with $[f]_0 = f(+0) - f(-0)$. It is interesting to note that the conditions in eqns. 14 and 15 are decoupled when $\xi_c = 0$, and they are easily reduced to two separate conditions for the E_z^{ext} and H_z^{ext} components in the case of a nonchiral thin dielectric slab.

 31 March 1998

Electronics Letters Online No: 19980869

M.A. Lyalinov and A.H. Serbest (*Department of Electrical and Electronics Engineering, Faculty of Engineering and Architecture, Çukurova University, Balcali, Adana, Turkey*)

M.A. Lyalinov: On leave from Department of Mathematical Physics, Institute of Physics, St. Petersburg University, Petergoff, Russia

References

1 LINDELL, I.V., SIHVOLA, A.H., TRETYAKOV, S.A., and VIITANEN, A.J.: 'Electromagnetic waves in chiral and bi-isotropic media' (Artech House, Boston, 1994)

2 BASSIRI, S., ENGHETA, N., and PAPAS, C.H.: 'Dyadic Green's function and dipole radiation in chiral media', *Alta Freq.*, 1986, pp. 83–88

3 ROJAS, R.G., and CHOU, L.M.: 'Generalized impedance/resistive boundary conditions for a planar slab'. Proc. 1991 URSI Radio Science Meeting, London, Ontario, Canada, June 1991, pp. 358

4 HOPPE, D.J., and RAHMAT-SAMII, Y.: 'Impedance boundary conditions in electromagnetics' (Taylor and Francis, Washington DC, 1995)

5 PELET, P., and ENGHETA, N.: 'The theory of chirowaveguides', *IEEE Trans. Antennas Propag.*, 1990, **AP-38**, (1), pp. 90–98

Adaptive filter bank reconstruction using fast multichannel RLS algorithms

Dah-Chung Chang and Wen-Rong Wu

The recursive least-squares (RLS) algorithm has been used in the adaptive synthesis filter bank for fast convergence. However, because of interpolation operations involved in the synthesis process, fast RLS algorithms cannot be applied. In this Letter, an approach is proposed that can formulate subband signal reconstruction as a multichannel filtering problem. This formulation allows the application of fast multichannel RLS algorithms and substantial reduction in computational complexity.

Introduction: Many design methods have been developed to achieve perfect reconstruction for a subband system. However, most designs assume that the output of the decimators is identical to the input of the expanders; in other words, that subband signals are free of any distortions. Unfortunately, in practical applications, this assumption is often invalid. For example, subband signals may be distorted by additive noise due to quantisation, by channels due to transmission, or by filters due to signal processing. Although some designs have considered the quantisation noise problem [1, 2], they are not general enough to encompass other applications. A more useful approach is to use an adaptive synthesis filter bank [3, 4]. It is known that the recursive least squares (RLS) algorithm has a fast convergence rate but requires extensive computation. Fast RLS algorithms, which can substantially reduce computation, have been developed. However, Paillard *et al.* [4] have pointed out that the fast RLS algorithms cannot be directly applied due to the interpolation operations involved in the synthesis process. In this Letter, we propose a new algorithm overcoming this problem.

Proposed reconstruction algorithm: An M-band filter bank system including channel and noise distortion is depicted in Fig. 1. The reconstruction signal $\hat{x}(n)$ in Fig. 1 can be expressed as

$$\hat{x}(n) = \sum_{i=0}^{M-1} \sum_{k=-\infty}^{\infty} f_i(n - Mk) z_i(k) \qquad (1)$$

where $f_i(n)$ denotes the nth coefficient of the ith synthesis filter. Let $n = Mm + l$. Then, we have

$$\hat{x}(n) = \hat{x}(Mm + l) = \hat{x}_l(m) \qquad (2)$$

where $\hat{x}_l(m)$ are the polyphase components of $\hat{x}(n)$ for $l = 0, 1, ..., M - 1$. Using this representation, we can rewrite eqn. 1 as

$$\begin{aligned}\hat{x}_l(m) &= \sum_{i=0}^{M-1} \sum_{k=-\infty}^{\infty} f_i(Mm - Mk + l) z_i(k) \\ &= \sum_{i=0}^{M-1} \sum_{k=-\infty}^{\infty} f_{li}(m - k) z_i(k) \\ &= \sum_{i=0}^{M-1} \left[\sum_{k=0}^{K-1} f_{l_i}(k) z_i(m - k) \right] \qquad (3)\end{aligned}$$

where $f_{li}(m) = f_i(Mm+l)$ are the polyphase components of $f_i(n)$. Here we assume that all $f_i(n)$s have length L, and that $K = L/M$ is an integer. Eqn. 3 indicates that the output signal $\hat{x}_l(m)$ can be seen as a result of multichannel filtering. There are M channel input signals $z_i(m)$ and M filters $f_{li}(m)$, $i = 0, 1, ..., M - 1$. To have a compact form, we express eqn. 3 as a product of two vectors. We define $\mathbf{f}_l = [\mathbf{f}_{l,0}^T\ \mathbf{f}_{l,1}^T \cdots \mathbf{f}_{l,M-1}^T]_{L\times 1}^T$ and $\mathbf{z}(m) = [\mathbf{z}_0^T(m)\ \mathbf{z}_1^T(m) \cdots \mathbf{z}_{M-1}^T(m)]_{L\times 1}^T$ where $\mathbf{f}_{l,i} = [f_{li}(0)\ f_{li}(1) \cdots f_{li}(K-1)]_{K\times 1}^T$ and $\mathbf{z}_i(m) = [z_i(m)\ z_i(m-1) \cdots z_i(m - K + 1)]_{K\times 1}^T$. Then, eqn. 3 can be written as

$$\hat{x}_l(m) = \mathbf{f}_l^T \cdot \mathbf{z}(m) \qquad (4)$$

After we obtain the polyphase components $\hat{x}l(m)$ for $l = 0, 1, ..., M-1$, the output signal $\hat{x}(n)$ can be reconstructed using a multiplexer. The reconstruction structure is depicted in Fig. 2.

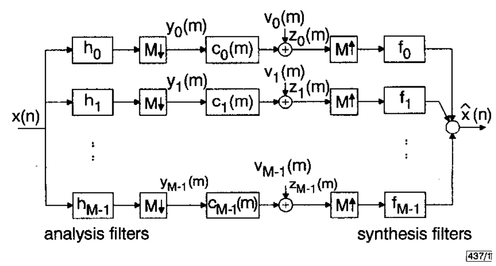

Fig. 1 *M-band analysis/synthesis filter bank system*

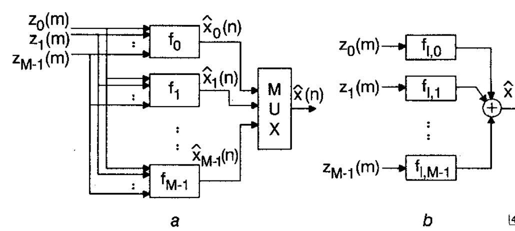

Fig. 2 *New subband reconstruction structure and structure of block* $\mathbf{f}_l$

a New subband reconstruction structure
b Structure of block $\mathbf{f}_l$

Our formulation is similar to that presented in [4]; however, the difference is that ours is a multichannel approach while the previous formulation is a single channel approach. The single channel formulation does not allow the use of fast RLS algorithms. This is why only the LMS algorithm was considered in [4]. Using our formulation, we can apply the fast multichannel RLS algorithm called the block step-up step-down (B-SUSD) algorithm [5] to find the optimal synthesis filter bank. To prevent the numerical stability problem, a stabilised version of the fast algorithm is usually required in practical implementation. The computational complexity of the stabilised B-SUSD FRLS algorithm is of the order of $O(6ML)$ while that of the standard RLS algorithm is $O(2L^2)$. The stabilised B-SUSD algorithm is shown below.

Initials

$\mathbf{w}_L(0) = \mathbf{f}_l(0) := \mathbf{0}_{L\times 1}$, $A(0) = B(0) := \mathbf{0}_{L\times M}$, $\alpha_M(0) := 1$,
$\alpha_M^f(0) = \alpha_M^b(0) := I_{M\times M}$, $K_i := 1$, $i = 1, 2, 3$

Time updating of the Kalman gain

$\mathbf{e}_M^f(m+1) = \tilde{\mathbf{z}}_M(m+1) - A^T(m)\mathbf{z}_L(m)$
$\beta_M^f(m+1) = \lambda^{-1}\alpha_M^{f,-1}(m)\mathbf{e}_M^f(m+1)$
$\epsilon_M^f(m+1) = \mathbf{e}_M^f(m+1)/\alpha_M(m)$

$$\mathbf{T}\mathbf{w}_{L+M}(m+1) = \begin{bmatrix} \mathbf{0} \\ \mathbf{w}_L(m) \end{bmatrix} + \begin{bmatrix} I_{M\times M} \\ -A(m) \end{bmatrix} \beta_M^f(m+1)$$

Partition $\begin{bmatrix} \mathbf{c}_L(m+1) \\ \delta_M(m+1) \end{bmatrix} := \mathbf{S}\mathbf{w}_{L+M}(m+1)$

$A(m+1)=A(m) + \mathbf{w}_L(m)\epsilon_M^{fT}(m+1)$

$\mathbf{w}_L(m+1) = \mathbf{c}_L(m+1) + B(m)\delta_M(m+1)$

$\hat{\mathbf{e}}_M^b(m+1) = \tilde{\mathbf{z}}_M(m+1-L) - B^T(m)Z_L(m+1)$

$\tilde{\mathbf{e}}_M^b(m+1) = \lambda\alpha_M^b(m)\delta_M(m+1)$

$\mathbf{e}_M^{b,i}(m+1) = K_i\hat{\mathbf{e}}_M^b(m+1) + (1-K_i)\tilde{\mathbf{e}}_M^b(m+1),\ i = 1, 2, 3$

$\alpha_{M+L}(m+1) = \alpha_M(m) + \mathbf{e}_M^{fT}(m+1)\beta_M^f(m+1)$

$\alpha_M(m+1) = \alpha_{M+L}(m+1) - \mathbf{e}_M^{b,1,T}(m+1)\delta_M(m+1)$

$\epsilon_M^{b,i}(m+1) = \mathbf{e}_M^{b,i}(m+1)/\alpha_M(m+1),\ i = 2, 3$

$B(m+1) = B(m)+\mathbf{w}_L(m+1)\epsilon_M^{b,2,T}(m+1)$

$\alpha_M^f(m+1) = \lambda\alpha_M^f(m) + \mathbf{e}_M^f(m+1)\epsilon_M^{fT}(m+1)$

$\alpha_M^b(m+1) = \lambda\alpha_M^b(m) + \mathbf{e}_M^{b,3}(m+1)\epsilon_M^{b,3,T}(m+1)$

Time updating of the synthesis filter bank

For $l = 0$ to $M - 1$ Do

$e_l(m+1) = d_l(m+1) - \mathbf{z}_L^T(m+1)\mathbf{f}_l(m)$

$\epsilon_l(m+1) = e_l(m+1)/\alpha_M(m+1)$

$\mathbf{f}_l(m+1)=\mathbf{f}_l(m) + \mathbf{w}_L(m+1)\epsilon_l(m+1)$

End For

Permutation matrices **T** and **S** are defined such that

$$\mathbf{z}_{L+M}(m) = \mathbf{T}^T \begin{bmatrix} \tilde{\mathbf{z}}_M(m) \\ \mathbf{z}_L(m-1) \end{bmatrix} = \mathbf{S}^T \begin{bmatrix} \mathbf{z}_L(m) \\ \tilde{\mathbf{z}}_M(m-L) \end{bmatrix}$$

where $\tilde{\mathbf{z}}_M(m) = [z_0(m)z_1(m)\ \dots\ z_{M-1}(m)]^T$.

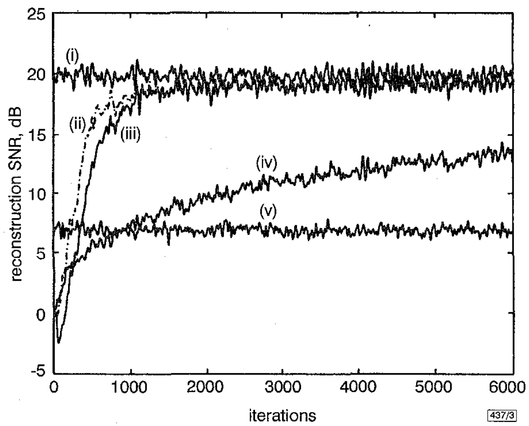

Fig. 3 *Learning curves for reconstructing AR(1) signal with input SNR = 30dB*

(i) Wiener filter
(ii) RLS algorithm
(iii) stabilised B-SUSD FRLS algorithm
(iv) LMS algorithm
(v) conventional synthesis filtering

Simulations: To demonstrate the effectiveness of the proposed adaptive reconstruction filter bank, a 55 tap five band system is implemented. The subband noise is assumed to be white Gaussian (SNR = 30 dB) and the channel to be $\mathbf{c}_i$ = [–0.077, –0.355, 0.059, 1, 0.059, –0.273]. The input is a first-order AR signal with a correlation coefficient of 0.8. Fig. 3 shows the learning curves for serveral algorithms. As we can see, while the convergence of the stabilised B-SUSD FRLS algorithm is slightly slower than that of the standard RLS algorithm, it is much faster than the LMS algorithm. Also, the reconstruction SNR of the stabilised B-SUSD FRLS algorithm is almost identical to that of the standard RLS algorithm. The reconstruction SNR for the LMS algorithm is much lower. The conventional synthesis filter bank has the worst performance since it does not consider the distortion of subband signals.

13 March 1998

Electronics Letters Online No: 19980877

Dah-Chung Chang and Wen-Rong Wu (*Department of Communication Engineering, National Chiao Tung University, Hsinchu, Taiwan 30050, Republic of China*)

E-mail: wrwu@cc.nctu.edu.tw

References

1 GOSSE, K., SAINT-MARTIN, F.M., and DUHAMEL, P.: 'Filter bank design for minimum distortion in presence of subband quantization'. Proc. 1996 ICASSP, May 1996, pp. 1491–1494

2 HADDAD, R.A., and PARK, K.: 'Modeling, analysis, and optimum design of quantized M-band filter banks', *IEEE Trans. Signal Process.*, 1995, **SP-43**, (11), pp. 2540–2549

3 DELOPOULOS, A.N., and KOLLIAS, S.D.: 'Optimal filter banks for signal reconstruction from noisy subband components', *IEEE Trans. Signal Process.*, 1996, **SP-44**, (2), pp. 212–224

4 PAILLARD, B., SOUMAGNE, J., MABILLEAU, P., and MORISSETTE, S.: 'Subband decomposition: An LMS-based algorithm to approximate the perfect reconstruction bank in the general case', *IEEE Trans. Signal Process.*, 1991, **SP-39**, (1), pp. 233–238

5 GLENTIS, G.O., and KALOUPTSIDIS, N.: 'Fast adaptive algorithms for multichannel filtering and system identification', *IEEE Trans. Signal Process.*, 1992, **SP-40**, (10), pp. 2433–2458

Disparity estimation using edge-oriented classification in the DCT domain

C.L. Pagliari and T.J. Dennis

A disparity estimation algorithm for stereo images is proposed, which attempts to achieve robustness to scene characteristics. Area-based matching is guided by an orientation classification derived from discrete cosine transform coefficient characteristics over small blocks.

Introduction: In this Letter, we use edge-oriented classification in the discrete cosine transform (DCT) domain, to aid in the task of finding the binocular disparities between a stereo image pair. A similar process is used in classified vector quantisation [1]. The main advantage is that the most likely matching points, those having the same edge orientation, are then known and hence the search range can be significantly reduced.

C(0,0)	C(0,1)	C(0,2)	C(0,3)
C(1,0)	C(1,1)	C(1,2)	C(1,3)
C(2,0)	C(2,1)	C(2,2)	C(2,3)
C(3,0)	C(3,1)	C(3,2)	C(3,3,)

956/1

Fig. 1 *4×4 DCT coefficient labelling*

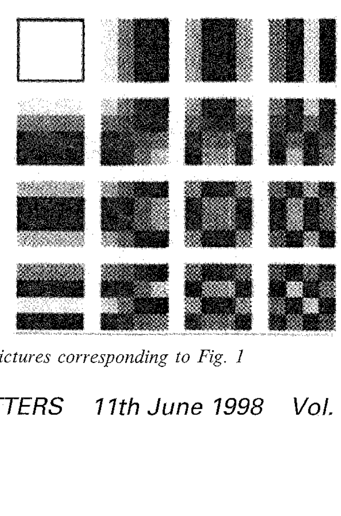

Fig. 2 *Basis pictures corresponding to Fig. 1*