Title:
Using Parametric Effectiveness for Efficient CAD-Based Adjoint Optimization

Authors:
Dheeraj Agarwal, d.agarwal@qub.ac.uk, Queen's University Belfast
Kapellos Christos, christos.kapellos@volkswagen.de, Volkswagen research, Germany
Trevor T. Robinson, t.robinson@qub.ac.uk, Queen's University Belfast
Cecil G. Armstrong, c.armstrong@qub.ac.uk, Queen's University Belfast

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Introduction:
With the advancements in the field of computers and it's increasing use within the industrial design process, the need for the physical design prototypes has been extensively reduced and replaced with digital models: made and analysed with computers. Nowadays, a product design typically starts with a Computer-aided design (CAD) geometry and eventually delivers an optimized geometry in CAD which is used for manufacturing. The commercial CAD systems like CATIA V5, SIEMENS NX, SolidWorks etc. use feature-based modelling strategies to create a parametric CAD model. For these models, the shape can be updated by changing values of the parameters defining different features used to create the model. The constraints on shape imposed by the features in the CAD model feature tree should mean that the optimized part can be manufactured, providing the features were well chosen. To a large extent this will depend on the skill and experience of the CAD model creator, and their ability to visualize and parameterize the design space. The downside of using a feature-based CAD model to optimize the design is that often it is not obvious from the parameterisation which parameter value(s) need to be modified to achieve the desired shape change, especially when the person implementing the change is not the creator of the CAD model. In industry today, the resulting modification becomes a case of trial and error, which is time consuming for simple models with tens of parameters, and is unfeasible for complex component models with hundreds or thousands of parameters.

Robinson et al. [8] used adjoint sensitivities [2,7] and design velocity [1] (the boundary shape movement resulting from a change in a CAD parameter) to define the effectiveness of CAD parameters to be used as optimization variables for minimization of a defined objective function. Adjoint surface sensitivity gives the information about how the objective function changes for an infinitesimally small movement of each surface mesh node in the normal direction. The primary attraction of adjoint methods is their ability to compute gradient information at a computational cost which is essentially independent of the number of design parameters. This, in turn, opens the possibility to explore significantly larger design spaces than those with traditional approaches, in time-scales which are acceptable for industrial design.

Overall Aim:
Parametric effectiveness is a rating of the quality of CAD parameters to be used for optimization. It compares the maximum change in performance that can be achieved using existing parameterization, to the maximum performance improvement that could be obtained if the model is not constrained by any parameterization. The aim of this work is to present an automated approach to efficiently calculate the parametric effectiveness for the set of parameters defined within a CAD modelling software CATIA V5. The approach is further developed to select a subset of parameters which provides the greatest potential for performance improvement. While one of the benefits of adjoint optimization is that the

cost of calculating sensitivities is virtually independent of the number of design variables, modifying the CAD model by using all parameters in the optimization step is potentially costly, and so identifying a selected set of key parameters from all parameters is advantageous.

Background:

In a feature-based CAD modelling system like CATIA V5, a part model is comprised of individual features which are combined to represent an overall shape. In order to capture the CAD surface movement with respect to the change in CAD parameters, the design velocity is calculated. This is the movement of the CAD model boundary in the normal direction due to a change in the parameter value, and can be mathematically formulated as

$$V_n = \delta X_s \cdot \hat{n}, \tag{1}$$

where δX_s is the movement of surface nodes and $\hat{n}$ is the outward unit normal of the surface at that point. The convention adopted throughout this work is that a positive design velocity represents an outward movement of the boundary, and negative is inward.

Parametric Sensitivity

It is a measure of change in performance (J) caused by the change in the value of a parameter for which a shape change occurs. If the design velocity (V_n) over the surface (A) for a parametric change (dP) is known, along with the adjoint surface sensitivity (φ) the parametric sensitivity, S_i is

$$\mathrm{S_i} = \frac{\mathrm{d}J}{\mathrm{dP}} = -\int_A \varphi V_n \, dA \tag{2}$$

In general, adjoint analysis results (φ in Eqn. 2) are produced as a set of values corresponding to a mesh over the model's boundary.

Parametric Effectiveness

The parametric effectiveness was proposed in [8] as the ratio of the change in performance achieved by perturbing all the parameters in an optimum way (assumed here to be the steepest descent direction) subject to the constraint of a unit root-mean-squared boundary movement. When computing parametric effectiveness, a constraint on overall boundary movement is imposed for each parametric perturbation.

The detailed mathematical derivation of the measure can be found in [8]. A summary is that the optimum change in performance per root mean squared design velocity over the boundary for a model which is not constrained in the manner in which it can move by its parameterization can be predicted as

$$\left(\frac{dJ}{dV}\right)_{optimum} = -\sqrt{A\int_A \phi^2 dA}\,. \tag{3}$$

Assuming the optimum parametric performance improvement is obtained by perturbing the parameters in the direction of steepest decent, the vector of parameter changes can be written as

$$dP = k\{S_1 S_2 \dots \dots\}, \tag{4}$$

where k is a multiplier specifying the magnitude of the steepest decent vector. The optimum performance change per unit of root-mean-square design velocity, for a parameterized model is given by

$$\left(\frac{dJ}{dV}\right)_{param} = -\sqrt{\frac{A}{\int_A \left(\sum_{i=1}^{n} S_i V_{ni}\right)^2 dA}} \sum_{i=1}^{n} (S_i)^2\,, \tag{5}$$

The parametric effectiveness is given by

$$Parametric\ effectiveness = \frac{\left(\frac{dJ}{dV}\right)_{param}}{\left(\frac{dJ}{dV}\right)_{optimum}}. \tag{6}$$

Parametric effectiveness ranges from 0 to 1. A low parametric effectiveness indicates that the parameters in the model will not be able to perturb the model shape in the manner the adjoint sensitivity map suggests.

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Automated Approach for CAD Parameter Selection:

It is shown in [8] that parameters selected based on parametric effectiveness are potentially better at localising the shape change in regions of high adjoint sensitivities. It also states that the optimum set of parameters may not include all parameters and should be identified using a power-set approach. Thus, to evaluate the quality of parameterization for the purpose of optimization it is beneficial to select the sets of parameters which give the highest parametric effectiveness. This requires the parametric effectiveness to be calculated for all possible combinations of parameters. While this could be achieved in a brute-force manner by formulating a power-set of the parameters and calculating parametric effectiveness of each combination, the power-set of any set $\mathbb{Q}$ of n parameters are the set of all subsets of $\mathbb{Q}$ (including the empty set) giving a total of $2^n - 1$ different parametric combinations. The implementation of power-set methodology becomes computationally prohibitive when number of parameters is large, as it is for most industrially relevant CAD models. So, in this work an approach is formulated to efficiently obtain the optimum parametric combination giving highest parametric effectiveness without exhaustively evaluating Eqn. 5 for all parametric combinations. This is achieved as:

Step 1: All parameters with an individual parametric effectiveness greater than 0.02 are selected. The number of parameters $= m$. (It is assumed parameters with an individual parametric effectiveness smaller than 0.02 can be ignored).

Step 2: For the m parameters in Step 1, all the possible combinations of 2 parameters are created, each referred as a **set**. Here, $\mathbf{C}_2^m$ sets are formed, where $\mathbf{C}$ is a combinatorial operator. Sets are ordered with the parameter with the lowest numerical identifier as the first member.

Step 3: The sets are grouped together such that $m - 1$ **groups** are created to contain parameter sets with the same first member. The parametric effectiveness of each set in each group is computed.

Step 4: The set with highest parametric effectiveness is selected for that group (and the other sets are deleted).

Step 5: For each group in Step 3, new sets are created by adding one of the remaining parameters to the set selected for each group in step 4.

Step 6: If the resulting parametric effectiveness calculated for a group in step 5 is less than that calculated for the same group in step 4, then the set from step 4 is selected and the new sets for that group are deleted and that group is considered complete. Else, Step 4 to Step 6 are repeated.

Step 7: when all groups are complete, the group containing the set with the maximum parametric effectiveness is identified. The parameters it contains are the subset of parameters which should be used to optimize the model

Application-DrivAer Model:

The developed framework was applied to an automotive noise reduction problem, with the use of a surrogate model for aeroacoustics [6]. The model under investigation is the TUM DrivAer vehicle [3], using a fast-back configuration with smooth underbody and closed wheels. The CAD model of the car mirror was created in CATIA V5 using a series of points, splines and surfaces. The wireframe of the mirror CAD model is shown in Fig. 1(a). The surface fitting methods in CATIA V5 (like multi-section surface and fill surface) were then used to create the outer surfaces and produce 3D CAD model of the mirror with 2925 CAD parameters which controlled the position of individual points. The flow equations are solved using the standard steady state incompressible OpenFOAM© solver simpleFoam. The adjoint equations are solved using the Helyx Adjoint solver, provided by ENGYS [4]. Moreover, to formulate the continuous adjoint method the fully differentiated Spalart-Allmaras turbulence model based on wall functions is used [5]. Here the optimization process alters the shape of the mirror geometry, targeting a shape which transmits less noise to the interior of the car. The low frequency noise perceived inside the cabin can be linked to the turbulence level at the area directly outside of the driver side window. In this sense, a surrogate aeroacoustics objective function is formulated as the integral of the squared turbulent viscosity over a volume near the side window.

$$F_{noise} = \int_{\Omega} \nu_t^2 \, d\Omega, \tag{7}$$

It is important here to note, that without the differentiation of the turbulence model, relying on the "frozen turbulence" assumption, dealing with an optimization problem of this kind would not be possible, as the objective function itself depends on the turbulent variable. For the flow and adjoint analysis, half of the car was meshed. The computational grid consisted of 5 million cells. The adjoint sensitivity map for minimizing noise inside the car is computed at the first optimization cycle and is presented in Fig. 1(b), where red areas must be pushed inward to the surface while blue are to be pulled outward to reduce the objective function.

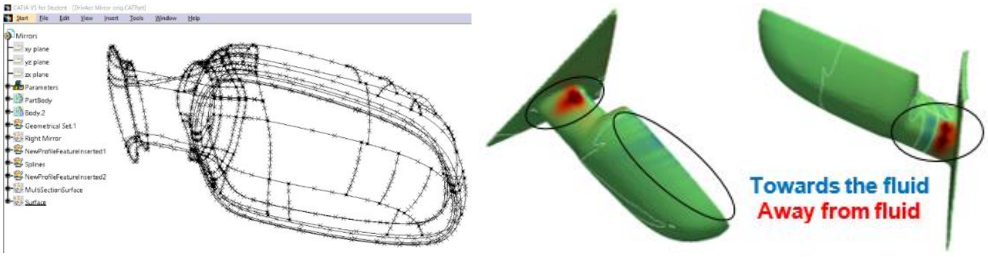

Fig. 1: DrivAer car mirror. (a) wireframe model, (b) adjoint sensitivity map.

The computational effort required to update the parametric DrivAer model in CATIA V5 is shown in Table 1 for all parameters and the set with highest parametric effectiveness. It can be seen that updating all the parameters of the CAD model is computationally much more expensive. Such an update would be required for each step in an optimization. Further, this step of CAD updating cannot be parallelized and thus updating only a selected set of CAD parameters is beneficial.

	Original CAD model (2925 parameters)	Most efficient parameter (48 parameters)
CAD update time	10716 s	129 s

Tab. 1: Time required to update the parametric CAD model.

Further, the benefit of using parametric effectiveness to select the set of parameters for optimization is substantiated by comparing the design velocities when the when the model is perturbed using the most effective parametric combination (consisting of 48 parameters) found using the approach presented in this work (Fig. 2(a)) to the design velocity when 48 parameters with highest parametric sensitivities are perturbed (Fig. 2(b)) in the steepest decent direction. The overall boundary movement for all these perturbations is kept equal to a small value $dV = 1E^{-4}$. It can be found that the parametric combination with highest parametric effectiveness moves the model mostly in the areas of high sensitivity and very little in other regions, while other parameter set move the boundary both in the areas of high and low adjoint sensitivity.

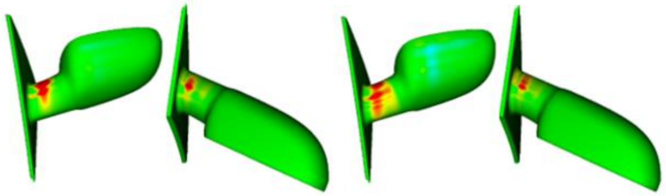

Fig. 2: Design velocity for the same overall boundary movement, (a) most effective parameteric combination, (b) 48 most sensitive parameters.

Optimization

The shape optimization of car mirror was performed using a steepest descent strategy to update the design variables with the computed gradients. After the optimization algorithm converged, the optimal geometry was by 6.8% “quieter” for the most effective parametric combination and 4.1% when 48 most sensitive parameters were used. Comparing the design velocities between the initial and optimized geometries obtained using most effective parameters (Fig. 3), it is seen that the top and bottom of the neck of the mirror has been pushed in to suppress the generation of turbulence on the wake of the mirror and consequently reducing the turbulence viscosity flowing through the volume over which the objective function is integrated.

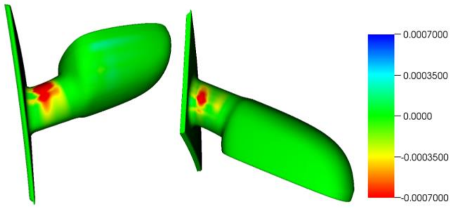

Fig. 3: Design velocity comparing boundary movement between starting and optimized geometry.

Conclusions:

In this work, an automated approach is described which calculates the parametric effectiveness of CAD model parameters and selects the optimum combination of parameters to be used for optimization. The rationale behind using this approach is outlined in terms of time required to update a complex parametric CAD model during the optimization, which is an important factor to be considered when using the optimization process in an industrial workflow.

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