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Advanced data transfer strategies for overset computational methods

Eliot W. Quon, Marilyn J. Smith *

School of Aerospace Engineering, Georgia Institute of Technology, Atlanta, GA, United States

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ABSTRACT

A data transfer strategy applicable to overset grid configurations has been developed that improves interpolation and extrapolation accuracy and eliminates orphan points. Traditional trilinear mappings based on interpolation stencils are replaced with a "cloud"-based algorithm which retains no dependence on grid connectivity. A variable number of donor points was sourced from a single grid in the vicinity of a receptor point, permitting consistent treatment of orphan points in the data transfer method. This cloud-based interpolation methodology demonstrates the ability to preserve flow-field features for configurations both with and without adequate mesh overlap. The approach eliminates problems associated with orphan points and reduces transient conservation errors by an order of magnitude.

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1. Introduction

Within the fluid mechanics community, many applications of interest involve predicting the unsteady behavior of configurations moving in multiple frames of reference. To facilitate the engineering analysis, an efficient means of handling the evolution of computational domains due to mesh motion, deformation, and/or grid adaptation is necessary. The state of the art in computational fluid dynamics (CFD) is to use an *overset* or *Chimera* approach [1,2], which applies overlapping grids for the time-accurate solution of unsteady problems and the modeling of complex geometries. This modular approach utilizes multiple body-fitted grids to model each moving component, in addition to one or more stationary background grids that model the remainder of the flow field. Overset grid systems permit interior grid boundaries to be placed arbitrarily so that different components may move freely relative to each other. The scheme has since been applied to both structured and unstructured grids for many engineering problems of interest [3–6].

1.1. The overset method

An overset scheme requires that flow-field data be exchanged between pairs of overlapping meshes at each solver iteration to enable a solution on each component grid that is globally consistent. Points on non-solid interior boundaries requiring data exchange are known as *fringe* points. Additional effort is needed to obtain a solution because of the potentially complex domain interconnectivity between multiple overlapped grids. Moreover, since fringe points from neighboring grids are in general non-coincident, data transfer requires interpolation at each time step. Hole-cutting to remove points interior to solid boundaries, search operations to identify donor/receptor pairs, and calculation of interpolation weights are typically performed by additional software, such as PEGASUS 5 [7], PUNDIT [8], or Suggar++ [9]. The data transfer entails calculating a new solution at target locations known as *receptors* based on the solution from source points known as *donors*. On a Cartesian or structured mesh, the most efficient approach is to directly apply trilinear interpolation [10]. The PEGASUS 5 grid preprocessor [7] employs this technique. A more general approach relies on isoparametric mappings with trilinear basis functions, applicable to both structured and unstructured grids. PUNDIT [8] and Suggar++ [11] both apply this technique.

Complications arise when acceptable donor points for interpolation cannot be found, giving rise to "orphan" points. This situation occurs if adjacent grids have insufficient overlap or if significant disparities in mesh spacing between grid levels exist. A point is considered to be an orphan when one or more of its donors is also a fringe point requiring an interpolated solution. An important consideration is that achieving higher-order spatial accuracy requires larger stencils. For example, an implicit sixth-order or explicit fourth-order scheme can require a five-point stencil which necessitates two levels of fringe points to maintain consistency with the interior of the computational domain [12,13]. When orphan points are present, solution fidelity may be lost because two levels of fringes cannot be resolved. Similarly, interpolation accuracy generally increases with overlap size because more points are available from which to perform the data transfer. The problem of orphan points is exacerbated

* Corresponding author.
E-mail address: marilyn.smith@ae.gatech.edu (M.J. Smith).

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Nomenclature

α	radial basis interpolation coefficient
β	polynomial interpolation coefficient
Δs	isotropic grid spacing
Δt	simulation time step size
Φ	radial basis kernel, $\Phi(\vec{x},\vec{x}_i) = \phi(\|\vec{x}-\vec{x}_i\|_2)$
ϕ	radial basis function (RBF), $\phi(r)$
h	hangar height
M	Mach number
N	number of interpolation source points
n	normalized frequency, fx_r/U_∞
Q	number of polynomial coefficients
r	radial (Euclidean) distance, $\|\| \vec{x} \|\|$
s	interpolant to an unknown function
V_∞	free-stream velocity
X	set of source data points
x_r	reattachment point
x_s	separation point

by relative mesh motion which can increase the number of orphans and/or change their locations over time.

Solutions at orphan locations are typically estimated by an averaging procedure [14,15,6]. Two general mitigation approaches exist when orphan points are present. First, the grids may be redesigned to improve the quality of mesh intersections. In a recent application of an unstructured near-body methodology coupled to a Cartesian off-body solver, Abras and Hariharan [16] had to manually adjust the trim distance dictating the amount of overlap between near-body and off-body meshes. However, manual adjustments are not always possible, especially when considering complex geometries, and grid refinement can significantly increase cost. For example, a wing-store configuration studied by Power et al. [6] had 0.5% of all cells orphaned. Application of an adaptive mesh refinement procedure was able to eliminate all orphans but increased the total cell count by 10%. Even if increased mesh sizes are acceptable, it may be difficult to guarantee that meshes in relative motion will be orphan-free for all time steps throughout the simulation. As an alternative, a dense interface grid may be added in the orphan region [17,6]. These approaches require user intervention and added cost, either in engineering hours or computational time.

1.2. Scattered data interpolation

Scattered or cloud-based data techniques can provide a continuous mapping between arbitrarily structured data samples and remain decoupled from solver type (e.g., unsteady Reynolds-averaged Navier–Stokes, vorticity-velocity, or potential flow methodologies) and topology (Cartesian, structured, and unstructured). More broadly described as kernel function interpolation, an interpolant is formed by a linear combination of nonlinear basis functions (kernels) to represent nonlinear functions. The approach is well established within other fields (e.g., computer graphics, digital elevation modeling, or optical design) but their application to CFD problems has been limited. This data transfer methodology has the potential to reduce or eliminate orphan points while increasing interpolation accuracy. Since donor points can be sourced from any location on any grid, the approach naturally precludes scenarios involving a lack of sufficient donor points.

When constructing an interpolant (s) to an unknown function (f) sampled from a set of scattered data points (X), a solution is readily obtained when interpolation conditions

$$s(\boldsymbol{x}_j) = f_j, \quad \boldsymbol{x}_j \in X, \tag{1}$$

are independent of rigid (Euclidean) transformation [18]. This is automatically the case when applying basis functions that depend only Euclidean distance ($r = \|\boldsymbol{x}\|_2$) [18], i.e., *radial* basis functions (RBFs). The quality of the results is then sensitive to the location of kernel *centers* [19]. In the case of the centers coinciding with the locations at which the solution is known, an interpolant exists per the Mairhuber-Curtis theorem [20]. An additional consideration is that RBFs are by definition isotropic because the function has the same evaluation in all directions. However, fluid dynamics data are often discontinuous in nature. Therefore an alternative approach is to use not radial but elliptical bases to introduce data adaptivity into the data transfer algorithm. The development of anisotropic basis functions based on local solution gradients is described in Ref. [21]. Rather than developing new basis functions, the present work focuses on applying established RBFs to the problem of overset data transfer.

Recommendations from a number of authors [22,23,20] have suggested that scattered data interpolation with RBFs is a general, accurate approach to transferring arbitrarily distributed data. These methods are especially attractive for overset data transfer because:

1. They permit interpolation and extrapolation [24] based on arbitrarily clustered clouds of points in any dimensional space.
2. They have in general higher-order accuracy that can be increased by freely adding data points.
3. They are directly applicable to unstructured methodologies since the interpolant is decoupled from the computational mesh, eliminating requirements on the spatial structure of the sampled data.
4. They can be readily applied to the problem of solution transfer in overset methods since they do not require connectivity information.

For these reasons, an RBF approach is ideally suited for data transfer with orphan points since there are no overlap or connectivity requirements on the donor points. Therefore the same data transfer approach may be applied regardless of grid configuration.

An RBF is a univariate function of Euclidean distance from a chosen center $\boldsymbol{x}_c$. Therefore the RBF (ϕ) is related to its kernel function (Φ) as follows:

$$\Phi(\mathbf{x},\mathbf{x}_c) = \phi(\|\, \mathbf{x}-\mathbf{x}_c \,|\,|_2) = \phi(r). \tag{2}$$

An RBF interpolant based on the set of data samples X has the following form:

$$s_{f,X}(\mathbf{x}) = \sum_{j=1}^{N} \alpha_j \Phi(\mathbf{x},\mathbf{x}_j) + \sum_{k=1}^{Q} \beta_k p_k(\boldsymbol{x}), \tag{3}$$

where s is the RBF interpolant of the function f evaluated at an arbitrary location $\boldsymbol{x}$; α_j and β_j are the interpolation coefficients to be determined; and $\boldsymbol{x}_j$ are the RBF centers that coincide with the data sampling locations. Typically, p_k is chosen to be a polynomial basis. An additional constraint is placed on the function p_k to ensure solvability of the interpolation system [20]:

$$\sum_{j=1}^{N} \alpha_j p_k(\mathbf{x}_j) = 0. \tag{4}$$

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