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Development of decision support tools by model order reduction for active endovascular navigation

Original article

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Abstract

Endovascular therapies consist in treating vascular pathologies mini-invasively by inserting long tools towards the area to treat. However, some trajectories are so-called complex (e.g. Supra-Aortic Trunks (SATs)). In order to facilitate the access to complex targets by catheterization, an active guidewire made of Shape Memory Alloy has been developed. Our study focuses on the navigation of this device and associated catheters towards neurovascular targets through the left carotid artery. In a previous study, a finite element model was developed to simulate the navigation of the active guidewire and catheters from the aortic arch to the hooking of the left carotid artery of

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patient-specific aortas. However, numerical simulations are time-consuming and cannot be used directly in the clinic routine to provide navigation assistance. We present in this study the development of numerical charts aiming to provide a real-time computation, based on high-fidelity FE simulations, of: 1. the behaviour of the active guidewire; 2. the navigation of the active guidewire and associated catheters within a given anatomy for specific guidewire and navigation parameters. These charts are developed using the HOPGD method and demonstrate their ability to provide an accurate real-time response from a limited number of preliminary high-fidelity computations.

Keywords: Model Order Reduction, Numerical chart, Endovascular, Catheters, Guidewire, Aorta

1. Introduction

Endovascular therapies have grown significantly in the recent years. It is estimated that in 2026, 80% of cardiovascular problems will be treated by endovascular therapies [1]. The first step to treat endovascular pathologies is to reach the pathologies area. However, clinicians may be confronted to so-called complex pathways (e.g. renal arteries or Supra-Aortic Trunks (SATs)). It is estimated that 20% endovascular therapies present these complexities which may jeopardize the intervention [2]. In order to facilitate the access to complex targets through catheterization, the French company BaseCamp Vascular (BCV) developed an active guidewire made of Shape Memory Alloy, which distal tip can bend under an electric impulse. This guidewire can include several active modules; for instance for 2 modules placed in opposite directions, the guidewire tip can take an S-shape.

Our work focuses on the access to neurovascular pathologies through the left carotid artery using the active guidewire and associated catheters. Access to cerebral targets is facilitated using the active guidewire but two challenges remain for a given anatomy: (i) to optimize the design of the active guidewire by assessing the number of required actuators and their respective curvature and (ii) to propose navigation sequences maximizing the chances of reaching the target. A Finite Element (FE) model was developed to simulate the navigation of the active guidewire and catheters from the aortic arch to the left carotid artery in patient-specific aortas [3]. The numerical model offers the possibility to test particular guidewire configurations and navigation sequences.

However, numerical simulations are time-consuming and cannot be used

26 directly in clinical routine to provide navigation assistance. An alternative
27 is to develop numerical charts to explore in a continuous way a wide range
28 of parameters for a limited computational cost.

29 Numerical charts are built using Model Order Reduction (MOR) tech-
30 niques. Two families of MOR are commonly used. The methods known as
31 POD (Proper Orthogonal Decomposition) require calculations in an offline
32 phase (learning phase), further allowing reduction and online resolution in
33 the reduced base (in real-time). In biomechanics and in particular for vas-
34 cular problems, POD was used for example to process hemodynamic data
35 [4, 5, 6] or to reduce the computational time of complex models [7]. The
36 methods known as PGD (Proper Generalized Decomposition) based on the
37 separation of variables, do not require upstream calculations. In particular,
38 PGD is used for inverse problem solving: in [8], PGD was used to speed up
39 the process of identifying conductivities of heart tissue. Other works have
40 used PGD for computational surgery, [9, 10, 11] for example. One of the lim-
41 itations of POD is that it is not adapted to non-linear problems (large strains
42 in particular) and that the enrichment of the reduced bases can quickly be-
43 come expensive for high dimensional problems and/or with relatively large
44 parameter intervals. By considering uniform grids, the number of snapshots
45 is exponential. For example, for a uniform grid of snapshots in a space of 8 pa-
46 rameters with 10 values to be considered in each direction, 10^8 finite element
47 calculations would be required. We then speak of *curse of dimensionality*.
48 PGD allows to overcome this problem since no snapshot is required. How-
49 ever, it remains an intrusive method and is therefore not adapted to the use
50 of commercial softwares. The method used in the present study is HOPGD

51 (High Order Proper Generalized Decomposition) [12]. It is an a posteriori
52 definition of PGD and has been used to produce 10D numerical charts in the
53 context of real-time numerical simulation of welding processes [13]. We aim
54 to build numerical charts based on our reference FE navigation model, to
55 efficiently answer specific questions regarding device design and navigation
56 sequences.

57 We first recall the main features of the high-fidelity numerical models
58 used in this study, namely the guidewire model and the active endovascular
59 navigation model. Then, HOPGD is briefly presented and the methods for
60 the development of numerical charts are detailed. Proofs of concept of such
61 charts ,developed to answer specific questions associated to endovascular ac-
62 tive navigation, are presented. The results are finally discussed in a last
63 part.

64 **2. Methods**

65 *2.1. High fidelity models*

66 In this section, we present the high-fidelity models used to develop the
67 numerical charts: first the active guidewire model and second the navigation
68 model.

69 *2.1.1. Active guidewire*

70 *2.1.1.1. Structure.*

71 The active guidewire is composed of a long shaft made of steel. At its ex-
72 tremity, a blade is attached and Nitinol wires are positioned on both sides of
73 the blade and connected to electric wires. A handle allows to send an electric

74 impulse to the Nitinol wires and by shape memory effect, the wires shrink
 75 causing the blade to bend [14, 15]. When two Nitinol wires are placed on
 76 each face of the blade, the distal tip of the active guidewire draws a S-shape
 77 to facilitate the endovascular navigation (see Fig.1).

78 *2.1.1.2. Numerical model.*

79 The model is built using Ls-Dyna (LSTC / ANSYS, USA). The active
 80 guidewire is simplified and represented as a long shaft with the blade. The
 81 Nitinol wires are placed on both sides of the blade and connected by rigid
 82 links. The guidewire is meshed with Hughes-Liu beam elements. The meshes
 83 were defined by convergence analysis and are visible in Fig.2. The consti-
 84 tutive law to model the mechanical behavior of the guidewire is hypoelastic
 85 and relates, in Eulerian form, the objective Jaumann derivative of the Cauchy
 86 stress tensor σ to the strain rate tensor \mathbf{D} by the elasticity tensor \mathbf{C} such
 87 that:

$$\sigma^\nabla = \mathbf{C} : \mathbf{D} \quad (1)$$

88 Tensor \mathbf{C} can be decomposed into a spherical part \mathbf{C}^{sph} and a deviatoric
 89 part \mathbf{C}^{dev} such that:

$$\mathbf{C} = 3K\mathbf{C}^{sph} + 2G\mathbf{C}^{dev} \quad (2)$$

90

91 with K the bulk modulus and G the shear modulus.

92 The mechanical properties of the various portions of the guidewire are
 93 given Tab.1. The guidewire activation is simplified and produced by a dis-
 94 placement command as explained in [3].

95 *2.1.1.3. Simulation of the guidewire activation.*

96 Simulation of the guidewire is useful for guidewire developers to under-
97 stand the guidewire performance, related to the Nitinol wires characteristics.
98 The shaft is embedded and a temperature control is applied to both moduli
99 for activation. The computational time for such a simulation is about 5 min-
100 utes. The output data are the displacements in 3D of the guidewire distal
101 parts nodes (73 mm blade of the active guide) at the end of the simulation.

102 *2.1.2. Endovascular navigation*

103 *2.1.2.1. Test bench.*

104 The endovascular activation simulated in this work has been validated
105 with respect to data acquired on a test bench including a phantom aorta
106 (Fig.1). The simulation features aim to reproduce this configuration and the
107 phenomena observed on this bench. The set-up is composed of a patient-
108 specific aortic arch which can be changed and a fixed cylinder representing
109 the descending aorta. The active guidewire is inserted and co-manipulated
110 along with catheters.

111 *2.1.2.2. Endovascular navigation model.*

112 The numerical model simulates the endovascular navigation of the active
113 guidewire and associated catheters in the aorta test bench. The catheters and
114 the aorta are meshed with Belytschko-Tsay shell elements. The mechanical
115 properties of the tools are either hypoelastic (using Eq.1) or hypoviscoelas-
116 tic depending on the different areas. The hypoviscoelastic properties are
117 modeled with the following law defined in [16]:

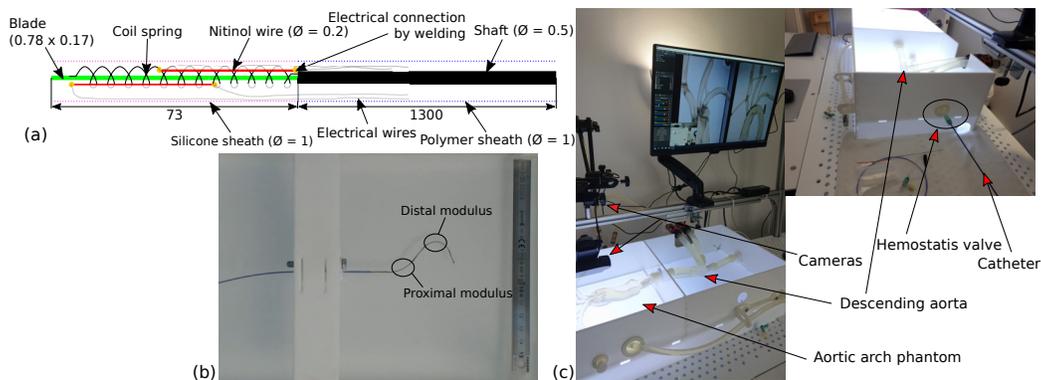


Figure 1: (a) Scheme of the active guidewire developed by BCV with two Nitinol wires placed on both sides of the blade and (b) its activation highlighting the proximal and the distal moduli. (c) Phantom aorta test bench used to test surgical tools in patient-specific aortas.

$$G(t) = G_{\infty} + (G_0 - G_{\infty})e^{-\beta t}$$

118 where G_{∞} and G_0 are respectively the long and short time shear moduli,
 119 parameter β is a constant expressed per time unit.

120 Fig.1 illustrates the tools design and dimensions as well as one aorta shell
 121 mesh. Table 1 synthetizes the tools mechanical properties, while the aorta is
 122 considered rigid. The full navigation model, involving guidewire activation
 123 but also tools translations and rotations within the aorta, was validated as
 124 described in [3] by confronting experimental navigations in patient-specific
 125 aortas to simulated ones.

126 The model is able to reproduce the main movements and phenomena
 127 occurring in active navigation: translations of the guidewire and the catheter,
 128 rotations of the guidewire and particular effects such as the snapping (Fig.3).
 129 Navigation sequences will be detailed later.

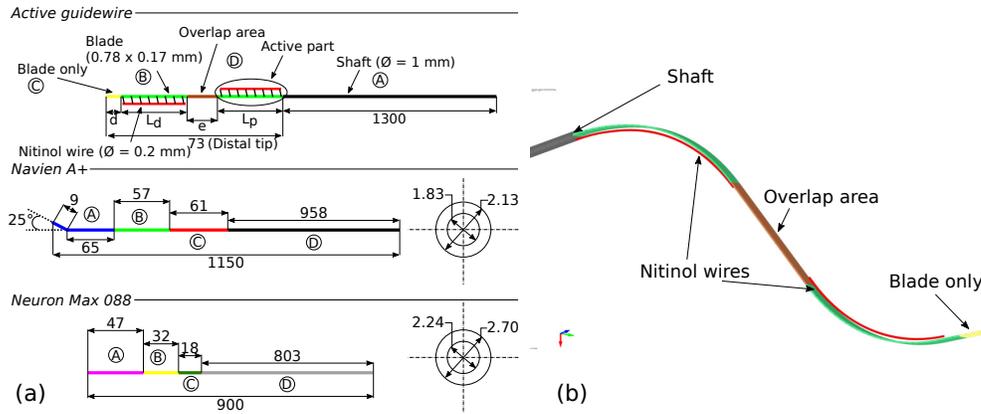


Figure 2: (a) Dimensions of the active guidewire and associated catheters. Each portion of the different tools is defined by a colour and has its own mechanical properties. (b) Activation of the device with two moduli. When the Nitinol wires are heated, they contract resulting in the S-shape bending. (c) Assembly of the different tools in the aorta. The aortic arch is a patient-specific anatomy while the descending aorta is represented by a rigid cylinder.

130 2.1.2.3. High fidelity simulations for the construction of decision support nu-
 131 merical charts.

132 Two numerical charts are built for the endovascular navigation in two
 133 typical aortas: the BH aorta, which is referred to as a standard aorta, and

Table 1: Mechanical properties along the surgical tools: areas A to D are related to those in Fig.2.

	A	B	C	D
Active guidewire	$E = 8047.8 \text{ MPa}$ $\nu = 0.3$	$E = 71130.0 \text{ MPa}$ $\nu = 0.3$	$E = 52720.0 \text{ MPa}$ $\nu = 0.3$	$E = 175000.0 \text{ MPa}$ $\nu = 0.3$
Navien	$\beta = 0.22 \text{ s}^{-1}$ $G_0 = 62.0 \text{ MPa}$ $G_\infty = 15.9 \text{ MPa}$ $K = 82.9 \text{ MPa}$	$\beta = 0.16 \text{ s}^{-1}$ $G_0 = 94.1 \text{ MPa}$ $G_\infty = 26.6 \text{ MPa}$ $K = 152.3 \text{ MPa}$	$\beta = 0.18 \text{ s}^{-1}$ $G_0 = 448.1 \text{ MPa}$ $G_\infty = 152.2 \text{ MPa}$ $K = 694.6 \text{ MPa}$	$E = 1519 \text{ MPa}$
Neuron	$\beta = 0.26 \text{ s}^{-1}$ $G_0 = 74.0 \text{ MPa}$ $G_\infty = 17.0 \text{ MPa}$ $K = 122.1 \text{ MPa}$	$E = 250 \text{ MPa}$	$E = 180 \text{ MPa}$	$E = 1701 \text{ MPa}$

134 the FM aorta, which includes a bovine arch (the left carotid artery and
135 the brachio-cephalic trunk share the same origin). The key steps of active
136 navigation into these aortas are illustrated Fig.4.

137 The distal modulus is systematically activated at the beginning of naviga-
138 tion to follow the shape of the arch and prevent the guidewire from entering
139 the left subclavian artery. Therefore, the time of activation of the distal mod-
140 ulus is not a parameter. The output data recorded are the displacements of
141 the guidewire distal part (73 mm blade) over time. The data are saved every
142 0.01s of the simulation over a total simulation time of 10.6s and 11.5s for
143 the BH and FM aorta, respectively. Using two 2.30 GHz Xeon cores, the
144 duration of a simulation is about 3h.

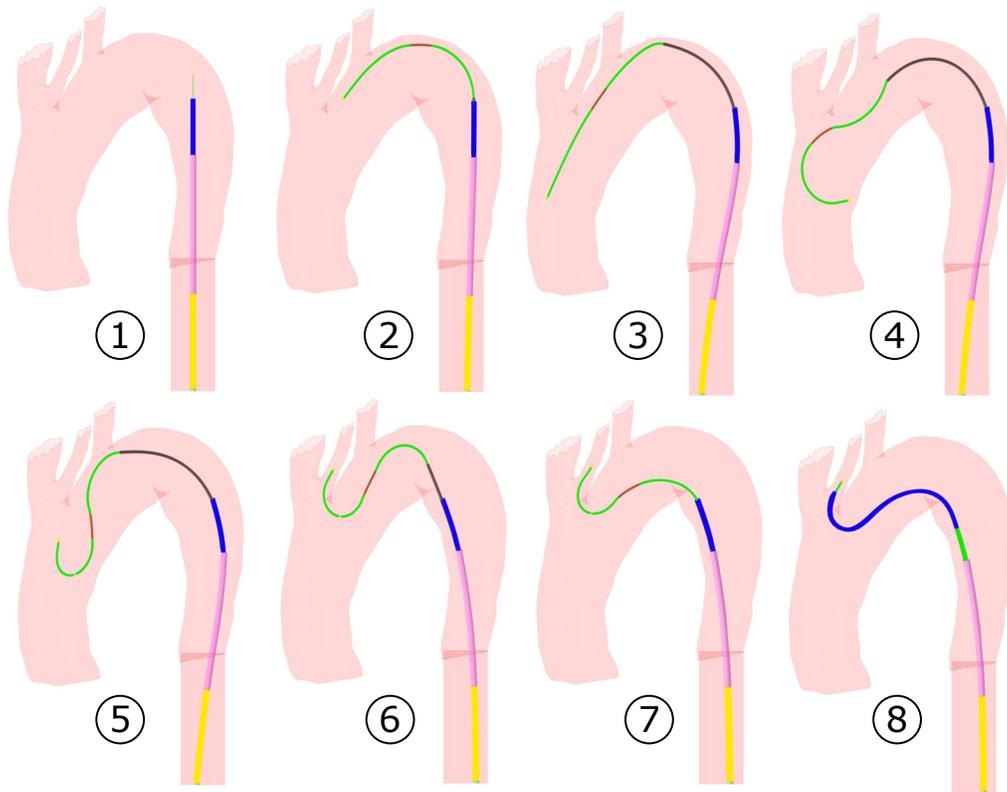


Figure 3: From ① to ③ the guidewire is initially pushed near the left carotid artery entrance. The two modules are activated in ④ while a rotation gesture is applied at the end of the active guidewire. As a consequence, the snapping effect appears(⑤) allowing to point the distal part of the guidewire in the desired direction and to stabilize the device. The guidewire is pulled from ⑥ to ⑦ to straighten the catheters with a deactivation of the proximal module to further tension it. Finally, the catheter slides over the guidewire until it reaches the left carotid artery in ⑧.

145 *2.2. Development of numerical charts using reduced order modeling*

146 Now that the high-fidelity FE models have been presented, the HOPGD
 147 method used to build the numerical charts is presented. A focus is proposed
 148 on the choice of the parameters of interest in this work, as it is a critical step.

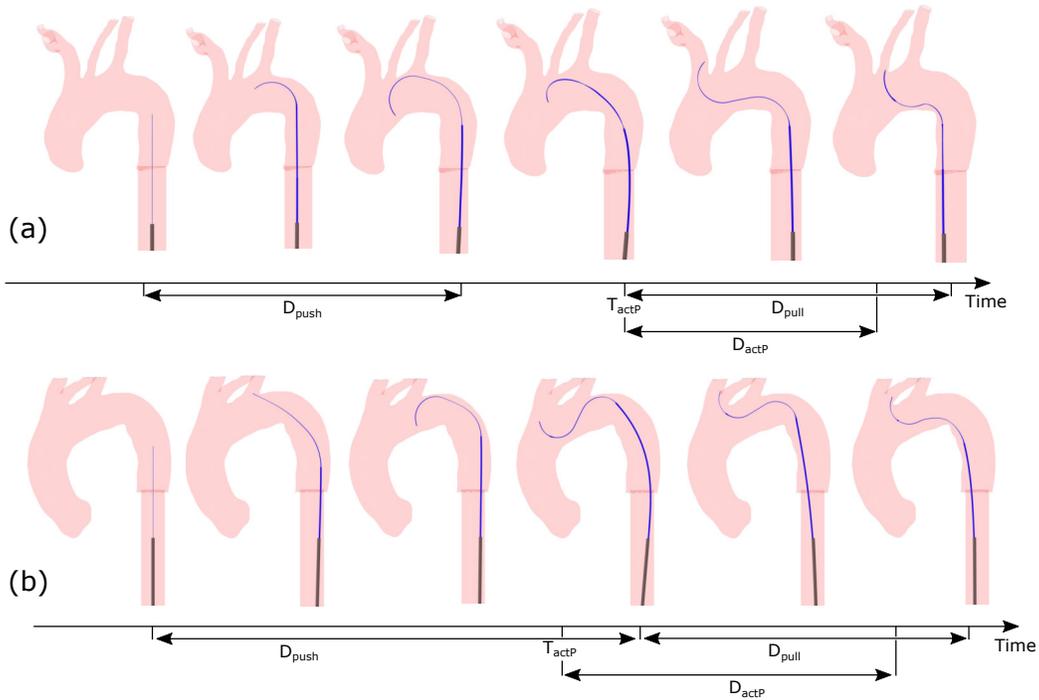


Figure 4: (a) Proposed navigation key steps for BH aorta hooking (standard aorta). The guidewire is pushed (during D_{push}) and the distal modulus is activated to prevent the device from inserting into the subclavian artery. After the guidewire is pushed, the proximal modulus is activated (at T_{actP} and during D_{actP}) and the snapping is initiated. The guidewire is then pulled (during D_{pull}). (b) The steps for navigation in the FM aorta (aorta with bovine arch) slightly differ: the guidewire navigates until it reaches the TSAs, the distal modulus is activated and snapping is triggered. The proximal modulus is then deactivated while pulling the guidewire to attempt to hook the carotid artery. Below each figure, navigation parameters driving the navigation are indicated on an axis representing time.

149 Then, two types of numerical charts are developed as proofs of concept:
 150 an active guidewire design tool focusing on design parameters and navigation
 151 assistance tools mixing design and navigation parameters. For each type of

152 numerical chart, the parameter space and the snapshot selection method are
 153 presented. An error is finally calculated to evaluate the chart accuracy.

154 *2.2.1. Methods*

155 *2.2.1.1. HOPGD.*

156 We consider a function u dependent on parameters $p_{i=1,d}$ which can be
 157 time, space or control parameters of the problem. These parameters are
 158 assimilated to extra-coordinates of the solution and discretized in the pa-
 159 rameter space. For each set of parameters, HOPGD seeks an approximate
 160 form u^n of u such that:

$$u(p_1, \dots, p_d) \approx u^n(p_1, \dots, p_d) = \sum_{j=1}^n \prod_{i=1}^d F_i^j(p_i) \quad (3)$$

161 n is the order of approximation and the functions $F_{i=1,d}^j$ are related to
 162 the j -th mode. These functions are determined by solving the minimization
 163 problem which consists in finding $u^n \in V_n \subset \mathcal{L}^2(\Omega)$ minimizing the cost
 164 function J such that:

$$J(u^n) = \min_{u^n \in V_n} \left(\frac{1}{2} \| u^n - u \|^2_{\mathcal{L}^2(\Omega)} \right) \quad (4)$$

165 This minimization problem can be solved by an alternating fixed point
 166 algorithm. For a new set of parameters, the new functions F_i are linearly
 167 interpolated from the existing functions. In this study, the version of the
 168 HOPGD algorithm does not use snapshot selection by *sparse grids* method
 169 as introduced in [17]. Thus, parameters discretization is conducted using
 170 uniform grids. Fig.5 illustrates the general procedure of the HOPGD method.

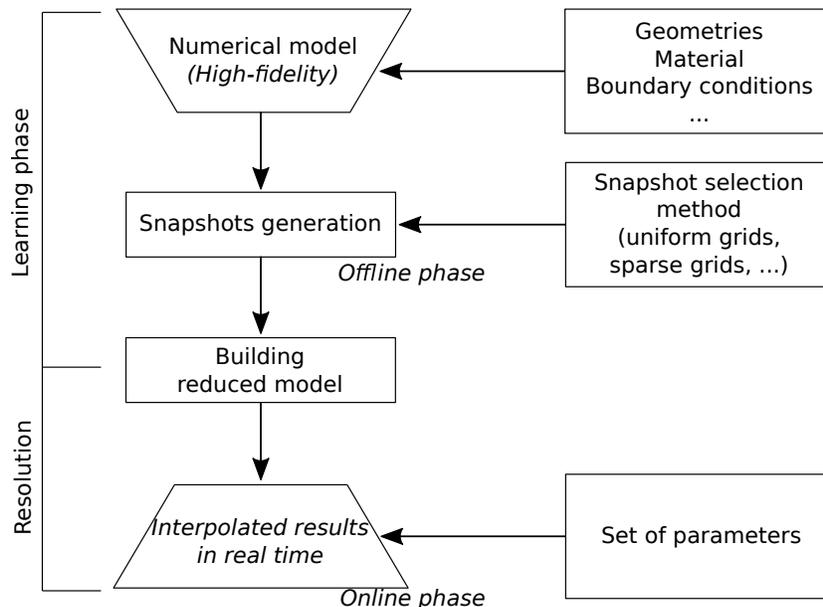


Figure 5: General procedure of the HOPGD method: starting from a high-fidelity numerical model, n parameters are considered among the geometry, material and boundary conditions. Then, the parameter space defined by the n axes is discretized using a snapshot selection method. For an uniform grid, m snapshots are selected along the axes forming a total of m^n snapshots. These snapshots are used to build the reduced model. Considering a new set of parameter within the parameter space, the HOPGD model is capable of providing a real-time response.

171 *2.2.1.2. Error evaluation.*

172 In order to evaluate the numerical charts performance, so-called evaluation
 173 points are selected in the center of the subdomains of the snapshot grid in
 174 the parameter space.

175 For each of these evaluation points, an additional finite element calcula-
 176 tion is performed and the displacements of guidewire distal part nodes are
 177 stored in a reference U^{ref} matrix, containing the so-called high fidelity re-
 178 sults. The reduced model is used to interpolate the results on this point

179 and the obtained displacements are in turn stored in a U matrix. For the
180 considered point, an error δ is computed such that:

$$\delta = \frac{\| U - U^{ref} \|}{\| U^{ref} \|}$$

181 With $\| \bullet \|$ the L_2 norm.

182 *2.2.2. Application*

183 Endovascular navigation involves many parameters. They can be clas-
184 sified into three categories: (i) those related to the design of the active
185 guidewire (e.g., lengths of the active moduli or distance between them), (ii)
186 the parameters related to navigation such as activation times or pushing /
187 pulling times of the surgical tools and (iii) those dealing with geometric pa-
188 rameters (patient-specific aortas). In our study, we decided to work with
189 fixed geometry, i.e. the parameters only relate to the design of the active
190 guidewire and those related to the clinician gestures during navigation. In
191 the following, two types of numerical charts are presented. First, an active
192 guidewire design aid tool with five control parameters that are related to the
193 device design is presented. This tool allows to compute the performance of
194 the activated guidewire for a given set of parameters. Then, considering the
195 design and navigation parameters, decision support numerical charts are also
196 proposed with seven control parameters.

197 *2.2.2.1. Active guidewire design tool.*

198 This first tool aims to provide a design aid tool. From a given guidewire
199 configuration, the tool computes in real time the deformation of the guidewire
200 after activation of the moduli. The high-fidelity model used to generate the

201 snapshots was presented in Section 2.1.1.3. The output of each snapshot
 202 corresponds to the distal guidewire position for a given design.

203 *Choice of parameters*

204 Five design parameters are selected for the development of the design support
 205 tool (Fig.6): the lengths L_p , L_d and e that are the lengths of the active
 206 moduli and the distance between them, respectively; parameters ϵ_L for the
 207 two Nitinol wires, which is the recoverable strain for the Nitinol wires in
 208 the shape memory effect loop representing the wire performances (change
 209 in current intensity or Nitinol grade for instance). Fig.6 also describes the
 210 parameter ranges.

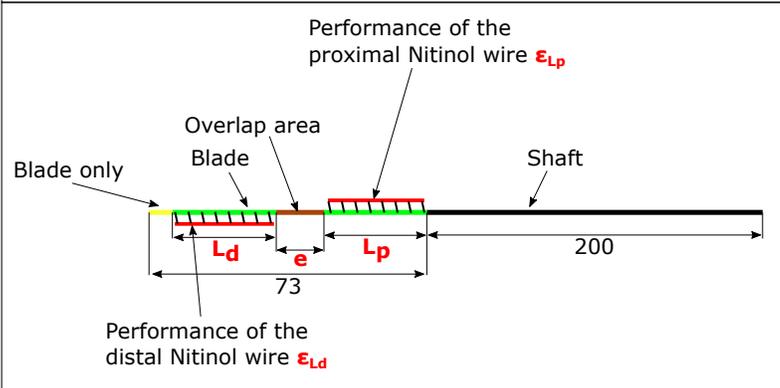
Model of the active guidewire highlighting the design parameters (bold red)	Parameters
	$L_p \in [15;20]$ (mm) $e \in [5;10]$ (mm) $L_d \in [15;40]$ (mm) $\epsilon_{L_p} \in [0.01;0.0347]$ $\epsilon_{L_d} \in [0.01;0.0347]$

Figure 6: Double stage guidewire activation model and design parameters ranges.

211 *Snapshots selection*

212 As previously mentioned, the version of HOPGD we use in this work does
 213 not include the sparse grids method and therefore does not allow for optimal
 214 selection of snapshots in the parameter space. Thus, it is chosen for this
 215 numerical chart to build a uniform grid with a discretization of three values

216 per parameter (extremal values and middle of each interval), yielding a grid
217 of $3^5 = 243$ finite element calculations to feed the HOPGD method and
218 create the reduced model. A MatLab (MathWorks, USA) routine is used to
219 automatically create the snapshots with the design parameters as input data.
220 Once the snapshots are computed, the HOPGD algorithm builds the reduced
221 model with a default number of modes fixed at 20. The reduced model is
222 then evaluated at the center of subdomains formed by the space parameter
223 and using the error defined Section 2.2.1.2.

224 *2.2.2.2. Navigation assistance tools.*

225

226 *Introduction*

227 In this part, more sophisticated numerical charts are proposed taking into
228 account both design and navigation parameters. These decision support
229 tools compute the active navigation in a given anatomy for various sets of
230 parameters. They are proofs of concept of decision support tools which
231 could be used in the preoperative phase. Their main advantage is the real
232 time response. The high-fidelity model used to generate the snapshots was
233 presented in Section 2.1.2.3.

234 *Choice of parameters*

235 Among the design parameters, we focused on the distal active modulus, which
236 plays a dominant role in active navigation. Thus, parameters L_d and ϵ_{L_d} are
237 included (Fig.6). Only the performance of the NiTi wire given by ϵ_{L_p} is
238 selected to drive the design of the proximal modulus (L_p fixed at 27 mm and
239 $e = 13\text{mm}$).

240 The other four parameters drive navigation. From a preliminary sen-

241 sitivity study, the choice is made to focus on the guidewire pushing and
 242 pulling time (D_{push} and D_{pull}) and the time and duration of the activation
 243 of the proximal modulus (noted T_{actP} and D_{actP} respectively). These param-
 244 eters are illustrated Fig.4. A MatLab routine was developed in this study
 245 to automatically generate the endovascular navigation models from selected
 246 parameters.

Table 2: Choice of the intervals for the seven parameters of the decision support charts. The intervals are given for the standard aorta case and with bovine arch.

<i>Parameters</i>	<i>Range of values for the standard aorta / with bovine arch</i>
$L_d(mm)$	[27 ; 32] / [27 ; 32]
ϵ_{L_p}	[0.026 ; 0.028] / [0.03 ; 0.033]
ϵ_{L_d}	[0.029 ; 0.033] / [0.033 ; 0.0347]
$D_{push}(s)$	[2.0 ; 3.5] / [4.2 ; 5.2]
$D_{pull}(s)$	[0.05 ; 1.5] / [1.7 ; 2.5]
$T_{actP}(s)$	[3.5 ; 4.5] / [4.7 ; 5.3]
$D_{actP}(s)$	[0.1 ; 0.6] / [1.8 ; 2.2]

247 *Refinement and model accuracy*

248 The accuracy of the navigation assistance tool is evaluated from an er-
 249 ror defined, as explained in Section 2.2.1.2, as the difference between the
 250 high-fidelity model result and the reduced model result at the center of the
 251 hypercube defined by the parameter grid. However, we also propose here
 252 to dynamically improve the accuracy by adding a control loop (refinement)
 253 during the learning phase. The general procedure is visible in Fig.7.

254 For the construction of these numerical charts, the generation of a uniform

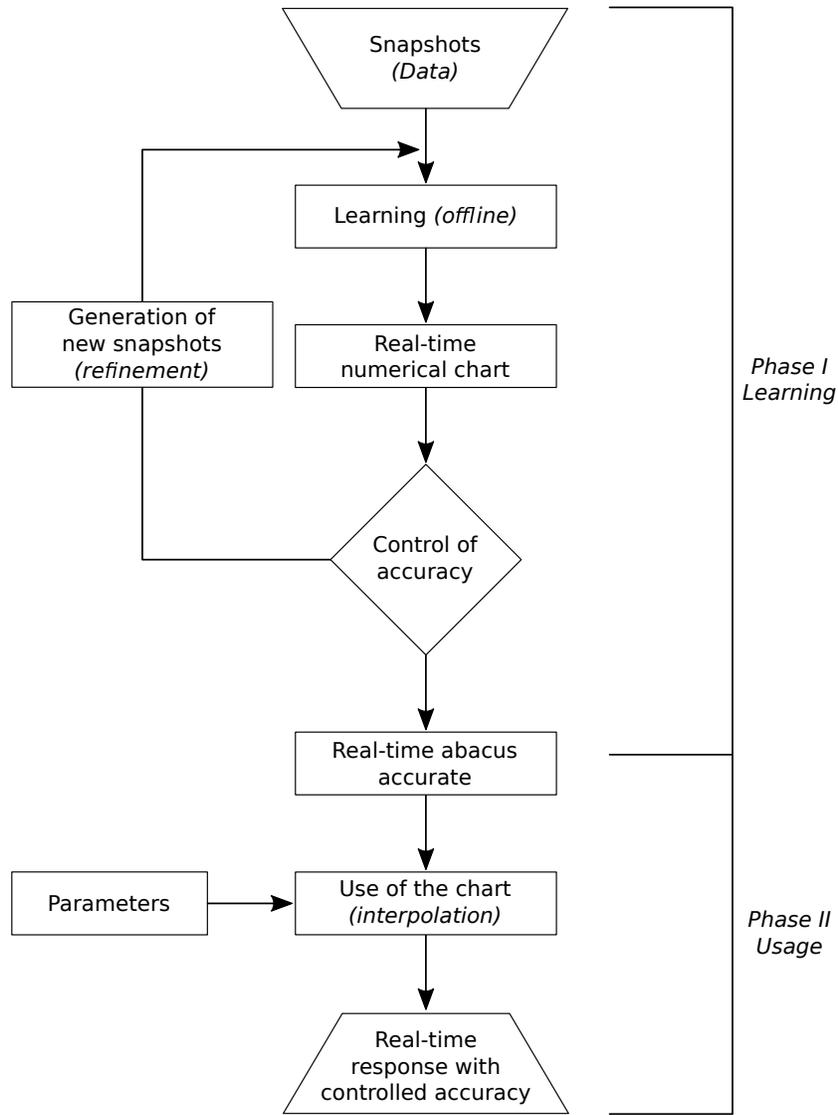


Figure 7: General procedure used for the development of decision support charts. From the snapshots computed in the parameter space in the learning phase, the reduced model is created and its accuracy is controlled. New snapshots are generated until the reduced model is considered as accurate enough. The real-time numerical chart is then used to give a real-time response given a set of parameters.

255 grid similar to the one used for the design aid chart (3 values per parameter)
 256 would have required $3^7 = 2187$ snapshots. A method is therefore proposed
 257 to limit the generation of many snapshots while allowing the creation of
 258 charts with a satisfactory accuracy. Fig.8. shows an overview of the process
 259 considering a 2D parameter space.

260 This additional procedure allows to determine the axes to be refined (re-
 261 quiring the addition of snapshots at the axis centers) when the error at the
 262 center of the hypercube is greater than a threshold value (here 5%). Let
 263 us note P^i the i -th parameter for $i = 1, \dots, 7$, P_{max}^i the maximum value at
 264 parameter P^i (upper limit of the interval in Tab.2) and P_{middle}^i the middle
 265 of the interval of admissible values for the parameter P^i . Seven evaluation
 266 points, related to the seven parameters, are considered in order to determine
 267 which parameters most affect the error sensitivity. The first evaluation point
 268 corresponds to $\{P_{middle}^1, P_{max}^2, P_{max}^3, P_{max}^4, P_{max}^5, P_{max}^6, P_{max}^7\}$, evaluating the
 269 contribution of the first parameter. In the same way the second evaluation
 270 point corresponds to $\{P_{max}^1, P_{middle}^2, P_{max}^3, P_{max}^4, P_{max}^5, P_{max}^6, P_{max}^7\}$ and so on.
 271 The error as a function of time is then calculated for each of these evaluation
 272 points. The parameter axes associated with evaluation points whose maxi-
 273 mum error exceeds 5% are refined by adding the midpoint on the parameter
 274 specific axis, for discretization of the snapshot grid. The procedure on a 2D
 275 case is illustrated Fig.8.

276 In this part, we limit ourselves to a level 1 refinement (adding only one
 277 snapshot per direction) on three axes at most, which represents a final grid
 278 of $3^3 \times 2^3 = 432$ snapshots.

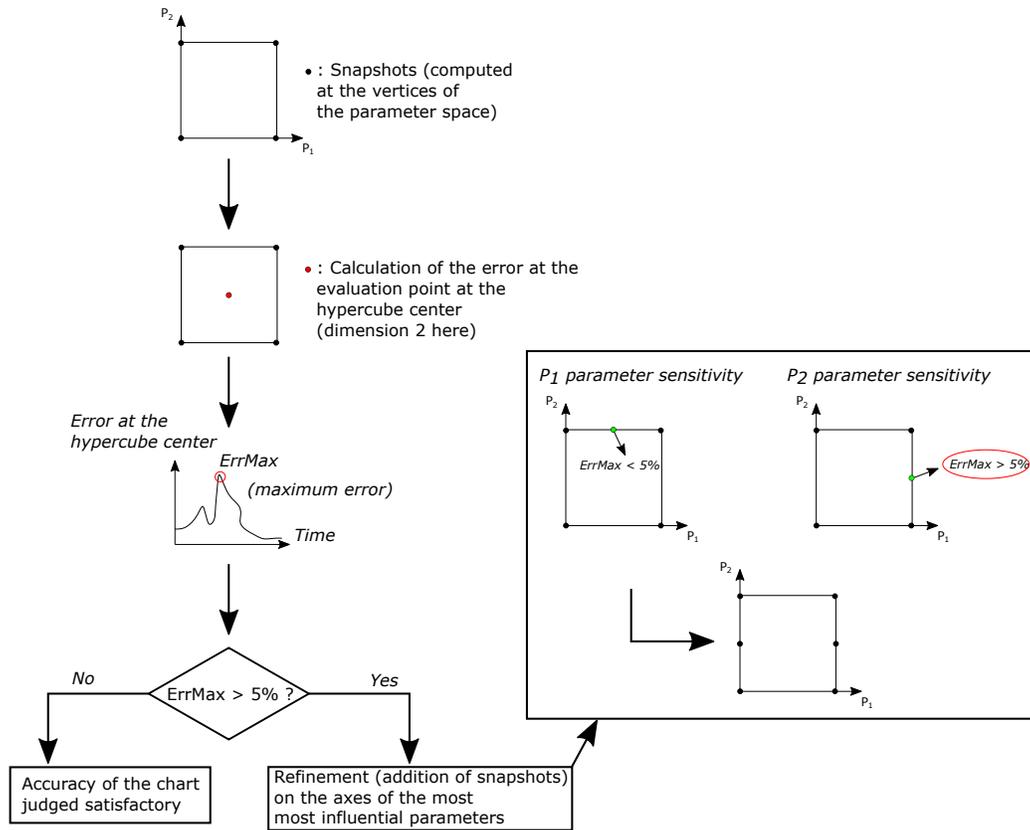


Figure 8: General procedure for the creation and refinement of decision support charts on typical aortas (learning phase in Fig.7). The first step is to perform the simulations on the parameter sets at the vertices of the grid. The error during navigation is then evaluated at the center of the hypercube. When this error exceeds a threshold fixed at 5%, the discretization in the parameter space is densified on the axes of the influential parameters (addition of snapshots at the center of these axes). Indeed, evaluation points (in green) are added at the middle of the parameter ranges to estimate sensitivity and errors are computed for both parameters. In the example, the error related to P_2 exceeds 5%. Consequently, the grid is refined to reduce the error at the hypercube center.

279 3. Results

280 3.1. Active guidewire design tool

281 From the 243 finite element snapshots, the reduced model is created by
 282 the HOPGD method in 17 seconds. ²¹The accuracy of the reduced model is

283 evaluated at the different centers of the subdomains of the parameter space,
284 i.e. on 32 evaluation points. The model is able to provide a solution in 10^{-5} s
285 against 5 minutes for a FE calculation. The percentage errors at the different
286 centers are given Tab.3.

287 The reduced model considerably decreases the computation time and al-
288 lows to create the numerical chart visible on Fig.9. The graphical interface
289 is developed with Qt Creator (Qt Group, Finland). The set of chosen pa-
290 rameters with the cursor interrogates the model and the interface displays
291 the corresponding guidewire displacements.

292 *3.2. Navigation assistance tools*

293 *3.2.1. Standard aorta*

294 From the snapshots at the grid vertices ($2^7 = 128$ snapshots), the reduced
295 model is created in 77 seconds. Using the method detailed in 2.2.2.2 to select
296 the axes to be refined, values at the middle of the parameters axes of L_d ,
297 D_{pull} and T_{actP} are added, with a total number of snapshots at $3^3 \times 2^4 = 432$.
298 The new model is built in 263 seconds and the error at the center of the
299 hypercube is reduced. The performance, precision and parameters of the
300 decision support tool developed are summarized in Fig.10.

301 *3.2.2. Aorta with bovine arch*

302 The procedure is similar for this chart applied to a bovine arch anatomy.
303 The first model is built in 44 seconds but the error at the hypercube center
304 required a refinement on the parameters axes of D_{pull} and T_{actP} leading to a
305 model created in 164 seconds based on $3^2 \times 2^5 = 288$ snapshots. The errors of
306 the model before and after refinement are displayed Fig.10 as well as the main

Table 3: Errors at the center of the subdomains of the 5 control parameters for the design aid chart.

<i>Subdomain number</i>	<i>Set of parameters</i>	<i>Error (in %)</i>
1	{15.5; 5.5; 20.5; 0.016175; 0.016175}	0.79
2	{18.5; 5.5; 20.5; 0.016175; 0.016175}	0.85
3	{15.5; 8.5; 20.5; 0.016175; 0.016175}	0.78
4	{18.5; 8.5; 20.5; 0.016175; 0.016175}	0.77
5	{15.5; 5.5; 33.5; 0.016175; 0.016175}	0.72
6	{18.5; 5.5; 33.5; 0.016175; 0.016175}	0.91
7	{15.5; 8.5; 33.5; 0.016175; 0.016175}	0.9
8	{18.5; 8.5; 33.5; 0.016175; 0.016175}	0.88
9	{15.5; 5.5; 20.5; 0.028525; 0.016175}	1.00
10	{18.5; 5.5; 20.5; 0.028525; 0.016175}	0.96
11	{15.5; 8.5; 20.5; 0.028525; 0.016175}	0.82
12	{18.5; 8.5; 20.5; 0.028525; 0.016175}	0.73
13	{15.5; 5.5; 33.5; 0.028525; 0.016175}	0.90
14	{18.5; 5.5; 20.5; 0.028525; 0.016175}	1.01
15	{15.5; 8.5; 33.5; 0.028525; 0.016175}	0.91
16	{18.5; 8.5; 33.5; 0.028525; 0.016175}	0.92
17	{15.5; 5.5; 20.5; 0.016175; 0.028525}	0.85
18	{18.5; 5.5; 20.5; 0.016175; 0.028525}	0.90
19	{15.5; 8.5; 20.5; 0.016175; 0.028525}	0.79
20	{18.5; 8.5; 20.5; 0.016175; 0.028525}	0.79
21	{15.5; 5.5; 33.5; 0.016175; 0.028525}	0.56
22	{18.5; 5.5; 33.5; 0.016175; 0.028525}	0.70
23	{15.5; 8.5; 33.5; 0.016175; 0.028525}	0.67
24	{18.5; 8.5; 33.5; 0.016175; 0.028525}	0.77
25	{15.5; 5.5; 20.5; 0.028525; 0.028525}	0.91
26	{18.5; 5.5; 20.5; 0.028525; 0.028525}	0.98
27	{15.5; 8.5; 20.5; 0.028525; 0.028525}	0.86
28	{18.5; 8.5; 20.5; 0.028525; 0.028525}	0.83
29	{15.5; 5.5; 33.5; 0.028525; 0.028525}	0.68
30	{18.5; 5.5; 33.5; 0.028525; 0.028525}	0.81
31	{15.5; 8.5; 33.5; 0.028525; 0.028525}	0.78
32	{18.5; 8.5; 33.5; 0.028525; 0.028525}	0.81

307 characteristics of this numerical chart. For the first numerical chart (standard
308 aorta) a peak occurs at t=2s with the distal module activation. At t=5s,

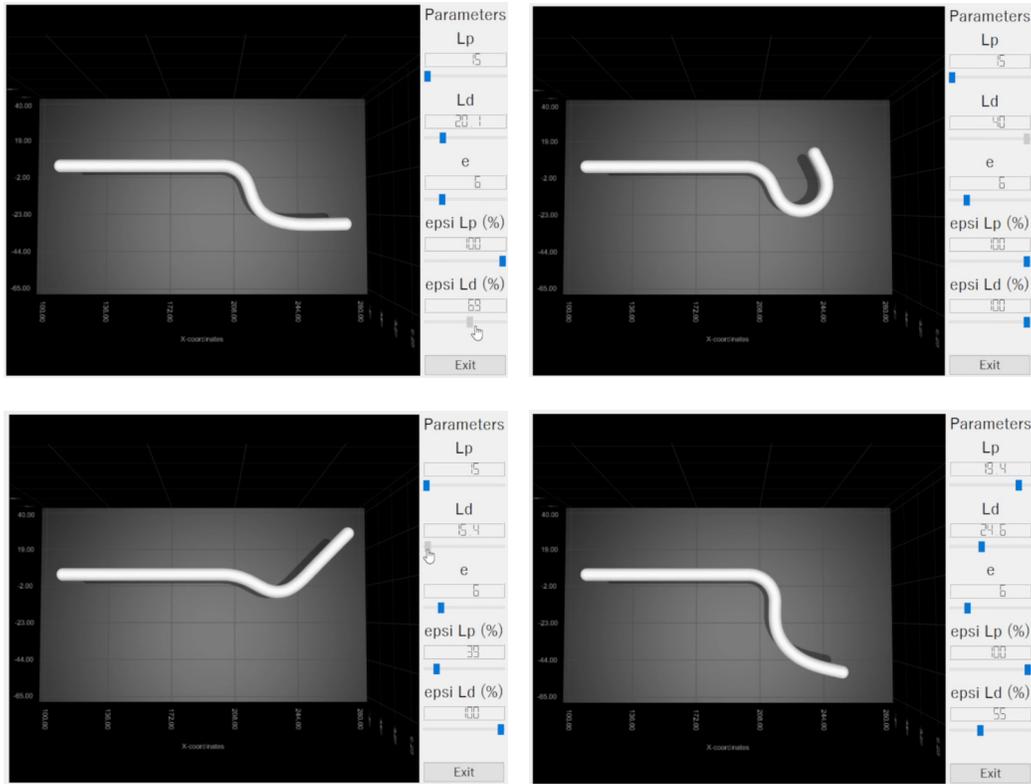


Figure 9: Numerical chart to help design the active guidewire. The five parameters can be modified and the tool allows to give a real time response of guidewire deformations with an accuracy of about 1%. A part of the rod is represented (left part of the rod) but has not been considered for the model construction. The figures represent different deformations of the guidewire according to the set of parameters defined by the user on the right panel.

309 snapping occurs and we can see that grid refinement highly improves the error
 310 with a better prediction of the position of the guidewire after snapping. For
 311 the second numerical chart, the error curves along time are fairly similar with
 312 a peak during snapping. At $t=8.5s$, grid refinement allows to better describe
 313 the position of the guidewire once pulled and the distal part abruptly hooked
 314 the aorta. The accuracy is considered satisfactory considering the relatively

315 low number of snapshots for such a problem.

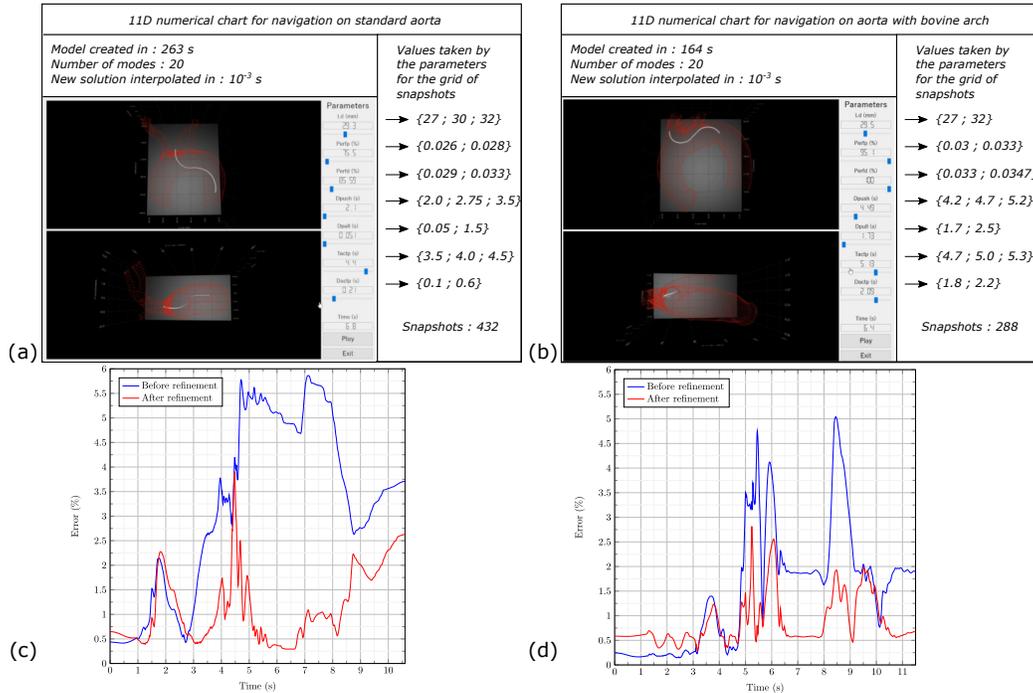


Figure 10: Characteristics of the numerical decision support chart on a standard aorta (a) and an aorta with bovine arch (b). In (c) and (d) the errors of the reduced model as a function of time evaluated at the hypercube center in the parameter space are displayed for the standard aorta and the aorta with bovine arch, respectively.

316 *3.2.3. Conclusions on decision support charts*

317 Overall, the charts show very satisfactory results. The snapping is cor-
 318 rectly replayed and the contact well represented. For each new set of pa-
 319 rameters, the tools provide an instantaneous response (10^{-3} s) compared to
 320 nearly 3 hours for a high-fidelity FE calculation. The response time of the
 321 numerical chart is well below the specifications.

322 Concerning the error curves in blue for the two charts (Fig.10), peaks

323 at key stages of the navigation are observed. The first peak occurs when
324 the distal modulus is activated. While snapping, the error increases sharply.
325 For the first chart, this error gradually decreases and then increases again
326 when the guidewire is pulled. The second chart error curve shows successive
327 peaks during snapping, mainly due to guidewire high frequency vibrations.
328 A second peak is visible when the proximal modulus is deactivated.

329 **4. Discussion**

330 *4.1. Main results*

331 The HOPGD method was used to build numerical charts and proved to
332 be efficient for problems with many parameters as it was the case in this
333 study.

334 A first chart has been developed to help the guidewire design optimiza-
335 tion. Only guidewire design parameters were studied. Considering the sim-
336 ulation time of the snapshots used to create the reduced model and the
337 preliminary tests, it was chosen to work on a uniform grid with three values
338 per axis. Since the ranges were relatively wide, the errors of the reduced
339 model were evaluated at the centers of the subdomains formed by the grid
340 and reached 1%. A refinement was therefore not required for this chart.

341 Then, the objective was to work on more complex charts combining design
342 and navigation parameters. These tools were thought of as proofs of concept
343 of what could be achieved using model reduction methods in a biomechanical
344 and in particular cardiovascular framework.

345 Some remarks about the choice of the navigation parameters and their
346 values can be formulated: these parameters are considered to be the most

347 influential for left carotid artery hooking. The extrema of these parameters
348 were determined by a preliminary analysis. With these values the guidewire
349 navigates between the origins of the left subclavian and the brachiocephalic
350 trunk. The values do not overlap and they are associated to specific navi-
351 gation sequences. Indeed, the extrema values were chosen such as the main
352 navigation steps are the same over the snapshots: considering the navigation
353 into the BH aorta for instance, the guidewire is first pushed, the proximale
354 module is activated and then the guidewire is pulled. Other sequences can
355 not be obtained with these charts.

356 In the context of this study, real time is of the order of a second, compa-
357 rable to the reaction time when using the graphical interface. For integration
358 of numerical chart in a medical robotics environment, we would target a re-
359 sponse time of the order of 0.1s maximum, to be able to capture and control
360 the fast movements of the tools. However it should be emphasized that this
361 chart provides the navigation over time and not only the final configuration.
362 After refinement, the error remains below 4% which can be considered as
363 very satisfactory, especially because this maximum error occurs at snapping.
364 We expected this phenomenon to be much less reductible.

365 In general, it was interesting to test the performance of the HOPGD
366 method in our problem associating nonlinearities, contact and fast phenom-
367 ena.

368 *4.2. Study limits*

369 Many tests (charts with less parameters, simulations to study the sensi-
370 tivity to some parameters) have been conducted beforehand and two main
371 difficulties have been highlighted: the choice of parameters and their range

372 of values. The active guidewire was developed during this work. As a con-
373 sequence, there was not the necessary hindsight to choose, in an optimal
374 way, the parameters to be incorporated in the chart. We then relied on the
375 experience gained from the numerous simulations performed.

376 Concerning the values ranges, charts with two or three parameters allowed
377 to show that too large ranges would require many simulations. In order to
378 develop proofs of concept and taking into account the available resources, a
379 maximum of 432 snapshots per chart was set. With seven control parameters,
380 the selected value intervals were therefore quite small and did not allow to
381 explore large variations of the guidewire navigation. The main limitation
382 came from the use of uniform grids. It would be interesting to improve the
383 generation of snapshots with a sparse grid method.

384 The errors for both decision support charts were evaluated at the cen-
385 ter of the hypercube. An error within 5% was considered satisfactory. This
386 criterion was determined by judging the displacements of the guidewire rel-
387 ative to the aorta: for the tested charts, a higher error corresponded to poor
388 management of the contact between the guidewire and the aorta. Moreover,
389 the peaks occurred during the fast phenomena: activation and deactivation of
390 the modules or even snapping. A solution to smoothen the curves could be
391 to save more data as a function of time (reduction of the time step used to
392 save the guidewire displacements) so as to better capture these phenomena.
393 However, it would require a large amount of storage.

394 A method, adapted specifically for this study, allowed us to select the
395 axes to refine the grid when this error exceeded 5%. For intervals with larger
396 extrema, further refinements in the sub-domains may be considered.

397 **5. Conclusion**

398 This study presents numerical charts for design and decision support tools
399 dedicated to the use of the active guidewire. These solutions serve as a proof
400 of concept and show very promising results. Fixed anatomy numerical charts
401 were proposed in this study. A more powerful tool could incorporate geo-
402 metric parameters and allow, for a new patient, to provide real-time decision
403 support.

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408 **7. Conflict of interest statement**

409 The authors declare that there are no conflicts of interest.

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