A Genetic Search Algorithm for Linear-Phase Filter Banks

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Abstract. A genetic algorithm is presented for searching optimization parameters in the factorization matrices in linear-phase filter banks. The genetic algorithm is combined with the simplex algorithm to accelerate the design process. The newly algorithm alleviates the problem of being trapped in local minimums, as the initial parameters are selected by the genetic algorithm. Less human interactions are required in the design of filter banks, especially when impulse responses are long. The experimental results show that the proposed algorithm is robust in the optimization of the filter coefficients. Design results of filter banks with 8 channels are included.

Introduction

Filter banks have drawn increasing attentions lately in image processing and biomedical engineering [1]-[5]. Wavelets and filter banks have also been used in power systems in electrical engineering. A method of power quality disturbances hierarchical identification which combines conversion, wavelet transform energy distribution and fuzzy nearness was proposed in [6]. An implementation for analyzing real time current and voltage signal harmonics for non-linear loads using wavelet transform based on virtual instrument concept was demonstrated in [7]. In [8], an adaptive wavelet filter banks and neural network (AWNN) based technique for low-order dominant harmonics estimation was described. An extensive review of applications of wavelets and filter banks in the measurement and analysis of harmonic distortion in power systems was given in [9].

In this paper, the design of analysis and synthesis filters in filter banks with FIR responses and linear-phase property is revisited by using genetic algorithm. In the design of filter banks, the number of parameters increases with filter length and number (M) of channels. Local minimums hinder the optimization programs from searching further especially when the number of design parameters becomes very large. The proposed approach is efficient as it combines genetic search with simplex optimization to mitigate the problem of local minimums. The initial parameters of simplex optimization are selected by the genetic algorithm. The experimental results show the proposed algorithm converges fast, and less human interactions are required in the design process.

Multirate Filter Banks

Fig. 1 shows analysis/synthesis systems in a filter bank, where analysis and synthesis filters are denoted as $H_k(z)$, $0 \le k \le M-1$ and $F_k(z)$, $0 \le k \le M-1$, respectively. The expression for the reconstructed signal $\hat{X}(z)$ is of the form [1].

$$\hat{X}(z) = \frac{1}{M}\sum_{\ell=0}^{M-1} X(zW^{-\ell})\sum_{i=0}^{M-1} H_i(zW^{-\ell})F_i(z), \tag{1}$$

where $W = e^{-j2\pi/M}$. The aliasing items are represented by $X(zW^{-\ell})\sum_{i=0}^{M-1} H_i(zW^{-\ell}) \ F_i(z), \ell \ne 0$.

As shown above, there are several kinds of distortion sources in maximally decimated filter banks: aliasing/imaging, amplitude and phase distortions. In the past decades, much effort has been devoted to this area to achieve a perfect-reconstruction property [1]. In a perfect-reconstruction filter bank, the overall transfer function is a pure delay,

$$T(z) = kz^{-r}, \tag{2}$$

where k is a constant and r is an integer. The initial solutions allowing perfect reconstruction were addressed for the two-channel case. In the general case of an arbitrary number (M) of channels, a useful analysis tool is the polyphase representation.

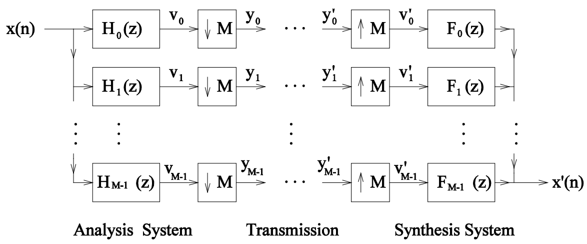

Figure 1. Analysis and synthesis subsystems in a filter bank

Let the filters $H_i(z) = \sum_{n=-\infty}^{\infty} h_i(n) z^{-n}$, $0 \le i \le M-1$ be written as [1]

$$H_i(z) = \sum_{l=0}^{M-1} z^{-l} E_{i,l}(z^M), \tag{3}$$

where $E_{i,l}(z)$ are the z-transforms of the M-fold decimated filters $e_{i,l}(n)$ defined by $e_{i,l}(n) = h_i(nM + l)$, $0 \le l \le M-1$. Equation (3) is referred to as Type 1 polyphase representation and $E(z) = (E_{i,l}(z))$ is the polyphase matrix [1]. The filters $H_i(z) = \sum_{n=-\infty}^{\infty} h_i(n) z^{-n}$, $0 \le i \le M-1$ can also be expressed as

$$H_i(z) = \sum_{l=0}^{M-1} z^{-(M-1-l)} G_{i,l}(z^M), \tag{4}$$

where $G_{i,l}(z) = E_{i,M-1-l}(z)$. Equation (4) represents a variation of (3) by reversing the order of the polyphase components $E_{i,l}(z)$ and is defined as Type2 polyphase representation [1].

Genetic Search

A straightforward searching approach is based on the simplex algorithm (SA). A simplex is the geometrical figure consisting of $N+1$ points (vertices) in N dimensions and all their interconnecting line segments and polygonal faces. In recent years, genetic algorithms (GA) have emerged as a robust optimization approach for locating global maximums or minimums in any arbitrary search space. Genetic algorithms mimic the mechanisms of evolution and natural genetics and have also found applications in areas of genetic synthesis, VLSI design, and machine learning.

The proposed approach combines genetic algorithm and simplex optimization for the design of filter banks. In the application, the multi-dimensional space (S) to be searched consists of chromosome vectors C. Each chromosome C represents a possible set of planar rotation angles corresponding to a possible solution for the design of filter banks. The proposed genetic search for linear-phase filter banks has the following characteristics.

a) Initial population - The genetic structures are based on the lattice structures. The length K of chromosome $C = (\theta_1, \theta_2, \ldots, \theta_K)$ is depended on the free parameters. The initial population of all the chromosomes (search points) is selected from a random number generator with uniform deviates within $(-\pi, \pi]$.

b) Evaluation -- The fitness value of each chromosome is evaluated. There are n chromosomes to be selected from N chromosomes for reproductions,

$$\Omega(C_1) \geq \Omega(C_2) \geq \ldots \geq \Omega(C_n) \geq \Omega(C_{n+1}) \geq \ldots \geq \Omega(C_N). \quad (5)$$

c) Crossover and mutation - Group θ_j, $1 \leq j \leq K$ in $C = (\theta_1, \theta_2, \ldots, \theta_K)$ in subsets C_i. Exchange the subsets C_i with a crossover rate of 0.3. Flip the sign of θ_j, $1 \leq j \leq K$ in $C = (\theta_1, \theta_2, \ldots, \theta_K)$ with a mutation rate of 0.005.

d) Searching - The simplex optimization program is employed to searching "better" chromosomes from each of the n chromosomes.

e) Repeat step b)-d) until a chromosome corresponding to a filter bank with desired frequency responses is achieved.

Fig. 2 shows the magnitude response plots for an 8-channel linear-phase filter bank with 32 taps. Table 1 shows the impulse responses of 8-channel filter banks. In the new algorithm, the problem of local minimums has been alleviated.

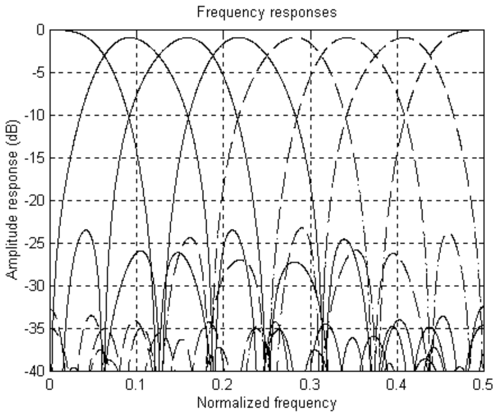

Figure 2. An 8-channel linear phase filter bank

Conclusion

A new design algorithm is presented for linear-phase filter banks based on genetic algorithms. The newly proposed approach helps to accelerate the design process and alleviate the problem of being trapped in local minimums. This is due to the initial points selected by the genetic algorithm. Experiments show that less human interactions are required in designing filter banks, especially when impulse responses are long.

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Table 1. Impulse responses of 8-channel filter banks

n	$h_0(n)$	$h_1(n)$	$h_2(n)$	$h_3(n)$
0	-0.005336	0.013032	-0.011571	-0.002494
1	-0.005108	0.005148	-0.004309	-0.000623
2	-0.006042	0.008393	-0.003295	0.006699
3	-0.015215	0.004426	0.001650	0.003358
4	-0.021915	0.035720	-0.017008	0.024019
5	0.009044	0.030617	-0.048899	-0.026869
6	0.018585	0.012751	-0.046939	-0.076080
7	0.043321	-0.040332	0.035753	0.012693
8	0.093588	-0.118828	0.119920	0.124015
9	0.112551	-0.153744	0.116121	0.059580
10	0.132910	-0.131523	-0.015586	-0.144894
11	0.140054	-0.052020	-0.166959	-0.114357
n	$h_4(n)$	$h_5(n)$	$h_6(n)$	$h_7(n)$
0	0.001050	0.005861	0.007994	-0.002069
1	-0.001498	-0.005324	-0.006040	0.004789
2	-0.007094	0.000903	0.005996	-0.003100
3	0.006228	0.001431	-0.005509	0.015985
4	-0.028193	0.004697	0.026283	-0.015613
5	-0.026063	-0.051136	-0.038538	-0.008565
6	0.076924	0.046099	0.014699	0.009734
7	-0.001581	0.035927	0.049773	-0.047041
8	-0.132892	-0.140030	-0.113126	0.080031
9	0.037724	0.114625	0.158983	-0.110656
10	0.152508	0.020681	-0.119958	0.127193
11	-0.100508	-0.139821	0.055651	-0.148909

References

[1] P. P. Vaidyanathan: *Multirate Systems and Filter Banks*, edited by Englewood Cliffs: Prentice-Hall, NJ (1993).

[2] Q. Luo, P. Li, Q. Ren, H.. He: *Optimization design of biorthogonal filter bank for image compressing* (in Proc. Int. Symp. Information Science and Engieering, p. 539-543, 2008).

[3] Y. Wei and D.-B. Liu: *A design of digital FIR filter banks with adjustable subband distribution for hearing aids* (In Proceeding of 8th International Conference on Information, Communications and Signal Processing (ICICS) , p. 1-5, 2011).

[4] Y. Lian and Y. Wei: A computationally efficient nonuniform FIR digital filter bank for hearing aids, IEEE Trans. Circuits and Systems I: Reg. Pap Vol. 52(2005), no.12, p. 2754-2762.

[5] J.-B. Maj, L. Royackers, M. Moonen, and J. Wouters: SVD-based optimal filtering for noise reduction in dual microphone hearing aids: A real time implementation and perceptual evaluation, IEEE Trans. Biomed. Engineer Vol. 52(2005), no.9, p. 1563-1573.

[8] D. Li, X. Yu, X. Wang, and T. Tang: *Power quality disturbances fuzzy identification based on DQ conversion and wavelet energy distribution* (In Proceeding of Second Int. Conf. Instrumentation, Measurement, Computer, Communication and Control (IMCCC), p. 1403-1407, Dec. 8-10, 2013).

[9] P. Roy, S. Saha, M. K. Ray, M. Chattopadhyay, and P. Acharjee: *Real time monitoring and analysis of signal harmonics for non-linear loads using virtual instrument* (In Proceeding of Int. Conf. Advances in Engineering, Science and Management (ICAESM), p. 516-521, 30-31, Mar. 2013).