The Case for Enhanced Abstract Data Types

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Abstract

The explosion in complex multi-media content makes it crucial for database systems to support such data efficiently. We make the case that the next generation of object-relational database systems should be based on Enhanced Abstract Data Type (E-ADT) technology, rather than on the "blackbox" ADTs used in current systems. An E-ADT is an abstract data type that exposes the *semantics* of its methods. Query optimizations are performed using these semantics, resulting in efficient query processing. The added functionality does not compromise the modularity of data types and the extensibility of the type system. Fundamental architectural changes are required to build such a database system; these have been explored through the implementation of E-ADTs in *Predator*. Initial performance results demonstrate an order of magnitude in performance improvements.

1 Introduction

We are witnessing an explosion in the volume and complexity of digital information that people want to access and analyze. If a DBMS is to appeal to application developers, it must support complex data types like geographic entities, chemical and biological structures, financial time-series and multi-media objects. Further, the level of functionality and performance should be comparable to special-purpose systems. Many relational database vendors are currently building "object-relational" extensions to support complex data.

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Current object-relational databases (OR-DBMSs) model complex content as "blackbox" abstract data types (ADTs), with procedural methods that can be used within SQL queries. While the DBMS optimizes relational operations like joins, there is hardly any optimization for ADT methods. Obviously, queries perform poorly if most of the execution cost occurs in expressions involving ADT methods. Instead, we propose the concept of Enhanced Abstract Data Types (E-ADTs) which expose the semantics of their methods to the DBMS. This allows the system to choose any specific implementation of each method, and importantly, *to optimize expressions involving a combination of method invocations*. For example, *Sharpen(Clip(Image, Region))* is likely to be more efficient than *Clip(Sharpen(Image), Region)*. Essentially, the use of E-ADT methods in an SQL query becomes declarative, rather than procedural. While E-ADTs are a simple idea, it is a non-trivial task to build a system that supports them. Several questions arise: what is the right architecture?, what are the right abstractions?, what are the appropriate internal interfaces? We are building the *Predator* object-relational database system to address these questions. Several E-ADTs have been developed for complex types like images, audio, video, rasters, polygons, etc. Our implementation indicates that E-ADTs are practical, and our experiments suggest the orders of magnitude in resulting performance improvements.

This paper has three goals: (1) to make the case that object-relational databases should be based on E-ADTs , (2) to demonstrate that E-ADTs are practical, based on the *Predator* implementation, (3) to open up new research opportunities on ways to improve and extend the functionality of E-ADTs.

1.1 Background

Most OR-DBMSs support type extensibility; new data types can be added to the system without changes to the existing code. The basic technology used is that of Abstract Data Types (ADTs), which was adapted from programming language concepts [Gut77, LZ74] to databases in the 1980s [SRG83, Sto86] in the Postgres [SRH90] system. The DBMS maintains a table of ADTs, and new ADTs may be added by a database developer. Each ADT implements a common internal interface through which the system can access and manipulate values of that type. The internal interface includes functions for the storage and indexed retrieval of values. Each ADT can also declare primitive methods for manipulating or querying values of the type. For example, an ADT for images might provide methods *Sharpen(I), Clip(I, Region)*, and *Overlay(I1, I2)*. Complex data types like images usually define a large number of primitive methods, that can be composed to form meaningful expressions. For example, *Overlay(Sharpen(I1), Clip(I2, {0, 0, 100, 200}))* is an expression over images *I1* and *I2*. Such expressions can be embedded within an SQL query, thereby providing an expressive query capability over image data. Libraries of primitive methods for each ADT are sometimes called "datablades" (Informix), "data extenders" (IBM), or "data cartridges" (Oracle).

There are two characteristics of the current support for ADTs that we should note. (1) Each ADT, along with its methods, is built modularly, so that it can be added to or removed from the OR-DBMS without affecting the rest of the system. In other words, each ADT is a "blackbox". (2) The DBMS understands minimal semantics about each method of the ADT. The method is merely a name and type signature for a function, often written in C or C++[1]. Existing systems also allow some simple semantics about methods to be defined: does it have side effects or not?, what is the cost of the method?, etc. Beyond this, each ADT method is a "blackbox" to the DBMS. This is the current state-of-the-art, which we refer to in this paper as the "blackbox" ADT approach. The proposed E-ADT paradigm eliminates the second characteristic (blackbox methods) while retaining the first characteristic (modular ADTs).

Several commercial database systems are adding support for blackbox ADTs. In practice, while many simple ADTs are added by database users, the important complex ADTs (like images) and their method libraries are usually written by experienced system developers. As the standardization of methods on these complex ADTs occurs[2], one can expect more efforts to be directed at building efficient implementations of them.

Two important issues not dealt with in this work are search and indexing techniques for complex data types, and delivery systems for continuous media types. These are topics of ongoing and future work.

2 Motivation

E-ADTs are motivated by a simple observation: methods on complex ADTs can be expensive (for example, *Sharpen(Image)*). In fact, the cost of ADT methods often dominates the overall execution cost of a query. Clearly, query processing and optimization should attempt to reduce the cost of ADT methods. There are two issues to consider:

- What are possible optimizations on ADT methods?
- How can the optimizations be applied systematically?

2.1 Possible Optimizations

Consider an OR-DBMS based on blackbox ADTs, and assume that an image ADT has been added with the methods *Sharpen(I)* and *Clip(I, Region)*. While image data is stored on disk in a compressed format (like JPEG), the ADT methods are implemented on an uncompressed main-memory image data structure (like an RGB array). Consequently, the image argument of any method is converted to its main-memory uncompressed form before an method is invoked on it.

An earth scientist maintains a table of geographic data, each entry having a satellite photograph and several other columns. An SQL query posed against this database may include an expression over the photographs:

```
SELECT Clip(Sharpen(G.Photo), 0, 0, 100, 200)
FROM GeoData G
WHERE G.Region = 'arctic'
```

The query asks for a sharpened portion of each photograph of the arctic region. The cost of this query is dominated by the methods on the images. We now describe the evaluation of this query using the blackbox ADT approach. For every data entry corresponding to the arctic region, the Photo attribute is retrieved from disk and decompressed into a main-memory image. The *Sharpen* method is then applied to it, and the resulting image is written to a compressed disk-resident form. The *Clip* method is then applied with the intermediate result image as its input. This input image is decompressed to a main-memory form, it is clipped to the desired dimensions, and the resulting image is written out to disk. Current OR-DBMSs like Illustra [Ill94] and Paradise [DKL+94] use essentially this approach with some individual modifications; we mention these variations at length in Section 5.

One could improve this execution strategy as follows:

- It is unnecessary for *Sharpen* to compress and write its result to disk. Instead, it could be passed directly in memory to *Clip*. This requires that the methods not be evaluated in isolation; instead, the system should recognize that these methods are part of a larger image query expression. This is a change to the blackbox ADT approach, which treats methods as isolated black-boxes[3].
- *Sharpen* is an expensive method, whose cost depends on the size of the image. It would be cheaper to evaluate the equivalent expression *Sharpen(Clip(G.Photo, {0, 0, 200,*

[1] SQL-3 will allow functions to be written using SQL too

[2] The SQL3 Multi-Media standards group is currently defining methods for full-text, spatial data and general mathematical data. Future data types to be standardized include still-images, still-graphics, animation, full-motion video, audio, seismic data, and music.

[3] Section 5 describes how Paradise uses caching to support this without visibly changing the ADT approach.

100})). By performing *Clip* early, there can be significant reductions in the cost of *Sharpen*. This requires the entire image query expression to be "optimized". The optimizations could be applied heuristically, but preferably in a cost-based manner. To the best of our knowledge, no existing OR-DBMS can apply such optimizations in a heuristic manner, let alone in a cost-based manner. An obvious question might be: why not require that the user write the query in an efficient manner? The answer is two-fold: (1) the choice of the most efficient expression may depend on costs and statistics that users may not be aware of, (2) queries are often created automatically, through GUIs, involving the merging of several views. It is, therefore, quite likely that inefficient E-ADT method expressions will exist in queries.

- If *Clip* is applied before *Sharpen*, the entire image does not need to be retrieved from disk. Only the appropriate portion of the image is needed[4]. Performing such optimizations requires a further enhancement to the system: the ADT methods should control the retrieval of the underlying ADT values.

The blackbox ADT approach violates a basic principle of database systems: *queries should be declarative*. The textual representation of an expression should not specify an evaluation plan. When the expression is treated declaratively, the combination of these optimization strategies can lead to performance improvements of an order of magnitude. Similar improvements can be applied to ADT expressions involving other complex data types. The actual optimizations are drawn from the semantics of the data type. When we apply these semantics in a database environment, we can identify four broad categories of optimizations:

- *Algorithmic:* Using different algorithms for each method depending on the data characteristics. For example, the best algorithm to use for the *Multiply* method on two matrices depends on the sizes of the matrices and the amount of memory available.
- *Transformational:* Changing the order of methods. The motivating example shows how *Clip* can be applied before *Sharpen*. In fact, the entire equational theory of the data type can be augmented with cost information to specify transformational optimizations.
- *Constraint:* Pushing physical constraints through the expression. The constraints may involve selecting a portion of the data, specifying a certain data resolution, or requiring a particular physical property. Consider the expression on images: *ChangeResolution(Sharpen(I), Res)*. The knowledge of the desired resolution can be used to ensure that *Sharpen* is applied to a low resolution image.
- *Pipelining:* Pipelining execution of methods to avoid materializing intermediate results. This is crucial for large data types like audio and video. It may not be possible to fit an entire uncompressed audio (or video) object in memory. The only reasonable way to access the data is to iterate over it (i.e. to treat it as a stream). When a sequence of methods has to be applied to such a large object (for example, *IncrTreble(DecrVolume(Audio))*), pipelining the methods is clearly better than generating entire intermediate results for each method.

As an analogy, consider how a "Relation" ADT would be supported. The relational algebra primitives would be the ADT methods. Queries on relations would be formed syntactically as relational algebra expressions and executed in the order specified, without any query optimization! Yet it is accepted today that relational queries should be declarative. The choice of join algorithms is an Algorithmic optimization. The choice of join order, and selection pushdown are Transformational optimizations. The use of "interesting order" in join optimization is a Constraint optimization. Pipelined join execution is a Pipelining optimization. We know that these query optimizations can greatly improve performance. Likewise, in next-generation applications, ADT expressions that dominate query execution cost should be treated declaratively and optimized.

2.2 A Framework to Apply the Optimizations

It is not sufficient to observe that these optimizations are possible. There must also be an architectural framework to specify and apply them in a correct and cost-based manner. At the same time, the type system should remain extensible, so that new types can be added incrementally. Continuing with the example using images, we note that:

- The best algorithms used for each method can depend on the size of the input image, the amount of memory available, the storage format of the image, and the values of arguments to the method.
- For any complex expression involving multiple image methods, there are several possible evaluation plans.
- Deciding between different plans requires cost-based optimization of the image expression.
- The image expression may be evaluated several times during the course of the query. Its evaluation plan should be chosen before the query starts executing, because it is unreasonable to repeatedly explore the options at runtime.
- The cost of the chosen plan is used by the SQL optimizer to "place" the evaluation of the expression at the appropriate position in the join evaluation tree [Hel95, CS96].
- In order to perform compile-time optimization, collective meta-information like the storage formats and size statistics need to be maintained over all the pertinent images (in this case, over all photographs in the GeoData table).

[4]When compression is used in storing the images, it is not always possible to retrieve a random portion of an image. For example, with the popular JPEG compression technique, the entire image needs to be retrieved sequentially. There are other compression techniques and variants of JPEG that allow a selective portion of the image to be retrieved and decompressed. [DKL+94] discusses these issues in more detail.

- The meta-information maintained and the optimizations to be applied are specific to each individual ADT.

Current OR-DBMSs do not perform such optimizations; further, they lack the structural framework to do so. In contrast, *Predator* is a practical demonstration of an architectural framework in which E-ADT optimizations may be applied. While the low-level implementation details are described in [SLR97], this paper describes the high-level system design.

3 *Predator* and E-ADTs

An Enhanced Abstract Data Type (E-ADT) enhances the concept of blackbox ADTs in database systems to improve the performance of query processing. The E-ADT paradigm has the following components:

- The methods of every E-ADT should be declarative (rather than procedural) expressions.
- The combinations of E-ADT methods should be declarative expressions.
- The optimization and execution of these declarative expressions should involve the semantics of the E-ADT.
- The modularity and extensibility of the database type system should not be compromised.

The last criterion (modularity) leads to a design requirement that the new capabilities or enhancements for complex data types be encapsulated behind standard interfaces. Specifically, in addition to providing the standard ADT functionality, each E-ADT may support one or more of the following enhancements through a uniform internal interface.

- *Query Operators and Optimization:* An E-ADT can provide an optimization interface that will translate a method expression into a query evaluation plan in its own evaluation algebra.
- *Query Evaluation:* An E-ADT can provide routines to execute the optimized plan.
- *Catalog Management:* An E-ADT can provide catalog routines so that schema information can be stored and statistics maintained on values of that E-ADT .
- *Storage Management:* An E-ADT can provide multiple physical implementations of values of its type. Some existing OR-DBMS systems already support this feature.

Predator[5] is a client-server OR-DBMS in which the server is a loosely-coupled system of E-ADTs. A detailed description of the system is presented in [SLR97]. The high-level picture of the system is shown in Figure 1. The core of the system is a main-memory table in which E-ADTs are registered. The server is built on top of a layer of common database utilities that all E-ADTs can use. An important component of the utility layer is the SHORE Storage Manager [CDF+94] library, which provides facilities for

[5]*Predator* stands for the PRedator Enhanced DAta Type Object Relational DBMS

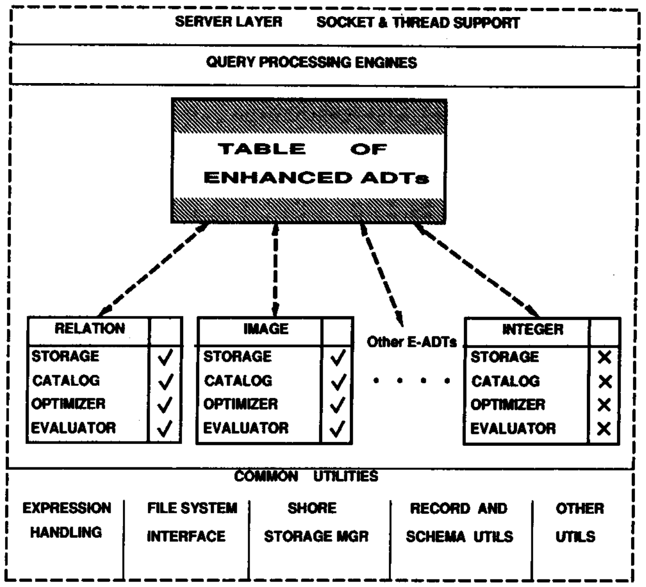

Figure 1: *Predator* System Architecture

persistent storage, concurrency control, recovery and buffer management.

Some of the basic types like integers do not support any enhancements. The figure shows two E-ADTs that do support enhancements: relations and images. Note that relations are also modeled as just another E-ADT! Several other E-ADTs including audio, polygon and raster have been added. A complex value like an image can be a field within a relational tuple. Since the type "relation" is also modeled as an E-ADT, nested relations can be supported. Object-oriented concepts like identity and inheritance are mostly orthogonal to the issues addressed by this research.

Queries are processed by one of a collection of query processing engines, that use the E-ADTs. In this paper, we focus on the SQL query processing engine. An important feature of the system design is that E-ADTs are modular, with all E-ADTs presenting an identical internal interface. This serves a dual purpose:

- The development of optimizations for each E-ADT can proceed independently. The extensibility of the system would be compromised if each E-ADT had to be aware of all the other E-ADTs in the system.
- The interaction between the E-ADTs (especially between the SQL query processing engine and the individual E-ADT expressions) is crucial. Because of the uniform internal interface of E-ADTs, the design of this interaction is independent of the details of each E-ADT.

3.1 Interaction between Data Types in *Predator*

Let us revisit the example query:

```
SELECT Clip(Sharpen(G.Photo), 0, 0, 100, 200)
FROM GeoData G
WHERE G.Region = 'arctic'
```

This query has an image expression embedded in the SELECT clause. How is this image expression handled? We present a simplified discussion. When the SQL engine parses the query, it passes the image expression to the image E-ADT , which performs type checking and returns an opaque parse structure (ParseStruct).

Query Optimization: The optimization of an SQL query uses cost-based techniques to search for a cheap evaluation plan from a large space of options. Typically, all sub-expressions need to be optimized before the SQL query can be optimized. To optimize the image sub-expression, the following interface of the image E-ADT is invoked:

```
Optimize(in: ParseStruct, in: ArgPlans, out: PlanStruct);
```

Optimize() takes the ParseStruct generated by parsing the image expression, and evaluation plans for its arguments, and returns a generic PlanStruct that represents an evaluation plan for that expression. The PlanStruct will only be interpreted by the image E-ADT. The PlanStruct has a well-known Cost() interface. The SQL optimizer uses this cost estimate to help determine the best plan for evaluating the SQL query. If the image expression is very expensive, it may be preferable to apply it as few times as possible.

Query Evaluation: The SQL query is evaluated based on its execution plan. While executing the SELECT clause, the image expression is evaluated through the following interface of the image E-ADT :

```
Evaluate(in: PlanStruct, in: ArgValues, out: ReturnValue);
```

Evaluate() is passed the plan for the image expression and the value of its argument (G.Photo). The image E-ADT executes the optimized image expression, and the return value is used to continue with the computation of the SQL query.

To summarize, the query is broken into components that correspond to method expressions of each E-ADT. Each method expression is treated as a declarative query and is optimized, and executed by its own E-ADT .

3.2 Opportunities for Optimization

Where do opportunities for E-ADT optimizations arise? As in the example, E-ADT method expressions in the SELECT and WHERE clauses of SQL queries are obvious candidates for optimization. Several commonly used data types have libraries of methods that form an algebra. Consequently, opportunities to optimize method expressions often exist.

There are two other cases where E-ADT optimizations can be beneficial.

- *Aggregates*: Aggregate methods are very important in "summarization" queries involving multi-media data types. For example, the Sequoia benchmark [SFGM93] includes a query that computes a weighted average of a number of clipped raster images. The query might equivalently be have been expressed as computing the average of the entire images, followed by a clip of the desired region of the averages.
- *Function Path Indexing:* Indexes in object-relational systems are often created on complex "path" expressions involving composed functions. The creation time for the index depends on the cost of computing the indexing expression. E-ADT optimizations enable the expression to be executed efficiently, thereby accelerating index creation.

4 Initial Performance Results

The purpose of this section is to demonstrate the orders of magnitude of performance improvements that arise from the E-ADT paradigm. While the results are not unexpected, it is nonetheless interesting to observe the dramatic effects of simple optimizations. We use an image E-ADT as the primary example to demonstrate performance improvements.

We use a simple data set containing 74 images of cars, compressed using JPEG. A *Cars* relation is created, with a name assigned to each image. Each image column value contains an *Id* for the image and its bounding box information. The size of the compressed images ranges from 23K to 266K, with an average of 65K. This is a relatively small amount of data, but it serves to demonstrate the issues involved. The average size of the uncompressed images in memory is 0.8MB representing more than a 10-fold increase from the size on disk. Standard JPEG libraries are used to perform compression and decompression. Experiments were run on a Sparc20 machine with 8 MB used as a database buffer pool (a small size to match the small data set). The buffer space was sufficient to hold the compressed data, and each individual uncompressed image easily fit in physical memory. The system is CPU-bound in all these experiments, since the image methods are expensive. The queries were chosen to be the simplest possible demonstrations of different optimizations. Real queries are likely to be more complex than these. All queries were run several times and average execution times were recorded.

Experiment 1: The first experiment examines the effects of the Pipelining optimizations. We noted in Section 2 that in the ADT approach, each method reads (and decompresses) its input from a disk-based representation, and writes (and compresses) its output. We call this strategy DISK. An improvement is to pass intermediate results in their main-memory form. We call this strategy MEM. Finally, if there is a sequence of methods, we could pipeline their execution by establishing an image row iterator. We call this strategy PIPE. We expect PIPE to be significantly better than MEM only when the intermediate results are larger than main-memory. This is not the case for these images.

```
SELECT Height(Negative(C.picture))
FROM Cars C;
```

In the query above, *Negative()*, which inverts the pixel values, is a relatively cheap method. For all three strategies, *C.picture* must be read and decompressed. The DISK strategy compresses and writes the result out, whereas the MEM strategy does not. The *Height* method is applied so that the display time for the result does not distort the measurements. The height is obtained from the image bounding box, so the actual image is not required. We disable any optimizations that move *Height* ahead of other methods. We gradually vary the query by introducing additional invocations of *Negative()*. For instance, *SELECT Height(Negative(Negative(C.picture)))* requires one additional compression and decompression using the DISK strategy. The results are shown in Figure 2. Along the X-axis is the number of *Negative* methods in the SELECT clause. The Y-axis shows the execution time.

As the number of methods in the image expression increases, the effect of the compression and decompression at the image boundaries dominates. Consequently, the MEM strategy which avoids these unnecessary costs is significantly cheaper than DISK. PIPE performs only marginally better than MEM, since the intermediate results fit easily in memory. For the rest of the image experiments, the MEM strategy has been used as the default.

Experiment 2: The second experiment examines the effects of Transformational and Constraint optimizations. The following query is used:

SELECT Height(Clip(Blur(C.picture, <radius>), <region>))
FROM Cars C;

The result of a *Blur* method is an image in which every pixel's value is the average of the pixels within *radius* of it in the input image. *Blur* is an expensive method, especially when *radius* is large. In the standard ADT approach, the images will first be blurred, then clipped to the appropriate region. We call this the STD strategy. Using the transformational optimization of reordering, *Clip* could be performed before *Blur*. We call this the ORD strategy. Finally, if *Clip* is being performed first, it can use the region to constrain the retrieval and decompression of the images. We call this the ORD+ strategy.

Figure 3 shows how these strategies perform when the *Blur radius* is fixed at 2 and the size of the Clip region is varied as a percentage of the image size. Since blurring an image is expensive, both ORD and ORD+ perform very much better than STD when a small region needs to be clipped. Further, it is evident that ORD+ is also significantly better than ORD because it requires a smaller portion of each image to be retrieved an decompressed. As the size of the *Clip region* increases, the absolute difference between ORD and ORD+ decreases because the savings due to the Constraint optimization are reduced. The relative difference also decreases because *Blur* starts to dominate the cost.

Figure 4 fixes the *Clip region* at 10% of the image size, and varies the *Blur radius* from 1 to 5. As the *radius* increases, the cost of the blurring grows quadratically. For the STD strategy, since this is the dominant cost, the overall execution time also grows quadratically. In comparison, in ORD and ORD+, the clips are performed early. The

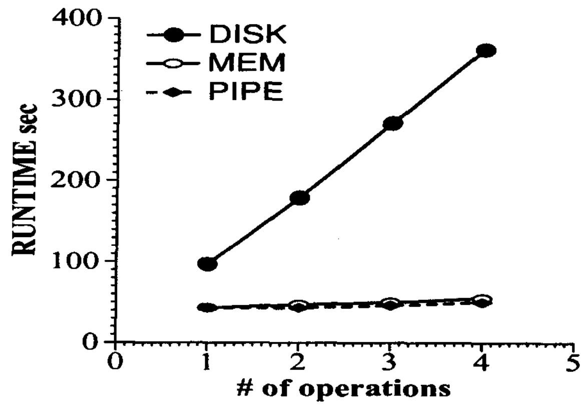

Figure 2: Effect of Pipelining

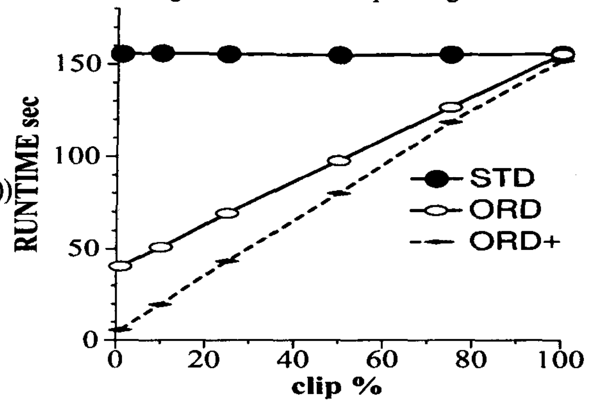

Figure 3: Effect of Varying Clip Size

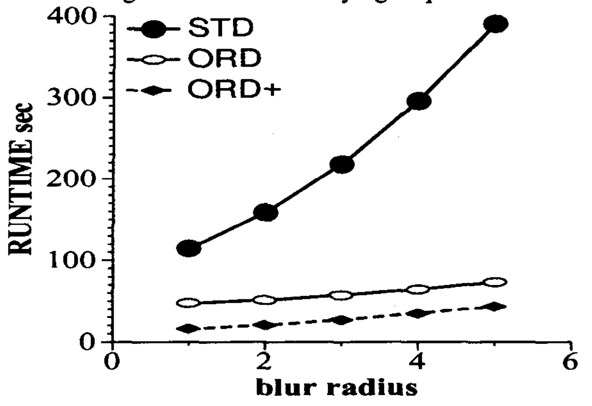

Figure 4: Effect of Varying Blur Radius

Without Optimization	With Optimization
79.5 secs	0.58 secs

Figure 5: Effect of Optimization

difference between ORD and ORD+ is the difference in the retrieval costs; it is evident that the execution time of ORD is dominated by the retrieval and decompression time. Consequently, the exponential change in the *Blur* cost is not apparent.

Experiment 3: The third experiment demonstrates a very simple optimization. Consider the query below: it needs to find the area of overlap between pairs of images. There is really no physical requirement to compute the actual overlap of the images; their bounding boxes contain the necessary information to find the area of overlap. This can be thought of as either a Transformational optimization (changing *Overlap* to a different function), or a Constraint optimization (pushing the physical requirements into the computation of *Overlap*). The result is greatly improved performance. Figure 5 shows the difference.

```
SELECT Area(Overlap(C1.picture, C2.picture))
FROM Cars C1, Cars C2
WHERE C2.name = "Alfa_Romeo_8C_2300";
```

Summary of Experiments: Each of the demonstrated optimizations can result in very significant improvements. Their combination clearly leads to orders of magnitude in performance gains. It is clear that even for these extremely simple queries, the E-ADT optimizations are radically more effective than the blackbox ADT approach. In practice, queries tend to be more complex than our examples, and the effects of optimization are even greater.

5 Discussion of the E-ADT Paradigm

We now conduct a short discussion of the proposed E-ADT paradigm. There are several complex data types that are amenable to optimizations. We are in the process of building E-ADTs for several of them. Prominent among these are the multi-media types like images, audio and video, and the geographic types like points, polygons and rasters. Optimization opportunities also exist for mathematical data types like matrices, financial types like time-series, and chemical structures like molecules. Due to lack of space, we do not describe them in further detail.

Creating a New E-ADT : An important concern is that the new enhancements might require a deep understanding of the workings of the DBMS, the internal interfaces, the cost metrics, etc. We have pushed much of this complexity into the Utility layer of *Predator*, and present suitable templates for data type developers. A developer takes the following steps to build a new data type like Image in *Predator*:

- Start with a template for a new E-ADT. The template contains a C++ header file with the appropriate class definition and member function declarations. There is also a C++ source file with stubs for all the member functions.
- Define Read() and Write() interfaces. This determines how the data wil be stored in the database, and involves very little actual new code. With images, the entire image would be loaded into the storage manager, and a handle to it (its OID) would be stored within a record.
- Specify the structure of meta-information, if any, that this E-ADT requires.
- Write code for each of the actual methods that will be supported on Images. This is usually the most time-consuming component, but existing libraries can often be used (for example, free JPEG libraries exist).
- Ensure that the method code is "registered" with the E-ADT ; this requires one line of code for each method.
- Specify individual optimization rules. Each rule has a precondition and an action. Existing rule templates provide the rule structure for the common categories of rules. Often, all that needs to be changed is the names of the methods that the rules match. More complex optimizations require that new rules be written.
- Register the rules with a rule engine. The utility layer pre-defines a simple rule engine class, so all that the E-ADT developer must do is register each rule (1 line of code each), and choose a search strategy (1 line of code).
- Add the new E-ADT to the Makefiles and register it in the system-wide table of E-ADTs. The system must then be recompiled. We could extend *Predator* to allow dynamic loading of the E-ADTs instead.

Of course, there are some other details involved, but they are not very significant or time-consuming. As class projects at Cornell in Fall 96, students built several E-ADTs using the image E-ADT as a template. One of our ongoing efforts is to build an E-ADT toolkit or "wizard" that will make it even simpler to develop new data types. The goal is that most of the specification must happen through a point-and-click interface. Currently, a data type like Image uses a standard template and requires a few hundred lines of code (in addition to the purely image-related algorithm code). All of the E-ADT enhancements are purely optional. The effort required to add a traditional ADT (with no E-ADT enhancements) to *Predator* is just the same as the effort required to add an ADT to a standard OR-DBMS.

Postgres, Illustra, and Informix: The issue of support for ADTs in relational database systems was first explored in [SRG83] and [Sto86]. This led to the development of the Postgres research DBMS [SRH90] and its commercial version, Illustra [Ill94]. The Postgres project explored issues dealing with the storage and indexed retrieval of ADTs. It also stressed that functions associated with ADTs could be expensive, and that special relational optimization techniques are necessary when such functions are present [Hel95]. The basic ADT approach described in Section 2 corresponds closely to Illustra's support for ADTs. The results of every ADT method are written to disk, and no inter-method optimizations are considered [Ols96]. While Illustra does have a rule engine, it is not used to apply optimization rules. Currently, Illustra's technology has been integrated with the Informix Universal Server and extended to exploit parallelism. Several modifications are being made to improve the evaluation of ADT expressions [Ols96]. The main improvements allow functions to retain the results in main-memory, or to present an iterator interface that helps pipelined execution as well as parallel execution. Transformational and Constraint optimizations are not supported.

The Paradise System: Among current research systems, the Paradise client-server DBMS [DKL+94] is developing ADT extensions for the parallel execution of methods on spatial, geographic, and scientific data. This work concentrates on issues of scalable parallelism and the use of tertiary storage for large ADTs. The importance of parallelism for ADTs arises from the large size of complex data types, and the high cost of methods on them. The approach used is to partition large objects into "tiles" and define functions to work on one tile at a time. From the E-ADT viewpoint, parallelism is yet another benefit of declarative ADT expressions. Paradise also reduces the overhead of passing results between functions by allowing each ADT to manage its own main-memory buffer of data; temporary results do not have to be written to disk. This approach has limitations for large data types like audio and video that do not fit in memory. Paradise does not support the re-ordering of ADT methods in either a heuristic or a cost-based manner. However, the tiling of objects allows a Clip function to simply retrieve the appropriate tiles rather than the whole image.

Object-Oriented Databases: Early work on semantic data models incorporated domain semantics into relational query optimization. More recently, the OO-DBMS community has been exploring techniques to optimize queries involving complex objects. Much of the work in object-oriented query optimization has focused on issues like path expressions [CD92] and not on method expressions, although [CD92] recognizes that methods can be very expensive and merit further attention. While the OQL query language [Cat94] for OO databases does permit a method to have several implementations, it does not suggest a mechanism for choosing between these implementations. We direct readers to [MDK+94] for an excellent survey of work on query optimization for complex data types in OO-DBMSs. Most closely related to E-ADTs is the REVELATION project [MDK+94] which correctly identifies that the semantics of methods should be revealed to the query optimizer. There is a notion of a common object algebra, and every complex type expands (or "reveals") its methods into expressions in the common algebra. In contrast, E-ADTs can use individual algebras to represent query plans for their expressions, since there is no notion of a global query optimizer. In [AF95], the actual method code was analyzed to determine the "meaning" of the method, which was then used in query optimization. We believe that this approach is not viable; most complex data types will be developed in some imperative programming language like C++ or Java. Instead, we allow the E-ADT developer to explicitly specify the method semantics.

Other Related Work: Rule-based query optimizers have received much attention recently [GM93, CZ96]. A common misconception is that a rule-based optimizer instantiated with the appropriate rules (in this case, with rules for E-ADT optimizations) provides all that E-ADTs do. This ignores several crucial aspects of E-ADTs — the maintenance of meta-information, the support for multiple algorithms for the same method, the ability to define multiple storage formats, etc. Rules provide one specific structuring mechanism for optimization semantics – in fact, *Predator* uses a rule engine to actually execute the optimizations for each E-ADT . An important distinction is that we promote local spheres of optimization for each E-ADT , with possibly different control strategies, different kinds of rules, etc. On the other hand, conventional rule-based optimizer proposals do not have such notions of optimization locality. The closest in spirit are the "region" architecture for query optimizers proposed in [MDZ93], the "module" architecture proposed in [SS90], and other research on extensible search strategies [RH87, LV91]. Our work differs in that it is focused on complex data type expressions, rather than relational expressions. In fact, we can make the interesting case that the E-ADT paradigm provides an excellent argument in favor of optimizer toolkits in general, and rule-based optimizer toolkits [GM93] in particular! Since the DBMS has several mini-optimizers, one in each E-ADT, a toolkit for optimizer generation is needed.

[CS93] suggests that queries involving "foreign" relations can be optimized by specifying the semantics of the foreign relations through high-level rules. The rules are syntactic, and cost-based optimization is performed after an exhaustive application of the rules.

Several distributed object broker architectures like CORBA and OLE have recently emerged. The capabilities of distributed objects are described using a common interface. The OLE-DB standard being promoted by Microsoft [Bla96] supports the notion of a component database system with well-defined interfaces between different modular components. However, there is a distinction between exporting query capabilities, and exposing query optimization semantics (as E-ADTs do).

We should note that method transformations of the kind suggested in this paper are common in the functional programming community. The pipelining optimizations are similar to the use of lazy evaluation [Jon87]. While the early work on ADTs [Gut77] did emphasize the equational theory of the methods, this aspect was not carried into the use of ADTs in database systems. Our work corrects this oversight, and focused on optimizations based on statistics and costs in a database environment.

Local vs Global Approach?: In contrast to our loosely-coupled approach of E-ADTs , others have taken a holistic approach. Instead of breaking a query into many components with local query optimization on each E-ADT expression, these approaches try to find a global solution. This requires that the entire query be modeled in an integrated framework. AQUA [SLVZ95] and KOLA [CZ96] are algebraic frameworks proposed for this purpose, while CPL/Kleisli [Won94] is a framework based on comprehensions as a query language and monadic operations. These are all frameworks for collection types (like sets, bags, lists, and arrays). However, many important complex data types including multi-media types do not fall in this category.

In theory, an integrated framework is bound to find at least as good an evaluation strategy as the E-ADT approach, if not a better one, because the space of possible evaluation plans is at least as large. A DBMS specially built for relations and images should be able to perform better than *Predator*. We have localized the optimizations to the E-ADT boundaries, purely in order to preserve the modularity of the data types. If we are willing to break this modularity (for instance, if we wish to have rules that span multiple data types), then this is a trivial extension of the E-ADT paradigm (in fact, the *Predator* implementation does support such extensions). However, any practical OR-DBMS must establish type modularity at some boundary, whether it corresponds to a single data type or a group of them. Any truly holistic query optimization approach compromises the extensibility of the system.

6 Future Work

SQL Query Optimization with E-ADT expressions: We have seen that E-ADT expressions can dominate the cost of an SQL query. One category of research issues deals with mechanisms to exploit interactions between relational query optimization and E-ADT query optimization. The blackbox ADT approach for executing expensive methods in SQL is to execute them once for each new combination of arguments. As an example using images, *Overlap(I1, I2)* and *Overlap(I1, I3)* would be executed separately. If it were possible to execute the overlap of *I1* with both *I2* and *I3* at the same time, we could exploit locality by reading *I1* only once from disk. As a generalization of this idea, any function can be executed with individual arguments, or can be called on a set of argument instantiations. The blackbox ADT approach cannot exploit this set-at-a-time strategy because the semantics of the ADT functions are not known to the DBMS. However, with E-ADTs , this is indeed feasible.

Since E-ADT expressions are expensive, where should they be placed in the SQL query evaluation plan? Expensive function placement has traditionally been studied purely in a tuple-at-a-time execution context [Hel95, CS96], with caching of function results (an exception to this is [CDY95]). The assumption has been that every ADT function has a fixed cost specified in the system catalogs. This assumption is not valid when ADT expressions are being optimized. Since these expressions may be able to provide more details on their evaluation plans (for example, the main-memory requirements), the SQL optimizer should be able to find better overall execution strategies (possible requiring set-at-a-time evaluation).

Optimization across E-ADTs: It is possible to improve the interaction between E-ADTs using a mechanism whereby each E-ADT specifies its query processing capability. For example, if an E-ADT specifies that it understands the notion of a boolean connective (AND or OR), the expression *f(X) AND g(X)* in the WHERE clause of an SQL query could be replaced by the expression *f_and_g(X)*. This is more efficient because X is only accessed once. In general, constraints and other such information should flow across the query optimization interfaces. It is an open problem to design such a mechanism and the appropriate E-ADT interfaces.

Open Issues: While the basic E-ADT paradigm has been presented here, many implementation details of *Predator* have been omitted. There are several unresolved issues with respect to the systems design – how are statistics maintained on E-ADTs?, how should recursive nesting of E-ADTs work?, how is cost information generated?. While we do have some existing solutions, these are topics that we are currently exploring further.

7 Conclusion

The E-ADT paradigm is a novel yet simple approach to database systems design. Every data type is given the opportunity to share the semantics of its methods with the DBMS. This allows several types of complex data to be efficiently supported within a single general-purpose DBMS. This paper makes the case that the next-generation of object-relational database systems should be based on E-ADTs. The *Predator* database system has been built as a demonstration of the E-ADT paradigm. Initial performance results provide empirical evidence of an order of magnitude increase in performance.

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