Attribute Grammars for Incremental Scene Graph Rendering

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Abstract: *Scene graphs*, as found in many visualization systems are a well-established concept for modeling virtual scenes in computer graphics. State-of-the-art approaches typically issue appropriate draw commands while traversing the graph. Equipped with a functional programming mindset we take a different approach and utilize attribute grammars as a central concept for modeling the problem domain declaratively. Instead of issuing draw commands imperatively, we synthesize first class objects describing appropriate draw commands. In order to make this approach practical in the face of dynamic changes to the scene graph, we utilize incremental evaluation, and thereby avoid repeated evaluation of unchanged parts. Our application prototypically demonstrates how complex systems benefit from domain-specific languages, declarative problem solving and the implications thereof. Besides from being concise and expressive, our solution demonstrates a real-world use case of self-adjusting computation which elegantly extends scene graphs with well-defined reactive semantics and efficient, incremental execution.

1 Introduction

In Computer Graphics the standard approach for representing virtual scenes in memory is the so-called scene graph. It is a directed acyclic graph with leaf nodes typically representing geometries in a scene and internal nodes used to organize geometries into groups, and associate various attributes. Examples for such attributes are transformation nodes (called *Trafo* for short) to place the geometries at different positions in the scene or shader nodes to associate material properties with geometries. An example of a simple table modeled as a scene graph is given in Fig. Figure 1.

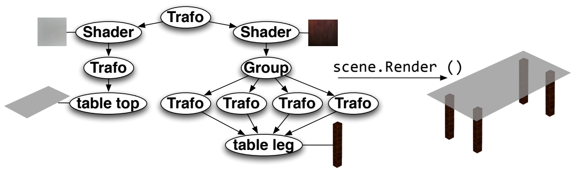


Figure 1: Table modeled using a scene graph. Shader nodes are used for specifying different material and lighting properties for wooden legs and the table top made of glass.

In order to create an image of a scene given its representation as a scene graph, appropriate commands to the underlying graphics hardware need to be issued. Operationally, each graphics command modifies the implicit graphics state (or GPU memory) in order to set the stage for performing the actual draw command. In the scene graph, each node type represents a type of state change to the rendering state. Transformation nodes for example, modify the transformation matrices of the underlying graphics implementation machinery (e.g. write data to GPU memory), whereas shader nodes activate the appropriate shader code in the graphics implementation that will be used to compute the color when a specific object is determined to be visible at a given pixel.

By traversing the scene graph from its root to the geometry nodes at the leaves in a depth first manner, and maintaining a traversal state containing the current value of all possible attribute types (e.g. the current transformation value, the current shader value, etc.), it is fairly simple to submit the appropriate graphics commands for generating a visual representation. Most current rendering engines are based on this traversal scheme.

In this paper we propose to utilize attribute grammars (Knuth, 1968) as the formalism for describing scene graph semantics. Whereas attribute grammars in their original form where introduced to compute static or dynamic semantics of languages, we use them to compute *render objects* (describing complete render state) on the structure of scene graphs. The declarative nature of this representation has a number of advantages to procedural and object-oriented implementations that are today's standard.

Wörister et al. (Wörister et al., 2013) already used incremental attribute grammar evaluation as *motivation* for the incremental update mechanism of so-called render caches, a flat and optimized runtime replacement for scene graph parts. In contrast to our work, which builds on general purpose incremental evaluation and allows arbitrary dynamism, they use a hand-written traversal to generate render caches on specific points in the scene graph and use a dependency index to update caches on value changes, e.g. transformation changes.

In addition to composability (Swierstra, 2005), another vital advantage of attribute grammars is their well-founded declarative dataflow via attributes. Attribute grammars are well understood and allow for a wide range of optimizations such as fusing traversals (Swierstra et al., 1999) and incremental evaluation (Reps et al., 1983). Our main contributions are:

- We show that attribute grammars can be used to model scene graphs elegantly and concisely (Section 2.2), while maintaining extensibility in terms of data and operations[1]. By just adding a new type and necessary semantic functions (equations defining only the necessary attributes for the new node type, see Figure 3) scene graph systems can be extended easily for specific domains. Due to its declarative nature, our system allows for much shorter (in terms of code length) implementations and is easier to understand, since for example, attributes do not need to be passed explicitly.
- Attribute grammar semantics need to be lightweight and flexible in order to easily integrate with existing applications, infrastructure and data processing modules. To that end we introduce an embedded domain-specific language (EDSL) for authoring syntax and semantics of attribute grammars (Section 2.2).
- For highly dynamic data, we extend our system with incremental evaluation of dynamic values. In contrast to previous work, we use no specialized algorithm for incremental evaluation of attribute grammars, but base our algorithm on recent advances in the field of *self-adjusting computation* (Acar et al., 2002; Acar, 2005; Hammer et al., 2014).

  Incremental evaluation is exposed via another EDSL (similarly to LINQ to SQL (Meijer et al., 2006; Syme, 2006)), which automatically generates a dependency graph while executing code. The underlying implementation (Hammer et al., 2014) takes care of external input modifications (e.g. mouse moves) and re-executes only code paths affected by those changes. This is called *change propagation* and takes away the burden of explicitly handling changes and updates.

  While hardware-accelerated rendering is roughly linear in the number of objects, traversal quickly becomes a bottleneck in non-trivial scene graphs, resulting in bad utilization of GPU resources (Wörister et al., 2013). Furthermore, traversal cost is proportional to the number of scene graph nodes, i.e. intermediate nodes used for factoring sub-graphs degrade performance of rendering even more. Although this is an inherent problem for scene graphs, due to incremental evaluation we pay for intermediate nodes only once at construction instead of each frame (Section 4.2). Finally, incremental evaluation of render objects goes hand in hand with work recently published in the field of high-performance rendering (see Section 2.3), works for arbitrary changes and requires no manual placement of render caches.

In our evaluation, we show that attribute grammars combined with incremental computation indeed solve aforementioned problems in an elegant way and with promising performance characteristics (Section 4). The incremental approach allows to track changes and perform low level GPU optimizations such as command buffer (Khronos Group, 2016) re-recording only when necessary. Moreover, we think that this work is a step towards filling the gap between low-level optimizations for efficient rendering and domain specific languages for scene representation and interaction (see Figure 4).

To summarize, the aim of this paper is to show the excellent interplay between attribute grammars, recent advances on incremental computation and advances in high-performance rendering.

2 Our approach: Self-Adjusting and Side-Effect Free Scene Graphs

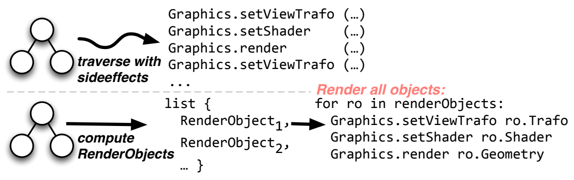
The remainder of this paper is structured as follows: Section 2.1 shows how to compute a set of render objects, which later can be updated incrementally.

In Section 2.2 we use attribute grammars to compute a set of render objects declaratively. Section 2.3 shows how to update sets of render objects incrementally. Sections 3.1 and 3.2 introduce EDSLs for authoring attribute grammars and incremental computations. Finally, we put everything together (Section

[1] note that the visitor pattern does not provide this extensibility due to the *expression problem* (Wadler, 1998; Torgersen, 2004)

3.3), evaluate and contrast our approach to related work (Section 4) and explain tradeoffs.

2.1 Computing Render Objects



```
Graphics.setViewTrafo (…)
Graphics.setShader    (…)
Graphics.render       (…)
Graphics.setViewTrafo (…)
...
```

```
list {
  RenderObject1,
  RenderObject2,
  … }
```

```
for ro in renderObjects:
  Graphics.setViewTrafo ro.Trafo
  Graphics.setShader ro.Shader
  Graphics.render ro.Geometry
```

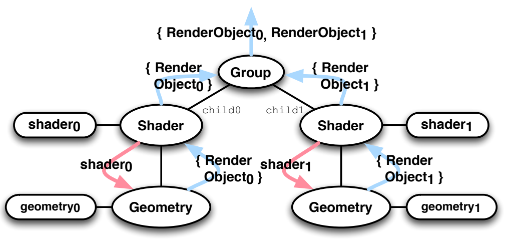
Figure 2: Traditional scene graph traversal issues graphics commands while traversing. In functional programming by contrast, we compute a set of render objects (purely functional) which can later be interpreted in order to issue graphics commands to the graphics hardware.

The basic concept of our approach is to compute values representing draw commands instead of issuing many small graphics commands while traversing a scene graph (see Fig. 2). For each leaf node we compute a *render object* which captures all arguments required for issuing an appropriate draw call. This flattens the scene graph to a list and eliminates traversal overhead. In the last step, render objects are mapped to concrete GPU graphics commands, which can be directly issued to the GPU batch-style, eliminating more overhead.

2.2 The Scene Graph Grammar

Scene graphs typically use shared leaf nodes in order to reuse the same geometry in different contexts, i.e. with different attributes. A desk, to give a trivial example, might use a shared instance of the table leg for all table legs, rendered with different spatial transformations (see Fig. 1). Traditionally, attribute grammars operate on tree-like structures. Semantics for shared nodes however, need to be computed on each path, so attribute grammars naturally carry over to graphs, when instancing attributes per path.

The main point of our approach is to use attribute grammars for modeling scene graph semantics, solving the task of computing sets of render objects purely declaratively. Fig. 3 gives attribute grammar equations for computing a set of render objects. Note that, in practice render objects need to capture the transitive closure of arguments required for rendering (not only *shaders*).



```
inh SEM shader:
| Group    child0.shader = this.shader;
           child1.shader = this.shader;
| Shader   child.shader = this.shader

syn SEM RenderObjects:
| Group    this.RenderObjects =
                  child0.RenderObjects ∪
                  child1.RenderObjects
| Shader this.RenderObjects = child.RenderObjects
| Geometry this.RenderObjects =
        { create RenderObject( this.shader,
                               this.geometry ) }
```

Figure 3: Attribution of a simple scene graph (top). Shader nodes propagate provided shader values (shader$_0$,shader$_1$) downwards, thus defining an inherited attribute. Geometry nodes produce rendering output by constructing a *render object* given its local geometry instance as well as the inherited shader attribute. Group nodes compute the union render object set, which in turn propagates towards the root node. This upward propagation makes sets of rendering objects a synthesized attribute. The text definition (bottom) shows attribute grammar equations in style of UUAGC (Swierstra et al., 1999) and reads as such: shader is an inherited attribute (flows downwards), e.g. for binary groups, the child‘s surface attribute is defined as the surface value valid at this point. RenderObjects is a synthesized attribute (is computed for sub graph, computed towards root), e.g. for geometry nodes, a render object set is computed by querying the inherited attributes shader and the geometry data contained in the geometry node itself.

2.3 Self-Adjusting Computation for Reactive Scene Graphs

Attribute grammars allow for purely functional evaluation of scene graph semantics. Still, the synthesized set of render objects is immutable and needs to be recomputed periodically, if input attributes or scene graph properties change.

Incremental computation, which has been investigated for a long time (e.g. Ramalingam and Reps (Ramalingam and Reps, 1993) provide an extensive survey), is a solid foundation for updating program outputs incrementally, given some changes in its inputs. Although various approaches for incremental evaluation of attribute grammars have been proposed (e.g. (Reps et al., 1983; Hudson, 1991)), we aim for a more general approach, which composes cleanly with

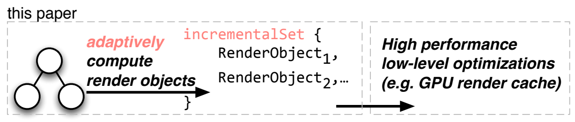

this paper
adaptively compute render objects
incrementalSet {
RenderObject1,
RenderObject2,…
}
High performance low-level optimizations (e.g. GPU render cache)

Figure 4: Given the input scene graph, we compute the set of render objects and the underlying dependency graph. Whenever the input graph is modified, we automatically map those changes to changes in the incrementally maintained set of render objects. Subsequently, the incremental set can be used to optimize and issue graphics commands to the graphics hardware (e.g. using command lists (Jeff et al., 2015) or vulkan command buffers (Khronos Group, 2016) which only need to be re-recorded whenever the set changes).

incremental algorithms outside the domain of the attribute grammar semantics.

To our rescue, Acar et al. introduced *adaptive functional programming* (Acar et al., 2002), a framework for incremental evaluation of arbitrary (purely) functional programs. In their library, they support meta operations, for modifying inputs for adaptive computations. In a subsequent step, all output values are made consistent again by selective re-execution of affected parts, determined by the dynamic dependency graph. Their approach is particularly well suited for our use case, since minimal modification of semantic functions yields incremental versions thereof and the change propagation composes with other algorithms implemented in their framework.

In our work, we use an implementation of *adaptive functional programming* by lifting all dynamic values into modifiable cells and modify all semantic functions to work adaptively, by utilizing combinators operating on these cells.

As a result, we synthesize render objects once and update the resulting set adaptively (see Figure 4). This not only solves efficiency issues for scene graph traversal as updates can be performed in $O(\Delta)$ instead of $O(n)$, where Δ is the size of the change and n is the total size of the scene, but also provides huge potential for optimizing execution of graphics commands. The incremental set of render objects can be subscribed for changes and combined with low level optimizations such as command lists in OpenGL (Jeff et al., 2015) or command buffers (Khronos Group, 2016), which only need to be re-recorded when the incremental set was modified, or other whole-scene optimization methods, such as the incremental rendering VM (Haaser et al., 2015), were applied (see Fig. 4).

To summarize, our method adheres to the following concepts:

Separation of effects We keep rendering traversals pure (no side-effects) by synthesizing a set of *render objects* including all parameters required for rendering in a subsequent step.

Declarative formulation By utilizing attribute grammars, our formulation is purely declarative. Furthermore, by using inherited and synthesized attributes we have clean semantics for data-flow within scene graphs.

Incremental evaluation Above concepts allow for a clean and concise implementation of scene graphs. At first glance, the high-level abstraction has intrinsic cost when compared to hand-tuned traversals. However, this high abstraction provides opportunity for optimization. In fact, by utilizing *adaptive functional programming* and our declarative formulation, we can significantly speed up rendering by uncoupling rendering performance from scene structure: as we exactly know which parts of a computation have not changed, we can safely reuse previously calculated values.

3 Implementation

Our implementation is part of a visual computing research platform and is used in several research prototypes, as well as for industrial projects. It targets .NET Core and is written mostly in *F#* and *C#*. Note that, our DSL for incremental evaluation uses *F#*'s *Computation expressions* (Petricek and Syme, 2014), which considerably improves readability, and maintenance of dependency graphs is completely transparent to the user.

3.1 An EDSL for Scene Graphs

Usually, attribute grammar systems automatically generate executable code out of an attribute grammar description (e.g. Utrecht University Attribute Grammar Compiler (Swierstra et al., 1999), JastAdd (Ekman and Hedin, 2007)).

As an alternative, embedded domain-specific languages (EDSLs) have been proposed for authoring attribute grammars (Sloane et al., 2010). In contrast to generators, well-foundedness checks, such as undefined attributes, are hard to implement in embedded languages. Viera and Swierstra introduced an embedding in Haskell, which performs static analysis (type checking) of attribute grammar definitions (Viera et al., 2009).

Since we aim for interoperability with existing code we utilize an embedded domain specific language written in F#. Our implementation is entirely dynamic and supports on-demand extensions of data types and semantic functions. To accomplish this, we scan for classes with specific annotations and register their member functions in a global table. On the API side, we use overloaded operators for accessing inherited and synthesized attributes. For querying attributes we use dynamically typed overloads of the `?` operator. The signature is given in Figure 5, while the implementation can be found online[2]. Those operators are dynamically typed, i.e. the result type can be any type, but in practice, type inference works notably well as attribute lookups typically appear in rich type contexts and using an attribute implicitly declares its actual type. This is similar to having `auto` variables in C++ code.

Our implementation is rather naive. When computing a synthesized attribute, we successively look for matching semantic functions and traverse downwards while maintaining a stack of parent nodes. When computing the value of an inherited attribute, we search up through this path until we find the proper semantic function.

For encoding the syntax we use an object-oriented encoding. In this setting, each production becomes a separate class. This way we can easily add further productions later (simply by inheriting the base class). While for scene graphs we need to compute a set of render objects, we first present a toy example computing the sum of a linked list, in order to get familiar with syntax and semantics of our DSL. For reference, the grammar for linked lists in EBNF can be written as follows (here we use the '`:`' operator as separator for list items[3]):

$$\begin{aligned}\langle \textit{list} \rangle &::= \langle \textit{nil} \rangle \\ &\mid\ \langle \textit{integer} \rangle\ \text{':'}\ \langle \textit{list} \rangle\end{aligned}$$

Consider the purely functional implementation of a linked list in *C#* (which models the list syntax in an object oriented manner):

```
public interface List {} // base interface for all lists
// class for linked list nodes (value and next pointer)
public class Cons : List
{
 public int Value; public List Rest;
 public Cons(int value, List rest){
  Value = value; Rest = rest;
 }
}
public class Nil : List {} // the the end of the list.
```

The *F#* version (to get familiar with the syntax) looks like this:

```
type List = interface end       // introduce syntactic form.
// in grammar notation, add a production: List :=
↪  Cons(v,xs)
type Cons(v : float, xs : List) =
   interface List
   member x.Rest = xs
   member x.Value = v
// in grammar notation, add a production: List := Nil()
type Nil() = interface List
```

The attribute grammar for computing the sum of a list can be written using equations operating on the syntactic nodes (in UUAGC syntax, as used in Figure 3):

```
syn SEM List:
| Nil    this.Sum = 0
| Cons   this.Sum =
  this.Value + this.Rest.Sum
```

The definition for the synthesized attribute `Sum` reads as follows: For empty lists (`Nil`), the sum is zero. For `Cons` cells, we add the list value and the synthesized attribute computed for the tail of the list. By utilizing the dynamically typed question-mark operator as defined in Figure 5 the synthesized attribute `Sum` can be described as such:

```
[<Semantic>] // the attribute grammar implementation looks
↪  for semantic attributes
type SumSem() =
    // each member corresponds to an equation in the
    ↪  attribute grammar.
    member x.Sum(cons : Cons) =
    cons.Value + cons.Rest?Sum()
    member x.Sum(nil : Nil) = 0
```

Note the similarity of the equations and our domain specific language implementation. Again, for clarity the *C#* version would look like:

```
[<Semantic>]
public class SumSem {
 public int Sum(Cons cons) {
  return cons.Value + queryInhAttribute(cons.Rest,'Sum');
 }
 public int Sum(Nil nil) { return 0; }
}
```

The translation to *C#* reveals the implementation technique we use. Each question-mark operator triggers the resolution of the queried attribute. Note that there is huge optimization potential, since the underlying traversals can be fused together and inherited attributes can be passed efficiently (Reps et al., 1983; Hudson, 1991) and inherited attributes can be computed while traversing downwards (Rosendahl, 1992).

Similarly, inherited attributes which in traversal-based scene graph systems need to be tediously passed via traversal state objects can be accessed at any point in semantic functions. The underlying evaluating scheme automatically builds the necessary traversal functions.

3.2 Computation Expressions for Adaptive Computations

Although theory and implementation of incremental evaluation frameworks is outside the scope of this paper, we give a short overview.

Typically, variables in functional programming languages are immutable and thus cannot be changed

[2]Our implementation extended with real world concerns such as thread safety, can be found at `https://aardvark-community.github.io/ag-for-scenegraphs`

[3]the syntactic expression would be: `1 : 2 : nil`, the *C#* equivalent: `new Cons(1,new Cons(2,Nil()))`, the *F#* version: `Cons(1,Cons(2, Nil()))`

```
(* Queries some node for the attribute attribName. As convention for function types (unit-> 'a) we query synthesized
attributes, where non-function types can be used for querying inherited attributes (in F# generic arguments are written as
↪ lowercase letters with tick ' prefix), e.g.
let a : AttribType = node?AttribName   // Compute inherited attribute `AttribName` on some node:
let b : AttribType = node?AttribName() // Compute synthesized attribute `AttribName` on some node: *)
val ( ? )   : node:obj -> attribName : string -> 'a
(* Assignes an attribute to some syntactic entity, usage: node.Child?Attribute <- someValue *)
val ( ?<- ) : node:obj -> attribName : string -> unit
```

Figure 5: F# operations as entry-points for accessing attributes dynamically. Note, that these special operators are provided by the F# language and can be overloaded (similar to overloading << in C++). While `?` is binary, `?<-` is a ternary operator, which can be used for overloading assignments. The operators also have special treatment in the compiler, since at call-site the user applies identifiers while at definition side those identifiers are bound to strings.

```
type ref<'a>() =
 member x.SetValue (v : 'a) = // sets internal value to v
 member x.GetValue () = // reads current value of reference
 ↪ (like dereference the value)
```

```
// read only reference type.
type aref<'a> =
 // One method to compute content of type 'a.
 abstract member GetValue : unit -> 'a

// changeable, dependency aware input reference (e.g. user
↪ input is stored in CRefs)
type cref<'a>() =
  // sets internal value to v and propagate changes in the
  ↪ dependency graph
 member x.SetValue (v : 'a) = ..
    interface aref<'a> with ...// implementation

type aset<'a> =
 abstract member GetSet : unit -> set<'a>

type cset<'a>() =
 member x.Add (v : 'a) = // add v to the set
 member x.Rem (v : 'a) = // remove v from the set
```

Figure 6: API for reference cells and mutable sets (top) and dependency aware, i.e. adaptive versions (bottom).

after initialization. Most (functional) languages however provide explicit data types for dealing with mutable cells (often called `ref` cells). Similarly to explicit reference cells, a central concept for incremental computation is to wrap modifiable data into a special type, called `aref<'a>` where `'a` is the type contained in the cell[4]. With this mechanism all writes and reads can be enriched in order to maintain a dependency graph underneath. Those datatypes we refer to as *adaptive* data-structures. Our examples in this paper use *adaptive references* (often called *modifiable* in the literature). We distinguish between two kinds of adaptive references:

- adaptive references (`aref`), which represent a dependency tracked cell which is part of the dependency graph and describes either an intermediate result or the final result of an adaptive computation.
- changeable references (`cref`), which represent a dependency tracked cell but can be modified externally (i.e. has a public setter).

Although such adaptive references are sufficient to track modifications in arbitrary data-structures, it is

```
module Mod =
 let map (f : 'a -> 'b) (a : aref<'a>) : aref<'b> = ...
 let bind (f : 'a -> aref<'b>) (a : aref<'a>) : aref<'b> = ..
 // creates readonly adaptive cell
 let constant (v : 'a) : aref<'a> = ..
 // creates changeable input cell
 let init (v : 'a) : cref<'a> = ..
module CSet =
 let init (l : list<'a>) : cset<'a> = // construct and
 ↪ initialize with l
```

Figure 7: Operators for adaptive references

often more efficient to provide special purpose implementations of standard data-structures such as, e.g. lists and sets (Acar et al., 2010). Since sets are indispensable in our use case we use a special purpose implementation (for transparency, an explicit sort-key needs to added to render objects) called `aset` and `cset` respectively. Stub implementations for mutable datatypes (reference and set) and their adaptive counterpart are shown in Figure 6.

The types `cref<'a>` and `cset<'a>` can be changed externally and trigger change propagation in the system. The types `aref<'a>` and `aset<'a>` serve as read only views on dependency graphs. For adaptive references there is one single additional operation (`bind`) required to describe arbitrary adaptive functional programs. Given an input cell of type `aref<'a>` and a function of type `'a -> aref<'b>` the `bind` operator computes an output reference of type `aref<'b>`. This operation allows to dynamically switch between dependencies depending on the current value of an adaptive reference. A less expressive version of this operator is `map` which maps values of type `aref<'a>` to `aref<'b>` by applying the mapping function of type `'a -> 'b`. The signature for the most common operators is given in Figure 7 with the `map` operator depicted in Figure 8.

Our internal implementation is based on out-of-date marking, similar to Hudon's lazy change propagation strategy (Hudson, 1991). For re-evaluation we use eager out-of-date marking paired with lazy evaluation, based on the approach of (Hammer et al., 2014). For details on the implementation of such a framework we refer to the literature, e.g. (Acar et al., 2002; Acar, 2005; Acar et al., 2010; Hammer et al., 2014).

[4]in *F#*, generic parameters are written in lowercase letters with tick (`'`) prefix

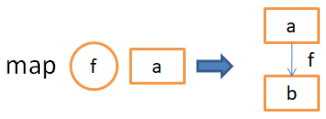
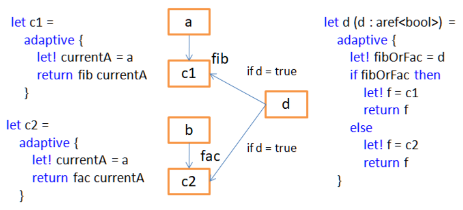


Figure 8: Dependency graph construction for `let b = map f a`. The map operator creates an output cell and adds a dependency graph edge into `a`'s edge list. Whenever `a` gets modified we mark all successors to be out-of-date (have inconsistent value). Each time the user requests the actual value of an `aref`, the value needs to be recomputed as efficiently as possible (and the out-of-date flags cleared again).



```
let c1 =
  adaptive {
    let! currentA = a
    return fib currentA
  }

let c2 =
  adaptive {
    let! currentA = a
    return fac currentA
  }
```

```
let d (d : aref<bool>) =
  adaptive {
    let! fibOrFac = d
    if fibOrFac then
      let! f = c1
      return f
    else
      let! f = c2
      return f
  }
```

Figure 9: *Computation expressions* provide a convenient way to write adaptive functions, even for more complex scenarios such as dynamic dependencies, where the value of another `aref` switches between dependency graph variants.

Inspired by Carlssons's monadic approach to self-adjusting computation (Carlsson, 2002), we use monads in order to make programming with incremental algorithms easier. To this end, we use *F#*'s *computation expressions* (Petricek and Syme, 2014) which provide syntactic expansion for monadic computations similarly to *Haskell*'s *do-notation* (Peyton Jones et al., 2003) or *LINQ* (Bierman et al., 2007). Most essentially, `let!` corresponds to monadic bind, which in our case reads the value of an `aref<'a>` and computes a new one in its continuation.

Subsequently, we provide signatures in order to make our examples work and refer to our open source implementation for details. A computation expression builder for adaptive computations of our implementation can be defined as such:

```
type Builder() =
  member x.Bind(m : aref<'a>, f : 'a -> aref<'b>) =
    Mod.bind f m
  member x.Return (v : 'a) =
    Mod.constant v :> aref<_>
  member x.ReturnFrom(m : aref<'a>) = m
  member x.Zero() = Mod.constant ()
```

Figure 10 (top) gives an example for `aref`'s with expanded code (middle), and the dependency graph for a slightly extended example is shown in Figure 9.

In contrast to the *do-notation* which operates on monadic operations, computation expressions allow to overload practically all *F#* language constructs making them a perfect fit for providing first class support for lists (e.g. *for* loops). An example demonstrating adaptive sets (`aset`) and computation expression builder syntax is given in Figure 10 (bottom).

```
type Builder() = ... // defines syntactic translation
// instantiate computation expression builder
let adaptive = Builder()

let test () =
 // creates an aref cell initialized with 1.
 let a = Mod.init 1
 let plus1 =
  adaptive {     // starts an adaptive block
   // adaptively reads value a into value a'
   let! a' = a
   // returns (a'+1) and writes the result to plus1.
   return 'a + 1
  }
 assert 2 = plus1.GetValue() // force evaluates plus1 to 2
 a.SetValue(2)   // changes a to 2
 assert 3 = plus1.GetValue() // force now evaluates plus1 to 3
```

```
let a = Mod.init 1
let b = Mod.init 2
let plus =
 adaptive {
  let! currentA = a // adaptively read a
  let! currentB = b // currentA has type int.
  return currentA + currentB // ordinary integer addition
 }
let plusDesugared = // the same as plus
 Mod.bind (fun currentA ->
  Mod.bind (fun currentB ->
   currentA + currentB
  ) b
 ) a
```

```
let aset = SetBuilder()
// construct changeable set given a F# list
let changeableSet = CSet.init([1,2,3])
let mapped = aset {
 // use overloaded `for` syntax defined in builder
 for x in changeableSet do
  // aset provides an implementation of yield which
  // emits a value into resulting the adaptive set
  yield x + 1
 }
mapped.GetSet() => {2,3,4}
// as side effect modify the input set
changeableSet.Add 4
// force the output, observe updated output
mapped.GetSet() => {2,3,4,5}
```

Figure 10: Computation expression builder example for `aref`'s (top), a simple example comparing the *builder* version with the expanded variant of the same code (middle), and an example involving `aset`'s (bottom).

3.3 Putting Everything Together

Our attribute grammar implementation is based on an object-oriented encoding for specifying syntax. Given `ISg` (**I**nterface for **S**cene **g**raphs) being the base type for all scene graph nodes, productions have the form: `ISg := Render | Group (..) | TrafoApp (..)...`. In our OOP encoding the root production (`ISg`) can be defined as follows:

```
(* emtpy base interface for all scene graph nodes *)
type ISg = interface end
```

The terminal production `ISg := RenderNode` can be described as:

```
(* introduces class RenderNode implementing ISg interface
↪  *)
type Render() = interface ISg
```

One common pattern in scene graphs is to use applicators to apply a value to a given sub-graph:

```
type IApplicator<'a>(value : aref<'a>, child : aref<ISg>) =
 member x.Value = value
 member x.Child = child
 interface ISg
```

```
[<Semantic>] (* runtime attribute which makes members
↪  available as ag rules to used by the system *)
type RenderJobs() =
  // create a render object using the local transformation
 let createRenderJob (n : Render) (t : Trafo3d) : RenderObject = ....
 // defines a member RenderObject for type RenderObject
 member sem.RenderObjects(node : Render) =
  aset {
   // queries inherited attribute Trafo
   let! trafo = node?Trafo
   // create a draw call and yield it into the set
   yield createRenderJob node trafo
  }
 member sem.RenderObjects( g : Group) : aset<RenderObject> =
  aset {
    // incrementally loop over sub scene graph set
   for x in g.children do
     // Compute synth. attribute for the child
    let ro = x?RenderObjects()
    // yield the computed set of render objects
    yield! ro

  }
 // ddefault rule for all nodes of type IApplicator<'a>
 member x.RenderObjects(app : IApplicator<'a>):aset<RenderObject>=
    aset {
      let! child = app.Child   // adaptively read the sub
      yield! child?RenderObjects()
    }
 member x.Trafo( trafo : TrafoApp) : unit =
    // applies local trafo to its sub graph
   // i.e. `assigns` the inherited attribute
   trafo.Child?Trafo <- trafo.Value
```

Figure 11: Semantic functions for synthesizing render objects from a scene graph.

Let us now define a node which applies a transformation (as `aref` since it should be changeable) to a subgraph (i.e. the production `ISg := Transform ISg`) and a group node with an arbitrary number of children:

```
type TrafoApp(value : aref<Trafo3d>, child : aref<ISg>) =
 inherit IApplicator<Trafo3d>(value,child)
type Group = { children : aset<ISg> }
 with interface ISg
```

The semantics for synthesizing render objects is given in Figure 11. All semantic functions have type `aset<RenderObject>` reflecting the fact that their result is an adaptive computation yielding a set of render objects. The rule for `Trafo` assigns an `aref` containing the applied transformation to its modifiable children.

3.4 Extensibility: Adding Operations

As an example for *adding operations*, we extend the system with the ability to compute the bounding box of an `ISg`. In object-oriented design, this additional method would require to modify *all* implementations (see the *expression-problem* (Wadler, 1998)). In contrast, our approach is extensible regarding operations and Figure 12 shows an example implementation. For leaf nodes we simply return the object space bounding box, lifted into a modifiable by utilizing the `adaptive` builder. For group nodes, we internally use an adaptive version of the fold function for combining the bounding boxes adaptively. For applicators we simply

```
[<Semantic>]
type BoundingBoxSem() =
 member x.BoundingBox(r : Render) =
  adaptive {
   return r.BoundingBox
  }
 member x.BoundingBox(app : IApplicator<'a>) : aref<BoundingBox> =
  adaptive {
    let! child = app.Child
    return child?BoundingBox()
  }
 member x.BoundingBox(trafo : TrafoApp) : aref<BoundingBox> =
  adaptive {
    let! child = trafo.Child
    let! childBB = child?BoundingBox()
    let! trafo = trafo.Value
    return transform trafo childBB
  }
 member x.BoundingBox(g : Group) : aref<BoundingBox> =
  combineBoundingBox g.children
```

Figure 12: Semantics for bounding box computation. Nodes of type `TrafoApp` are handled explicitly in order to transform the computed bounding box, while others are handled implicitly by the `IApplicator` function.

compute the bounding box for the child and return the result, while for transformation nodes, we compute the bounding box of the child graph and transform it appropriately.

3.5 Extensibility: Adding Nodes

Let us now extend the system with a new node which toggles between a high-quality and a simplified representation of the scene. Figure 13 shows the new node and specialized semantics for existing synthesized attributes, like bounding boxes and render objects.

Note that, not all types need to be handled here, since unrelated nodes, such as `TrafoApp` are automatically handled by the semantic function for `IApplicator` previously defined.

4 Evaluation and Discussion

The evaluation of our system is twofold. Firstly, does our approach really provide a valid solution to scene graph programming and how does it compare to existing systems? Secondly, since our implementation focuses on a succinct implementation and a clean separation of data and semantics, we are interested in actual run-time performance.

4.1 Comparison to Related Work

Our new approach solves the following problems that are typical in current systems:

Modularity Most rendering systems using scene graph traversal are implemented in an object-oriented

```
type LevelOfDetail =
 { simple : aref<ISg>;      // represent low quality version of the contained sub graph (fast rendering)
   // note that, in order to allow dynamic changes for those sub graphs,
   // we use aref<ISg> instead of plain ISg.
  detailed : aref<ISg>;    // represent high quality version of the contained sub graph (slow rendering)
  useSimple : BoundingBox -> bool // given the world space bounding box of the child graph, compute whether simple
 } with interface ISg       // is sufficient (i.e. the object is far enough so that a simple rendering suffices)

[<Semantic>]
type LodSemantic() =
 member x.BoundingBox( lod : LevelOfDetail) = adaptive { return! lod.simple?BoundingBox() }
 member x.RenderObjects( lod : LevelOfDetail ) : aset<RenderObject> =
  aset {
   let! low = lod.simple          // read the simple version adaptively
   let! box3d = low?BoundingBox() // adaptively synthesize bounding box attribute for the child
   match lod.useSimple box3d with // apply lod decision function
   | true  -> yield! low?RenderObjects() // synthesize render jobs for low
   | false -> let! high = lod.detailed // adaptively read detailed child graph
        yield! high?RenderObjects() // synthesize render jobs for high
  }
```

Figure 13: Extending the scene graph with a new node type for specifying level-of-detail syntactically. Note that, we do not need to add semantic functions for unrelated nodes such as `TrafoApp`, since the previously defined semantic function for `IApplicator` covers this case.

style, where each node needs to implement all necessary methods for scene graph management and traversal, e.g. OpenSceneGraph (Burns and Osfield, 2004). Adding scene graph nodes can be easily accomplished, but adding new operations usually is fairly intricate, e.g. for the visitor pattern all implementations need to be modified. Our declarative definition of both scene graph structure and attributes, makes it simple to add both nodes *and* operations.

Communication Via attributes, our approach intrinsically supports declarative data-flow between semantically related nodes, without the need for using ad hoc mechanisms, such as user-defined global state.

Dynamism Another source of complexity in many systems is dynamic data, ubiquitous in many visualization tasks. Tobler introduced a separate, semantic scene graph in order to allow dynamic changes in an associated rendering scene graph, which needs to be explicitly implemented (Tobler, 2011). Our incremental evaluation EDSL provides an automatic solution for this idea by implicitly tracking changes to all inherited and synthesized attributes.

Efficiency As scene graph traversal quickly becomes a bottleneck for large scenes (Wörister et al., 2013), systems either directly optimize scene graphs by applying persistent transformations for compacting the graph (Strauss and Carey, 1992), or use caching in order to reduce traversal overhead (Durbin et al., 1995; Wörister et al., 2013). Instead of fighting symptoms, our approach effectively decouples runtime cost from scene graph complexity via incremental evaluation. This greatly reduces or, in absence of change, even eliminates traversal overhead.

Interopability Most visualization systems require developers to convert all domain-specific data into framework-specific structures. This is costly in terms of runtime and memory. Our system allows to directly leverage existing types and data structures without modification by specifying application-specific semantic functions instead of implementing a predefined set of functions or interfaces. As an example, consider the `assimp` library[5] with its own scene graph, which has been integrated into our system by providing semantic functions interacting with the compiled types in the `assimp` library.

4.2 Performance

Our proposed incremental system has runtime complexity proportional to change $O(\Delta)$ as opposed to $O(n)$ in traversal-based systems. Asymptotically, we therefore outperform classical non-incremental systems independent of implementation technique or optimizations. In practice, this holds true only for reasonable scenes which change gradually over time.

When discussing tradeoffs of our system, we need to distinguish the two main sources of overhead. First, incremental evaluation requires to maintain a dependency graph, and second, attributes need to be resolved at runtime, involving a dictionary lookup.

Clearly, after initialization, the overhead is zero for static scenes. If no dependencies change, no reevaluation takes place and no attributes need to be computed. With increasing size of change, we expect change propagation cost to increase, and eventually to reach a point where the cost of maintaining the dependency graph outweighs its benefit. Thus, the fraction of change per frame seems to be the parameter best describing the tradeoffs in our system.

We compare three different implementations to better understand when this crossover occurs. 1. An optimized implementation of classical scene graph

[5]The open asset import library `http://assimp.sourceforge.net`

traversal. We use the *semantic scene graph* as it is closest with respect to extensibility and expressiveness. 2. Our system. 3. Our system, but with hardwired attribute grammar evaluation in order to separate overhead from incremental evaluation and to simulate an optimal attribute grammar implementation.

For 1 we measure the time to perform the update and traverse the scene without executing rendering specific code. This effectively simulates an underlying zero-overhead graphics API and GPU driver. For 2 and 3 we update the scene and loop over the set of render objects. In each case we measure the average runtime over 30 update/loop cycles. Note, that at startup, we once perform a dry run to avoid measuring unrelated JIT initialization costs.

In order to adequately test the limits of our approach, we created two test setups deliberately introducing maximum stress in the two main components of our system.

First we investigate the performance of the incremental system regarding to value changes in an artificial test scene with 9000 leaf nodes, each with its own transformation node as well as a group node on top.

The benchmark shows (see Figure 14) that changing values in the scene graph indeed is roughly proportional to the number of value changes and the involved overheads seem reasonable. Beside from runtime costs we measured approximately factor 4 in memory footprint, mostly for storing the dependency graph.

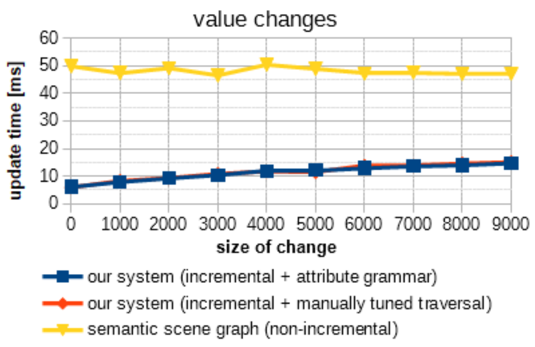


Figure 14: Runtime in *ms* for varying number of changes (from no change, to modifying all 9000 transformations). For a fair comparison, our system performs updates and loops over the resulting `aset`, thus for 0 updates, we still spend some milliseconds in that loop. The *manually tuned traversal* version tracks dependencies, but the incremental change propagation algorithm directly manipulates transformation values of the render objects, involving no additional overhead. As it turns out the incremental evaluation system performs well for this task and outperforms the classic traversal based approach since its runtime is proportional to size of the change.

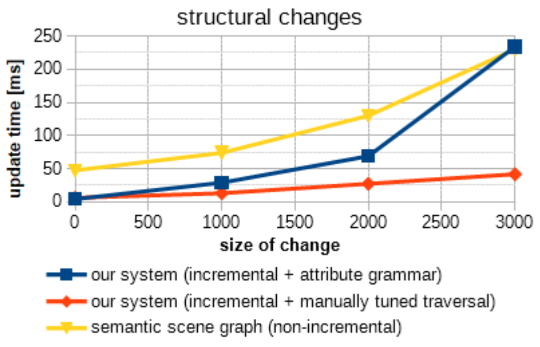


Figure 15: Runtime in *ms* for varying size of structural change (removed and created nodes) for a scene with 9000 leaf nodes. Starting at 3000 changes per frame, i.e. one third of the scene, reevaluation takes longer than simply traversing the scene using the *semantic scene graph* approach. With the *manually tuned traversal*, which tracks dependencies but only handles required attributes, i.e. does not resolve attributes at runtime, the cost of our naive implementation becomes apparent. In a nutshell, our general but naive implementation pays off as long as less than one third of the scene is replaced per frame.

Note that attribute grammar evaluation incurs no overhead in this setting. Furthermore, since due to incremental evaluation value changes directly modify the affected data (transformation values of render objects in our case), no attributes need to be computed. Thus, for value changes, in contrast to traversal based approaches, we only pay traversal cost once on construction instead of each frame. Although such value changes are the most frequent change in many use cases, often the scene changes modify not only values within the scene graph but also its structure (e.g. new characters spawn in a game scene). Although less frequent, we need to analyze this type of change. In another test setup, instead of modifying the transformation values within the scene we modify whole subgraphs and replace old parts with new scene graphs (see Figure 15). Although the attribute grammar evaluation incurs significant cost, almost one third of the scene can be modified until traditional scene graph implementations perform better. Although this is an artificial setting and scenes typically change gradually (typically not one third of the scene is replaced in one frame), the cost is not neglectable. A better attribute grammar implementation could improve on that, but in practice this worst-case rarely happens and the advantages outweigh the cost in most use cases.

Although our system performs reasonable for typical workloads with semi-static scenes, we see further potential for optimization.

The most promising being low level optimizations enabled by incremental change tracking. By using callbacks from the dependency graph, operations such as re-recording command lists/buffers could be triggered much more targeted. Moreover this work should motivate and enable research in connecting methods particularly developed for high-performance rendering (e.g. (Wörister et al., 2013; Haaser et al., 2015)) with domain specific languages for scene and interaction specification (e.g. Vega-lite's grammar (Satyanarayan et al., 2017)). Another interesting research direction might be to connect declarative scene descriptions to shader-centered methods as recently explored by He et al. (He et al., 2017).

4.3 Experience and Future Work

Clean concepts and semantics are noble goals. Our experience with the system shows that a declarative approach greatly reduces application complexity without sacrificing expressiveness and performance and that attribute grammars give structure to computer graphics problems. In previous versions of our system we used conventional scene graph implementations, and it was crucial for our new approach to compose with existing code and not to alienate developers with too many tools and abstraction layers. In retrospect we find that our new implementation is much smaller, while having many more features, is easier to work with and easier to extend. In the future we would like to improve our naive attribute grammar implementation with native code generation in order to push even more towards high-performance rendering.

5 Conclusions

Although concepts from computer language theory are applicable to a wide range of use cases, we see surprisingly little interdisciplinary work in this regard. In this paper, we demonstrated a non-trivial application of attribute grammars and self-adjusting computation in the field of visual computing. As our evaluation shows, this approach solves a number of typical problems of state-of-the-art scene graph systems in a clean and well-founded manner.

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