

A Multiobjective Genetic Algorithm for the Design of Asymmetric FIR Filters

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OVERVIEW

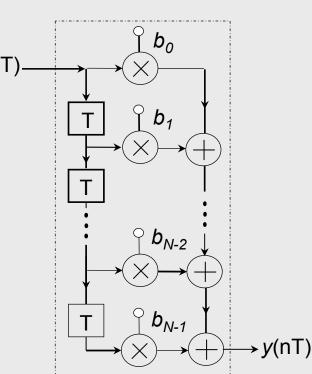


- Introduction
- Classical vs. genetic optimization
- Multiobjective optimization
- The elitist nondominated sorting genetic algorithm approach
- Design example
- Conclusions



INTRODUCTION

- FIR filters are usually designed with symmetric coefficients to achieve linear phase response with respect to the baseband, i.e., b₀ = b_{N-1}, b₁ = b_{N-2}, etc.
 - Efficient design methods are available, e.g., window method, Remez algorithm
 - Large group delay



FIR Filter





INTRODUCTION (Cont'd)



- Filters with Asymmetric Coefficients
 - Approximately linear phase response in passband
 - Relatively small group delay
 - Can be designed by using classical optimization methods with a multiobjective formulation.
 - Can also be designed by using a multiobjective genetic algorithm (GA) known as the *elitist nondominated sorted GA* (ENSGA).



CLASSICAL OPTIMIZATION ALGORITHMS

- Fast and efficient
- Very good in obtaining local solutions
- Unbeatable for the solution of convex (concave) problems
- In multimodal problems, they tend to zoom to a solution in the locale of the initialization point.
- Not equipped to discard inferior local solutions in favour of better solutions.



GENETIC ALGORITHMS



- Are very flexible, nonproblem specific, and robust.
- Can explore multiple regions of the parameter space for solutions simultaneously.
- Can discard poor local solutions in favour of more promising subsequent local solutions.
- They are more likely to obtain better solutions for multimodal problems than classified methods.





- Owing to the heuristic nature of GAs, arbitrary constraints can be imposed on the objective function without increasing the mathematical complexity of the problem.
- Multiple objective functions can be optimized simultaneously.
- They require a very large amount of computation.





- In many applications, several objective functions need to be optimized simultaneously.
- In classical optimization, multiple objective functions are used to construct a more complex unified objective function with or without constraints.
- On the other hand, with GAs multiple objective functions can be optimized directly to obtain a set of compromise solutions of the problem at hand.





• A multiobjective optimization problem with *k* objective functions can be represented as:

Minimize $\mathbf{f}(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), ..., f_k(\mathbf{x})]$ subject to $\mathbf{x} \in \mathbf{X}$ where \mathbf{X} is the solution space

- A set of compromise solutions obtained by multiobjective approaches is known as a *Pareto optimal* solution set.
- The user can select the best compromise solution from a Pareto-optimal set.



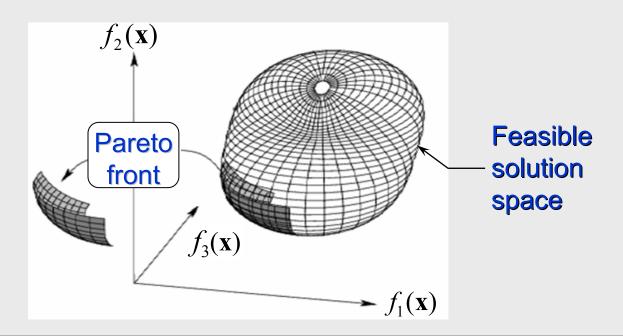


- A solution *x*₁ *is said to dominate a solution x*₂ if the following conditions hold:
 - Solution x_1 is no worse than x_2 for all objectives
 - Solution x_1 is strictly better than x_2 in at least one objective
- A solution that is not dominated by any other is said to be a *nondominated solution*.
- A set of nondominated solutions in the solution space is a *Pareto-optimal* solution set.





- The nondominated set of the entire feasible solution space is the *globally Pareto-optimal* set.
- The solution space corresponding to the Pareto optimal solution set is called the *Pareto front*.







- ENSGA introduces diversity in solutions by sorting the population according to the nondomination principle.
- classifies the population into a number of mutually exclusive classes
- assigns highest fitness to the members of the class that are closest to the Pareto-optimal front
- uses the elitism principle to increase the number of Pareto solutions.



ENSGA STEPS



Initialize population

Evaluate fitness of individuals

Select nondominated solutions

by using *nondominated sorting*

by assigning fitness values according to *crowding distance*

Perform crossover to obtain new offsprings

Mutate individuals in the offspring population

Evaluate offspring solutions

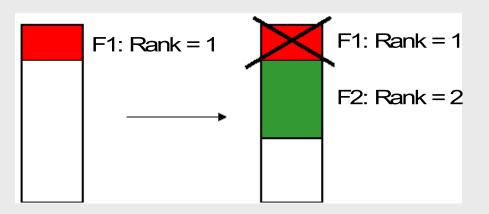
Perform *elitist replacement*



NONDOMINATED SORTING



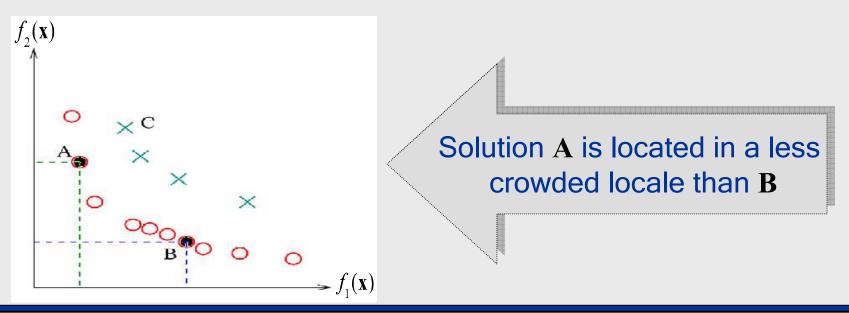
- Identify the best nondominated set.
- Discard the nondominated solutions from the population temporarily.
- Identify the next best nondominated set.
- Continue till all solutions are classified.



CROWDING DISTANCE



- Crowding distance is a diversity metric.
- Crowding distance is defined as the front density in a specific locale.
- Each solution is assigned a crowding distance.
- Solutions located in a less crowded space are preferred.

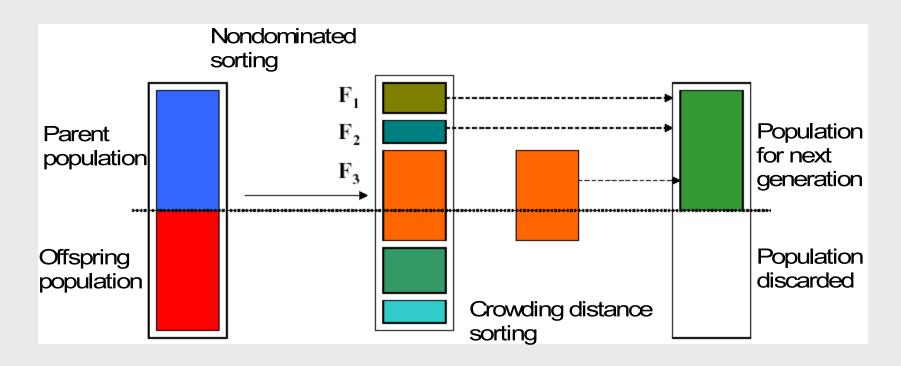




ELITIST REPLACEMENT



- Combine parent and offspring populations.
- Select better ranking individuals and use crowding distance to break any ties.







- A population of potential solutions is created from an initial least-squares solution.
- *Simulated binary crossovers* and *polynomial mutations* are applied according to predefined probabilities of occurrence, P_x and P_m , respectively.
- The objective functions used to evaluate the fitness of the individual solutions are based on the amplitude response and group-delay errors.
- The ENSGA is terminated after a prespecified number of generations.





- Chromosome (*candidate solution*) :
 - The coefficient vector of the FIR filter, **b**, is used as the candidate solution.
 - To avoid very long binary strings, a floating-point representation is used in encoding the chromosomes.



OBJECTIVE FUNCTION



- Three objective functions have been used:
 - L_{∞} norm of the passband amplitude-response error $F_p = \max \left| 1 - H(e^{j\omega}) \right|$ for $\omega \in \text{Passband}$
 - L_2 norm of the stopsband amplitude-response error with a constrained imposed on the peak error

$$F_a = \sum_{k=1}^{K_a} \left| H(e^{j\omega_k}) \right|^2 \quad \text{for } \omega_k \in \text{Stopband}$$

subject to $\min\left\{-20 \log_{10} |H(e^{j\omega_k})|\right\} \ge \delta_a \, \mathrm{d}B$

- A parameter Q which measures the degree of flatness of the passband group-delay characteristic $Q = \frac{100(\tau - \tau)}{(\tau + \tau)}$



DESIGN EXAMPLE



• Specifications: Highpass FIR filter,

$$\omega_a = 0.4, \ \omega_p = 0.55, \ \omega_s = 1 \text{ rad/s},$$

 $\delta_a = 52 \ dB, \ \ \tau = \frac{\tau + \tau}{2} \le 16.5, \ N = 35$

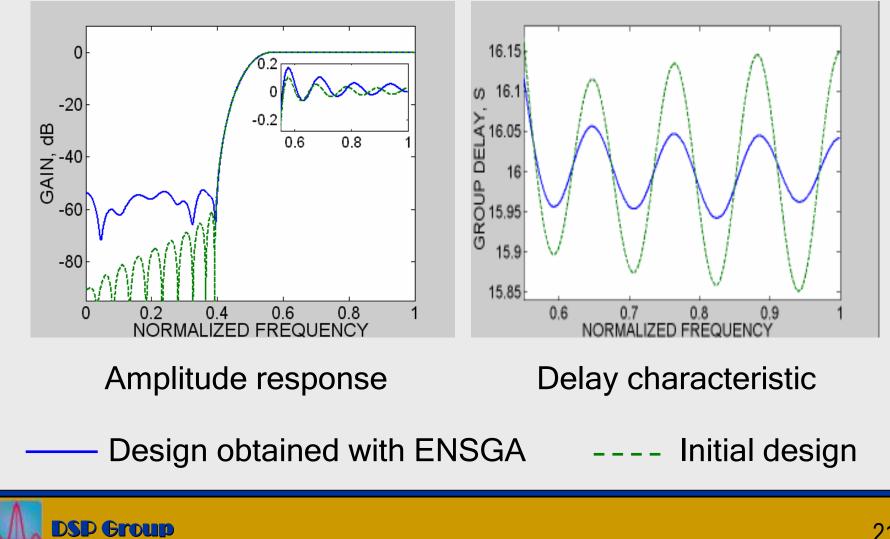
- Initialization: An FIR filter with nonsymmetric coefficients designed using a weighted leastsquares method was used as the initial design.
- **Solutions:** The next two slides give the results for two solutions from the Pareto-optimal solution set.



DESIGN EXAMPLE (Cont'd)



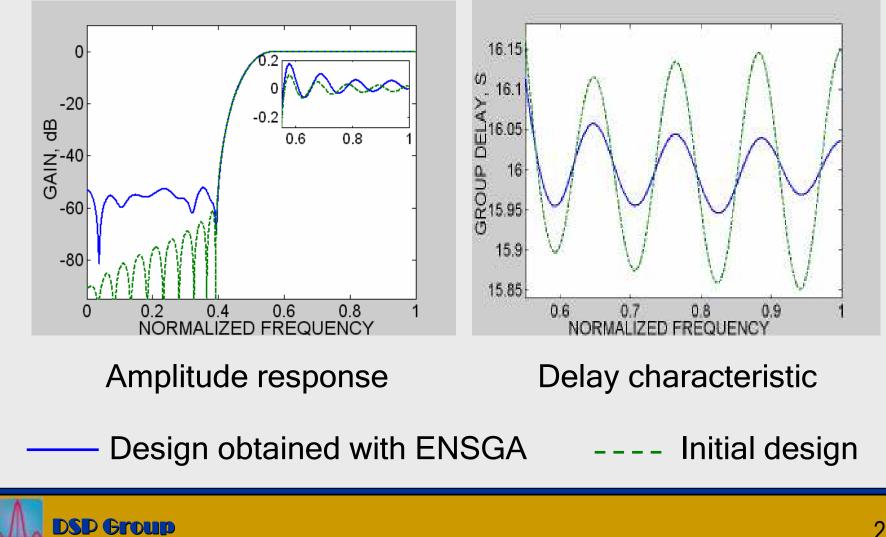
Solution 1:



DESIGN EXAMPLE (Cont'd)

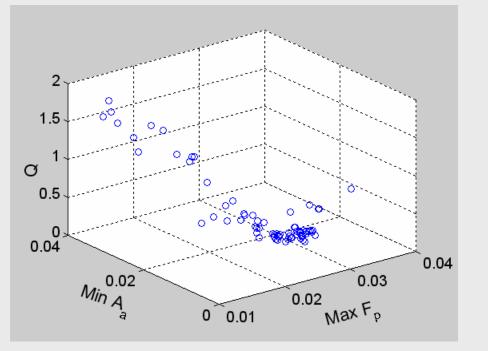


Solution 2:





3-D scatter plot of the Pareto-optimal solutions obtained by using the ENSGA



 $A_a = -20 \log_{10} |H(e^{j\omega})|$ for $\omega \in \text{Stopband}$



CONCLUSIONS



- The ENSGA can be used to design nonsymmetric FIR filters that would satisfy multiple requirements imposed on the amplitude response and the delay characteristic.
- The approach yields an improved design with respect to the initial weighted least-squares design.
- The design that is best-suited to a specific application can be chosen from the set of Paretooptimal solutions obtained.
- In common with other GAs, the ENSGA requires a large amount of computation. However, this is not a serious problem unless the filter design has to be carried out in real or quasi-real time.







Thank you

