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Semantizing Complex 3D Scenes using Constrained Attribute Grammars

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Abstract
We propose a new approach to automatically semantize complex objects in a 3D scene. For this, we define an expressive formalism combining the power of both attribute grammars and constraint. It offers a practical conceptual interface, which is crucial to write large maintainable specifications. As recursion is inadequate to express large collections of items, we introduce maximal operators, that are essential to reduce the parsing search space. Given a grammar in this formalism and a 3D scene, we show how to automatically compute a shared parse forest of all interpretations — in practice, only a few, thanks to relevant constraints. We evaluate this technique for building model semantization using CAD model examples as well as photogrammetric and simulated LiDAR data.

Categories and Subject Descriptors (according to ACM CCS): I.2.10 [Artificial Intelligence]: Vision and Scene Understanding—3D/stereo scene analysis I.3.5 [Computer Graphics]: Computational Geometry and Object Modeling—Object hierarchies I.4.8 [Image Processing and Computer Vision]: Scene Analysis—Object recognition I.5.4 [Pattern Recognition]: Applications—Computer vision

1. Introduction
We consider here the problem of semantizing complex objects in a 3D scene. The need for interpreting such scenes is an old problem but still largely unsolved. The recent availability of inexpensive 3D data has stimulated progress on this topic. It is now cheap and easy to make real world acquisition, e.g., using photogrammetry, time-of-flight cameras or active stereovision systems such as the Kinect. Purely synthetic 3D data has become mainstream too, with 3D modeling software such as SketchUp, making it possible for anybody to easily create 3D models.

Scene semantization has many uses. In large 3D repositories (such as Aim@Shape or Trimble 3D Warehouse), semantic information is needed to perform relevant and efficient queries. Applications include, e.g., virtual sets for games or movies, interior design, product design for e-manufacturing [ARSF09], etc. However, manually annotating geometry with semantics is a time-consuming and tedious task, which is error prone and expensive. Besides, the size of some repositories is such that a systematic manual treatment is unfeasible in practice. Automation is required.

Businesses such as the building industry are also rapidly moving toward relying heavily on high-level semantized 3D models for the whole lifecycle of their products, from sketch and design to construction, operation and dismantlement. These industries typically work from data acquired using devices such as laser scanners, whose expensive price has also greatly reduced lately. The stakes are high as semantized 3D models enable much quicker, safer and cheaper developments and decisions. However, while 3D models tend now to be created for new products, they are generally not available for existing ones. In particular, old buildings — i.e., by
or surface decomposition, either from “perfect” geometry
graphs may originate from volume skeletons [94] fitting and
reconstruction of 3D shapes. Most methods concerning
semantic segmentation, classification, matching, retrieval,
fitting and reconstruction of 3D shapes. Most methods con-
cerning complex objects rely on graph-based analysis. The
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Related work. There is a large amount of work regarding
semantic segmentation, classification, matching, retrieval,
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The challenge is thus to efficiently produce 3D models
that are not limited to geometry but that are also structured
with respect to their semantics, e.g., building elements: floor,
roof, wall, windows, stairs, etc. What we propose in this pa-
paper is a new technique to semantize an existing high-level
geometry. We assume we are given a geometric model as a
set of 3D polygons and we produce labels for these polygons
identifying the semantic part of the model they belong to.

Interestingly, architects can also make use of such a se-
manitizer after they sketch a building for presentation to bid-
ders or customers, to get approval before producing detailed
design and plans. Although CAD systems do offer rendering
features, quality is often poor and inadequate for ambitious
projects. Architects have to go to a graphic designer to ob-
tain spectacular views of their proposal. For this, they have to
communicate the model with information about the nature of
building elements. They usually do so by assigning different
colors to geometric components and telling the graphic de-
signer how to interpret and replace them by relevant textures
for quality rendering. We can do this labeling automatically
(see Fig. 1). A similar issue arises at a large scale in the game
industry. Level designers tend to focus on the geometry and
structure of what they create, providing little information to
graphic artists, that often have to “paint” each scenic element
separately (architecture, objects, etc.) [CLS10].

However, we are interested here in objects, e.g., buildings,
that are complex in the sense that (1) they have a high de-
gree of compositionality, i.e., they can be broken down into a
deep hierarchy of components, (2) the number of parts is un-
known and potentially highly variable, and (3) the relations
between the different parts can be sophisticated, not limited
to adjacency and relative position or orientation. For this
kind of objects, the relevant underlying structure seems to
be a grammar: (1) each production rule represents an alterna-
tive decomposition level in the hierarchy, (2) recursive rules
can express an arbitrary number of items, and (3) the gram-
mar can express constraints to cope with complex relations
between parts. Furthermore, grammars are naturally modu-
lar to some extent, enabling the writing and maintenance of
large specifications, contrary to hard-coded approaches relying
on weak, hard-coded domain knowledge [MMWVG12].

Shape grammars have been popular for the procedu-
ral generation of model instances [MWH+06], but hardly
reversed to perform analysis: such uses are scarce, with
simplified grammars (e.g., split grammars) and reduced to
fronto-parallel image parsing, i.e., 2D [MZWVG07, RB07,
TKS+11]. Generative models in 3D have little been consid-
ered for analysis and are then restricted to specific, hard-
coded grammars such as roofs [HBS11] and Manhattan-
world buildings [VAB10, VAB12]. Only very recently has
procedural modeling been associated to multi-view 3D for
parsing [STK+12]. However, it reduces to the incorporation
of a depth term in a basically 2D energy; it does not com-
pute 3D from parsing. Moreover, the search space is so huge
that it requires a heavy optimization machinery, and it is not
clear how it can scale to complete buildings and full 3D.

As opposed to the above top-down parsing techniques,
bottom-up approaches have also been proposed, with inter-
leaved top-down predictions of missing or occluded compo-
nents [HZ09, WZ11]. However, they are currently restricted
to images and compositions of basic primitives, e.g., projec-
tions of 3D rectangles or circles. A multi-view variant with
a 3D grammar interpreter that hard-codes some operations
and exhaustively checks shape composability (without con-
straint propagation) has been used for reconstructing Doric
temples [MMWVG11]. In 3D, a grammatical approach has
been used to construct building shapes from airborne LiDAR
data [TMT10], but the parsing is hard-coded, e.g., rules are
applied in a specific order and specific structures are sought
“outside the grammar” such as maximum spanning trees; it
cannot be generalized to any set of grammar rules.
Our approach. We present here a purely bottom-up approach, although it can be complemented by top-down predictions to treat incomplete data (see Section 6). It relies on a constrained attribute grammar with geometry-specific predicates. Terminals are detected 3D primitives that are combined using production rules to construct higher-level nonterminals. This could normally lead to a combinatorial explosion. But one of the key to the practicality of our approach is the use of constraint propagation to reduce the search space incrementally as much as possible, in particular with the use of invertible predicates, which drastically reduce the involved domains as soon as part of their arguments are known. “Constrained” attribute grammars have been proposed in the past but in much more restricted settings, e.g., without constraint propagation and with a single greedy interpretation, to parse the layout of mathematical formulas [Pag98]. Our contributions are as follows:

- We propose a constrained attribute grammar formalism for specifying complex objects, including 3D objects.
- It provides a practical conceptual interface as opposed, e.g., to low-level graph node descriptions, which is arguably crucial to write large maintainable specifications.
- As complement to recursion, we introduce maximal operators, that are essential for space search reduction.
- Given a grammar in this formalism and a scene, we show how to efficiently compute a shared parse forest.
- We evaluate our approach both on synthetic and real data (CAD models, photogrammetry and simulated LiDAR).

Though we illustrate here building semantization, our technique is general and could be applied to other domains too.

The rest of the paper is organized as follows. Section 2 presents the formalism. Section 3 describes what a corresponding parse tree is. Section 4 explains how to efficiently compute a shared parse forest. Section 5 shows experimental results with building grammars. Section 6 studies the advantages and perspectives of grammars and Section 7 concludes.

2. Constrained attribute grammar

We consider a scene containing objects that have a hierarchical decomposition into parts having complex relations. This can be modeled using a constrained attribute grammar.

Basic grammar ingredients. We consider a grammar $G = (N, T, P, S)$ consisting of a set $N$ of nonterminals, a set $T$ of terminals disjoint from $N$, a set $P$ of production rules and a set $S \subset N$ of start symbols. A terminal corresponds to a geometric primitive in the scene, e.g., polygon with holes, cylinder. A nonterminal corresponds to a complex form in the scene; it can be decomposed via $G$ into other grammar elements. A production rule $r \in P$ is of the form $r = Y \rightarrow X_1 \ldots X_k$ where the rule’s left-hand side (LHS) is $Y \in N$ and the right-hand side (RHS) is $(X_i)_{1 \leq i \leq k} \in (N \cup T)^*$, e.g.,

$$step \rightarrow riser, tread$$

Some nonterminals may be introduced in a grammar as auxiliary constructs, that are meaningless for end users. We use start symbols to identify parses only of relevant objects.

We use the vertical bar for disjunction: $Y \rightarrow W \mid W'$ is equivalent to the two rules $Y \rightarrow W$ and $Y \rightarrow W'$. And $Y \rightarrow X_1$, optional $X_2$ is equivalent to $Y \rightarrow X_1 \mid X_1 X_2$, although with a semantic nuance (see “Collections” below). This definition of a grammar is refined in the following.

Constraints. Contrary to 1D grammars and split grammars, a rule $r = Y \rightarrow X_1, \ldots, X_k$ only expresses dominance of $Y$ over $X_i$, not precedence of $X_i$ over $X_{i+1}$. To cope with 3D, complex association constraints between $X_1, \ldots, X_k$ are shifted into a separate condition $C$ attached to the rule, which we note $r(C)$. (See below for predicates usable in conditions.) Additionally, as there might be several occurrences of the same grammar element in a rule, we also introduce the possibility to name each occurrence with a corresponding variable: $Y \rightarrow X_1 x_1, \ldots, X_k x_k$, e.g.,

$$\text{step } s \rightarrow \text{riser } r, \text{tread } t \langle \text{edgeAdj}(r, t) \rangle$$

Attributes. Moreover, we consider that each grammar element has attributes, describing features of the underlying geometric primitive or complex form. An attribute can be of a primitive type (e.g., Boolean, integer, float, 3D-vector) or correspond to a grammar element. We thus actually consider an attribute grammar $G = (N, T, P, S, A)$ where $A$ is a set of attribute names and each rule in $P$ is of the form $Y \rightarrow X_1 x_1, \ldots, X_k x_k \langle C \rangle \langle \{E\} \rangle$ where the condition $C$ may refer both to rule variables $(x_i)_{1 \leq i \leq k}$ and to associated attributes $(x_i, a)_{1 \leq i \leq k, a \in A}$, and where $E$ is a set of evaluation rules defining attributes of $y$ among $(y, a)_{a \in A}$, e.g.,

$$\text{step } s \rightarrow \text{riser } r, \text{tread } t \langle \text{edgeAdj}(r, t) \rangle \langle \{x, \text{len}\} = \{r, \text{len}\} \rangle$$

We currently consider only inherited attributes: in a rule $Y \rightarrow X_1, \ldots, X_k$, the attributes of $Y$ are determined by the attributes of $X_1, \ldots, X_k$, but the attributes of $X_i$ do not depend on the attributes of $Y$ nor on other $X_j$ with $j \neq i$. Some attributes are also predefined for every form. For example, each nonterminal has a smallest bounding box and provides breadth, length, breadth vector and length vector.

Predicates. A condition $C$ is a conjunction of predicates applying to rule variables $x_i$, possibly via attributes $x_i, a$. Predicates primarily express geometric requirements but can
more generally represent any constraint on the underlying object(s). Most predicates apply both to terminals and non-terminals. The main available predicates are:

- \text{edgeAdj}(x, y)\), \text{intEdgeAdj}(x, y), \text{extEdgeAdj}(x, y), \text{vertexAdj}(x, y)\): \(x\) is adjacent to \(y\) via an edge (resp. interior hole edge, exterior contour edge, vertex), as primitive or via any underlying primitive,

- \text{horizontal}(x)\), \text{vertical}(x)\): \(x\) is horizontal (resp. vertical), as a primitive or all of its underlying primitives,

- \text{parallel}(x, y), \text{orthog}(x, y), \text{above}(x, y), \text{under}(x, y)\): \(x\) is parallel to \(y\) (resp. orthogonal, above, under), as primitives or all of their underlying primitives,

- \(x = y, x = y, x < y, \ldots\): \(x\) is equal to \(y\) (resp. different from, less than, etc.), \(y\) can be a literal constant.

Exact predicates are actually relaxed to allow approximate satisfaction: adjacency and relative height position is up to a given distance; horizontality, orthogonality, parallelism and orthogonality is up to some angle error. Predicates can also be user-defined in the implementation language of our prototype for more complex checking but then, they are not specifically optimized (see below).

**Collections.** A collection \(Y\) of items of the same kind \(X\) can be expressed with a recursive rule, e.g., \(Y \rightarrow X, Y | \emptyset\). However, if there are \(m\) instances of \(X\), there can be up to \(2^m\) different groups \(Y\). This is useless in practice for semantizing 3D models. Indeed, we are generally interested in the largest group, e.g., all windows in a wall, all steps of a stair, not every subset of windows or steps. For this, we introduce collection operators (default value in brackets):

- \text{maxset}(X, c, [c' = \text{true}]): maximal set of \(m \geq 0\) instances \(x_1, \ldots, x_m\) of \(X\) such that for all \(1 \leq i \leq m\), condition \(c(x_i)\) holds, and for all \(1 \leq i < j \leq m\), both conditions \(c'(x_i, x_j)\) and \(c'(x_j, x_i)\) hold.

- \text{maxconn}(X, [c = \text{true}], c'): maximal set of \(m \geq 0\) instances \(x_1, \ldots, x_m\) of \(X\) such that for all \(1 \leq i \leq m\), condition \(c(x_i)\) holds, and for all \(1 \leq i < j \leq m\), there exists a sequence of indices \(1 \leq e_1 \ldots e_l \leq m\) such that \(i = e_1, e_1 = j\) and for each \(1 \leq k < l\), both conditions \(c'(x_{e_k}, x_{e_{k+1}})\) and \(c'(x_{e_{k+1}}, x_{e_k})\) hold.

- \text{maxseq}(X, [c = \text{true}], c'): maximal sequence of \(m \geq 0\) instances \(x_1, \ldots, x_m\) of \(X\) such that for all \(1 \leq i \leq m\), condition \(c(x_i)\) holds, and for all \(1 \leq i < m\), condition \(c'(x_i, x_{i+1})\) holds.

- \text{cycle}(X, [c = \text{true}], c'): collection of \(m \geq 0\) instances \(x_1, \ldots, x_m\) of \(X\) such that for all \(1 \leq i \leq m\), conditions \(c(x_i)\) and \(c'(x_{i+1}, x_i)\) hold, noting \(x_{m+1} = x_1\).

Depending on expected arity, arguments \(c\) and \(c'\) can be unary or binary predefined predicates, e.g., \text{edgeAdj}, or “lambda-terms” such as \(x \mapsto c\) or \((x, y') \mapsto c'\).

A operator \text{oper}(X, x \mapsto c, (x, x') \mapsto c') is context-free iff the only variables that \(c\) and \(c'\) refer to, if any, are the non-contextual variables \(x\) and \(x'\). Otherwise, it is context-sensitive: it refers to at least one contextual variable, i.e., a rule variable or attribute in the RHS different from \(x\) and \(x'\).

All operators define an attribute “size” that can be used to constrain in \(C\) the number of elements in the collection. Note that the optional statement actually is a maximal operator too. \(Y \rightarrow X_1, \text{optional} X_2\) means that \(X_1\) is enough to build a \(Y\), but \(X_2\) has to be associated if present. It is equivalent to \(Y \rightarrow X_1, \text{maxset}(X_2)\) \(\{x_2\text{ size }\leq 1\}\), which has a single interpretation, whereas \(Y \rightarrow X_1 \mid X_1, X_2\) has two. A simple grammar example for a stairway is given in Figure 4. Mentioned grammar elements are pictured in Figure 5.

**Scene interpretation.**

Interpreting a scene, given primitives and a grammar, consists in producing one or several parse trees. A parse tree reflects the structure of the scene w.r.t. the grammar. It provides primitives with semantic labels and relations.

**Parse tree.** A parse tree is a tree anchored on primitives that reflects the instantiation and combination of grammar rules. Each node \(n\) in \(t\) corresponds to a terminal or non-terminal \(\tau(n) \in T \cup N\), that is called the type of \(n\). A terminal node is associated to each geometric primitive in the scene according to its type: polygon, cylinder, etc. Each nonterminal node \(n\) corresponds to the instantiation of a rule \(Y \rightarrow X_1, \ldots, X_k\) \((C)\ | \text{E}\) in the sense that:

- \(n\) has type \(\tau(n) = Y\),

- the sons of \(n\) are nodes \((n_i)_{1 \leq i \leq k}\) of type \((X_i)_{1 \leq i \leq k}\),

- assigning \((n_i)_{1 \leq i \leq k}\) to variables \((x_i)_{1 \leq i \leq k}\) satisfies condition \(C\) and defines via \(E\) the attributes \(v.a\) of \(n\).

The set of all terminals under node \(n\) if called a form, of type \(\tau(n)\). (We detail in Sect. 4 the case of collection operators.)

With a 1D grammar, the ordered sequence of terminals in a parse tree is equal to the input string, each terminal being counted once and only once by construction. In our relaxed grammatical setting, we have to explicitly require an exclusivity constraint to prevent the multiple occurrence of the same terminal in a parse tree. E.g., if a step belongs to a stair, it cannot be used in another stair in the same building.

**Parse forest.** In 1D, parsing generally has to derive the whole input string from the start symbol. In contrast, for 3D scene interpretation, we are interested in locating as many objects as possible among possibly uninterpreted data. In
can be applied anymore. The exclusivity constraint guaran-
test a rule application that constructs a new node of type
forest for nodes of type as specified in the RHS, checking
est. Applying a rule (see below) consists in looking in the
bottom-up, starting with a forest made of all geometric prim-
procedure is fully automatic.

We now describe how to efficiently parse a scene, given ge-

Figure 4: Grammar example for a stairway (units in meter).

4. Bottom-up parsing
We now describe how to efficiently parse a scene, given ge-
ometric primitives and a grammar as described above. This
procedure is fully automatic.

Parse forest computation. Our parsing algorithm operates
bottom-up, starting with a forest made of all geometric primitives
as terminal nodes, and iteratively applying all possible
grammar rules to create new nonterminals nodes in the for-
est. Applying a rule (see below) consists in looking in the
forest for nodes of type as specified in the RHS, checking
that the rule condition holds, and generating a new node cor-
responding to the LHS, with associated attributes.

To enforce sharing and guarantee termination, (1) we
merge all identical trees as they are constructed, (2) we re-
ject a rule application that constructs a new node of type X if
it already contains a node of type X as a succession of only-
child descendants, and (3) we stop iterating when no rule
can be applied anymore. The exclusivity constraint guaran-
tees that all rule application eventually fail as the number of
primitives involved in a nonterminal instance is bounded by
the number of primitives in the scene.

Besides, building a maximal collection oper(X, . . .) prac-
tically requires that all instances of X are known. For this,
we partition the grammar rules into layers that are fully pro-
cessed in an order that guarantees this requirement. We con-
sider the graph of the nonterminal dependency relation de-
defned as follows: given a rule Y →X1, . . . ,Xk, then Y depends
on each nonterminal Xr, or on Xr′ if Xr = oper(Xr′, . . .). We
then construct the graph strongly connected components. If
any component includes an edge corresponding to a maxi-
mal operator dependency, e.g., Y depends on oper(X, . . .)
and X depends on Y, then the grammar is deemed unusable
for parsing. Last, the condensation of the dependency graph,
i.e., the contraction of each component to a single vertex, is
a DAG that we order using a reverse topological sort, yield-
ing an ordered partition ((Yi1), . . . ,Yi}), 1 ≤i ≤d of the nonter-
ninals. The layers ((Ri1), . . . ,Ri}), 1 ≤i ≤d that we consider consist of the
rules ri,j that have Yi,j as LHS. All this computation of or-
dered layers is linear in the number of nonterminals.

This iterative scheme is summarized in Algorithm 1. Note
that terminals are encapsulated primitives, predeining extra
information, such as the bounding box, in the form of gram-
mar attributes. In the following, we consider the case of a
rule r = Y y =X1,x1, . . . ,Xk,xk (C) {E}. We explain how to ef-
iciently look for nodes in F that match types τ(Xi)1≤i≤k
and that satisfy C and the exclusivity constraint. We 
first de-
scribe the case of simple grammar elements and general con-
straints, then extended it to reversible predicates as well as
context-free and context-sensitive collection operators.

Algorithm 1 Parse forest computation

\[
F \leftarrow \{\text{terminal}(p) \mid p \text{ geometric primitive}\} \\
(Ri1), . . . ,Ri}), 1 ≤i ≤d \leftarrow \text{ordered partition of } P \text{ (see text)} \\
\text{for } i = 1 \text{ to } d \text{ do} \\
\text{repeat} \\
\text{unchanged } \leftarrow \text{true} \\
\text{for each rule } r \in R_i \text{ do} \\
\text{F }' \leftarrow \text{applyRule}(r,F) \\
\text{if } F \neq \emptyset \text{ then} \\
\text{unchanged } \leftarrow \text{false} \\
F \leftarrow F \cup F' \\
\text{until unchanged} 
\]
Basic rule application. The basic idea consists in assembling the sets \( D(x_i) \) of nodes in \( F \) whose type is \( X_i \), i.e., \( D(x_i) = \{ n \in F \mid \tau(n) = \tau(x_i) \} \). This can be computed for the whole rule in a single pass on \( F \), or maintained in a separate data structure. If any domain \( D(x_i) \) is empty, the rule does not apply. Then all node combinations \( (n_1)_1 \leq i \leq k \in \prod_{1 \leq i \leq k} D(x_i) \) can be checked to see if condition \( C(n_1) \) is satisfied, before a corresponding new \( Y \) node is constructed, with specific attributes \( E(n_1)_1 \leq i \leq k \).

For efficiency, it is critical to order variable instantiations and constraints checking so that impossible combinations are discovered as soon as possible to prune the search space. The general principle consists in instantiating the most constrained variables first, as it may fail early. All unary predicates \( p(x_i) \) in \( C \) are thus checked before a new node \( n_i \) is inserted into \( D(x_i) \). Besides, without prior knowledge, variables \( x_i \) with the smallest domains \( D(x_i) \) are more likely to participate in failing predicates \( p(\ldots n_i \ldots) \) and should be instantiated first. Similarly, variables involved in many predicates are more likely to fail before variable involved in few or no predicate, and should also be instantiated first. As often in constraint programming, we heuristically stipulate a constraint degree to order variables (in decreasing degree):

\[
\text{deg}(x) = \frac{\text{number of predicates on } x \text{ in } C}{|D(\tau(x))|}
\]

Invertible predicates. This simple scheme can be made more efficient using specific predicate knowledge. Considering a binary predicate \( p(z_i, z_j) \) where \( z_i = x_i \) or \( x_j \) \( a_i \), we say it is invertible if, given a value \( v_i \) for argument \( z_i \) (and conversely for \( z_j \)), the set \( N_j \) of values \( n_j \) satisfying \( p(v_i, n_j) \), or respectively \( p(v_i, v_j, a_j) \) if \( z_j = x_j \) \( a_j \), is small and can be efficiently enumerated. It is used to narrow the domains: \( D_j \leftarrow D_j \cap N_j \). If \( D_j \) becomes empty, variable assignments backtracks and next possible node for \( x_i \) is considered.

Adjacency predicates are invertible: given a primitive or form \( n_i \), it is in general adjacent to just a few other primitives or forms \( n_j \). For primitives, a rich adjacency graph is computed before rules are processed, yielding immediate adjacency answers. For forms, to list all nodes of a type \( \tau \) adjacent to a node \( n \), we go down node \( n \) to its primitives, get adjacent primitives, and go up the forest from these adjacent primitives to look for nodes of type \( \tau \). A cache of already visited nodes prevents redundant traversals.

Equality \( z_i = x_i \) is invertible too: given a node or value \( v_i \) for argument \( z_i \), there are in general few nodes \( n_j \) such that \( v_i = n_j \). This is also true for \( z_i = x_j, a \) and \( v_i = n_j, a \). (Note that strict equality only makes sense for discrete domains.) Efficient retrieval of such nodes can be achieved by hashing: before processing a rule, a map is built for each argument of such an equality, associating to each possible value \( v_i \) of argument \( z_i \) the set of nodes \( n_j \) such that \( v_i = n_j \) and likewise symmetrically. Again, this is also true for \( v_i = n_j, a \). These maps can be constructed with a single, linear pass on all nodes of \( F \).

On the contrary, predicates such as above or orthog are not considered invertible: many primitives or forms can be above another one and, in a man-made environment such as a building, many primitives are orthogonal to each others.

Last, as variables occurring in an invertible predicate are by definition more constrained, they should be instantiated first. For this, we introduce a constraint degree \( \text{deg}_{\text{inv}}(x) \) defined as follows and list variables lexicographically in descending order, first according to \( \text{deg}_{\text{inv}} \), then \( \text{deg} \).

\[
\text{deg}_{\text{inv}}(x) = \frac{\text{number of invertible predicates on } x \text{ in } C}{|D(\tau(x))|}
\]

Context-free operators. Collection operators \( \text{oper}(X, x \mapsto c, (x, x') \mapsto c') \) are treated as any terminal or nonterminal \( X_i \). The only difference is in the computation of domain \( D(x_i) \), that is not built via a linear traversal of \( F \).

The exclusivity constraint is a major issue for such operators. In general, the set of valid collections (i.e., that satisfy exclusivity) that are maximal cannot be easily deduced from the set of maximal collections. Our approach is to approximate the set of maximal valid collections, staying on the safe side: we may underestimate it, i.e., miss some collections, but not overestimate it, i.e., build non-valid or non-maximal valid collections. Besides, if there is no exclusivity between elements of a given type, maximal collections also are maximal valid collections. Users can thus be told if a parsing result is complete or if solutions could be missing. In practice, grammars can often be written to prevent incompleteness.

To build \( D(x_i) \) if the operator is context-free, i.e., if variables in \( c \) and \( c' \) are only \( x \) and \( x' \), we construct a graph \( G = (V, E) \) where \( V = \{ n \in F \mid \tau(n) = X \land c(n) \} \) and \( E = \{ (n, n') \mid c'(n, n') \land \neg \text{excl}(n, n') \} \), where \( \text{excl} \) checks exclusivity. \( E \) is symmetrized for maxset and maxconn. Maximal collection instances are then computed as described in Table 1. The exhaustivity of maximal valid collections is always satisfied for maxset as there is no edge between exclusive nodes. It is not for other operators. Besides, excl-

<table>
<thead>
<tr>
<th>Operator</th>
<th>Graph components</th>
<th>Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>maxseq</td>
<td>maximal acyclic paths</td>
<td>depth-first search (DFS) to find extremal vertices, then DFS to find paths</td>
</tr>
<tr>
<td>cycle</td>
<td>elementary cycles</td>
<td>Tarjan’s algorithm</td>
</tr>
<tr>
<td>maxset</td>
<td>maximal cliques</td>
<td>Bron-Kerbosch’s algorithm</td>
</tr>
<tr>
<td>maxconn</td>
<td>strongly connected components</td>
<td>DFS (as the graph is undirected owing to the symmetry of edges)</td>
</tr>
</tbody>
</table>

Table 1: Maximal collection operators and corresponding graph algorithms to enumerate all instances.
gles are not exactly co-planar and what we actually con-
co-planar triangles sharing two vertices. In practice, trian-
holes with proper adjacency, and feeded to our parser. The
of 3D triangles, which we merged into 3D polygons with
mat. Using IfcObj, we extracted their geometry, i.e., a soup
proach is not restricted to surface parsing though.

Context-sensitive operators. Semantic and complexity is-
issues arise when context is introduced in the conditions of
maximal collection operators. For this reason, we impose
all contextual variable in \( c \) and \( c' \) are instantiated before
the operator is considered for instantiation.

It excludes rules with circular dependencies between op-
operators. It does not seem a practical limitation: this was in
fact never needed in our experiments. Also, the prior instan-
tiation condition never was a sacrifice to efficiency. On the
contrary, collections are more efficiently grown from known
anchors, rather than without constraints and later discarded.
If a valid variable instantiation ordering exists (no cycle),
it is given by a topological sort on the variable dependency
relation. This order is partial and previously mentioned cri-
teria concerning constraint degrees \( \text{deg} \) and \( \text{deg}_{\text{inv}} \) are then
used for optimizing backtracking efficiency. Last, variables
with identical constraints for instantiation ordering are kept
sorted as written in the rule to let the writer of the grammar
possibly specify his/her own heuristics.

5. Experiments

We have implemented a parser prototype that supports the
above features (except the syntactic sugar). We present here
results obtained both on CAD models with a relatively clean
graph, and on real or realistic data with incomplete and
partly wrong geometry. In all experiments, we have used
grammars where terminals are surfaces rather than volumes.
It is consistent with a semantization task from surfacic data
obtained, e.g., with a laser scan or photogrammetry. Our ap-
proach is not restricted to surface parsing though.

Results on CAD models. We processed 5 building informa-
tion models (BIM) created with CAD software, in IFC for-
mat. Using IfcObj, we extracted their geometry, i.e., a soup
of 3D triangles, which we merged into 3D polygons with
holes with proper adjacency, and feeded to our parser. The
buildings are listed in Table 3, with size information.

In theory, one could construct polygons by just merging
coplanar triangles sharing two vertices. In practice, trian-
gles are not exactly co-planar and what we actually con-
struct as “3D polygons” are sets of almost co-planar 3D tri-
angles (angular difference less than 3°). More importantly,
CAD models do not feature proper triangulations. The rea-
son is they are in general constructed mostly by replicating,
stacking and stacking already meshed components (2D or
3D), rather than by appropriately meshing the surface of a
well-defined volume. Besides, some points or surfaces are
not always properly snapped one to another. The actual task
to form polygons is thus to merge possibly overlapping tri-
angles with approximate adjacency, rather than just connect
them via simple and exact adjacency (sharing two vertices).
This a difficult problem, for which we have used a simple
heuristics that works well on our examples. We first establish
the inclusion relation or approximate adjacency of triangle
edges in other triangles. To that end, for each vertex of a
triangle \( T \), we look for neighboring triangles \( T' \) (at a small
distance, typically 1-10 mm), using an AABB tree. If two
vertices \( v_1 \) and \( v_2 \) of \( T \) are inside or nearly adjacent to the
same triangle \( T' \), then we merge the two triangles. There are
actually two cases. If triangles \( T \) and \( T' \) share both vertices
\( v_1 \) and \( v_2 \), this is a simple ordinary fusion. If not, we create
a new vertex \( v' \) at the centroid of \( T' \) as well as a new trian-
gle \( T'' = (v', v_1, v_2) \), and then merge the three triangles.
The process is iterated from a given triangle in a region-growing
fashion: merging it with nearly adjacent or overlapping tri-
angles, and putting them into a worklist from which new tri-
angles are drawn to continue growing the region. The actual
fusion of triangles consists in projecting them into the plane of
the seed triangle and merging the projected triangles (with
the 2D-polygon tools of the CGAL library). This defines a
2D polygon with holes, whose edges are back-projected to
the corresponding 3D triangles, forming a 3D polygon.

We ran the parser with a general building grammar (not
particular to a specific kind of architecture) to recover build-
ing elements: walls, roofs, floors, stairs, openings (windows
and doors). Some results are pictured in Figures 2, 3, 6 and
7. The color code is given in Table 2. Table 4 provides quanti-
tative evaluation for stairs and outside building elements.

<table>
<thead>
<tr>
<th>Element</th>
<th>Color</th>
<th>Element</th>
<th>Color</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wall</td>
<td>gray</td>
<td>Opening</td>
<td>cyan, blue</td>
</tr>
<tr>
<td>Roof</td>
<td>terracotta</td>
<td>Stair</td>
<td>red, orange</td>
</tr>
<tr>
<td>Floor</td>
<td>green, brown</td>
<td>Not assigned</td>
<td>black</td>
</tr>
</tbody>
</table>

Table 2: Color assignments for semantized elements.

<table>
<thead>
<tr>
<th>Floor</th>
<th>Wall</th>
<th>Roof</th>
<th>Opening</th>
<th>Stair</th>
<th>Not assigned</th>
</tr>
</thead>
<tbody>
<tr>
<td>gray</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>green</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>brown</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>brown</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>black</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>black</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 6: Automatic semantization of roofs, walls, openings in CAD models. Top: LcG. Bottom: LcA (left), LcD (right).
As can be visible from this table as well as illustrations, we properly recognize most elements. We only have a few false positives (stairs with a spurious riser, openings including a spurious window ledge) and some false negatives (missed stairs and openings). We actually discovered that the geometry originating from CAD models was not as clean as expected. Triangles happened to reflect the history of building block composition, with meaningless interpenetrating volumes causing spurious polygon adjacencies and bogus sizes. For instance, some steps are missed because some risers go deep inside the slab or the preceding step, leading to sizes larger than expected and wrong adjacencies. Missed steps in LcF are due to the strange geometry of the stairs, that looks like two interlaced stairs with twice as large risers and treads. There are missed adjacencies too due to bad block snapping. Those were by far the major cause of missed and spurious detections. In fact we would not have such problems with (clean) real data, e.g., laser scans, as only the visible geometry would be modeled. Concerning false negatives, a few frameless doors are geometrically part of a wall plane in LcC, LCD and LcF, and thus included in wall polygons before having a chance to be parsed (see Section 4 though). Missed openings in LcA and LcG are due to limitations in our grammar, which does not take into account dormer windows (with small walls sticking out of the roof) nor skylights (non vertical windows). There are also many French windows/doors in these buildings because of balconies, but model designers disagree: some tag them as doors in the original model, others as windows. This is why we do not report here separate figures for doors and windows; we just labeled them as openings.

Running times are given in Table 3, with a prototype implementation that is far from being optimized. The grammar has been split here in two parts to measure the relative contribution of the two main complex objects: stairs and openings. Table 3: Models and parsing time (w/o polygon processing).

<table>
<thead>
<tr>
<th>Name</th>
<th># of triangles</th>
<th># of polygons</th>
<th>Parsing time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LcG</td>
<td>48332</td>
<td>9705</td>
<td>5</td>
</tr>
<tr>
<td>LcA</td>
<td>111979</td>
<td>26585</td>
<td>14</td>
</tr>
<tr>
<td>LcC</td>
<td>385541</td>
<td>111732</td>
<td>33</td>
</tr>
<tr>
<td>LcD</td>
<td>313012</td>
<td>75257</td>
<td>25</td>
</tr>
<tr>
<td>LcF</td>
<td>286996</td>
<td>84347</td>
<td>39</td>
</tr>
</tbody>
</table>

Table 4: Evaluation of stair & opening semantization: number of items (#), precision (Prec., %) and recall (Rec., %).

<table>
<thead>
<tr>
<th>Name</th>
<th># of stairs</th>
<th># of steps</th>
<th>Stairs (%) Prec. Rec.</th>
<th>Openings</th>
<th># Prec. Rec.</th>
</tr>
</thead>
<tbody>
<tr>
<td>LcG</td>
<td>3</td>
<td>45</td>
<td>100</td>
<td>93</td>
<td>83</td>
</tr>
<tr>
<td>LcA</td>
<td>6</td>
<td>84</td>
<td>100</td>
<td>100</td>
<td>62</td>
</tr>
<tr>
<td>LcC</td>
<td>30</td>
<td>210</td>
<td>100</td>
<td>100</td>
<td>196</td>
</tr>
<tr>
<td>LcD</td>
<td>5</td>
<td>61</td>
<td>100</td>
<td>93</td>
<td>74</td>
</tr>
<tr>
<td>LcF</td>
<td>7</td>
<td>98</td>
<td>100</td>
<td>50</td>
<td>99</td>
</tr>
</tbody>
</table>

Figure 7: Semantization of slabs and stairs in CAD models.

(It has little impact on the overall parsing time.) We can observe good asymptotic properties. In particular, even though we use a bottom-up approach, it is not exponential, which is a key feature and major originality of our parser. The whole point of our constraint-processing approach is precisely to prune the search space to prevent exponential exploration. For instance, when parsing stairways, a first step is drawn as a potential element of a “maxseq(step)”. Being a maxseq, a stairway is grown with more steps in two directions starting from this initial step, based on the adjacency graph, which is basically linear. The steps belonging to the resulting stairway are recorded as such and when they are later considered as other potential seed steps to find other stairways, no growing is attempted in the same directions as it has already been performed. This mostly linear behavior is reflected in the time measurements of Table 3, w.r.t. the number and size of stairs (Table 4). Considering the most complex model (LcC), an exponential approach would not be able to determine in 33 s that the 210 detected steps exactly form 30 different stairways. This generalizes to more complex situations. In practice, the running time depends mostly on constraint rigidity and on the average vertex degree in the adjacency graph, little on the number of rules or the number of variables in a rule (assuming rule conditions constrain rule application enough). A combinatorial explosion is theoretically possible, but does not seem to happen on realistic cases.

In the current implementation of the algorithm, rules are applied sequentially. But they could be applied in parallel too, in particular independant rules. Rule dependency has to be obeyed though (see Section 4). For instance, the computation of walls and stairs are independent, but it is not the case for walls and floors or stairs and floors as walls must be adjacent to floors, so as stairs; floors must be detected first.

Results on real data. To evaluate our algorithm on real data, we consider a multi-view photogrammetric reconstruction of a castle courtyard using images in Strecha’s dataset [SvHVG*08]. This is a kind of worst case scenario as noise here is typically 5-10 cm, which is huge compared to window ledges. Yet, the 3D mesh is precise enough to display a number of edges of windows looking onto the yard. To construct polygons, we segment the underlying point cloud
Considering introducing simultaneous alternative detections (the future work, to make our approach more robust, we are considering continuously relaxing some constraints to provide approximate matching. Of course, detection alternatives and contrast relaxation would make the search space much larger. But this could be addressed by taking into account detection likelihoods and fitness measures for relaxed constraints, which could be combined with rule probabilities too. As a result, inferred nonterminals could be given scores and the shared parse forest would then be pruned according to this score to allow exploring large spaces while keeping a reasonable size. Along this line, a useful feature would be to possibly split (as alternatives) a shape into several pieces, e.g., to address the detection of doors that are merged into wall too early in the process. This could either be supported by photometric information at primitive detection level for a better segmentation, or by late splitting during parsing if shape cues are provided (e.g., the recognition of the other side of the door). Photometric cues could also be used to assign labeling likelihoods, as in top-down approaches [TSKP10], to later participate in shape scoring.

Besides, we believe the strength of our approach will be fully distinctive with a proper treatment of partial information, e.g., due to occlusions or fragmentary acquisitions. The fact that all the structure and regularity is expressed formally in the grammar makes it easier to reason on it, to complete existing elements and to hypothesized missing ones [HZ09]. Our preliminary results on this kind of top-down completion are encouraging, including when several elements are missing, such as a few steps between two floors. To infer likely objects like this, comprehensive grammar constraints are essential. An open issue is to find the right level to enforce general regularity such as dimension repetition and symmetry [PMW08], whether by explicit operators or meta rules.

Actually, we argue that formulating structure, including regularity, as expressed in a grammar, is crucial for semantic analysis. With real (noisy, incomplete) data, structure is essential to prevent spurious and missed detections. For instance, grid alignment constraints would be crucial to recover missed windows in Figure 8. Even on perfect CAD data, spurious step objects are detected in the polygon soup, and regularity is required to compose individual steps into consistent stairways, filtering out false detections. One of the nice things about grammars is that each rule is simple; complexity only originates from their composition. For example, all 9 rules in the actual stairs grammar are indispensable to obtain the accurate recognition of Table 4.

Structure can be hard-wired in code performing semantic
analysis. But such programming would not scale to complex objects and scenes. A formalism to represent structure is required, both to allow systematic optimization (pruning via constraints) and to facilitate the expression of rules by humans. We see a grammar formalism as a domain-specific language to express regularity. In fact, rules here are assumed written by experts, e.g., architects, not computer scientists. A separate issue is the automatic inference of grammar rules from a database of annotated examples. Another one is shape approximation, to prevent exhaustive grammatical descriptions and gain robustness. For instance, although our actual grammar for stairs easily accommodates complex (but regular) noses, it would be better to specify a simple “generic” nose and a basic shape matching approximation. Anyway, structure and regularity have to be made explicit.

7. Conclusion

We have presented a high-level grammar formalism to specify complex objects, and a practical parsing procedure. Although it relies on efficient graph algorithms, the low-level node-and-edge machinery remains hidden, allowing large and maintainable specifications, to be written by non computer scientists. Thanks to alternatives, maximality and to the mixing of adjacency conditions with other kinds of constraints, it is superior to graph grammars too.

Although we have good results for CAD models, concerning both accuracy and running times, work clearly remains to properly handle noise and incomplete data. We actually consider that this paper constitutes a well-delimited first step towards more general scene parsing. We enumerated (Section 6) a number of sensible and promising research directions to address more complex issues arising with real data.

References


