Robust Methods for Engineering Design Optimization

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Outline

- Introduction
- Robust Algorithms for Design Optimization
- Example Applications
- Application to ADVENTURE project
- Conclusion & Future Work
Introduction

• Design optimization coupled with accurate computer simulation and large computer resources allow for better designs in a shorter time with less experienced engineers

• Objective: find values for design variables that either minimize or maximize one or many global objectives while satisfying a number of user specified equality and inequality constraints

• Classical mathematical optimization methods (mostly gradient based) don’t work well for most current engineering applications

What is Robust?

• Black box - problem independent

• Handle noisy analysis code (unstructured meshes)

• Meet multiple constraints, including equality constraints

• Handle failure of analysis codes without breaking down

• Deal with discontinuous design space (objectives, constraints, discrete variables)

• Efficient – allow for computationally expensive analysis codes

• Use of any analysis code without need for extensive modification in either code

• Take full advantage of available computer resources (distributed heterogeneous parallel platforms)
Popular Robust Algorithms

- Genetic and Evolutionary Algorithms (GA)
- Hybrid Algorithms
- Approximation based methods

Genetic and Evolutionary Algorithms

- Based on principle of survival of the fittest
- True global search algorithm that can avoid local minima
- Can handle all types of discontinuities
- Straight forward implementation of multi-objective algorithms
- Can require many function evaluations
- Many parameters that require extensive tuning by experience
Parallel Genetic Algorithm

- GA is a naturally coarse grained parallel algorithm
- One node maintains the population (master) and distributes jobs to the slave nodes
- Only simple synchronous message passing is needed to implement on distributed memory
- Population size need not match the number of slave nodes
- Asynchronous models are also being developed for use when function analysis computation times vary dramatically.

Multidisciplinary Analysis, Inverse Design, and Optimization (MAIDO)

Parallel Computer

Grendel at University of Texas at Arlington
54 Pentium III 500 MHz processors
Switched fast Ethernet
Dual Pentium systems
512 MB RAM per node

Multidisciplinary Analysis, Inverse Design, and Optimization (MAIDO)
Parallel GA Example

- Optimization of turbine stator blade shape
- Improve aerodynamic efficiency, no constraints
- Use of 3-D compressible Navier-Stokes CFD code (4 hours for 1 analysis)
- Optimization completed in 3 days on 32 processors
- Gradient search method attempted but required more than one week and achieved little design improvement and poor parallel efficiency

Optimization of Turbine Stator

- Optimized design is 3% more efficient than usual straight blade

Initial straight blade

Optimized blade
Optimization of Turbine Stator

Velocity vectors for flow at the outlet for straight blade

Velocity vectors for flow at the outlet for optimized blade

Hybrid Algorithms

- Use a combination of algorithms plus a switching strategy for searching design space
- Such algorithms may include gradient search method, a genetic algorithm (GA), the Nelder-Mead simplex method (NM), etc.
- Computationally efficient for problems with several local minima
- Some problems with robustness due to use of gradient search
- Requires esoteric heuristics based switching rules that are problem based
- Requires flexible software architecture so users can implement custom strategies easily
Flowchart of automatic switching among modules in a hybrid optimizer

Hybrid Example
- Optimization of turbine cascade (2-D) with hybrid GA/SQP
- Improve aerodynamic efficiency, 4 equality constraints, 1 inequality constraint
- GA used to minimize objective and analysis dependent constraints while SQP used to enforce geometric constraints
- Use of 2-D compressible Navier-Stokes CFD code (15 minutes for 1 analysis)
- Optimization completed in 2 days on 1 processor
- Gradient search method attempted (SQP) but could not find a single feasible design
- Hybrid algorithm enforced constraints better than GA alone
Cascade Shape Parameterization

Multidisciplinary Analysis, Inverse Design, and Optimization (MAIDO)

Results for GA/SQP Hybrid Optimization

Multidisciplinary Analysis, Inverse Design, and Optimization (MAIDO)
Approximation Based Methods

- Most current research focused here
- Algorithms based on construction of surrogate models (response surfaces) that can be evaluated quickly
- Computationally efficient
- Very robust
- Most methods don’t scale well (quadratic response surface requires $n^2$ samples to build the approximation)

Kinds of Approximations

- Kriging (Moving Least Squares)
- Polynomial (cubic, quadratic)
- Artificial Neural Networks (ANN)
- Multivariate Regression Splines
- Self-Organizing (IOSO)
- Many others
Approximation Based Strategies: IOSO

- Indirect Optimization based on Self Organization
- Stochastic optimization algorithm combine with a response surface approach
- Capable of handling multiple objectives
- Does not require derivatives of objective function or constraints
- Can handle mixed continuous and discrete design variables

IOSO Method Cont.

- This approach allows for low number of trial points to build the initial approximation (30-50 samples for 100 variables)
- This approach also allows for improvement of the response surface in a localized search area
IOSO Method Cont.

The optimization method basically works as follows:
1. Build initial approximation based on a given sample set
2. Use stochastic optimization method to find the minimum of the approximation to get a new design
3. Evaluate the new design with the full analysis code
4. Use the new results to improve the accuracy approximation in the local search area
5. Goto 2. until termination criteria is met

IOSO Example

- Multi-objective Optimization of turbine cascade (2-D) with hybrid GA/SQP
- Used conditions for an actual “human” designed airfoil (VKI) to compare IOSO design with an existing design
- Improve aerodynamic efficiency, reduce number of blades, maximize lift
- 3 equality constraints, 1 inequality constraint
- Use of 2-D compressible Navier-Stokes CFD code (15 minutes for 1 analysis)
- Optimization used 32 processors and completed in less than one day
IOSO Results

• IOSO based optimization generated a shape that improved all objectives over the original VKI airfoil. The IOSO designs met all the specified constraints as well.

![Graph showing IOSO Results](image1)

Application of Robust Optimization in ADVENTURE Project

• Couple existing and/or modified robust optimization algorithms to ADVENTURE system software
• Perform example of design optimization that involves large scale FEA via ADVENTURE modules

![Graph showing Application of Robust Optimization](image2)
Example of Structural Optimization

- Verify that the system is working by performing a simple but realistic structural optimization problem
- Objective: Minimize weight of control rod by optimizing the shape
- Constraint: Equivalent stress must not exceed yield stress
- This is a common test problem that can be found in the literature
Generation of Rod Geometry and Surface Patch

- Outer shape and inner shape are parameterized by B-splines
- Surface patches of generated automatically using Delauney triangulation
- Volume meshes of arbitrary density can by constructed automatically with ADV_TET module

Conclusions & Future Work

- Several popular robust design optimization methods were described
- Engineering examples from my research were shown to illustrate the effectiveness of these methods
- Connection between optimization software and ADVENTURE system is nearly complete
- Example problem in structural optimization will be performed soon