Ph.D. Topic – 3IA Côte d'Azur

Cognitive and Physics-Informed 3D Modeling for Digital Twins and Smart Territories

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Abstract: *the main objective is to explore the concept of "cognitive 3D model", which is searchable, physics-informed and continuously updated. Such a concept is relevant for digital twin simulation and design exploration: two prevalent problems for the smart territories.*

Context. The initial great promise of 3D geometric modeling and processing was to achieve for shapes what had been done in digital signal processing for sound and images. Over the last twenty years, it has matured into an established research community seeking automatic, computerized processing of 3D geometric data obtained through measurements or designs. As our understanding of real-world data has progressed, we have expanded our focus to real-world systems and problems involving multiple practitioners. The following developments have shaped this Ph.D. topic proposal:

- The problems posed by digital twins reveal that increasingly, geometry is only one dimension of the end goal in real-world applications. The latter often mingle remote visualization, inspection and simulation of virtual processes and physical phenomena. Many of the current 3D modeling approaches focus on geometry and color attributes only. They overlook the importance of cognition and physics.
- The move to large-scale physical scenes and proliferation of real-time sensor systems operating in open environments make it possible to consider digital twin simulations, with continuous scene capturing. Digital twins have emphasized real-world problems that transcend geometry, cognitive tasks and computational physics.
- Multiphysics simulation, recognized as engineering's new frontier, is increasingly required for conceiving complex systems. Multiphysics problems correspond to the intersection of several physics, which often becomes a 'grey area', as practitioners are rarely experts in all the intersecting physics. The challenge is even harder as modern design exploration methods require many simulation queries, interlaced with cognitive queries. In this context, cognitive, physics-informed geometric modeling can provide a common ground.

- Recent advances in machine learning and data-intensive approaches facilitate a new era of frontier research where geometry, cognition and physics operate in tandem, rather than in silos.

State-of-the-art. The conventional approach to geometric modeling seeks to understand, represent and process the static geometry and visual appearance of 3D models, be they designed or acquired from the physical world [2], [3]. The problems posed within such a static, geometry-centric viewpoint are limited as they are stated without reference to the scene dynamics and physics. Accurate geometric representations can be acquired with laser scanning systems that deliver fine-grain data in the form of 3D point clouds with color attributes and images. However, and despite its high density, such representations only capture visible information, but no semantic or functional information. Their added value is limited as it consists of raw massive data. Many digital twin applications instead require data analytics and insights: i.e., the ability to perceive, abstract, memorize, learn and retrieve information such as presence, types, locations, functions, states of physical objects or systems, parameters and reference to a database. Today, the process of converting point cloud data into cognitive 3D models is still performed by manual or semi-automated tools, and limited to static scenes. As large-scale sites such as industrial facilities contain myriads of objects, the time and therefore the cost of such a conversion process is prohibitive. More specifically, the effort spent on modeling is estimated to ten times the time spent on capturing the scenes, e.g., in the order of months before a BIM (building information model) model is ready and usable for re-configurating a production facility. This greatly hampers the adoption of digital twins in industrial processes. More and more tools are available to reduce the efforts to generate BIM or CAD models, but they are often focused on narrow problems such as detection of pipes or walls.

Similarly, most conversion methods, such as surface reconstruction from measurement data, rely upon basic geometric priors [4], but not on physics or cognition. The main consequence of a physics-unaware approach is that the post-reconstruction output models are both imperfect and unfit to simulation. Of particular concern is the additional conversion step that is required for repairing [5], [6] then discretizing each class of objects. Chaining multiple steps renders the simulation-from-measurements pipeline inconsistent with physics and brittle due to trial-and-error processes. Geometric modeling for the simulation of physical phenomena commonly states the problem via a broader set of requirements: e.g. ‘model and discretize geometric shapes adequately and provide high accuracy in important areas’. However, improving simulation accuracy is only one dimension of design exploration’s initial promise to efficiently iterate between simulation and modeling. Such iterations are tightly entangled in acquisition systems operating continuously in open physical environments.

Methods such as error estimation and adaptive mesh refinement adapt the geometric model according to the characteristics of the physical solution. However, the common belief that sampling error dominates discretization error needs to be reevaluated due to uncertainties in error estimation methods. The isogeometric analysis (IGA) paradigm, introduced more than a decade ago [7], has been presented as the ultimate paradigm for bridging the gap between simulation and geometric design. Yet despite significant advances [8], rendering the core method (converting imperfect computer-aided-design (CAD) surface models into volumetric B-Splines [9]–[11]) versatile and simulation-ready is still an open problem. In addition, IGA-based modeling of large-scale scenes is currently out of reach due to the inherent complexity of IGA models.

Geometric modeling for digital twins requires cognitive- and physics-informed principles. In such a paradigm shift, physics becomes not just an end but also a means to contribute novel methods and tools.

Objectives. The main scientific objective is to combine geometry, cognition and physics. To this end, we will pursue two specific challenges: (1) enabling inspection and simulations on virtual replicas of the physical world accessible through sensing, and (2) enabling continuous modeling of physical scenes with time-varying objects. Ultimately, we seek geometric fidelity with rich cognition ability and consistency with physics. In the proposed research direction, consistency with physics is used to resolve the ill-posed problems that abound in geometric modeling and processing.

Analysis through leveraging physical properties. Analysis is concerned with the understanding of 3D shapes [12], shape collections [13], [14], scenes [15] and situational awareness. As geometry and physical properties contribute jointly to several physical phenomena occurring in a scene, considering physics can improve the understanding of a scene's geometry. More specifically, we will look beyond conventional analyses of visual and geometric data by utilizing any physical properties that can be measured and possibly simulated. We will obtain physical properties through direct sensors such as multispectral LiDAR or thermal imaging cameras. Coupling sensors with active devices such as infrared illuminators, we will model radiative transfers happening in the scene. Similar principles will be utilized for non-local light transport and sound capture. Offline, we will calibrate the acquisition system and train it to infer physics properties and geometry jointly. Online, the system will be fine-tuned by leveraging the active properties of sensors. Our physics-informed standpoint also enables us to consider the defects of sensors as relevant features. We will revisit sensor calibration to infer physical properties from defects, and generalize the idea of purposefully generating defects, such as out-of-focus blur [16], during acquisition to enhance physics-informed discrimination, where necessary.

Continuous reconstruction. Assuming input measurement data, reconstruction is the process of recovering shapes that fit these data, while dealing with defect-laden data. The reconstruction problem is inherently ill-posed as an infinite number of shapes may fit the data. The common wisdom consists of regularizing the problem via adding a geometric [4] or semantic prior [17]. However, using a single type of prior is insufficient for large-scale scenes with many diverse objects. We will instead utilize physics-informed priors, leveraging them to devise a *continuous reconstruction* approach.

We will explore a *progressive physics-informed approach* capable of jointly improving data fitting and simulation accuracy. Such a progressive approach suits difficult tasks such as discovering sharp features and boundaries, and enables exploring a supervised prediction method for resolving the so-called '*hp*-dilemma' [21]. Physics-informed principles will then be applied to all degrees of freedom of this approach: spatially regularized priors, error metrics, objective functions and predictions. As digital twins become increasingly prevalent for industrial facilities or construction sites, we anticipate the need for continuous, cognitive reconstruction of complex scenes. The cognitive 3D scenes, dynamically updated as new sensor-information is acquired, could overcome the limitations of the current mapping techniques. Key improvements include honing via learning physics-informed priors for static objects, and tracking time-varying objects with physics-informed principles. Ultimately, we wish to devise a framework that continuously reconstructs while seeking physical consistency with respect to properties such as light, radiosity, heat and motion behaviors.

Approximation informed by physical properties/laws or the discovery thereof. Geometric approximation is a central component of the standard geometry processing toolbox [22], [23]; it is used to obtain fast approximations of various tasks such as rendering, processing, modeling or simulation. Some current approximation methods are judged 'relevant' for simulation problems [24], but a generic method suitable to a broad range of simulations has yet to be developed. Real-time simulations applied to complex shapes require approximate simulations that trade accuracy for processing time while preserving some characteristics of the full order model. Such approximations are commonly achieved via geometric simplification or model reduction [25], [26]. Despite major advances, these methods still simplify the physics in a manner that is insufficiently related to the geometry. We seek to explore a generic method that approximate geometry and physics while discovering the physical laws of settings where we can only invoke a black-box physics engine, i.e., when physical laws are unknown. These cases abound in multiphysics problems, when differentiable physics engines are inoperative. The problem amounts to discovering the laws of physics while only having access to physical experiments. The favored research direction is an adaptive learning framework invoking a physics engine on diverse geometric training data [29].

Application to digital twins. We will apply our algorithms for cognitive digital twin modeling, in collaboration with local academic or industrial partners. A key issue is to model during continuous acquisition in dense, crowded or hazardous environments. We will validate the relevance of our methods on digital twins for industrial facilities.

References

[1] P. Alliez and A. Fabri, “CGAL-The computational geometry algorithms library. ACM SIGGRAPH 2016 Courses.,” 2016, doi: 10.1145/2897826.2927362.

[2] J. A. Bærentzen, J. Gravesen, F. Anton, and H. Aanæs, *Guide to Computational Geometry Processing*. 2012.

[3] M. Botsch, L. Kobbelt, M. Pauly, P. Alliez, and B. Lévy, *Polygon Mesh Processing*. 2010.

[4] M. Berger *et al.*, “A Survey of Surface Reconstruction from Point Clouds,” *Comput. Graph. Forum*, vol. 36, no. 1, 2017, doi: 10.1111/cgf.12802.

[5] M. Attene, M. Campen, and L. Kobbelt, “Polygon mesh repairing,” *ACM Comput. Surv.*, 2013, doi: 10.1145/2431211.2431214.

[6] Y. Hu, Q. Zhou, X. Gao, A. Jacobson, D. Zorin, and D. Panozzo, “Tetrahedral meshing in the wild,” *ACM Trans. Graph.*, 2018, doi: 10.1145/3197517.3201353.

[7] J. A. Cottrell, T. J. R. Hughes, and Y. Bazilevs, *Isogeometric Analysis: Toward Integration of CAD and FEA*. 2009.

[8] A. Buffa, “New challenges for (adaptive) PDE solvers: the interplay of analysis and geometry". https://cordis.europa.eu/project/id/694515.

[9] G. J. Hettinga and J. Kosinka, “Conversion of B-rep CAD models into globally G1 triangular splines,” *Comput. Aided Geom. Des.*, 2020, doi: 10.1016/j.cagd.2020.101832.

[10] B. Marussig and T. J. R. Hughes, “A Review of Trimming in Isogeometric Analysis: Challenges, Data Exchange and Simulation Aspects,” *Arch. Comput. Methods Eng.*, 2018, doi: 10.1007/s11831-017-9220-9.

[11] J. Shen, J. Kosinka, M. A. Sabin, and N. A. Dodgson, “Conversion of trimmed NURBS surfaces to Catmull-Clark subdivision surfaces,” *Comput. Aided Geom. Des.*, 2014, doi: 10.1016/j.cagd.2014.06.004.

[12] K. Mo *et al.*, “StructEdit: Learning Structural Shape Variations,” 2020.

[13] R. Huang, P. Achlioptas, L. Guibas, and M. Ovsjanikov, “Limit Shapes – A Tool for Understanding Shape Differences and Variability in 3D Model Collections,” *Comput. Graph. Forum*, 2019, doi: 10.1111/cgf.13799.

[14] A. Cohen and M. Ben-Chen, “Robust Shape Collection Matching and Correspondence from Shape Differences,” *Comput. Graph. Forum*, 2020, doi: 10.1111/cgf.13952.

[15] N. J. Mitra, M. Pauly, M. Wand, and D. Ceylan, “Symmetry in 3D geometry: Extraction and applications,” *Comput. Graph. Forum*, 2013, doi: 10.1111/cgf.12010.

[16] M. Carvalho, B. Le Saux, P. Trouvé-Peloux, A. Almansa, and F. Champagnat,

"Deep Depth from Defocus: how can defocus blur improve 3D estimation using dense neural networks?," *CoRR*, vol. abs/1809.0, 2018.

[17] C. Hane, C. Zach, A. Cohen, R. Angst, and M. Pollefeys, "Joint 3D scene reconstruction and class segmentation," 2013, doi: 10.1109/CVPR.2013.20.

[18] J.-P. Bauchet and F. Lafarge, "Kinetic Shape Reconstruction," *ACM Trans. Graph.*, vol. 39, no. 5, 2020.

[19] J. Feydy, "https://www.kernel-operations.io/geomloss/." .

[20] L. Feng, P. Alliez, L. Busé, H. Delingette, and M. Desbrun, "Curved optimal delaunay triangulation," *ACM Trans. Graph.*, vol. 37, no. 4, 2018, doi: 10.1145/3197517.3201358.

[21] O. Bartoš, V. Dolejší, G. May, A. Rangarajan, and F. Roskovec, "A goal-oriented anisotropic hp-mesh adaptation method for linear convection–diffusion–reaction problems," *Comput. Math. with Appl.*, vol. 78, no. 9, pp. 2973–2993, 2019, doi: https://doi.org/10.1016/j.camwa.2019.03.046.

[22] D. Cohen-Steiner, P. Alliez, and M. Desbrun, "Variational shape approximation," in *ACM Transactions on Graphics*, 2004, vol. 23, no. 3, doi: 10.1145/1015706.1015817.

[23] M. Mandad, D. Cohen-Steiner, and P. Alliez, "Isotopic approximation within a tolerance volume," *ACM Trans. Graph.*, vol. 34, no. 4, 2015, doi: 10.1145/2766950.

[24] A. Thakur, A. G. Banerjee, and S. K. Gupta, "A survey of CAD model simplification techniques for physics-based simulation applications," *CAD Computer Aided Design*. 2009, doi: 10.1016/j.cad.2008.11.009.

[25] M. Deiml, M. Suderland, P. Reiss, and M. Czupalla, "Development and evaluation of thermal model reduction algorithms for spacecraft," *Acta Astronaut.*, 2015, doi: 10.1016/j.actaastro.2015.01.018.

[26] G. Fernández-Rico, I. Pérez-Grande, A. Sanz-Andres, I. Torralbo, and J. Woch, "Quasi-autonomous thermal model reduction for steady-state problems in space systems," *Appl. Therm. Eng.*, vol. 105, pp. 456–466, 2016, doi: https://doi.org/10.1016/j.applthermaleng.2016.03.017.

[27] J. Feydy, T. Séjourné, F. X. Vialard, S. I. Amari, A. Trouvé, and G. Peyré, "Interpolating between Optimal Transport and MMD using Sinkhorn Divergences," 2020.

[28] Q. Xia, "Motivations, ideas and applications of ramified optimal transportation," *ESAIM Math. Model. Numer. Anal.*, 2015, doi: 10.1051/m2an/2015028.

[29] S. Koch *et al.*, "ABC: A big cad model dataset for geometric deep learning," 2019, doi: 10.1109/CVPR.2019.00983.

[30] J. R. Shewchuk, "What is a Good Linear Element ? Interpolation , Conditioning , and Quality Measures," *Elev. Int. Meshing Roundtable*, 2002, doi: 10.1.1.68.8538.

[31] C. Jamin, P. Alliez, M. Yvinec, and J.-D. Boissonnat, "CGALmesh: A generic framework for delaunay mesh generation," *ACM Trans. Math. Softw.*, vol. 41, no. 4, 2015, doi: 10.1145/2699463.

[32] T. Gantumur, "Adaptive boundary element methods with convergence rates," *Numer. Math.*, 2013, doi: 10.1007/s00211-013-0524-x.

[33] J. Kim, T. Panitanarak, and S. M. Shontz, "A multiobjective mesh optimization framework for mesh quality improvement and mesh untangling," *Int. J. Numer. Methods Eng.*, 2013, doi: 10.1002/nme.4431.

[34] I. Fried, "Bounds on the spectral and maximum norms of the finite element stiffness, flexibility and mass matrices," *Int. J. Solids Struct.*, 1973, doi: 10.1016/0020-7683(73)90013-9.

[35] Q. Du, D. Wang, and L. Zhu, "On mesh geometry and stiffness matrix conditioning for general finite element spaces," *SIAM J. Numer. Anal.*, 2009, doi: 10.1137/080718486.

[36] R. E. Bank and L. R. Scott, "On the Conditioning of Finite Element Equations with Highly Refined Meshes," *SIAM J. Numer. Anal.*, 1989, doi: 10.1137/0726080.

[37] L. Branets and G. F. Carey, "Condition number bounds and mesh quality," *Numer. Linear Algebr. with Appl.*, 2010, doi: 10.1002/nla.758.

[38] W. Huang, "Measuring mesh qualities and application to variational mesh adaptation," *SIAM J. Sci. Comput.*, 2005, doi: 10.1137/S1064827503429405.

[39] M. Ainsworth, W. Mclean, and T. Tran, "The conditioning of boundary element equations on locally refined meshes and preconditioning by diagonal scaling," *SIAM J. Numer. Anal.*, 1999, doi: 10.1137/S0036142997330809.

[40] J. A. Tropp, "Column subset selection, matrix factorization, and eigenvalue optimization," 2009, doi: 10.1137/1.9781611973068.106.

[41] B. M. Klingner and J. R. Shewchuk, "Aggressive tetrahedral mesh improvement," 2008, doi: 10.1007/978-3-540-75103-8_1.

[42] J. Shen, L. Busé, P. Alliez, and N. Dodgson, "A line/trimmed NURBS surface intersection algorithm using matrix representations," *Comput. Aided Geom. Des.*, vol. 48, 2016, doi: 10.1016/j.cagd.2016.07.002.

[43] G. Walton, "http://view3d.sourceforge.net/." .

[44] ITP Aero, "https://www.esatan-tms.com/." .