\s(\omega)^{T}\end{bmatrix} \cdot h\right\| \equiv \left\|T(\omega) \cdot h\right\|$$

$$\Rightarrow |H_0(e^{j\omega}, h^{(k)} + d^{(k)})| = ||T(\omega) \cdot (h^{(k)} + d^{(k)})|| = ||T(\omega)d^{(k)} + g^{(k)}||$$

• This converts the minimax problem into

minimize
$$\eta$$

subject to: $||T(\omega_i)d^{(k)} + g^{(k)}|| \le \eta$ for $\{\omega_i\} \subseteq [\omega_a, \pi]$
 $Ad \le b$

$$\begin{bmatrix} C^{(k)} \\ D \end{bmatrix} d = \begin{bmatrix} u^{(k)} \\ v^{(k)} \end{bmatrix}$$

which is an SOCP problem.

5. Experimental Results

5.1 Comparison with designs by Smith-Barnwell's method

Filter H ₀ (z)		Largest Eq. Error
N = 8	<i>H</i> ₀ (<i>z</i>) of [2]	8.3168×10^{-8}
	Refined $H_0(z)$	< 10 ⁻¹⁵
N = 16	<i>H</i> ₀ (<i>z</i>) of [2]	2.6356×10^{-6}
	Refined $H_0(z)$	< 10 ⁻¹⁵
N = 32	<i>H</i> ₀ (<i>z</i>) of [2]	2.1623×10^{-6}
	Refined $H_0(z)$	< 10 ⁻¹⁵



5.2 LS and minimax designs with N = 96 and L = 0, 1, ..., 5

Least squares with N = 96, $\omega_a = 0.56\pi$

L	Energy in Stopband	Largest Equation Error
0	5.6213×10^{-10}	< 10 ⁻¹⁵
1	5.6660×10^{-10}	< 10 ⁻¹⁵
2	5.6660×10^{-10}	< 10 ⁻¹⁵
3	5.8954×10^{-10}	< 10 ⁻¹⁵
4	5.8954×10^{-10}	< 10 ⁻¹⁵
5	6.2901×10^{-10}	7.6190×10^{-10}

Minimax with N = 96, $\omega_a = 0.56\pi$

	Instantaneous Energy in Stopband	Largest Equation Error
0	2.8649×10^{-9}	< 10 ⁻¹⁵
1	3.0323×10^{-9}	8.8247×10^{-7}
2	3.0654×10^{-9}	2.5128×10^{-5}
3	3.4075×10^{-9}	1.0654×10^{-6}
4	3.1281×10^{-9}	4.0553×10^{-7}
5	3.7121×10^{-9}	1.0982×10^{-5}

Minimax design with N = 96, L = 3, $\omega_a = 0.56\pi$:

