Huge Data But Small Programs: Visualization Design via Multiple Embedded DSLs

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Abstract. Although applications of functional programming are diverse, most examples deal with modest amounts of data – no more than a few megabytes. This paper describes how Haskell has been used to address a challenging astrophysics visualization problem, where the complete uncompressed dataset is nearly a terabyte. Our solution makes extensive use of three novel *domain-specific languages*: to specify data resources, to abstract over rendering operations, and most significantly, to design the desired visualization. The result is a powerful framework for time-varying multi-field visualization. This approach represents a significant departure from standard practices in the visualization field, and has application well beyond the original problem. That our solution consists of less than 4.5K lines of code is itself a notable result. This paper motivates and describes the overall architecture of our solution, and technical features of the DSLs that are used in place of the traditional visualization pipeline.

1 Introduction

Drawings, diagrams and graphs have a long history of use within scientific discovery, e.g. Snow's map correlating cholera cases with water pump location in London, 1854. Use of computer graphics for visualizing data is usually traced to an influential 1987 report produced for the National Science Foundation of the United States [1]. Data from instruments and supercomputer simulation was accumulating faster than it could be interpreted, and the report called for new methods to process these 'firehoses'. Visualization became established as a new research field within computing, and foundational work on data models, processing paradigms and depiction techniques for large-scale data led to rapid progress [2,3]. Much of this work concentrated on *scientific* visualization, where the data are located within some physical space. Data that has no 'natural' spatial component, for example metabolic networks, web sites, market trends, etc., is addressed by *information* visualization. The relationship between these two branches of visualization has been the subject of much debate [4]. Our concern is with scientific visualization.

A. Gill and T. Swift (Eds.): PADL 2009, LNCS 5418, pp. 31–45, 2009.

Huge dataset size is one of the defining characteristics of the field; other issues that arise include the need to design a new bespoke interactive tool for every new problem, typically by building a set of toolkit components into a so-called 'pipeline' (actually a directed graph). As an example, the widely-used open source VTK [3] toolkit has components written in C++, that can be plumbed together by Tcl scripts. This paper reports how we tackled these and other issues in a declarative way: through the creation of several *domain-specific languages* (DSLs), embedded in Haskell, to address a major design challenge problem, the 2008 IEEE Visualization Design Contest [5]. Three DSLs, respectively for large dataset management, for low-level rendering and interaction, and for high-level description of the desired picture, capture many of the interesting architectural aspects of the domain. The middle-level components for generating visual depictions are also implemented in Haskell [6,7]. In total, the code size is extremely small, especially given the range and flexibility of visualisations it can deal with. The use of the DSL strategy gave us a new and elegant way of *combining* visualization techniques, as well as an efficient way of managing large data resources.

Section 2 introduces the contest and explains its importance and relevance to practical applications of scientific visualization. Our solution utilises a two-stage pipeline, separating the management of datasets from the synthesis of pictures. The architecture is described in Section 3, with data management and picture synthesis forming sections 4 and 5. Section 6 sets out an evaluation of our work. We contrast our approach to the contest with entries from previous years, and reflect on the design decisions that were made. In the conclusion, Section 7, we pay particular attention to our use of domain-specific languages, and their further potential within visualization.

2 The IEEE Visualization Design Contest

Since its inception in 1990, IEEE Visualization has been the leading forum for research in the field. In 2004, the conference instituted a visualization contest, designed "to foster comparison of novel and established techniques, provide benchmarks for the community, and to create an exciting venue for discussion".

The logistical difficulties presented by the contest can be appreciated from an outline of the 2008 edition [5]. The dataset comprises 200 timesteps from an astrophysics simulation, modelling interaction between a radiation ionisation front and primordial gas within a $0.6 \times 0.25 \times 0.25$-parsec volume of space (sampled as a regular $600 \times 248 \times 248$-point grid). Understanding this interaction would provide new insight into structure formation in the early universe, and the contest itself sought answers to six specific questions relating to these interactions. At each point in the space, the simulation tracks ten scalars and one 3D vector, with the scalars recording temperature and density of the gas, and the relative densities of 8 chemical species. Data are stored using a 11-character ASCII representation of fixed-precision format numbers; uncompressed, the total size of the dataset would be ≈960GB.

Tackling the visualization design contest requires access to domain expertise, robust and scalable software, and significant time to explore the problem and solution space. Past entries have used mature off-the-shelf systems, either commercial products including the open-source VTK, or the output of long-running research initiatives.

In a series of papers [8,6,7] we have explored the use of a functional language such as Haskell to reconstruct visualization techniques, taking advantage of lazy evaluation to implement streaming of data, and the expressive type system to create new kinds of generic abstraction. This work provides a necessary foundation for our solution. However, it was not in itself sufficient. Central to the 2008 design contest is the problem of time-varying multi-field data, a challenge in many visualization applications. Although our previous implementations supported a combination of techniques, for the most part they only supported visualization of a single field within a single timestep.

3 Architecture of a Solution

Before designing a solution, we need first to unpack the problem. Visualization is used in three ways: to present known data, to confirm a known hypothesis, or to discover what might be present within unseen data. The six contest questions fall into the latter two categories. Five ask about interactions between specific fields. For example, here is question two:

> "Over 100 chemical reactions occur in primordial H and He (many of which are driven by radiation in the I-front) but what most interests those studying first structure formation in the universe is H_2. It allowed primeval gas clouds to collapse and form the first stars before galaxies later coalesced. Where is H_2 most prevalent in the simulation?" [5]

Although this question only mentions one field (H_2) explicitly, the answer has to be framed in terms of the relationship between H_2 concentrations and other features, e.g. the hottest regions, and the advancing I-front. This requires multiple fields. The final question is more open-ended and invites wholesale exploration:

> "Question 5 posed a very specific hypothesis about the cause of turbulence. The broader question of interest, and the one for which visualization offers the most promise of displaying something unexpected, is 'What is causing the turbulence?' Can you do an open-ended visualization of all variables to try and help answer this question? This is the 'seeing the unexpected' question that will hopefully provide new hypotheses." [5]

Putting aside the temporal element for now, there are two general strategies for dealing with multi-field data. (1) combine a number of standard techniques; for example, extracting an isosurface from one field and colouring it by probing into a second field, or by using multiple cutting planes. Or (2) use a visual technique designed specifically to expose relationships between fields. *Scatterplots* can be

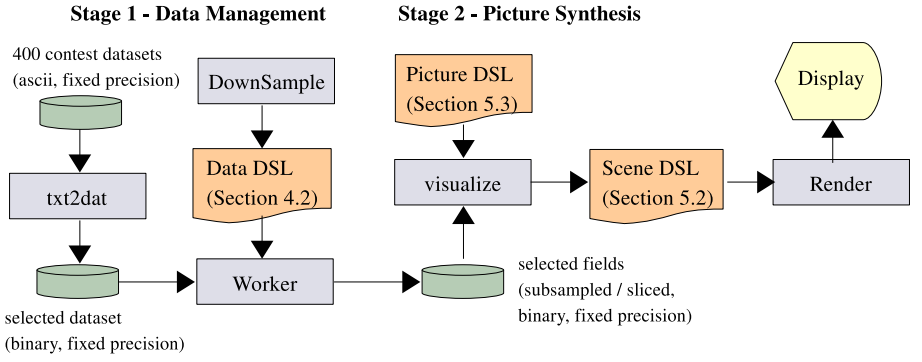

Fig. 1. System architecture

used for two or three fields, while *parallel coordinates* generalise to higher dimensions [9], but in both cases it is difficult to see correlation with 3D spatial locations, or features (e.g. the shockwave) mentioned in the contest questions. These needs could be addressed by *brushing* and other forms of interaction, but we took an early decision to focus our work on the first strategy, combining standard techniques within the physical space of the simulation.

For dealing with time, there are again two general strategies; either (1) represent it explicitly as a spatial dimension, for example plotting a graph with time as one axis, or (2) represent it implicitly, by using animation. Following a meeting with astrophysicists to obtain a better understanding of the problem, we were encouraged to explore animation. As we will see, our solution actually creates interesting possibilities for combining time and space within one representation. It consists of two stages:

Stage I: Data Management – conversion of datasets into a more compact binary representation, support for fixed-precision calculation, selection of fields, slicing, and downsampling.

Stage II: Picture Synthesis – specification of picture parameters, selection of files, synthesis and rendering of geometry, and interaction.

These stages are loosely coupled, driven by separate executables, and linked through the filesystem. Figure 1 shows the structure, and highlights the central role of three DSLs in mediating the transformation from data to rendered image. The architecture maps onto the remainder of the paper as follows: Section 4 is concerned with Stage I, including the DSL for managing transformation and downsampling of data. Section 5 addresses the design of Stage II. The visualization process (Section 5.1) constructs a graphical scene from the specification of a desired picture. Both the scene (Section 5.2) and the picture language (Section 5.3) are structured as DSLs, and it is this strategy that provides the expressive power to explore the complexity of multi-field data.

4 Stage I: Data Management

The contest data consists of 400 primary files, 200 holding the scalar field values for each timestep, and a further 200 carrying the vector (velocity) data. Within a scalar file, the value for each of the 10 fields is given for the first point, then the 10 values for the second point, and so on. Consequently the entire file must be traversed, even if only one or two fields are of interest. We decided to define our own storage model for this data, and at the same time to convert the ASCII encoding into a more compact binary form.

4.1 Fixed-Precision Values

Numeric computation in visualization and computer graphics often uses the 32 or 64-bit IEEE floating point representation, and it would have been straightforward to convert the given fixed-precision representation into this form. However, as part of the analysis we would need to carry out derivation of new fields from the existing data, for example computing the turbulence of the flow as the magnitude of the velocity field curl. The numerical ranges for some fields are large and, concerned about loss of precision, we decided to work as much as possible using our own fixed-precision representation. Each value was represented in mantissa-exponent format, with 15 bits for each value (plus a sign bit). Internally, this format was stored using a Haskell constructor with two 16-bit integer components, while externally values could be stored as 4 bytes in a binary file.

This representation required support from a small library of arithmetic operations, which we defined first in Haskell, as an instance of the *Num* type class. More importantly we utilised SmallCheck [10] to test expected properties of the system, for example commutativity:

$$prop\_plusCommutes :: FixedPrecision \rightarrow FixedPrecision \rightarrow Bool$$
$$prop\_plusCommutes\ x\ y = x + y \equiv y + x$$

This was invaluable in quickly teasing out a number of bugs. Just as importantly, having established confidence in the Haskell 'specification', we were able to use it as a reference model for implementing the fixed precision library within C. Functions in the C implementation were exposed to Haskell via the FFI, and equivalence between C and Haskell representations was tested via commuting-diagram properties, e.g.

$$prop\_times :: FixedPrecision \rightarrow FixedPrecision \rightarrow Bool$$
$$prop\_times\ x\ y = (x * y) \equiv fromCFP\ (toCFP\ x * toCFP\ y)$$

4.2 Downsampling DSL

We next addressed the resolution and bounds of the data. There are good reasons for *not* working directly from the full $600 \times 248 \times 248$-point grid at each timestep:

- A standard strategy in visualization is to first gain an overview of the data, and then descend into lower levels of detail, saving unnecessary computation.
- Our volume renderer has a very simple implementation, but one based on nested lists, and could not render the volume at full resolution.
- Our astrophysics colleagues suggested that for a number of the contest tasks, 2D slices might provide a more useful view (see Section 5.1).

So we needed a flexible mechanism for extracting subsets of the data, both by downsampling, and/or by restricting the range of one or more dimensions. Our implementation consisted of three components:

- a regular *naming scheme* for resources (files) that encodes information about the spatial bounds, sampling, and fields;
- a high-level *planner* that, given the specification of a required resource, computes the cheapest plan for generating that resource from the available files; and
- a *worker* program that implements a given plan.

The naming scheme forms a tiny DSL in its own right. Three examples of the resource naming conventions are:

```
x0-599y0-247z0-247t10.DGHH+HeHe+He++H-H2H2+.dat
x0-4-599y0-4-247z0-4-247t100.G.dat
x0-599y0-247z124t60.H2xD.dat
```

The first example specifies a full-resolution sampling of the entire grid, at time step 10, containing each of the 10 scalar attributes (D, G, H, H+, etc). In the second specification, the grid at time 100 has been downsampled, with every 4th sample selected in each spatial dimension, and only the G scalar component selected. The final example specifies a 2D slice at time step 60 corresponding to the plane $z = 124$, with full resolution along the remaining two axes, and carrying a derived field H_2xD, the product of H_2 and D.

The *planner*, implemented in Haskell, takes a resource specification as parameter, and then inspects the available files, deciding the cheapest method for generating the resource. Selection is implemented by defining a partial order over data files. This is an inclusion relation defined in terms of data files' bounds (spatial and temporal), granularity (spatial and temporal) and the set of fields present. After selecting the least dominator under the ordering, the planner invokes a *worker*. The worker, implemented in C for performance reasons, converts the plan into a tight set of nested for-loops that traverse the input and generate the output resource. It takes the worker around two minutes to downsample/slice from the largest resource file (1.48Gb), whilst starting from the least dominator can often reduce the time to a few seconds. In the case of *derived* fields, part of the worker traversal involves per-point numeric computation over selected samples from the input.

5 Stage II: Picture Synthesis

Before the announcement of the design contest, we had already implemented a modest library of *3D* visualization techniques, specifically:

- isosurface extraction;
- hedgehog rendering of a vector field;
- probing; and
- pseudo-volume rendering.

Experience gained in implementing these algorithms is reported in [7]. For addressing the contest tasks, three further techniques were implemented:

- slice visualization;
- 2D contouring; and
- 3D scatterplot.

Building on the Stage I work, we were easily able to adapt our infrastructure to process contest datasets, obtaining initial results such as the volume rendering of gas density, and isosurfaces of gas temperature, shown in Figure 2.

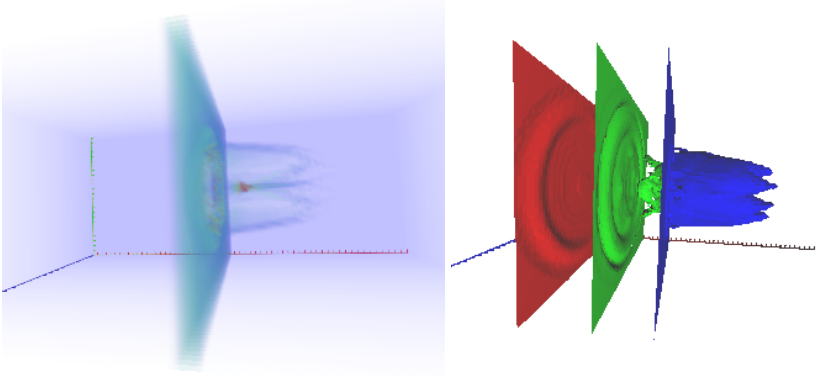

Fig. 2. Left: gas density as a volume rendering. Right: isosurfaces for gas temperature at 2.5K (blue), 16K (green) and 20K Kelvin (red). Both pictures are generated from time step 60, downsampled to a $150 \times 62 \times 62$ grid.

This figure highlights both the power of visualization to present data, and the limitations of standard 3D techniques for this particular challenge. The aim is to explore correlations between multiple fields. Superimposing 3D representations, even where they are known to be disjoint, creates problems of occlusion. This problem is avoided in Section 5.1 by utilising 2D techniques.

In Section 5.2 we introduce the rendering layer that mediates between specific visualization techniques and low-level graphical IO. Then Section 5.3 describes the high-level DSL for creating the compound images that enable effective exploration of the dataset.

5.1 Contours and Slices

Isosurfaces are a 3D generalisation of an older method for depicting scalar fields, the contour plot. Contour plots have the advantage that nesting of contours can be easily seen and interpreted. Contouring a field at regular intervals also highlights areas of high gradient, a feature that we found useful in addressing one of the contest questions. Similarly, a 2D slice through a dataset can also be rendered directly, by using a transfer function to associate a colour with each point, and then smooth-shading the resulting mesh. Figure 3 shows the same datasets as Figure 2, this time using slicing and contouring on a single plane. We found these images more useful in revealing details of the underlying field. In particular the contour plot reveals a region of hot gas embedded within the shell of the shockwave. As we shall see, these representations are also more amenable to composition.

The *implementation* of contouring provides a compelling example of the value of abstraction, and Haskell's type class system. Following our initial work on the 'marching cubes' algorithm [6], we generalised our dataset representation and implementation of the algorithm, to be independent of dimension, geometric organisation, and cell-shape. The signature of our isosurfacing algorithm now consists almost entirely of type variables and constraints:

$$\begin{aligned} &\mathit{isosurface} :: (\mathit{Interp}\ a, \mathit{InvInterp}\ a, \mathit{Interp}\ g, \mathit{Cell}\ c\ v, \mathit{Enum}\ v) \Rightarrow \\ &\qquad a \to [c\ v\ a] \to [c\ v\ g] \to [[g]] \end{aligned}$$

It requires three parameters: a threshold to be extracted (type a), a stream of sample values (also a), and a stream of the geometric locations g at which the samples were obtained. The two streams are structured into topological cells c defining local neighbourhoods within the grid. A cell c in turn is simply some instance of a type predicate that describes the capability to select a vertex v,

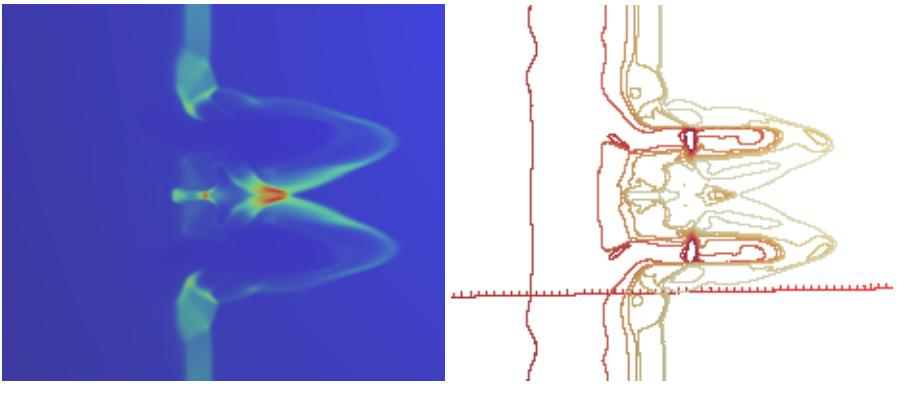

Fig. 3. Left: gas density as a slice. Right: contour lines for gas temperature, range 2K, 3K ... 21K Kelvin. Both pictures again from time step 60, now at full resolution within the plane $z = 124$.

and a case table that maps a *marking*, indicating which vertices of the cell are above a threshold, to the list of cell edges that are intersected by the surface. It took us less than one hour to implement *2D* contouring as a specific instance of this generalised algorithm. We had only to:

1. define a data constructor for 2D (square) cells;
2. implement the two *Cell* methods—the case table consisting of just 16 lines;
3. implement a function to turn a stream of values (samples or geometry) into a stream of square cells, a simpler instance of the technique described in [6]; and
4. wrap the output of the "isosurfacer" with the appropriate geometry for rendering at a set of line segments.

5.2 Rendering and Interaction DSL

The output of a single visualization algorithm, such as isosurfacing, contouring, or volume rendering, is a bag of primitives: coloured line segments, triangles, and surface normals. These must then be rendered to a display, in some fashion that allows for interactive exploration, e.g. rotation, translation and zooming of the "camera". Ultimately, the visualization front-end is implemented using the HOpenGL library that we have found to provide an excellent interface to OpenGL and GLUT [11]. However, rendering and event handling in OpenGL are handled through callbacks, which represent an unfortunately low-level intrusion into the functional environment of our visualization system. To mitigate this, we have implemented an intermediate layer, in the form of a *scene-graph* [12] abstraction for purely functional event handling. This provides a DSL for graphics, and serves as the target language into which the picture DSL, described in the next section, is compiled:

```
type HsHandler a = Maybe (Event → a → a)
type HsMovie     = (Bool, [HsScene], [HsScene])
data HsScene
  = Camera      (HsHandler HsView)        HsView HsScene
  | Geometry    (HsHandler [HsGeom])      PrimitiveMode [HsGeom]
  | Transform   (HsHandler HsTransform)   HsTransform
  | Group       (HsHandler [HsScene])     [HsScene]
  | Compiled    HsCompiledHandler         Extent DisplayList
  | Switch                                HsScene HsScene HsScene
  | Imposter                              HsScene HsScene
  | Animate     (HsHandler HsMovie)       HsMovie
  | Special                               (IO ())
```

There are expressions in this DSL for: scene geometry, transformations, groups of subtrees, compiled scenes (OpenGL display lists), and animations. Each animation is represented as a pair of lists along with a 'playing' flag. The lists hold the frames yet to be played, and the frames that have been played. The *Animate*

event handler can be instantiated with a basic movie player supporting playback, pausing, and stepping through individual frames. Lazy evaluation means that one frame can be on the display while the next frame is still being generated.

In response to OpenGL's callback architecture, the rendering module uses a global IORef to store the root of the scene. Most scene expressions include an *event handler*, a pure function over the expression's substructure. When an OpenGL callback is invoked, for example due to a mouse or timer event, the scene graph is traversed: for each expression with a handler, a new expression is generated by evaluating the handler with the new event and previous expression as parameters. After the new scene description is computed, its value is written back to the IORef.

Although this solution hides some of the non-functional features of OpenGL's architecture, there is clearly room for further improvement. One possible direction is work on functional reactive programming; the Yampa library has for example been used to create interactive graphics applications [13], though it is unclear how well this would interface with the structured approach to rendering adopted here.

5.3 The Picture DSL

Slicing and contouring yielded simple static views of a single timeframe, but our greatest insights came from creating compound images and animations that exposed the relationship between fields over time. To achieve this, we wrote a small DSL of pictures that provides a task-oriented vocabulary, mediating between the rendering and data-management languages. A *picture* is either the output from one of our visualization techniques, or a compound of simpler pictures:

```
data Picture = Contour Colour (Range Float) DataExpr
             | Surface  Colour (Range Float) DataExpr
             | Volume   Colour DataExpr
             | Slice    Colour DataExpr
             | Scatter  DataExpr DataExpr DataExpr
             | Draw     [Picture]
             | Anim     [Picture]
```

There are two kinds of compound picture; *Draw* combines a list of subpictures within one display frame, while *Anim* creates an animation, rendering pictures into successive frames. Novel combinations of time and space are possible, e.g. by composing slices from multiple timesteps into one frame, or animating a plane moving through a single timestep. *Picture* uses a small number of supporting definitions. For example, the *Range* type provides a vocabulary for sampled intervals:

```
data Eq a ⇒ Range a = Single a
                    | Range a a
                    | Sampled a a a
```

It is used to specify the thresholds at which a scalar field is contoured or surfaced, and is also used to describe the spatial sampling of grids. The *Colour* data type specifies a number of schemes for mapping sample values onto colours, while *DataExpr* is used to select the time-volume-field to be visualized, including support for derived fields. (*DataExpr* compiles straightforwardly to the resource management scheme outlined in Section 4.2.) *Embedding* of the DSL within Haskell allows the use of host-language features such as comprehensions and let-sharing, to generate animations with an elegant specification:

```
overDensity =
    let slice t s = Use (From (Range 0 599) (Range 0 247) (Single 124) t s)
    in Anim [ Draw [Slice mblues       (slice t D)
                   ,Contour mgreens (Sampled 200 400 1000) (slice t Mv)
                   ,Contour reds       (Sampled 0 0.02 0.4)    (slice t H2xD)
                   ]
            | t ← [5,10..195]]
```

This example creates an animation showing correlation between the shockwave (as captured by overall gas density D), turbulence (Mv), and the absolute density of H_2, captured by the derived field $H2xD$. Figure 4 shows a snapshot from the animation, revealing that H_2 formation (white) is concentrated in regions bracketed by the shockwave (blue) and higher-turbulence regions (green).

Evaluation of a picture DSL expression is carried out in the context of an *environment* that carries the various data grids referenced from within the expression. A *Picture* expression is interpreted by a function *eval_picture* that pattern matches each of the *Picture* constructors, extracts appropriate grids from the environment, and constructs an expression in the scene graph DSL for

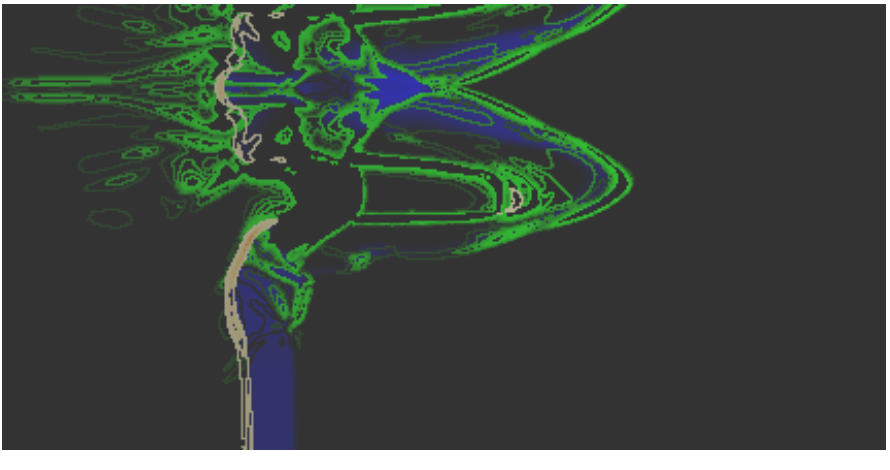

Fig. 4. Combination of gas density (slice), turbulence (green contours), and absolute H_2 concentration (white contours)

rendering the visualised geometry. Here, for example, are the cases for *Contour* and the two compound picture types:

```
eval_picture :: Environment → Picture → HsScene
eval_picture env (Contour pal thresholds dexpr)
  = Group static geomlist
    where
      levels    = range_to_list thresholds
      nr_levels = float ∘ length $ levels
      field     = eval_data env dexpr
      plane     = slice_plane dexpr
      mkgrid    = squareGrid (cell_size_2D field plane)
      points    = mkgrid $ plane_points dexpr field
      values    = mkgrid $ samples field
      colour    = transfer pal 1.0 1.0 nr_levels
      contours  = map (λt → concat $ isosurface t values points) levels
      colours   = map colour [1.0 .. nr_levels]
      geomlist  = zipWith contour_geom contours colours
eval_picture env (Draw ps)
  = Group static (map (eval_picture env) ps)
eval_picture env (Anim ps)
  = Animate anim_control (True, map (eval_picture env) ps, [])
```

The brevity of the compound cases, *Draw* and *Anim*, is particularly pleasing. Constructors for compound *pictures* are interpreted directly in terms of an analogous low-level *rendering* constructor acting on the interpretation of the subpictures. Composition of pictures is thus essentially an application of *map*. The only differences between the interpretations of *Contour* (2D) and *Surface* (3D) are (i) the *mkgrid* function for *Surface*s builds a cubic grid, and (ii) the geometry is constructed by *surface_geom* rather than *contour_geom*.

6 Comparisons with Other Approaches

Previous entries to the visualization contest have used large-scale visualization tools such as VTK and Amira, and/or specialised graphics hardware. We used a small, lightweight Haskell library running on a modest desktop PC. A direct comparison is difficult. Our solution consists of less than 4000 lines of Haskell and 630 lines of C, whilst for example VTK [3], a powerful toolkit for visualization developed over more than a decade, consists of nearly 1000 C++ classes, and 600K lines of code. Even comparing specific features such as isosurfacing is non-trivial; the VTK module has to deal with more complex data and execution models, but excludes the machinery for building and executing pipelines, which arguably should be counted. Despite these caveats, this overall comparison, along with the figures presented in [7] do highlight the brevity and expressive power that come with functional abstractions.

We found it necessary to use C to implement data conversion and selection. A Haskell utility for converting the input data files into our binary fixed-precision format required ≈45 minutes per file. The C utility runs in less than 2 minutes per file. When processing 200 files, this is a significant difference. Haskell's support for generating tight, fast loops is not yet ideal. Although it might have been possible to utilise recent work on ByteString fusion [14], our experience has been that, for very simple tasks over large data, the effort required to persuade a Haskell compiler to generate fast code is more time-consuming than simply writing it in a lower-level language. Any worries about the correctness of the low-level implementation were mitigated through initial specification and automated testing in Haskell.

Our major success was the high-level DSL for pictures, which gave us considerable freedom to explore the data. We are far from the first to realise the benefits of this approach in the context of graphics. 'Picture combinators' go back at least as far as Henderson's 1982 paper on functional geometry, recently revisited [15], and Arya's work on functional animation [16] provides a rich set of operators for constructing movies. More recently, Elliott has produced a series of papers showing the value of DSLs for image manipulation (Pan [17]) and graphical synthesis (Vertigo [18]).

7 Conclusions and Prospects

This paper is not *just* about the use of Haskell for one specific problem, however challenging. The rationale for the IEEE visualization contest is to explore new approaches to difficult visualization problems. The scenario explored here, with large volumes of multifield data, is one that is found widely in practice. Our contribution is to show how functional languages enable rapid exploration of new visualization techniques, and a particularly elegant way of describing novel *combinations* of technique.

Brevity is particularly valuable in the context of *exploratory* visualization. Although we started with a number of algorithms already implemented, the contest tasks required new infrastructure and techniques. These were developed on the fly within the four weeks in which the authors were working towards an entry. Isosurfacing and volume-rendering were reused, but slicing, contouring, animation, 3D scatterplots, and of course the fixed precision library and downsampling infrastructure were all new. Even so, we would estimate that less than 1000 lines of Haskell were written or modified specifically for the contest.

> *The practical implication is that, when faced with a novel visualization problem, it may well be easier to write a new bespoke technique in 20-30 lines of Haskell than to assemble a collection of coarse-grained modules within a large toolkit, let alone create a set of new modules.*

Our picture DSL was implemented only in the final week of the contest. Initially, we had concentrated on data management and visualization techniques. The driver for change was the need to include animation. At this point we finally appreciated how much our previous ad-hoc construction of pictures was

a hindrance. With the picture DSL, we were able to make rapid progress. Significant insights emerged literally within the final hour before submission. Even then, we did not fully exploit our system. We had for example implemented a 3D scatterplot, to explore correlations between ion concentrations. Given our animation facilities, it would be interesting to create a time-varying scatterplot, showing how the relative concentrations evolve over time as the shock-front passes through space.

The primitives of our picture DSL can be seen as analogs to the modules of a pipelined architecture [3]. However, we are working towards a different strategy. The contour code in Section 5.1 uses stream-based operations that generalise our initial work [6]. We would like to exploit these, and possibly a similar library on array-like structures, to provide an *intermediate* language for visualization algorithms. We see a visualization system as a hierarchy of languages. At the top, a declarative result specification (the picture DSL) is interpreted within a language of stream/array operations, which are then mapped onto a language for dataset management (cf our 'Stage I' as described in Section 4), generating datasets on demand, before finally a rendering language constructs scenes for display and interaction. Stages I and II would then be coupled directly, with the downsampler invoked directly from the visualization engine to provide datasets on demand.

The work presented here addresses *scientific* visualization. There is another challenge where functional programming may provide profoundly new insights, namely providing new levels of abstraction for managing *information* visualization (aka *infovis*). A key challenge here is the diversity of both data organization and visual metaphor. As a result, tools tend to be specialised to limited types of data and/or applications, and it is difficult to identify generic, reusable abstractions. The first task in any infovis application is to impose some structure on the data, one that enables translation into a suitable visual representation, for example a tree or graph. Could the strategy of creating layers of DSLs help also to structure infovis applications? An equally interesting question is whether the richer type system of functional languages, possibly including ideas like polytypism, can be used to find unexplored regularities within both data and display techniques. Recent work [19] on using Haskell for *visual analytics*, a new synthesis of information visualization and statistical analysis, suggests that the conversation between functional programming and visualization has only just begun.

Source code for our implementation is available from the project web site, `www.comp.leeds.ac.uk/funvis/`

Acknowledgements

The work reported in this paper was funded by the UK Engineering and Physical Sciences Research Council.

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