



Adaptive Post-Processing Method to Represent High-Order Numerical Solutions

Vincent Mouysset, Sébastien Pernet

9-11 March 2016



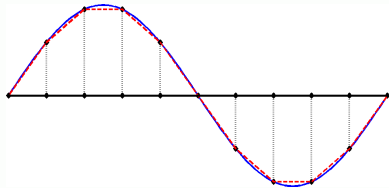


Figure : P^1 interpolation for $\Delta x = \lambda/10$.

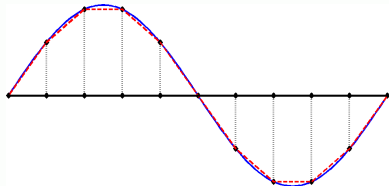


Figure : P^1 interpolation for $\Delta x = \lambda/10$.

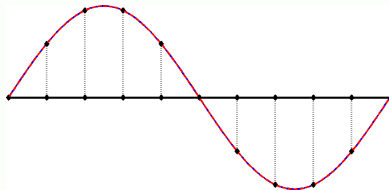


Figure : P^2 interpolation for $\Delta x = \lambda/10$.

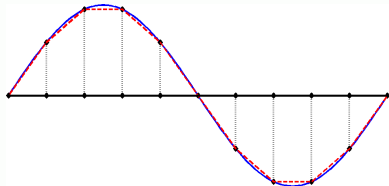


Figure : P^1 interpolation for $\Delta x = \lambda/10$.

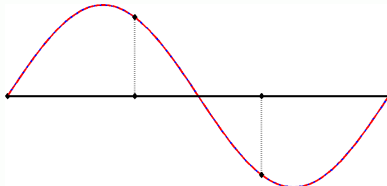


Figure : P^2 interpolation for $\Delta x = \lambda/3$.

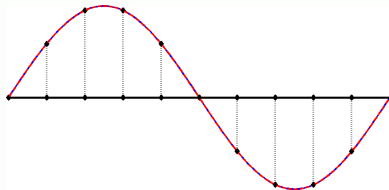


Figure : P^2 interpolation for $\Delta x = \lambda/10$.

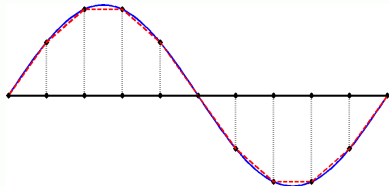


Figure : P^1 interpolation for $\Delta x = \lambda/10$.

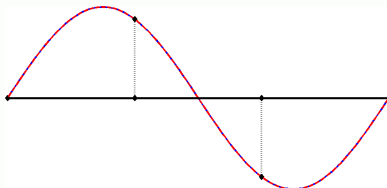


Figure : P^2 interpolation for $\Delta x = \lambda/3$.

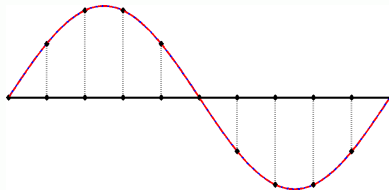


Figure : P^2 interpolation for $\Delta x = \lambda/10$.

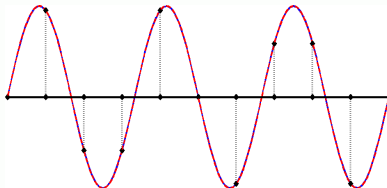


Figure : P^2 interpolation on a 3λ domain.

- **These methods are characterized by:** (one or both)
 - **sophisticated functions:** high order polynomials, eigen or special functions, approaches of collocation or modal type,
 - ⇒ the value at each point is given by a function which is not linear.
 - **mesh cells different from simplexes:** quadrangle, hexahedra, isogeometric elements...
 - ⇒ representation of the element is not linear.
- ***hp* numerical methods have a great potential:**
 - **Very accurate solutions** which can contain lots of physical informations in each cell.
 - They allow to **decrease the computational costs**.
- **Numerous declinations in literature and industrial codes:**
 - FEM, DG, high-order FV and FD,
 - isoparametric methods,
 - high-order BEM,...

- What do we want to do with a *hp* solution?
 - Depict it.
 - Extract some informations (pointwise values, isolines, slices, gradient,...).
- How?
 - With dedicated subroutines in the computational code,
 - ⇒ consumes expensive execution time on servers (cpu efforts and hdd accesses).
 - By mean of a given visualization software (GMSH, PARAVIEW, TECPLOT,...),
 - ⇒ post-treatment is led apart from calculus (on different computers).

However

- input formats are not necessarily suited to the considered *hp* element,
 - common format is "low precision": nodal values on simplexes or other cells,
 - there are some "open formats" (GMSH...), transformation to display informations is automated.
- To summarize, two main options are:
 - adapt to what exists → we make interpolations/projections to write the *hp*-solution in the chosen format,
 - (when available) use an "open format" allowing to describe the *hp* solution → the visualization software controls itself the interpolations/projections.

Classical approach to represent a hp solution

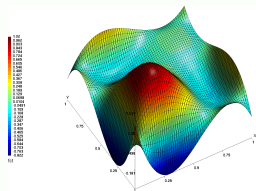


Figure : function to depict: a Gauss-Legendre basis function

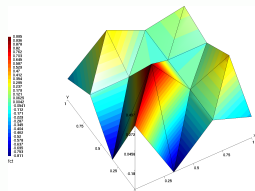


Figure : Usual depiction: 1 point by dof

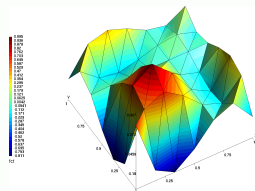
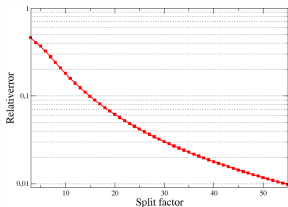


Figure : Refined depiction: 2 points by dof (4 times more elements)

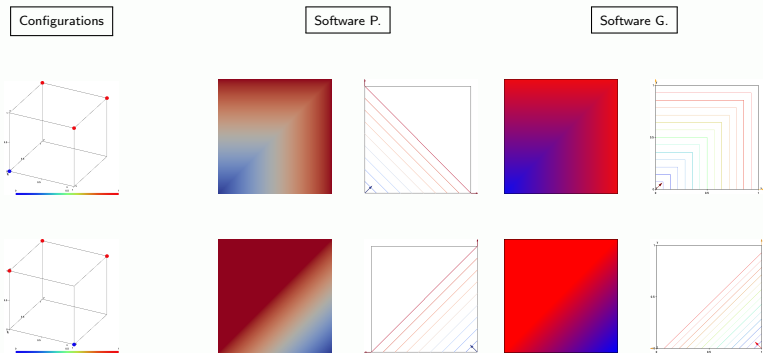


Some practical questions:

- How many subdivisions to perform for a given accuracy?
- How many data will be generated?
- Is this representation giving correct analysis tools to interpret (physically) the hp results?

Is this representation giving correct analysis tool to interpret (physically) the hp results?

Choice of the format and extractions



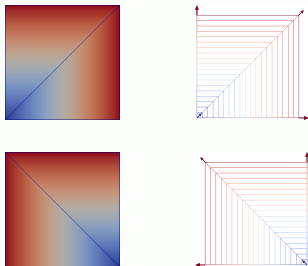
Summary:

- Same function but representations not identical (up to a rotation by 90°)!
- Representations seem affine on simplexes (but data is given on a quadrangle).
- Split of the cell into two triangles independent of the function to represent?
- Isolines and gradients follow or not the depiction.

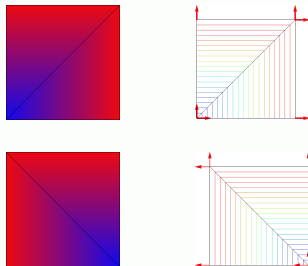
Is this representation giving correct analysis tool to interpret (physically) the *hp* results?

Choice of the format and extractions

Software P.



Software G.



Input format = linear on simplexes \Rightarrow **consistent representations and extractions!**

Formalization

Linear representation suited to the *hp* solutions

Construction of the visualization

Examples

Example 1: what happens on basis functions?

Example 2: what happens when combining basis functions?

Example 3: what happens on more realistic simulations?

Perspectives

- **Our point of view:** usual exploitation of *hp* solutions are not optimal as
 - the balance accuracy-cost (number of data) required to have a good rendering,
 - the difficulty to give some *a priori* (number of subdivisions, target error) which ensure the quality of rendering.
- **Our aims:** better exploitation (by a classical visualization software) of data produced by *hp* numerical simulations
 - ← provide a reliable information through the representations,
 - ← developments compatible with different *hp* codes,
 - ← reliable extraction of quantities of interest straightforwardly with the visualization software.

Our approach to define a well-suited visualization for hp solutions is summarized into 4 objectives:

(O_1): The representation f_{vis} of f_{num} is obtained by plotting piecewise affine functions on k -simplexes, where k is the (local) dimension of the (local) support of f_{num} ,

(O_2): Error between f_{num} and its representation is controlled in L^∞ -norm,

(O_3): At the prescribed tolerance, the representation shows gaps if and only if f_{num} has.

+(O_4): Specific control to be defined according to extractions realized from f_{vis} .

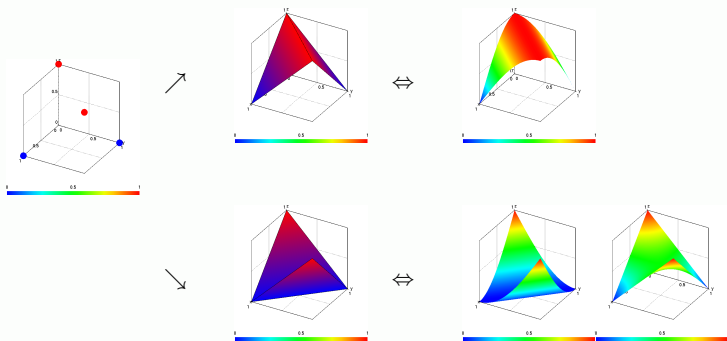


Figure : Interpretation with respect to Q^1 -consistent splitting.

O_1 Representation by piecewise linear functions on k -simplexes,

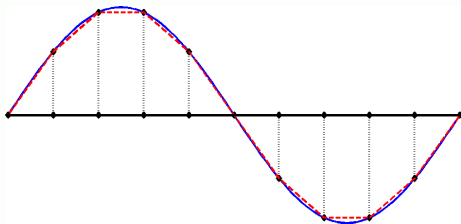


Figure : P^1 -approximation, $\Delta x = \lambda/10$.

→ fine L2 candidate but associated "colorbar" not matching on expected values.

- O_1 Representation by piecewise linear functions on k -simplexes,
- O_2 Error control in L^∞ norm,

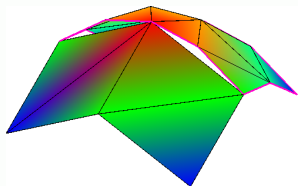


Figure : Representation of a continuous function on non-coincident meshes.

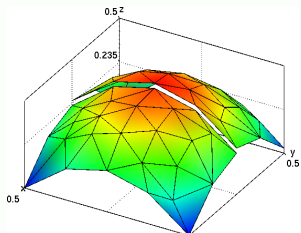
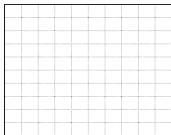


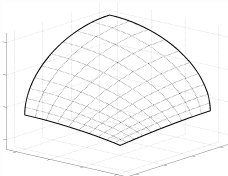
Figure : Representation of a function with jump on coincident meshes.

- O_1 Representation by piecewise linear functions on k -simplexes,
- O_2 Error control in L^∞ norm,
- O_3 Representation of jump if and only if it exists.

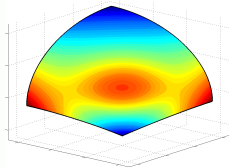
$$\widehat{K} \subset \widehat{\mathbb{X}}_K$$


 $\xrightarrow{g_K}$

$$K \subset X \subset \mathbb{X}$$


 $\xrightarrow{f_{num}^K}$

$$K \times f_{num}^K(K) \subset \mathbb{X} \times \mathbb{Y}$$



Ingredients of the numerical solution f_{num} :

- **mesh:** $\mathcal{T}(X)$ is a mesh of X ,
- **reference cell:** $\forall K \in \mathcal{T}(X)$, $g_K : \widehat{K} \rightarrow K$ bijection,
- **basis functions:** $\forall K \in \mathcal{T}(X)$, $\forall i = 1 \dots N_K$, $\varphi_i^K : \widehat{K} \rightarrow Y$ (at least continuous).

Then, for each $K \in \mathcal{T}(X)$, the definition of f_{num} on K , noted f_{num}^K , is expressed by means of coefficients (degrees of freedom) f_i^K via the following decomposition

$$\forall x \in K, f_{num}^K(x) = \sum_{i=1}^{N_K} f_i^K \varphi_i^K (g_K^{-1}(x)),$$

Formalization

Linear representation suited to the *hp* solutions

Construction of the visualization

Examples

Example 1: what happens on basis functions?

Example 2: what happens when combining basis functions?

Example 3: what happens on more realistic simulations?

Perspectives

Ingredients of the representation function f_{vis} :

- f_{num} has a local definition on $\mathcal{T}(X)$ so f_{vis} will be, (f_{vis}^K denotes its local representation on $K \in \mathcal{T}(X)$),
- **Objective O_1 :** f_{vis}^K is a linear function on simplexes (when f_{num}^K is more sophisticated) so we introduce
 - **(sub)-mesh:** a mesh made of simplexes of K , noted $\mathcal{T}(K)$,
 - **basis functions:** for any $S \in \mathcal{T}(K)$ let $\mathbb{P}^1(S)$ be the space of polynomial of total degree less than or equal to 1.

Thus, f_{vis}^K will verify

$$\forall S \in \mathcal{T}(K), f_{vis}^K|_S \in \mathbb{P}^1(S).$$

Remark: f_{vis}^K is defined on the physical cell K (the one to be plotted) when f_{num}^K is on the reference one \hat{K} .

Definition of f_{vis} : construction of the representation mesh

f_{num}^K is evaluated from reference cell \widehat{K} so $\mathcal{T}(K)$ will be constructed from a mesh composed of simplexes $\mathcal{T}(\widehat{K})$ of \widehat{K} .

The construction of $\mathcal{T}(K)$ is then performed in the following way:

- 1 For $K \in \mathcal{T}(X)$, we define the topology of $\mathcal{T}(\widehat{K})$ by

$$\widehat{\mathcal{N}} := \{\widehat{N} := (\widehat{N}_i)_{i=1, \dots, n_K+1} : \Lambda(\widehat{N}) \in \mathcal{T}(\widehat{K})\}$$

where Λ associates $n + 1$ points $P := (P_i)_{i=1, \dots, n+1}$ to the n -simplex $\Lambda(P)$.

- 2 We define the set of nodes of $\mathcal{T}(K)$ as well as its topology by

$$\mathcal{N} := \{N = (N_i)_{i=1, \dots, n_K+1} := g_K(\widehat{N}) : \widehat{N} \in \widehat{\mathcal{N}}\}$$

with $g_K(\widehat{N}) := (g_K(\widehat{N}_i))_{i=1, \dots, n_K+1}$ où $\widehat{N} := (\widehat{N}_i)_{i=1, \dots, n_K+1}$.

- 3 The mesh in simplexes of K is defined by

$$\mathcal{T}(K) := \{\Lambda(N) : N \in \mathcal{N}\}.$$

Remark: one can have $\widetilde{K} := \cup_{S \in \mathcal{T}(K)} S \neq K$ and $f_{vis}^K(\widetilde{K}) \neq f_{num}^K(K)$

Lemma (identification of $\mathcal{T}(K)$)

For all $K \in \mathcal{T}(X)$, the \mathbb{P}^1 interpolation of g_K constructed from $\mathcal{T}(\hat{K})$, noted $P^1 g_K$, is

- 1 a bijective function between $\mathcal{T}(\hat{K})$ and $\mathcal{T}(K)$,
- 2 a bijective function between the sets $\hat{\mathcal{N}}$ and \mathcal{N} ,
- 3 a surjective function from \hat{K} onto \tilde{K} .

Remark : This construction does not ensure the injectivity of $P^1 g_K$ from \hat{K} onto \tilde{K} .

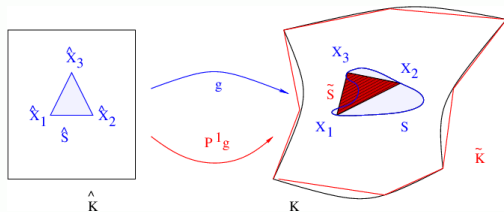


Figure : possible loss of injectivity in the construction of $\mathcal{T}(\hat{K})$.

The function f_{vis}^K is then defined on each simplex $\Lambda(N)$ of $\mathcal{T}(K)$ by:

- 1 for each node $N_i \in N$, $f_{vis}^K(N_i) := f_{num}^K(N_i)$,
- 2 f_{vis}^K is an affine function on $\Lambda(N)$ and is defined by

$$x = \sum_{i=1}^{n_K+1} x_i N_i \in \Lambda(N) \mapsto f_{vis}^K(x) = \sum_{i=1}^{n_K+1} x_i f_{num}^K(N_i),$$

where $(x_i)_{i=1, \dots, n_K+1} \in [0, 1]^{n_K+1}$.

$\Rightarrow f_{vis}$ fulfils the objective O_1 .

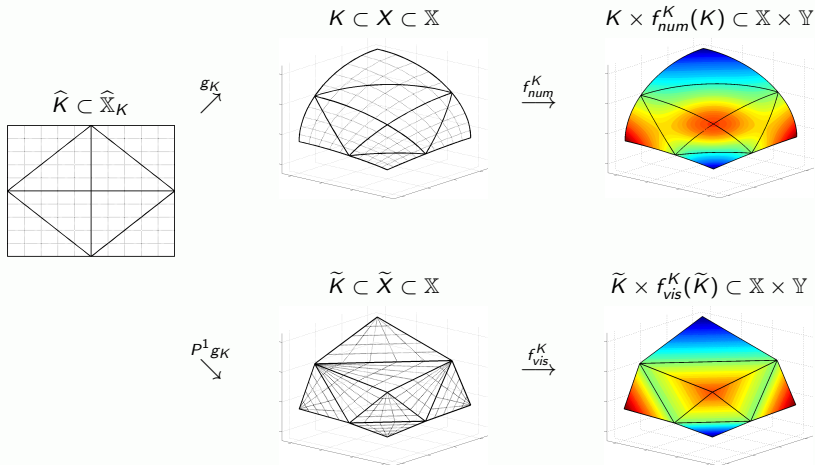


Figure : Construction of the representation f_{vis} of the hp solution f_{num} .

Formalization

Linear representation suited to the *hp* solutions

Construction of the visualization

Examples

Example 1: what happens on basis functions?

Example 2: what happens when combining basis functions?

Example 3: what happens on more realistic simulations?

Perspectives

- f_{num} and f_{vis} have a local definition on each $K \in \mathcal{T}(X) \Rightarrow$ **local estimate**
- Difficulty : **supports are not coinciding** in the physical space X ($K \neq \tilde{K}$).
- Solution : **the Hausdorff distance** (convergence of graphs)

$$d_H : (f, f') \in (C_c^0(\mathbb{X}, \mathbb{Y}))^2 \mapsto \max \left(\sup_{x \in \text{Supp}f} \inf_{x' \in \text{Supp}f'} d((x, f(x)), (x', f(x'))), \sup_{x' \in \text{Supp}f'} \inf_{x \in \text{Supp}f} d((x, f(x)), (x', f(x'))) \right),$$

where d is a distance on $X \times Y$, with α and β be positive parameters:

$$d : ((x, y), (x', y')) \in (\mathbb{X} \times \mathbb{Y})^2 \mapsto \max(\alpha \|x - x'\|_{\mathbb{X}}, \beta \|y - y'\|_{\mathbb{Y}}).$$

- But, it is too expensive to be calculated.
- Idea: "localization" (inside K)!

Proposition (local *a posteriori* estimate)

Let $K \in \mathcal{T}(X)$. The following estimate holds:

$$d_H \left(f_{num}^K, f_{vis}^K \right) \leq \delta_{\mathcal{T}(K)} \left(f_{num}^K, f_{vis}^K \right),$$

where d_H is the Hausdorff distance and

$$\delta_{\mathcal{T}(K)} : (f, \tilde{f}) \in C^0(K, \mathbb{Y}) \times C^0(\tilde{K}, \mathbb{Y}) \\ \mapsto \sup_{\hat{x} \in \tilde{K}} \max \left(\alpha \|g(\hat{x}) - P^1 g(\hat{x})\|_{\mathbb{X}}, \beta \left\| (f \circ g)(\hat{x}) - (\tilde{f} \circ P^1 g)(\hat{x}) \right\|_{\mathbb{Y}} \right),$$

with α and β be dimensioning constants.

Lemma (Generic fulfilment of objectives)

If for all cell $K \in \mathcal{T}(X)$, one has

- $\delta_{\mathcal{T}(K)} \left(f_{num}^K, f_{vis}^K \right) \leq \varepsilon,$
- $\forall K' \in \mathcal{T}(X) : F := \partial K \cap \partial K' \neq \emptyset,$ meshes $\mathcal{T}(K)$ and $\mathcal{T}(K')$ lead to

$$\mathcal{T}(F) = \mathcal{T}(F')$$

where $\mathcal{T}(F)$ and $\mathcal{T}'(F)$ are the meshes in simplexes of F obtained by restriction of those of K and K' , respectively.

Then the representation f_{vis} of f_{num} fulfils the objectives (O_1) , (O_2) and (O_3) .

→ we need to grant $\mathcal{T}(F) = \mathcal{T}(F')$!

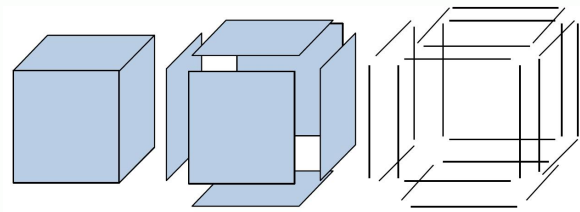


Figure : $\tilde{\mathcal{T}}_{3D}(X)$ (left), $\tilde{\mathcal{T}}_{2D}(X)$ (center) et $\tilde{\mathcal{T}}_{1D}(X)$ (right)

One decomposes $\mathcal{T}(X)$ into sets of elements of lower dimension $\tilde{\mathcal{T}}_{iD}(X)$ for $i = 1, \dots, 3$:

$$\tilde{\mathcal{T}}_{3D}(X) := \mathcal{T}_{3D}(X)$$

$$\tilde{\mathcal{T}}_{2D}(X) := \mathcal{T}_{2D}(X) \cup \left(\bigcup_{K \in \mathcal{T}(X): \dim(K)=3} \mathcal{F}(K) \right)$$

$$\tilde{\mathcal{T}}_{1D}(X) := \mathcal{T}_{1D}(X) \cup \left(\bigcup_{K \in \mathcal{T}(X): \dim(K)=2} \mathcal{E}(K) \right) \cup \left(\bigcup_{K \in \mathcal{T}(X): \dim(K)=3} \mathcal{E}(K) \right)$$

where $\mathcal{F}(K)$ and $\mathcal{E}(K)$ are the faces and the edges of K respectively.

Proposition (fulfilment of O_3)

Let $(\mathcal{T}(\Sigma))_{\Sigma \in \tilde{\mathcal{T}}_{kD}(X), k=1,2,3}$ be a set of meshes in simplexes satisfying: for $k = 2, 3$, $\forall \Sigma \in \tilde{\mathcal{T}}_{kD}(X)$,

$$\mathcal{T}(\Sigma)|_{\partial \tilde{\Sigma}} = \bigcup_{F \in \mathcal{F}(\Sigma)} \mathcal{T}(F) \text{ avec } \tilde{\Sigma} = \bigcup_{S \in \mathcal{T}(\Sigma)} S \quad (2)$$

then the representation f_{vis} of f_{num} constructed from $\mathcal{T}(K)$ for $K \in \mathcal{T}_{kD}(X)$ fulfils the objective O_3

This proposition provides a "simple" algorithm to ensure the objective O_3 :

- 1 construction of representation meshes of elements of $\tilde{\mathcal{T}}_{1D}(X)$,
- 2 construction of representation meshes of elements of $\tilde{\mathcal{T}}_{2D}(X)$ from those of $\tilde{\mathcal{T}}_{1D}(X)$ and satisfying (2),
- 3 construction of representation meshes of elements of $\tilde{\mathcal{T}}_{3D}(X)$ from those of $\tilde{\mathcal{T}}_{2D}(X)$ and satisfying (2).

Rough description of the algorithm:

- 1 decomposition in lower dimensions \rightarrow functions and traces are connected to corresponding element,
- 2 meshing of all 1D cells in $\tilde{\mathcal{T}}_{1D}(X)$ such that
$$\max_{f_{1D}^{num} \text{ connected to the element}} \delta(f_{num}^{1D}, f_{vis}^{1D}) \leq \varepsilon,$$
- 3 interior meshing of all 2D cells in $\tilde{\mathcal{T}}_{2D}(X)$ - boundaries meshed before - such that
$$\max_{f_{2D}^{num} \text{ connected to the element}} \delta(f_{num}^{2D}, f_{vis}^{2D}) \leq \varepsilon,$$
- 4 same process for 3D cells.

Proposition (Convergence via meshing with respect to dimensions)

If the algorithm of construction implies:

- 1 For all $K \in \mathcal{T}(X)$, the P^1 interpolation of g_K constructed from $\mathcal{T}(\hat{K})$ is an injective function from \hat{K} onto \tilde{K} ,
- 2 The convergence toward the target error ε is achieved.

Then the representation f_{vis} of f_{num} fulfils the objectives (O_1) , (O_2) and (O_3) .

Formalization

Linear representation suited to the *hp* solutions

Construction of the visualization

Examples

Example 1: what happens on basis functions?

Example 2: what happens when combining basis functions?

Example 3: what happens on more realistic simulations?

Perspectives

Formalization

Linear representation suited to the *hp* solutions

Construction of the visualization

Examples

Example 1: what happens on basis functions?

Example 2: what happens when combining basis functions?

Example 3: what happens on more realistic simulations?

Perspectives

Example 1: what happens on basis functions?

Q^3 Gauss-Legendre basis function

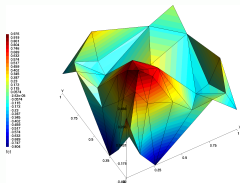


Figure : Adaptive remeshing
 $\varepsilon = 10\%$

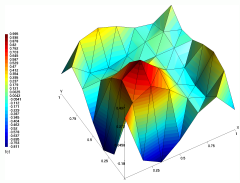


Figure : Uniform 6×6 (same number of elements than adaptive 10%)

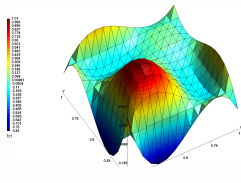


Figure : Uniform 14×14
(same accuracy than adaptive 10%)

Example 1: what happens on basis functions?

Q^3 Gauss-Legendre basis function

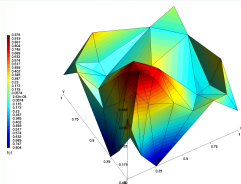


Figure : Adaptive remeshing
 $\varepsilon = 10\%$

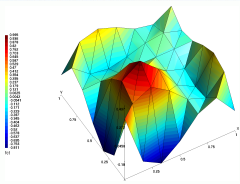


Figure : Uniform 6×6 (same number of elements than adaptive 10%)

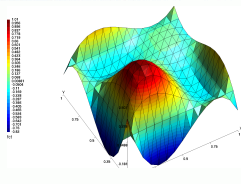


Figure : Uniform 14×14
(same accuracy than adaptive 10%)

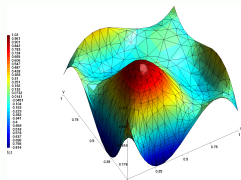


Figure : Adaptive remeshing
 $\varepsilon = 1\%$

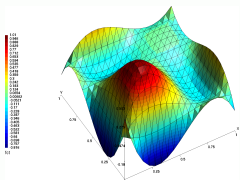


Figure : Uniform 18×18
(same number of elements than adaptive 1%)

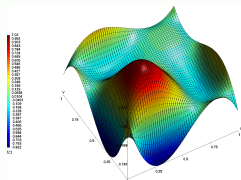
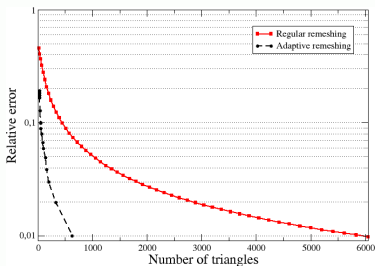


Figure : Uniform 54×54
(same accuracy than adaptive 1%)

Example 1: what happens on basis functions?

Q^3 Gauss-Legendre basis function

Meshing	number triangles	relative error
Adaptive 10%	56	9.91%
Uniform 6×6	72	32.27%
Uniform 14×14	392	11.0%
Adaptive 5%	138	4.88%
Uniform 9×9	162	20.77%
Uniform 22×22	968	5.22%
Adaptive 1%	630	1.00%
Uniform 18×18	648	7.34%
Uniform 54×54	5832	1.01%



Formalization

Linear representation suited to the hp solutions

Construction of the visualization

Examples

Example 1: what happens on basis functions?

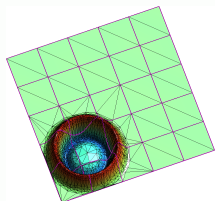
Example 2: what happens when combining basis functions?

Example 3: what happens on more realistic simulations?

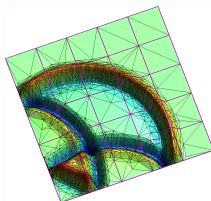
Perspectives

Example 2: what happens when combining basis functions?

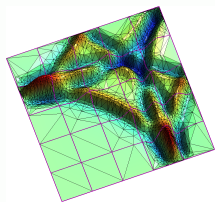
Simulation of the propagation of a source point by a DG method



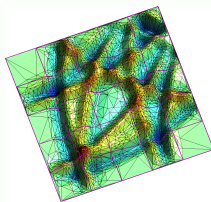
(a) time 1



(b) time 2



(c) time 3

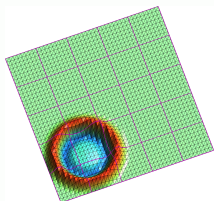


(d) time 4

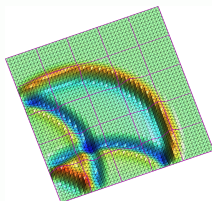
Figure : Propagation of a source point in a cavity by DG Q^{10} on 5×5 uniform mesh : **adaptive remeshing 1%**

Example 2: what happens when combining basis functions?

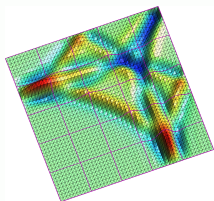
Simulation of the propagation of a source point by a DG method



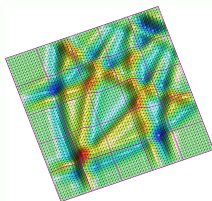
(a) Uniform 8×8 : time 1



(b) Uniform 9×9 : time 2



(c) Uniform 9×9 : time 3

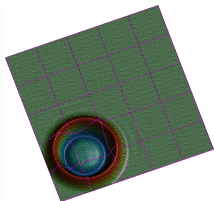


(d) Uniform 11×11 : time 4

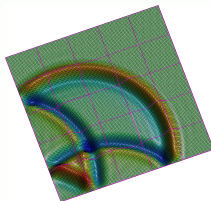
Figure : Propagation of a source point in a cavity by DG Q^{10} on 5×5 uniform mesh : **uniform remeshing with same number of elements as adaptive 1%**

Example 2: what happens when combining basis functions?

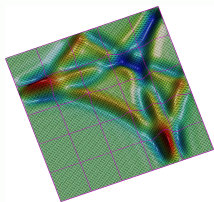
Simulation of the propagation of a source point by a DG method



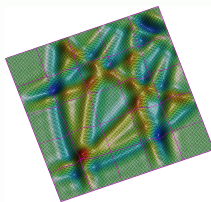
(a) Régulier 35×35 : time 1



(b) Régulier 25×25 : time 2



(c) Régulier 22×22 : time 3



(d) Régulier 24×24 : time 4

Figure : Propagation of a source point in a cavity by DG Q^{10} on 5×5 uniform mesh : **uniform remeshing with same accuracy as adaptive 1%**

Example 2: what happens when combining basis functions?

Simulation of the propagation of a source point by a DG method

Method	time 1		time 2		time 3		time 4	
	triangles	error	triangles	error	triangles	error	triangles	error
Previsio 1%	3088	1.00%	3728	1.00%	3928	1.00%	5580	1.00%
Uniform 8×8	3200	14.30%	-	-	-	-	-	-
Uniform 35×35	61250	1.04%	-	-	-	-	-	-
Uniform 9×9	-	-	4050	5.72%	-	-	-	-
Uniform 25×25	-	-	31250	1.02%	-	-	-	-
Uniform 9×9	-	-	-	-	4050	5.82%	-	-
Uniform 22×22	-	-	-	-	24200	1.07%	-	-
Uniform 11×11	-	-	-	-	-	-	6050	4.43%
Uniform 24×24	-	-	-	-	-	-	28800	1.03%

Summary:

- Good stability of the number of triangles created adaptively (not controlled).
- Uniform refinement much less stable \rightarrow the number of refinements is difficult to *a priori* predict.

Formalization

Linear representation suited to the *hp* solutions

Construction of the visualization

Examples

Example 1: what happens on basis functions?

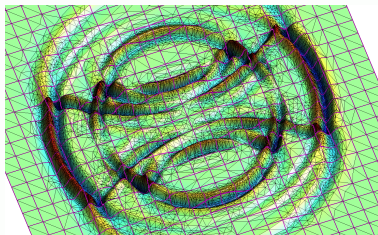
Example 2: what happens when combining basis functions?

Example 3: what happens on more realistic simulations?

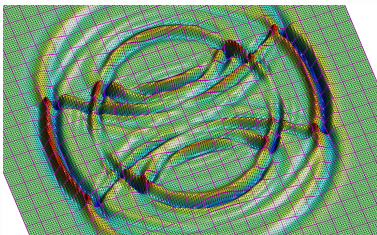
Perspectives

Example 3: what happens on more realistic simulations?

Elastic wave in a three layered medium



(a) Adaptive 1%



(b) Uniform 7×7 (1 point per dof)

Figure : Propagation of an elastic wave in a 3 layered medium by DG Q^7 on 24×24 uniform mesh:
global view

→ No notable differences between those results!?

Example 3: what happens on more realistic simulations?

Elastic wave in a three layered medium

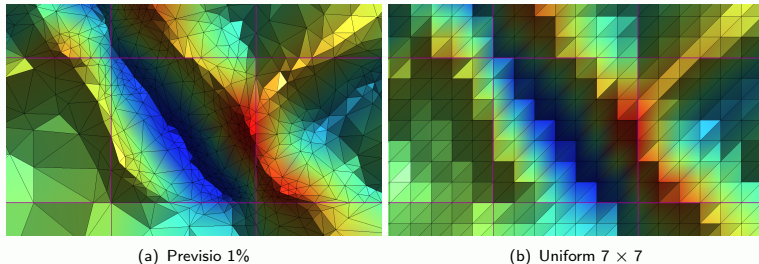


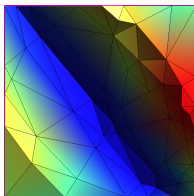
Figure : Propagation of an elastic wave in a 3 layered medium by DG Q^7 on 24×24 uniform mesh:
zooming on one cell

→ Accuracy problems are expected for later extractions!!

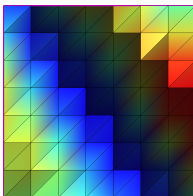
(this cell is meaningful from a physical point of view: interface between two layers with reflection and refraction processes)

Example 3: what happens on more realistic simulations?

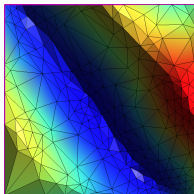
Elastic wave in a three layered medium



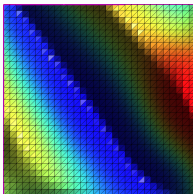
(a) Adaptive, same number of elements than uniform 7×7



(b) Uniform 7×7



(c) Adaptive 1%

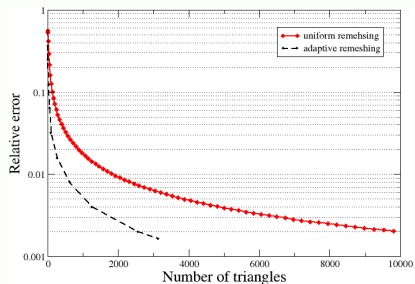


(d) Uniform 1%

Figure : Propagation of an elastic wave in a 3 layered medium: **same cell, comparisons**

Example 3: what happens on more realistic simulations?

Elastic wave in a three layered medium



	number of triangles	relative error
Uniform 7×7	98	12.65%
Adaptive	97	3.19%
Uniform 14×14	392	4.10%
Adaptive 1%	453	0.99%
Uniform 30×30	1800	1.03%
Uniform 70×70	9800	0.2%
Adaptive 0.2%	2553	0.2%

Example 3: what happens on more realistic simulations?

Elastic wave in a three layered medium

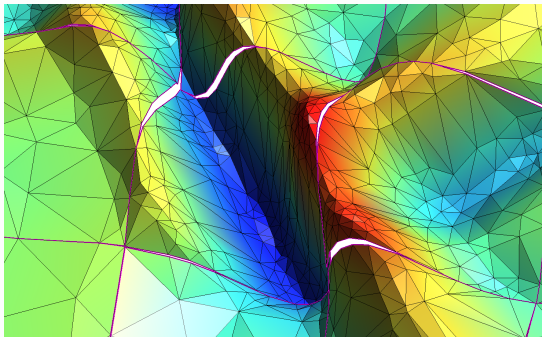


Figure : Adaptive 1%: zoom on solution gaps

Formalization

Linear representation suited to the *hp* solutions

Construction of the visualization

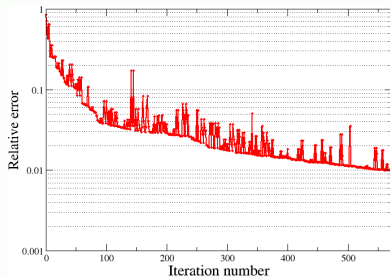
Examples

Example 1: what happens on basis functions?

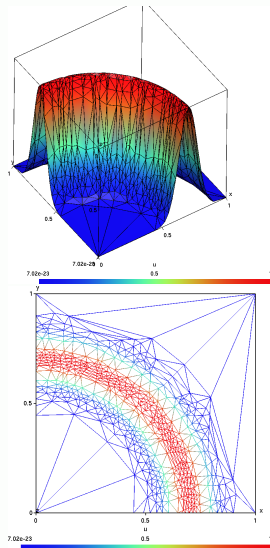
Example 2: what happens when combining basis functions?

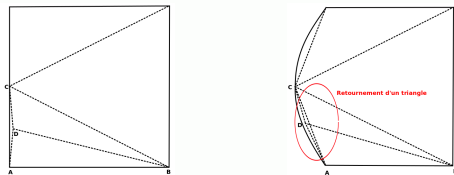
Example 3: what happens on more realistic simulations?

Perspectives

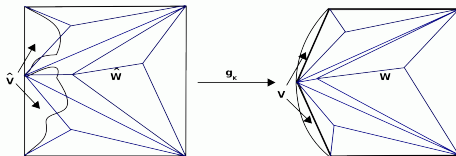


- L^∞ norm \rightarrow no monotonicity.
- Voronoi swaps can yield an increase of the error.
- Idea: swaps driven by a metric associated to g_K and $f_{num} \circ g_K$.





Loss of the injectivity of $P^1 g_K$ when the point D is added \rightarrow loss of the objective O_3 .



Solution: add only points in the domain \widehat{V} where $P^1 g_K$ is an injective function.

Remark: domain \widehat{V} defined by geometry but new points driven by both geometry and f_{num} !

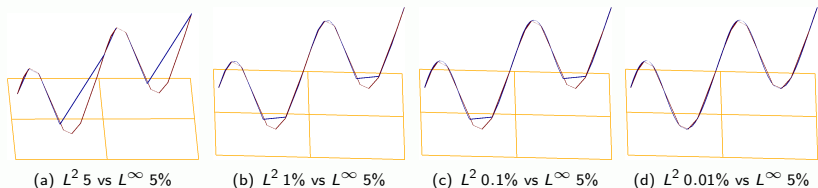


Figure : Extraction over a rectilinear curve: comparison between L^∞ and L^2 approaches.

- However, the construction driven by $\delta_{\mathcal{T}(K)}(f_{num}^K, f_{vis}^K)$ is not sufficient to control the extractions of quantities of interest:

$$\leftarrow |f_{vis} \circ P^1 g_K(\hat{x}) - f_{num} \circ g_K(\hat{x})| \leq \varepsilon \text{ where } P^1 g_K(\hat{x}) \text{ can be different of } g_K(\hat{x})$$

→ For example, $f_{vis}(x)$ does not necessarily "control" the value $f_{num}(x)$.

Fixed by introducing additional constrained (objective O_4) **linked to the quantity of interest and the way it is extracted from linear function on simplexes.**

Thank you for your attention.

