An optimization approach for automated as-built 3D modeling

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Outline







Background & Opportunity



As-built Modeling as Optimization



Discussion & Future Research

Section 1 **BACKGROUND & OPPORTUNITY**



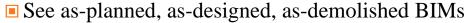
1.1 As-built 3D modeling of civil infrastructures







- Construction management
- Facility management
- Built env. conservation
- o Business with VR/AR, etc.





- Photogrammetry (videogrammetry)
- Point cloud
- 3D Geographic information system
- Others (statistical rules, deep learning [2], etc.)









An example of photogrammetry: Kowloon Wall City (Source: patrick-@sketchfab.com)



An example of point cloud: Pompei City (Source: MAP-Gamsau lab, CNRS, France)



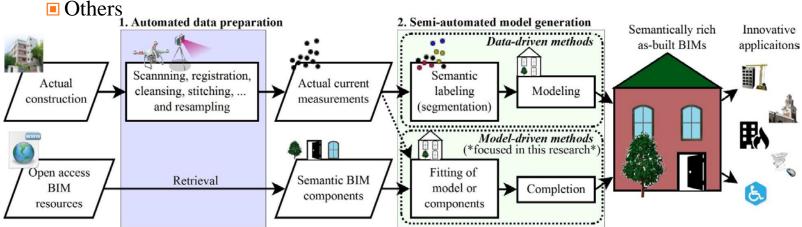
An example of GIS-based: 3D Berlin (Open Data, source: berlin.de)



1.1 The (semi-)automated as-built 3D modeling



- ♦ Two categories of methods
 - Data-driven v.s. Model-driven
- ♦ Some challenges remains
 - Unsatisfactory semantic/abstraction discovery
 - → huge size (data-driven), poor reusability(model-driven)



F Xue: Auto as-built 3D modeling (Staff Seminar)



1.2 Derivative-free Optimization in OR[†]





 $\max f: \mathbb{R}^n \mapsto \mathbb{R}$

An example of optimization

- the selection of a *best* element (with regard to some criteria) from *some* set of available alternatives.
- ♦ Nonlinear optimization
 - When *objective function* or some *constraints* are nonlinear
- ♦ Derivative-free Optimization (DFO) [3]
 - Objective function or constraints are unknown



DFO: Manipulating a black-box (Figure adapted from Wikipedia)

- E.g., model selection, parameter tuning in simulations
- Especially when function is *very expensive* or *unanalyzable*
- Challenging (*NP*-hard), but achieved significant success
 - In applied science and engineering such as molecular biology and material sciences

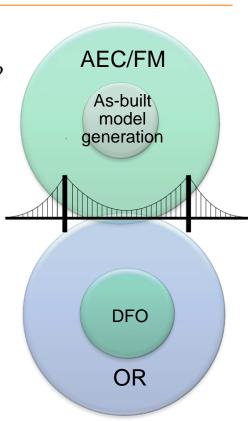
^{†:} Operations Research



1.3 An opportunity



- ♦ The questions
 - Can the model generation be generally solved by DFO methods?
 - o If true, can semantic data be discovered at the same time?
- ♦ If all true, we can
 - Map between a typical problem in AEC/FM and a class of powerful algorithms in OR
 - Also expose as-built model generation to many other nonlinear methodologies
 - Discover semantic (abstraction) information



Section 2 **AS-BUILT MODELING AS OPTIMIZATION**



2.1 A meta-model of as-built 3D modeling





- Given a reference measurement, a set of parametric components
 - $\max f(X)$
s. t. $A(X) \le 0$



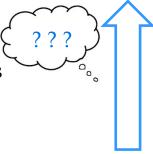
♦ A meta-model of optimization is from such a formulation:

Meta-model of constrained optimization & its solution space

Tells computers:
What to change
What is good

 \blacksquare The **variables** (X) are the parameters of the components;

■ The **objective function** (f) is to maximize the similarity (or minimize dissimilarity) between the 3D model (as combinations of the parametric components) and the measurement; and



The **constraints** (A) over the variables are the topological relationships between components.



from Greek prefix μετά-, "beyond"



measurements

Reference





Parametric (& semantic) components



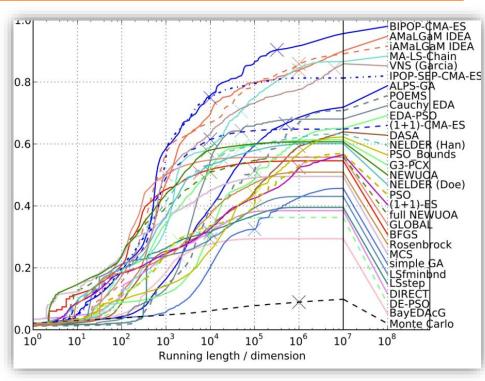
2.1 Computational algorithms for the meta-model



♦ Brutal-force search is impractical



- ♦ Fortunately, there are a long list of off-the-peg algorithms for solving such a meta-model as a black-box:
 - Surrogate methods
 - CMA-ES (Covariance matrix adaptation with evolution strategy) [5]
 and its variants are competitive
 - Trust-region methods
 - Metaheuristics (GA, PSO, VNS, etc.)
 - Hyper-heuristics, data mining
 - ... and Monte Carlo



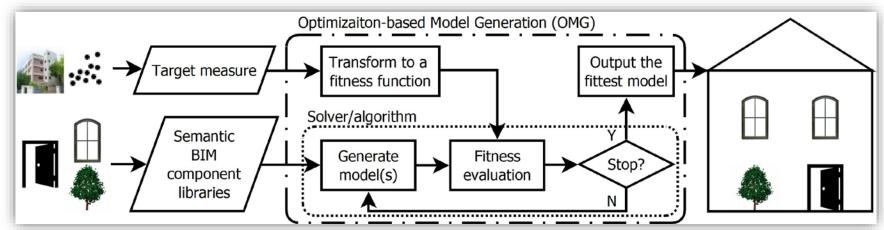
Comparison of algorithms for BBOB-2009 (Black-Box Optimization Benchmarking, higher is better) [4]



2.1 The framework: A bird's-eye view



- ♦ The full framework of optimization-based model generation
 - Input 1: Reference measurements (photo, point clouds, video)
 - Input 2: Semantic and parametric components
 - Process: Systematically finding the fittest model by solving meta-model with DFO methods
 - Output: A semantic as-built model





2.2 A pilot: A demolished building at campus



- ♦ The pilot case
 - A demolished baroque-style two-storey building
 - Once occupied by School of Tropical Medicine and School of Pathology, HKU
 - Input: A photo
- Preparing parametric components
 - Only apparent (>1m) components (for feasibility test)
 - 7 components were collected from 3D Warehouse of SketchUp
 - With a keyword filter "baroque"
 - With limited (3) pairs of conflicting components
 - Adjusting components for the case
 - Removing extra parts, alignment



A historical photo (Source: MTR HKU Station, re-photographed by an Android phone)



(Contributors: Mohamed EL Shahed, Richard, KangaroOz 3D, Yoshi Productions, 3dolomouc, Architect, Ben @ 3D Warehouse)



2.2 The meta-model





- Minimize the dissimilarity
 - Between the projected image of model and the input photo
 - o E.g., Mean square error (MSE) of pixels or SSIM [6] †
- With respect to topological constraints
- Computational functions implemented on SketchUp (2016 Pro) Ruby API
 - Objective function interface
 - Variables as parameters (per component)

Manifolds (0, 1) + scaling
$$(xyz)$$
 + location (xyz) + rotation $(\alpha\beta\gamma)$ = 4 ~ 6 variables

- Constraints of topological relationships
- A virtual *Ground* object is placed at first

min f = dissimilarity= 1-SSIM[†]

(or maybe f =MSE of pixels)

s.t. Semantic constraints of position, scaling, and ABOVE/ BELOW/ CONTAINS_ON for each component

†: Structural similarity



2.1 Details of the topological relationships



- ♦ Topological relationships
 - Categories
 - o Adjacency: ABOVE, BELOW, NEXT_TO, ...
 - Separation: SEPERATED
 - Containment: CONTAINS_ON, CONTAINS_IN
 - Intersection: INTERSECTS_WITH
 - Connectivity: CONNECTS_TO
- Semantic definition
 - Adding properties like *scaling* and *topological relationships* to their SketchUp dictionaries
 - o E.g., ABOVE, BELOW, CONTAINS_ON, etc.



An example of the dictionary of component in SketchUp

Time of preparation of components

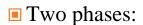
- Collection (~15 minutes)
- Adjustment (~30 minutes)
- Semantic def. (~15 minutes)



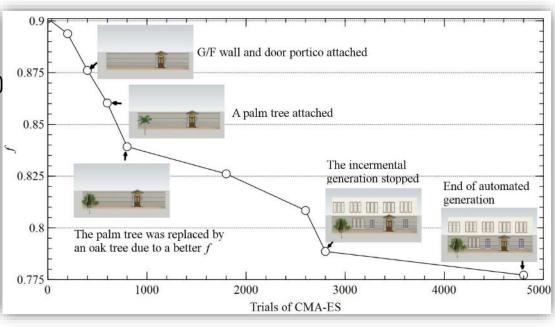
2.2 An earlier computational experiment in 2016







- Incremental (2,800 trials)
- Refinement (2,000 trials)
- The Solver: CMA-ES (C++ code [7] in a Ruby wrapper)
- Time: 3,822.4s[†]
 - After so much simplification
- Fault-tolerant (see the trees)
- Semantic/grammar-enhanced



Automated generation of semantic as-built model as solving the nonlinear optimization problem, by a well-known DFO algorithm CMA-ES in 3,822.4 seconds (4,800 trials, single thread) on an Intel i5-6500 CPU (3.2 GHz)

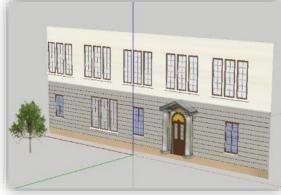
^{† :} Should be much faster now.



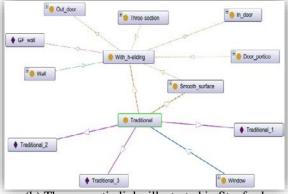
2.2 Results and post-processing



- Obtained
 - The facade in the photo
 - **■** Semantic links
- Post-processing
 - Manual completion
 - Copy & paste
 - Georeferencing and display in 3D



(a) Direct result: The façade in the photo



(b) The semantic links illustrated in Stanford Protégé (Circle denotes a component class and a



(c) Manually completed approximate model (~15 minutes)



(d) Georeferencing and illustration on Google Earth, near MTR Exit A (~5 minutes) 16



3.3 OMG & live demonstration





♦ A library OMG (optimization-based model generator) is under development

- A shared computational library with specific plugins for
 - o SketchUp, Revit, etc.
- Multiple meta-models with various
 - Objective functions
 - Measurement types, and
 - Solving algorithms
- Multiple modeling options
 - Ontology-guided, free discovery, finetuning, etc.
 - Extended the earlier pilot study
- Demo (more efficient now)







OMG







One click





Section 3 DISCUSSION & FUTURE RESEARCH



3.1 Discussion



- ♦ Meta-modeling of as-built 3D modeling as constrained optimization
 - Pros: General, simple, no explicit object recognition/segmentation (also challenging)
 - Cons: A larger search space (slower), slow full projection, limited by pixels, less accurate
- Semantic definitions of components
 - Pros: Realized 'grammar' of components, simplified optimization
 - Cons: Some manual work needed, subject to redefinition from a project to another
- ◆ The framework as a whole
 - Pros: High automation, reusing components and abstractions, less requirements on equipment, tolerant to errors, scalable to new environments, (hopefully) semantically rich
 - Cons: Less accurate in geometry, still in its *infancy*
 - Answers to the question: 1) True; 2) Applicable to some relations
 - Semantic recognition/segmentation is another pillar for semantic BIM



3.2 Future research





- More didomains (e.g. infrastructures, etc.)
- Advanced DFO methods
- More objective functions
- On real BIM/CIM models instead of surface models

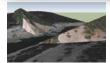


- Efficient ways of manipulating point clouds (working...)
 - E.g., *k*d-tree, approximate *k*NN, convex hull, planar and object detection
- Extensions
 - Shared component libraries for reusability (e.g., IFC-compatible)
 - Handling other challenging AEC/FM problems



We are still on the way (Source: clipartpanda.com)







The Roman aqueduct Pont du Gard (Source: Wikipedia/ 3Dwarehouse.com)²⁰



References



- [1] Volk, R., Stengel, J., and Schultmann, F. (2014). Building Information Modeling (BIM) for existing buildings—Literature review and future needs. Automation in Construction, 38: 109-127.
- [2] Patraucean, V. (2016). Deep machine learning: key to the future of BIM? Cambridge: University of Cambridge, Mar 14 2016. Accessed July 15 2016. http://www-smartinfra structure.eng.cam.ac.uk/news/viorica-patraucean-featured-in-infrastructure-intelligence-.
- [3] Conn, A. R., Scheinberg, K., and Vicente, L. N. (2009). Introduction to derivative-free optimization. MPS-SIAM book series on optimization (Vol. 8). SIAM.
- [4] Auger, A., Finck, S., Hansen, N., and Ros, R. (2010). BBOB 2009: Comparison tables of all algorithms on all noisy functions (PhD thesis, INRIA).
- [5] Hansen, N., and Ostermeier, A. (2001). Completely derandomized self-adaptation in evolution strategies. Evolutionary Computation, 9 (2): 159-195.
- [6] Wang, Z., Bovik, A. C., Sheikh, H. R., and Simoncelli, E. P. (2004). Image quality assessment: from error visibility to structural similarity. IEEE Transactions on Image Processing, 13 (4): 600-612.
- [7] CMA-ESpp, an open source library, see: https://github.com/AlexanderFabisch/CMA-ESpp

