Visualization for Multiparameter Aircraft Designs

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ABSTRACT

We describe an aircraft design problem in high dimensional space, with D typically being 10 to 30. In some respects this is a classic optimization problem, where the goal is to find the point that minimizes an objective function while satisfying a set of constraints. However, evaluating an individual point is expensive, and the high dimensionality makes many approaches to solving the problem infeasible. The difficulty of the problem means that aircraft designers would benefit from any insights that can be provided. We discuss how simple visualizations have already proved beneficial, and then describe how visualization might be of further help in the future.

KEYWORDS: Multidimensional visualization, aircraft design, multidisciplinary design optimization.

INTRODUCTION TO AN INITIAL DESIGN PROBLEM

We describe a problem in aircraft design that should be of interest to the visualization community due to the opportunity it provides for visualization to affect the aircraft industry. However, the problem is especially difficult, and most known visualization techniques are of little help.

Typically the aircraft design process is comprised of three distinct phases: conceptual, preliminary, and detailed design. In the conceptual design stage, major design parameters for the final configuration are defined and set. Although perturbations to the initial parameter values may occur in subsequent design stages, decisions made at this stage are important since they determine approximately 80% of the aircraft life cycle cost [11].

The conceptual design phase models an aircraft with a set of values for significant parameters, relating to the aircraft geometry, internal structure, systems, and mission. Examples of such parameters include the wing span, sweep, and thickness; the fuel and wing weights; the engine thrust; and the cruise altitude and climb rate.

Individual initial designs can be (and are) viewed as a point in a multidimensional space. One design problem, the design of a High-Speed Civil Transport (HSCT), uses a design space with as many as 29 parameters [2, 10]. There are two important features to be determined for any proposed initial design point: (1) it is *feasible* if it satisfies a series of constraints, and (2) it has a value under an objective function. The goal is then to find the point with the smallest value under the objective function that is feasible. In the HSCT design, takeoff gross weight (TOGW) is chosen as the objective function because it is a rough indicator of the aircraft lifecycle cost. Constraints are organized into two groups: geometric versus aerodynamic/performance. Examples of geometric constraints include wing chord length limits and fuel volume limits to allow fuel storage in the wings. Aerodynamic constraints impose realistic performance and control capabilities. Examples include range requirements, landing angle of attack limits, and criteria to prevent wing and tail runway scrape.

These are complicated, nonlinear constraints dependent on aerodynamic forces and moments, stability and control derivatives, and weight and inertia estimates. Due to the complexity of these evaluations, many of these quantities are evaluated using simplified aerodynamic and structural models. In contrast to traditional conceptual design practices which use only simple models, computational fluid dynamics (CFD) analyses have been implemented to calculate of the range constraint for the HSCT design [9]. This simplified range calculation requires two CFD analyses per design at cruise conditions, giving the variation in drag with the lift and aircraft weight.

In some respects, this is a classic optimization problem, wherein the goal is to find that point which minimizes an objective function while meeting a series of constraints. However, this particular problem is difficult to solve for several reasons. First, evaluating an individual point to determine its value under the objective function and check if it satisfies the constraints is computationally expensive. A single aerodynamic analysis using a CFD code can take from 1/2 hour to several hours, depending on the grid used and flight condition considered. Second, the high dimensionality of the problem makes it impractical for many approaches that are often applied to difficult optimization problems. For example, genetic algorithms work poorly for this problem, since they require far too many function evaluations just to build a rich enough gene pool from which to begin the evolution. Third, the high dimensionality makes it difficult to even think about the problem spatially. Most people's intuitions about two and three dimensional space transfer poorly when considering behaviors in ten or more dimensions, or even in four dimensions. For instance, the true import of the 4-D Klein bottle is hard to grasp, and to apply in other contexts. The fact that most of the volume in a 29-D sphere lies very near the surface is exactly opposite to the situation in 2-D and 3-D.

In practice, we can only hope to ever evaluate a small fraction of the points. This is not only because evaluating a single point is expensive, but the also because the number of points is impossibly large. Consider evaluating only the points that represent combinations for the extreme ends of the range in each parameter. In three dimensions, this would be equivalent to evaluating the eight corners of a cube. In 29 dimensions, $2^{29} \approx 1/2$ billion point evaluations would be required.

SOME HEURISTIC CONSIDERATIONS

Since any sort of complete search of the design space is impractical, and since traditional approaches to solving optimization problems have so far met with little success, this problem has been attacked with a number of ad hoc heuristics.

One such method involves systematically reducing the size of the region of interest using simple and approximate constraint evaluations to rule out some candidate points as infeasible [8, 6]. First, simple geometric constraints are applied to eliminate infeasible/unreasonable designs. Then constraints are evaluated using inexpensive low fidelity disciplinary models to further weed out grossly infeasible designs. By eliminating these infeasible points and reducing the region of interest in which to look for prospective designs, computational time is saved and accuracy of function approximations made within that space is improved.

Bayesian estimation can be used to select the next candidate point for evaluation [12]. Given a set of points and function values at those points, one can ask (using Bayesian statistics) where to place another point within some box such that the prediction variance at any other point within the box is minimized. This is, in a precise sense, the "optimal" point at which to acquire more information, since it will minimize the prediction uncertainty at any other new point.

Another approach is to use fast approximations for the evaluation function. A full evaluation is first conducted on a candidate point, yielding an accurate assessment for its objective function value. Nearby points are then evaluated using the approximation. With the original value as a guide, the designer can often rely on the approximation to give a value accurate within some error estimate, such as 20% of the true value.

This brings up the issue sensitivity. In some regions of the design space, nearby points have similar values for the objective function. In other words, the "surface" is relatively smooth in some regions. However, there are other sections of the design space with a sharp gradient in the objective function value. In other words, at some points, the value of the objective function is highly sensitive to the exact values of the parameters. This is significant for two reasons. First, when the gradient is high, approximations cannot be relied upon. Second, designs near such gradients are undesirable, since minor changes imposed later in the design cycle may result in significant loss of performance for the overall design. Thus, a designer may well prefer a design point that is relatively insensitive to minor changes in the parameter values so as to allow for some flexibility in future design modifications.

At this point, it is worth noting how designers often work in practice to select new designs. Typically, they start with a region of the design space that includes a known, successful design. A design subspace around the known point is selected. Depending on the computational resources available and the judgment of the designer, the range of this subspace may be relatively small or large. The size of the subspace affects the fraction of the space that is feasible, since existing designs tend to be insensitive in the sense that small changes in any of the parameters do not lead to gross changes in the objective function, nor are such designs close to violating one or more of the constraints.

THE VISUALIZATION CHALLENGE

Given the difficulty and practical significance of the initial design problem, aircraft designers are searching both for new ways to find better design points, and for new insights into the nature of the problem itself. Visualization holds some promise of providing insights into the problem through the ability to provide new interpretations on available data. Visualization might also help, in conjunction with some form of organization for earlier point evaluations, to allow the designer to search through the design space in some meaningful way.

Thus, the challenge to the visualization community is to devise techniques that help aircraft designers during the conceptual design stage. The hope is that visualization can be used to let engineers apply their design expertise to the problem, and to guide the computation.

Unfortunately, existing techniques for visualizing multidimensional spaces [4] do not apply to this problem.

Since the dimension of the problem is so large, any attempt to directly visualize the entire space through time series techniques, animation, use of color and transparency, sound, etc., cannot succeed. Of course, it may be of help to visualize relatively low-dimensional sections of the design space (a simple example of this approach is described in the next section).

Techniques for visualizing multidimensional spaces include parallel coordinates [7] and a scatterplot matrix. Both essentially allow comparisons of (arbitrary) pairs of variables, and do not help with recognizing spatial relationships between points in the N-dimensional space. Various clustering methods have been proposed that attempt to map similarities in data records from a high dimensional space into a two- or three-dimensional space [13, 1]. Unfortunately, it is not clear what it means for design points to be "similar" aside from obvious measures such as value under the objective function, nor is it clear how this approach would provide insight to designers.

Iconic representations for multidimensional data in the form of glyphs have been widely reported. An ad hoc version of glyph representation appears to be of some value for our aircraft design problem, as described below (see Figure 1).

It is interesting to compare the aircraft design problem described here to other problems in multidimensional data analysis more frequently encountered. To illustrate this class of problems, consider locating a place to retire. You might have 10 or 20 variables to consider when evaluating possible retirement places, such as climate, population density, crime rate, etc. Typically, data analysis for the retirement problem depends on building an objective function that attempts to assign values to each parameter on some linear scale and relative weights to the various parameters.

Note some important differences in the two problems that affect their visualizations. In the retirement problem, for each variable, more (or less) of most parameters is absolutely better. But, there is effectively a fixed number of destinations, and there may not exist a point A differing from B only in one variable. In the aircraft design problem, all points in the parameter space are possible for consideration. However, one cannot simply choose the point that independently optimizes each parameter for two reasons. One reason is that the constraints supply an independent limitation on the values of various parameter combinations, so that improving one parameter independent of the others may violate some constraint. More importantly, however, is that

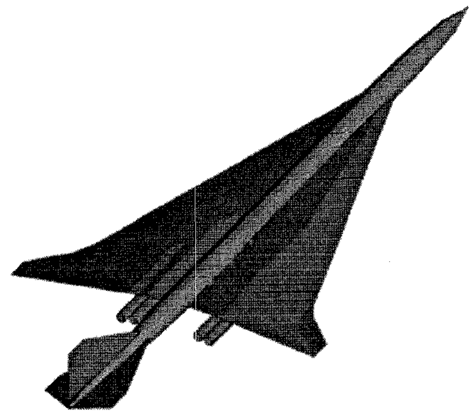

Figure 1: Graphical representation derived from a multi-parameter aircraft design.

there is a nonlinear relationship between the parameters as they affect the objective function in the the aircraft design problem. In particular, the objective function is non-monotonic with respect to individual parameters.

EXAMPLES OF VISUALIZATION USE

Visualization techniques have already been applied to the aircraft design problem in two ways. First, a point in multidimensional space corresponds to a rough aircraft design. It is of use to the designer to be able to see an iconic representation of the airplane shape that corresponds to a given point, such as illustrated by Figure 1. The parametric representation is transferred to physical coordinates and stored in the Craidon geometry format [5] which serves as input to several of the analysis methods. These physical points are then formatted as input to a plotting package. We are currently developing design tools that allow engineers to shift easily between visual representations of the design, and points in design space.

The second use of visualization illustrates the power of even simple visualizations to provide insight to a difficult problem. Figure 2 [9] shows a triangular section of a 2-dimensional slice through the multidimensional design space. This figure is somewhat misleading in that it is normally unusual to have gathered so much information about a particular region of the design space. The relatively large number of point evaluations were performed expressly to generate the image.

The use of this 2D slice visualization has proved to be significant. The reason for developing this visualization was to gain some insight into the properties of the design space. The original motivation came from the results of an automated optimizer applied to the problem. It was known that the optimizer was sensitive to initial conditions, in that providing one point yielded a local optimum, while providing another point yielded another local optimum which is 2000 *lb* lighter. Prior to creating the visualization, it was not recognized that the constraints break the design space into disjoint (at least in some hyperplanes) regions of feasible points. This insight came as a result of the visualization.

Knowing whether to accept (or reject) what the optimizer tells us is an important issue. Optimizers can have trouble in high-dimensional, highly constrained problems. Using visualization in conjunction with optimization can provide understanding of the optimization process and trade-offs involved, but it also has the potential to provide guidance by an experienced engineer when the optimizer runs into trouble (such as when the gradient of the objective function is nearly perpendicular to a constraint boundary).

A DESIGN VISUALIZATION SYSTEM

Absent a better automated technique for solving the problem, aircraft designers would benefit from better visualization tools for helping select better designs. One approach might be a visualization system that helps better manage the information available. In particular, designers over time build up a collection of information in the form of evaluations for specific data points. It may be possible to provide a design environment that has the following characteristics.

- Allow for visualization of the spatial relationships between points in the database
- Provide transformations between design points and a graphical representation of the associated aircraft.
- Give designers a feel for objective function and constraint sensitivity relative to the parameter space.
- Give designers a feel for objective function and constraint sensitivity relative to the aircraft geometry.
- Give designers a feel for the topology (e.g., connectedness) and size of the feasible design space.

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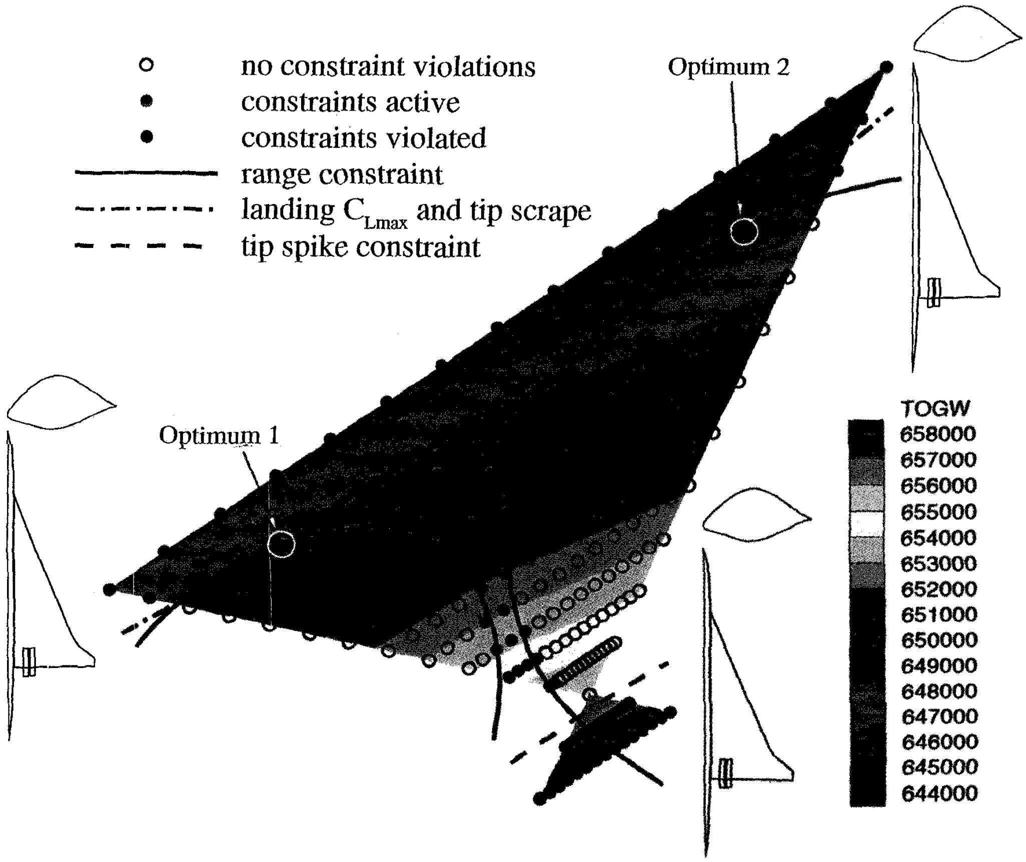

Figure 2: A two-dimensional slice through the multidimensional parameter space. The plane is defined by the two local optima and a third suboptimal, feasible point. The circles represent specific design points. These points are either filled circles (indicating that certain constraints have been violated) or open circles (indicating that all constraints are satisfied). The value of the objective function is indicated by the shading. In this particular region of the design space, the objective function is relatively insensitive, resulting in a smooth "surface." The lines on the plot represent the boundaries of four constraints. The lines are actually generated from interpolating the data achieved from the point evaluations—there do not exist simple independent equations that can be used to discriminate large sets of points as satisfying or violating an individual constraint, except as gross approximations. Other slices through the design space have been investigated by using a different suboptimal, feasible design point to define the plane. While the specific variation in objective function and the shape and number of constraint boundaries are different for each slice, they all reveal the disjointed structure of the feasible design space and other features that create problems for automated gradient based optimizers.