Programming in JoCaml — Extended Version

Louis Mandel — Luc Maranget

N° 6261

Août 2007

Thème COM

ISSN 0249-6399 ISRN INRIA/RR--6261--FR+ENG

Programming in JoCaml — Extended Version

Louis Mandel , Luc Maranget

Thème COM — Systèmes communicants
Projets Moscova

Rapport de recherche n° 6261 — Août 2007 — 24 pages

Abstract: JoCaml is a language for concurrent and distributed programming. We here present a non-trival distributed application written in JoCaml: a ray tracer. Thereby, we show how to program the coordination of multiple cooperating agents in a concise manner, in the spirit of functional programming. We also adress the issue of agent failure.

Key-words: concurrency, distributed programming, programming language, functional programming, join-calculus, ML

Programmer en JoCaml

Résumé : JoCaml est un langage pour la programmation concurrente et distribuée. Ici, nous décrivons une application conséquente écrite en JoCaml : un lanceur de rayons. À l'occasion de cet exemple, nous montrons comment programmer de façon concise la coordination de multiples agents coopérants, dans l'esprit de la programmation fonctionnelle. L'échec possible d'un agent est pris en compte.

Mots-clés : concurrence, programmation distribuée, language de programmation, programmation fonctionnelle, join-calcul, ML

1 Introduction

Concurrency has always been a fact of life in the areas of system and network programming. Networks now being standard, the interest for concurrency has long shifted from specialists to ordinary programmers. Moreover, the ever growing availability of multi-core machines augments the population of those that wish to have several computing "agents" to cooperate. However, as everyone who has tried knows, writing a distributed application, one that runs on several machines, is not an easy task.

The join-calculus [?] is a process calculus in the tradition of the π-calculus [?]. The main purpose of such calculi is to describe concurrent and distributed systems; programming such systems is a different, although related, issue. The issues are related because a good model offers suitable abstractions that help programmers. To shorten the distance between model and program, the join-calculus has been designed with implementation in mind. We will not discuss this point on theoretical grounds, but rather on practical grounds. Indeed, we are developing a programming language based upon the join-calculus.

Our language, JoCaml, is an extension of Objective Caml (OCaml) [?], a popular dialect of ML. By choosing to extend an existing language, and not to design one of our own, we first intend to minimize our work. We also intend to benefit of functional programming, of pre-existing code base, and of a population of programmers open to innovation.

In this work, we more illustrate the JoCaml language than the JoCaml system (however, see Section 2), by showing how a middle-sized OCaml program can be made into a JoCaml program (Sections 3–7) suited for execution on a network of computers. We then conclude after a few performance figures.

The complete source for the program is available at `http://jocaml.inria.fr/pub/joex/JoCamlsRUs.tar.gz`.

2 The new JoCaml

The new JoCaml system [?] is a re-implementation from scratch of the previous prototype [?]. The old JoCaml focussed on language expressiveness, by providing all the features of the underlying process calculus. In particular, the old system provides extensive support for the hierarchical *location tree* of the join-calculus, which acts as a model for the migration of processes from one computer to another. Implementing this feature has two consequences, which both hinder compatibility with OCaml:

1. Code migration makes native code execution problematic[1].
2. Code migration implies extending the byte-code machine and the linking mechanism of OCaml, leading to serious incompatibilities at the binary level.

Besides, the extensive alterations performed over the version 1.07 of OCaml that was taken as a starting point for developing JoCaml, made it very difficult to follow the evolution of OCaml, of which current version is 3.10.

[1]The OCaml system does not provide just-in-time compilation

By contrast with the old system, the new JoCaml focusses on compatibility with OCaml. Briefly, we proceed by altering the OCaml compiler from parsing phase to first intermediate code generation, and by enriching the thread library of OCaml with specific support. Compiler alteration is justified by specific typing and pattern matching compilation [**?**, **?**], which both need to be perform inside the compiler. Compiler alteration is limited in the sense that we change or add a few thousand lines in the compiler original source files, add a few source files, and retain the OCaml formats for binary files. Moreover, the JoCaml compiler produces compiled signatures files that are the same as the ones of OCaml, which is of crucial importance to the simple versioning policy of OCaml.

Our focus over compatibility and limited alteration of OCaml, made us abandon the mobility features of the join-calculus. Nevertheless, there are useful distributed programs that can be written without code mobility. Full compatibility with OCaml not only means that we can write such programs starting from existing, sequential, source code in OCaml, but it also means that the existing source code may call external libraries that need not be re-compiled.

3 An introduction to join-definitions

We first provide a "survival kit" introduction to the basic concept of the join-calculus: the join-definition. The JoCaml tutorial [**?**] presents join-definitions from a programming perspective in greater detail.

An OCaml program is a set of definitions. Definitions introduce types, values or functions. JoCaml extends OCaml with join-definitions. A join-definition is a list of *reactions rules* that are processes guarded by *join-patterns*. A join-pattern is a list of channel names with formal arguments. A *guarded process* is fired when there are messages present on all the channels of its join-pattern. A typical process is the parallel composition (operator "&") of elementary processes.

In JoCaml there are two kind of channels: asynchronous and synchronous. Asynchronous channels are the classical channels of the join-calculus. Message sending on an asynchronous channel is an example of an elementary process. Synchronous channels can engage in any kind of join-pattern but the guarded process must send back a result to the emitter. In that aspect, sending a message on a synchronous channel can be seen as a function call.

Let us now consider an example of a join-definition: a concurrent buffer based on the two-lists implementation of functional FIFO queues.

```
def state(xs,ys) & put(x) = state(x::xs,ys) & reply () to put
 or state(xs,y::ys) & get() = state(xs,ys) & reply y to get
 or state(_::_ as xs,[]) & get() =
   state([], List.rev xs) & reply get() to get
val put : '_a -> unit
val state : ('_a list * '_a list) Join.chan
val get : unit -> '_a
```

Join-definitions are introduced by def, reaction rules are separated by or, and the channel names in join-patterns are separated by "&". The join-definition above defines one asynchronous channel (`state`) and two synchronous channels (`put` and `get`). Asynchronous channels have type τ `Join.chan` where τ is the type of the message.

The idea of this buffer is to store the FIFO queue (implemented by a pair of lists) as a message on the channel `state`. By the organization of join-patterns, which all include `state`, exclusive access to the internal state of the buffer is granted to the callers of synchronous `put` and `get`.

The first join-pattern `state(xs,ys) & put(x)` is satisfied whenever there are messages on both `state` and `put`. The behavior of the guarded process is to perform two actions in parallel: (1) send a new message on `state` where the value `x` is added to the list `xs` and (2) return the value `()` to the caller of `put`.

The second join-pattern `state(xs,y::ys) & get()` is satisfied when there are messages on both `state` and `put` *and* that the message on `state` matches the pattern `(xs,y::ys)`. That is, the message is a pair whose second component is a non-empty list. The process guarded by this join-pattern removes one value from the buffer and returns it to the caller of `get`. The last join-pattern `state(_::_ as xs,[]) & get()` is satisfied when there is a message on `get` and a message on `state` that matches a pair whose first component is a non-empty list and second component is an empty list. The corresponding guarded process transfers elements from one end of the queue to the other and performs `get` again. Notice that there is no join-pattern that satisfies `state([],[]) & get()`. As a consequence, a call to `get` is blocked when the buffer is empty.

To initialize the buffer, a message is sent on `state`. An expression that performs such a sending is `spawn state([],[])`. The `spawn` construct executes a process asynchronously. Syntactically, `spawn` lifts a process into an expression. It is to be noticed that processes and expressions are distinct syntactical categories.

To be able to create several buffers, the previous definition is encapsulated into a function `create_buffer`.

```
type 'a buffer = { put : 'a -> unit; get: unit -> 'a }

let create_buffer () =
  ... (* same definition of put/get/state as before *)
  spawn state([],[]) ;
  {put=put; get=get;}
val create_buffer : unit -> 'a buffer
```

A buffer is in fact a record, whose fields are the `put` and `get` synchronous channels. That way, we make buffers first-class values and additionally hide the internal channel `state`.

4 Organizing concurrent computations

We first present iterators (type `enum`) over the elements (type `elt`) of a collection (type `t`) [?].

```
val start : t -> enum
val step : enum -> (elt * enum) option
```

The function `start` builds an enumerator from a structure of type `t`, while `step` returns the first value built from an enumerator and the enumerator that builds the next values. We illustrate the idea of iterators by an enumerator over an integer interval.

```
type elt = int and t = int * int and enum = int * int
let start c = c
let step (n,m) = if n > m then None else Some (n,(n+1,m))
```

4.1 Concurrent iteration

We then define a channel `par_iter` that applies a function `worker` to all the values produced by an enumerator, function calls being performed concurrently.

```
def par_iter (worker, enum) = match step enum with
  | None -> 0
  | Some (x,next) -> par_iter(worker, next) & begin worker x ; 0 end
val par_iter : ((elt -> unit) * enum) Join.chan
```

If `step enum` does not return a value, then there is nothing to do (`0` is the empty process). Otherwise, a recursive sending to `par_iter` and a call to `worker` are performed concurrently. The construct `worker x ; 0` lifts the expression `worker x` (of type `unit`) into a process.

An example of `par_iter` usage is to print the integers from 1 to 3 in unspecified order:

```
let print x = print_char '(' ; print_int x ; print_char ')'
let _ = spawn par_iter(print, start (1,3))
```

A possible output is: `(2)(1)(3)`[2]

To share parallel computations between several "agents", we introduce the notion of a pool of functions.

```
type 'a pool =
  { register: ('a -> unit) Join.chan; compute: 'a -> unit; }

let create_pool () =
  def compute(x) & agent(worker) =
    worker x ;
    agent(worker) & reply () to compute in
  { register=agent; compute=compute; }
```

A `pool` exports two channels: `register` and `compute`. Viewed from caller side, `register` is for offering computational power, whereas `compute` is for exploiting computational power. The pool implementation matches computing agents and exploiting agents with a straightforward join-pattern.

Internally, available computing agents are messages pending on channel `agent`. Notice that several instances of a given `worker` agent cannot execute concurrently. Namely, a computation can start only when an agent is available, and an agent engaged in a computation returns to available status only when the computation (`worker x`) is over.

To illustrate the use of the pool, we introduce a second function to print integers:

```
let print_bis x = print_char '<' ; print_int x ; print_char '>'
```

Then, we create a pool and register the `print` and `print_bis` functions.

[2]Due to abundant concurrency, another possible output is `((2)1)(3)`.

```
let pool = create_pool ()
let () = spawn (pool.register(print) & pool.register(print_bis))
```

Finally, by combining `par_iter` and the `compute` component of the pool, we have the integer interval printed by two agents:

```
let () = spawn par_iter(pool.compute, start (1,3))
```

A possible output is `(2)<1><3>`. Due to concurrency of *distinct* agents, another possible output is `(<1>2<)3>`.

4.2 Collecting the results of concurrent iteration

In the previous example, `par_iter` is an asynchronous channel. This clearly expresses that it cannot be known when `par_iter` has finished its work. We now wish not to perform side effects, as `print` does, but instead to collect returned values.

More precisely, we aim at building a new kind of pool, with a "fold" function that behaves as `par_iter` as regards concurrency, but additionally returns a combination of results.

```
type ('a,'b) pool =
  { register: (elt -> 'a) Join.chan;
    fold: t -> ('a -> 'b -> 'b) -> 'b -> 'b; }
```

Interface for exploiting the pool is the `fold` function that, with respect to the previous `par_iter`, takes the combination function and an initial value for the result as extra arguments, and returns a combined result of type `'b`. Interface for offering computational power is `register` as before, but now registered functions return a result of type `'a`.

The new pool is controlled by the following *monitor*, of which primary job is to collect results.

```
type ('a,'b) monitor =
  { enter: unit -> unit; leave: 'a Join.chan;
    wait: unit -> 'b; finished: unit Join.chan; }

let create_monitor combine init =
  def state(n,r) & enter() = state(n+1,r) & reply () to enter
  or state(n,r) & leave(v) = state(n-1,combine v r)
  or state(0,r) & wait() & finished() = reply r to wait
  in spawn state(0,init) ;
  { enter=enter ; leave=leave ; wait=wait; finished=finished ; }
val create_monitor : ('a -> 'b -> 'b) -> 'b -> ('a, 'b) monitor
```

A monitor provides four channels: `enter`, `leave`, `finished` and `wait`. Channel `enter` (resp. `leave`) is used by the monitored pool (see below) to signal that a new task starts (resp. ends). The monitored pool will send a message on `finished` when iteration has come to an end. Finally, `wait` is a function that returns the combination of all the results of the monitored tasks.

A monitor has an internal state of which first component `n` counts the number of tasks being computed. This counter is updated with the channels `enter` and `leave`. Additionally, the message on `leave` is a task result to be combined with the second component `r`. The last join-pattern (`state(0,r) & finished() & wait()`) states that when there are no more tasks, either active (`state(0,_)`), or to be allocated (`finished()`), then the call to `wait` can be answered.

We now present the pool implementation:

```
let create_pool () =
  def loop(monitor,enum) & agent(worker) = match step enum with
    | Some(x, next) ->
        monitor.enter() ;
        loop(monitor,next) & call_worker(monitor, x, worker)
    | None -> monitor.finished() & agent(worker)
  and call_worker(monitor,x,worker) =
    let v = worker(x) in monitor.leave(v) & agent(worker) in

  let fold x combine init =
    let monitor = create_monitor combine init in
    spawn loop(monitor, start x) ;
    monitor.wait () in
  { fold=fold ; register=agent ; }
```

Let us examine the definition of `fold`: it first creates a monitor, then starts the iteration, and finally calls the `wait` function of the monitor.

The `loop/agent` definition is essentially a combination of the previous pool implementation and of `par_iter`, with worker calls being put aside for clarity (channel `call_worker`). The combination has the effect that various instances of a given `worker` agent now execute in sequence, following iteration order. Additionally, calls to the monitor are inserted at appropriate places. A remarkable point is that we can be sure that all calls to `monitor.enter` have been performed before the message on `monitor.finished` is sent. This is almost obvious by considering that the recursive sending on `loop` is performed only once the call `monitor.enter()` has returned, by the virtue of the sequencing operator "`;`". Moreover, the internal counter of the monitor indeed counts active tasks: as "`&`" binds more tightly than "`;`", the process `call_worker(monitor,x,worker)` executes once `monitor.enter()` has returned, and thus once the monitor counter has been incremented. Similarly, the counter is decremented (by `monitor.leave(v)`) only once the worker has returned.

The new pool is quite powerful, since it can serve as a meeting place between several agents that offer computational power and several agents that exploit it. Let us define the former agents and register them.

```
let double x = print x; 2*x and double_bis x = print_bis x; x+x
let pool = create_pool ()
let () = spawn (pool.register(double) & pool.register(double_bis))
```

Exploiting agents are two functions, with different combination behavior.

```
let sum x = pool.fold x (+) 0 and prod x = pool.fold x ( * ) 1
```

Finally all agents meet through the pool.

```
def echo(c,x) = print_char c ; print_int x ; print_char c ; 0
let () = spawn echo('+',sum(1,3)) & echo('*',prod(4,5))
```

A possible output is `<1>(2)<4>(5)*80*<3>+12+`.

4.3 Distributed computations

In JoCaml, concurrent and distributed computations are based on the same model: different programs (abstracted as *sites*) may communicate by the means of channels. More precisely, site A may send messages on a channel of which definition resides on another site B. In that situation, guarded processes execute on site B. One practical problem in distributed applications is for the communicating partners, first to know one another, and then to have at least a few channels in common. To solve the issue, JoCaml provides library calls to connect sites and a *name service*, which basically is a repository for values (more specifically channel names) indexed by plain strings.

As an example, this first program runs on machine A.

```
let pool = create_pool()
let () = Join.Ns.register Join.Ns.here "reg"
  (pool.register: (int -> int) Join.chan)
let () = Join.Site.listen
  (ADDR_INET (Join.Site.get_local_addr(), 12345))
let () = print_int (pool.fold (1,3) (+) 0)
```

This program creates a pool. Then, by calling `Join.Ns.register`, it stores the channel `pool.register` associated to the name `"reg"` in the local name service (`Join.Ns.here`). Then, `Join.Site.listen` starts to listen for connections on the default Internet address of the local site (`Join.Site.get_local_addr()`) on port `12345`. Finally, the program calls `pool.fold`. This call blocks, since no computing agent has entered the pool yet.

To become such a computing agent, machine B runs the following program.

```
(* master_addr is the Internet address of A *)
let a_site = Join.Site.there (ADDR_INET(master_addr,12345))
let ns = Join.Ns.of_site a_site
let register = (Join.Ns.lookup ns "reg": (int -> int) Join.chan)
def double(x) =
  print_char '(' ; print_int x ; print_char ')' ;
  reply x+x to double
let () = spawn register(double)
```

Here, B first gets the site identity of the program running on A, with the function `Join.Site.there`, and its name service with `Join.Ns.of_site`. Then, it retrieves the (synchronous) channel associated to the key `"reg"`. The name service is *not* type safe[3]. For instance, the type of `Join.Ns.lookup` is `Join.Ns.t -> string -> 'a`. As a minimal precaution, we insert explicit type constraints. Finally, B defines and registers the synchronous channel `double`. The effect of A calling the registered `double` is the one of a remote function call. Hence, console output is `12` on A and `(1)(2)(3)` on B.

Another issue deserves mention. The program of B above is not complete: as `spawn register(double)` returns immediately, execution goes on. For the program not to terminate by reaching its end, we deadlock it purposely.

```
let () = def dead() & lock() = reply () to dead in dead()
```

[3]A weakness of JoCaml, we agree.

But B is now blocked for ever, whereas a desirable behavior is for B to be released when A does not need B anymore, or at least when the program running on A terminates.

The function `Join.Site.at_fail` provides a convenient solution. It takes a site A and a channel (of type `unit Join.chan`) as arguments, and returns `()`. When it is detected that A has failed, then a message is sent on the channel. Thus, we replace the code above by:

```
let () =
  def wait() & release() = reply () to wait in
  Join.Site.at_fail a_site release ;
  wait()
```

5 Ray tracing and its parallelization

Ray tracing [?, ?] is a now classical technique for computing 2D-images from 3D-scenes. The general principle of ray tracing is to cast light rays from the viewpoint of an observer into the scene. To render a scene as a $w \times h$ bitmap image, one casts the $w \times h$ rays defined by the observer viewpoint and the position of the $w \times h$ picture elements (*pixels*) of the *image plane*, which stands in front of the observer. One then computes the intersection of this *primary* ray with the scene. Reflections on object and the computation of illumination imply casting more rays. The whole process involves much computation.

This simple introduction should be sufficient to grasp the basic structure of a ray tracer. Our sequential ray tracer has not been written by us, but by the team "Camls R'Us" as an entry [?] for the ICFP programming contest of year 2000. Although written in three days, the program is of significant size (1729 lines, disregarding comments and empty lines).

Scenes are represented internally as the following (OCaml) record type, a field of module `Scene`.

```
type t =
  { file : string ; wid : int ; ht ; int ; obj : Obj.t ; ... }
```

In the type above, `file` is the name of the file where to save the image, `wid` and `ht` are the image width and height respectively. The `obj` field holds the internal representation of the scene. We omit some of the fields in the scene record, such as the definition of lights, observer field of view, etc. Bitmap images are PPM images, a simple image format, where an image file basically is a sequence of colors encoded as three eight-bits values.

In the original ray tracer, rendering operations are performed by the module `Render` that exports only one function `render`, as shown by its interface file.

```
  val render : Scene.t -> unit
```

Notice that `Render.render` returns `()` because it saves the bitmap it computes. Let us assume a function `Ray.render_pxl` of type `Scene.t -> int -> int -> color` that performs the casting of a primary ray and all subsequent operations, finally returning the color[4] of the pixel of the image plane of which coordinates

[4]`color` is the type of colors, in practice a color is an integer of which 24 bits are used.

are given as arguments. Then, one easily writes `Render.render` by two nested for loops.

```
let render sc =
  let oc = open_out_bin sc.file in (* open output, ppm, file *)
  Printf.fprintf oc "P6\n%d␣%d\n255\n" sc.wid sc.ht; (* Ppm header *)
  for j = sc.ht - 1 downto 0 do
    for i = 0 to sc.wid-1 do
      let color = Ray.render_pxl sc i j in
      ouput_color oc color
    done
  done ;
  close_out oc
```

The problem statement of the contest [?] defines a language, GML, for both describing the scene and the rendering conditions. This specification naturally impacts the design of the Camls'R Us ray tracer.

1. The GML program is parsed.
2. The resulting abstract syntax tree is evaluated by an interpreter (module `Eval`), with the following peculiarities:
   (a) To execute the instruction *render* that commands the production of an image, the interpreter calls `Render.render`, all scene components being retrieved from the interpreter stack. It is to be noticed that there can be several *render* instructions in a given program.
   (b) Other instructions are Constructive Solid Geometry operations, 3D-transforms, arithmetics, *if* instructions, function calls, etc.
3. The ray tracer ends once the interpreter has returned.

Our strategy for distributed execution is straightforward: all programs involved will execute the same GML program, however they will react to the *render* instruction differently. A distinguished program, the *master*, controls the work of others. All other programs are *slaves* and they perform the rendering operations. For the master to distribute the work to the slaves, we need to define an unit of work smaller than the image. We call this unit a *subimage.* A simple choice for the subimage is a line (or several lines), since images are easily encoded as arrays of lines. More precisely master and slaves behave as follow

Master

1. Parse the GML file and make the abstract syntax tree available to slaves.
2. Interpret the GML program. Instruction *render* starts the concurrent process of allocating subimages to slaves and of collecting their results. When all subimages are present, the image is saved.
3. End when all the images have been saved.

Slave

1. Connect to the master, register as a potential worker, and retrieve the GML abstract syntax tree.
2. Interpret the GML program. Instruction *render* starts accepting subimages descriptions from the master, computing subimages, and sending them back to the master.
3. End when the master is done.

Observe that master and slaves agree on the scenes because they execute the same GML program, GML being a deterministic language.

Our design has the merit of simplicity: alterations to the original, sequential, ray tracer are minimized. In particular, the source of the sequential ray tracer includes the compilation unit `Eval` of which idealized code is as follows: a definition of the values of GML (type `value`), a recursive function that implements a stack-based interpreter (function `eval`), and a function that starts the evaluation (function `eval_program`) — see Figure 1 for the original implementation and signature file. The new implementation of `Eval` simply abstracts out module `Render`, that is, it defines a functor — see Figure 2. Master and slave apply the functor `Eval.Make` to different modules, `RenderMaster` and `RenderSlave` respectively, yielding two different interpreters.

Another modification is worth signaling: as subimages are made of lines, we separate the nested loops of the sequential `render`. The inner loop goes into the `Ray` module, yielding a new `Ray.render_line` function of type `Scene.t -> int -> string` that takes a scene and a line number as arguments, and that returns a compact representation of the colors of the pixels in the line.

6 The `Render` modules

6.1 Master side

The iterator on scenes in defined in the `Scene` module. For simplicity we present iteration by the line.

```
type elt = string * int and enum = string * int
let start sc = (sc.file, sc.ht-1)
let step (file,n) = if n < 0 then None else Some ((file,n),(file,(n-1)))
```

The master uses the fold pool of section 4.2, of which `register` function is stored in the local name service.

```
let img_pool = create_pool ()
let () = Join.Ns.register Join.Ns.here "reg"
  (img_pool.register : (Scene.elt -> int * string) Join.chan)
```

Figure 1: Original source files for `Eval`

Implementation, file `eval.ml`

```
type value =
 | ...
 | I of integer
 | S of string
 | O of Obj.t (* 3d object *)
 | ...

let rec eval env stack code = match code, stack with
| ...
(* Example of an instruction: integer addition *)
| Op_addi::code, I i2::I i1::stack -> eval env (I (i1+i2)::stack) code
(* Render instruction *)
| Op_render::code, S file::I ht::I wid::O obj::...::stack ->
    let sc = { file=file ; wid=wid ; ht=ht ; obj=obj ; ... } in
    Render.render sc ;
    eval env stack code
| ...

(* Entry point *)
let eval_program code = eval [] [] code
```

Interface, file `eval.mli`

```
val eval_program : Gml.tok list -> unit
```

Figure 2: New source files for `Eval`

Implementation, file `eval.ml`

```
module Make (Render : sig val render : Scene.t -> unit end) =
struct
    ··· Original code ···
end
```

Interface, file `eval.mli`

```
module Make :
  functor (Render : sig val render : Scene.t -> unit end) ->
  sig val eval_program : Gml.tok list -> unit end
```

As specified by the type constraint above, remote workers return pairs of a line number and of a line of pixels.

Finally, the following function commands the rendering of scene `sc` and saves the resulting image.

```
let render_image sc =
  let img = Array.create sc.ht "" in
  let combine (n.line) = img.(n) <- line in
  img_pool.fold sc combine () ;
  save_image sc.file img
```

Notice that the combination function performs an update of the bitmap `img`. It should be noticed that `render_image` above returns only when the image is saved. We can then define `RenderMaster.render` as being `render_image`.

```
let render = render_image
```

As a consequence, all images are saved when the interpreter terminates and the master can terminate.

In our implementation, we in fact save the image asynchronously, for disk operations not to delay the interpreter. Termination of the master is then controlled by a simple monitor (page 7) that counts images.

```
let monitor = create_monitor (fun () r -> 1+r) 0

let render_image sc =
  monitor.enter () ;
  let img = Array.create sc.ht "" in
  let combine (n.line) = img.(n) <- line in
  img_pool.fold sc combine () ;
  spawn begin
    save_image sc.file img ;
    monitor.leave ()
  end
```

The monitor is made public by the module `RenderMaster`, for the code after the call to the interpreter to wait on it.

```
...
(* Call interpreter, gml is the abstract syntax tree *)
  let module E = Eval.Make(RenderMaster) in
  E.eval_program gml ;
(* Interpreter is over *)
  let m = RenderMaster.monitor in
  spawn m.finished() ;
  let nimages = m.wait() in
  Printf.eprintf "My␣slaves␣have␣computed␣%d␣images\n" nimages ;
  exit 0
```

6.2 Slave side

A slave executes two tasks concurrently. It (1) interprets the Gml program so as to build the scenes and (2) computes subimages on master demand. For the two agents to communicate, we introduce a suitable mapping from filenames to scenes.

```
type ('a,'b) hashtbl = { find : 'a -> 'b; add : ('a * 'b) -> unit; }

let create_hashtbl () =
  let t = Hashtbl.create 17 in
  def state(blocked) & add(k,v) =
    Hashtbl.add t k v ;
    List.iter (fun release -> spawn release()) blocked ;
    state([]) & reply () to add
  or state(blocked) & find(k) =
    let v = try Some (Hashtbl.find t k) with Not_found -> None in
    match v with
    | Some v -> state(blocked) & reply v to find
    | None ->
        def release() & wait() = reply () to wait in
        state(release::blocked) & reply wait() ; find(k) to find in
  spawn state([]) ;
  { find=find; add=add; }

let scenes = create_hashtbl ()
```

The code above is a wrapper of the (OCaml) hashtable `t`. There are two points to notice. First, by very existence of `state` the internal hashtable `t` is protected against concurrent modification, as usual. Second, the synchronous channel `find` blocks when the table `t` does not associate any value to the key `k`, until a value for `k` is added into the table. This block/release process implies a form of communication between find and add operations. Such a communication is by the means of the message that is pending over the internal channel `state`.

More precisely, the code of `find` first changes the interface to `Hashtbl.find` "return value `v` or raise exception `Not_found`" into the new interface "return `Some v` or return `None`". In the first, successful, case the caller of `find` gets `v` as a reply. In the second, failed, case the reply to `find` is delayed, by inserting a call `wait()` before calling `find` again. The call to `wait` will return when a message is sent on the asynchronous channel `release`, which the code for `add` does. A find operation is then attempted again. The coding is slightly inefficient, but it suffices here. Namely, the pool of the master does not allow several concurrent calls to `find` in a given slave. Thus the list `blocked` cannot hold more than one element.

Actual subimage computations are performed by the following definition.

```
def compute_subimage (tag,n) =
  let pxls = Ray.render_line (scenes.find tag) n in
  reply (n,pxls) to compute_subimage
```

Additionally, `compute_subimage` is registered into the pool of the master, we omit the code which is the same as the one of section 4.3. Finally, `RenderSlave.render` simply stores the scene at the intention of `compute_subimage`.

```
let render sc = scenes.add (sc.file,sc)
```

As regards termination, the simplest solution is for slaves to terminate when the master does — see the end of section 4.3.

7 Failures

We claimed that local and remote message sendings were the same. Obviously we over-simplified the issue: the remote site may crash or become unreachable.

7.1 Detected failures

In the case of our ray tracer, the remote message sending is a synchronous one, *i.e.* is a remote function call, which is performed by `call_worker` (section 4.2).

```
...
 and call_worker(monitor,x,worker) =
    let v = worker(x) in monitor.leave(v) & agent(worker)
...
```

The definition of `worker` resides on a remote site. If the remote site fails and that the failure is detected by the JoCaml runtime system, then the call to `worker` will result in raising the exception `Join.Exit` and `monitor.leave(v)` will never execute. As a very untimely consequence, the image will never be completed.

To correct this misbehavior, it suffices to re-issue a failed task, as performed by the following, new definition of `call_worker`.

```
...
  or agent(worker) & compute(monitor,x) =
    call_worker(monitor,x,worker)

  and call_worker(monitor,x,worker) =
    let v = try Some (worker(x)) with _ -> None in
    match v with
    | None -> compute(monitor,x)
    | Some v -> monitor.leave(v) & agent(worker)
...
```

The re-issued task is made available to other agents by the means of a new channel `compute`, and of a new, straightforward, join-pattern. Additionally the worker that failed is forgotten about, since there is no `agent(worker)` process when `v` is `None`.

Observe that all exceptions are caught, not only `Join.Exit`. Here, the master/slave protocol does not rely on exceptions and we can thus consider any exception to express a failure. This can occur in practice, for instance if the remote site consumes all available memory (exception `Out_of_memory`), since the JoCaml runtime system transmits exceptions.

7.2 Undetected failures

Unfortunately not all failures are detected. More concretely, we cannot assume that `worker(x)` will always either return a value or raise an exception. To solve the problem, we keep a record of all active tasks *i.e.* of all tasks that are being computed. Then, near the end of image computation, we re-issue active tasks until the image is completed.

This technique requires a new kind of monitor, of which join-definition is as follows.

```
  def state(next_id, active, r) & enter(x) =
      state(next_id+1, (next_id,x)::active, r) &
      reply next_id to enter
  or state(next_id, active, r) & leave(id,v) =
      if List.mem_assoc id active then
        let active'= List.remove_assoc id active in
        state(next_id, active', combine v r)
      else state(next_id, active, r)
  or state(next_id, [], r) & wait() & finished() =
      state(next_id, [], r) & reply r to wait
(* New channels: is_active and get_active *)
  or state(next_id, active, r) & is_active(id) =
      state(next_id, active, r) &
      reply List.mem_assoc id active to is_active
  or state(next_id, active, r) & get_active() =
      state(next_id, active, r) & reply active to get_active
```

The code above is a refinement of the previous monitor (page 7). The message on `state` is now a triple, of an identifier (`next_id`, an integer), of a mapping from identifiers to task descriptions (`active`, an association list of which keys are identifiers), and of a partial result (`r`, as before). Identifiers permit the safe identification of task descriptions. They can be avoided when we are sure that tasks descriptions are pairwise distinct, which need not be the case with general enumerators.

The new monitor exports two additional synchronous channels: `is_active`, a predicate to test if a given task is active, and `get_active` that returns the list of active tasks. The guarded processes for these new channels are straightforward (`List.mem_assoc` is from the OCaml library and has obvious semantics). The exported channels `enter`, `leave`, `finished` and `wait` are still here, with a few changes. Channel `enter` now takes a task description `x` as argument and returns a fresh identifier `next_id`. The counter increment performed by the previous monitor is now replaced by adding `(next_id,x)` to the internal association list. Channel `leave` now takes an identifier `id` as an extra argument, which it uses to remove the completed task from the list of active tasks (by calling the library function `List.remove_assoc`). Notice that, as a given task can now be computed by several slaves, we take some care not to combine the result of a given task more than once. Finally the reaction rule for `wait` undergoes a small, but important, change: the message on `state` is re-emitted. Otherwise, subsequent calls to `is_active` would block.

The pool is also modified. The crucial modification regards re-issuing tasks when iteration has come to an end.

```
  def loop(monitor,enum) & agent(worker) =
    match step enum with
    | Some(x, next) ->
        let id = monitor.enter(x) in
        loop(monitor,next) & call_worker(monitor, id, x, worker)
    | None -> do_again(monitor) & agent(worker)
```

When iteration is over (`step enum` returns `None`), a message on the internal channel `do_again` is sent. The worker that has not been called is also released.

The guarded process for `do_again` is in charge of retrieving active tasks from the monitor.

```
or do_again(monitor) & agent(worker) =
  begin match monitor.get_active() with
  | [] -> monitor.finished()
  | xs -> again(monitor,xs)
  end & agent(worker)
```

The synchronization on `agent(...)` above is not necessary. Nevertheless, it is clearly a good idea to wait for at least one slave to be available before re-issuing active tasks. The available slave is not used yet and the message on `agent` is re-emitted. If there are no active tasks left, (`get_active()` returns the empty list), then the pool informs the monitor that it will not allocate any additional task (by `monitor.finished()`). In fact, from all calls to `enter` being performed before `do_again` is called for the first time, it can be deduced that the image is now complete. Hence the join-pattern for `wait` in the monitor could have avoided testing that `active` is empty.

If there are some active tasks left, then channel `again` is in charge of re-allocating them to available slaves.

```
or again(monitor,(id,x)::xs) & agent(worker) =
  again(monitor,xs) &
  if monitor.is_active(id) then
    call_worker(monitor,id,x,worker)
  else agent(worker)
or again(monitor,[]) = do_again(monitor)
```

The code above basically scans the list of active tasks. However, before calling `call_worker`[5], a last check is made. Indeed it can be that the task `id` has been completed while `again` was scanning the list. Observe that when the scanning is over (join-pattern `again(...,[])`), then `do_again` is called again, resulting in another re-allocation of active tasks to slaves, if there still are active tasks.

It may seem that our solution is a waste of processing power. However, if we compute one image only, there is little waste. Having n slaves computing the same subimage is not less efficient than having one slave computing the subimage and $n-1$ slaves being idle, up to communication costs. Furthermore, it can be more efficient on an heterogeneous network. If a slow slave is allocated a task at the end of the image, then other slaves will be allocated the same task quickly. As a result, image completion is delayed by the fastest amongst the slaves that are working on the last subimages.

If there are several images to compute, one can lower the amount of useless work by having the master to control the rendering of several images at a time. Namely, remember that the fold pool of section 4.2 can manage several exploiting agents. So as to control several images concurrently, we need change the function `render` of the module `RenderMaster`. The new definition of `render` simply stores the freshly computed scene in an instance of the buffer of section 3.

```
let buffer = create_buffer ()

let render sc = buffer.put sc
```

[5]We omit the code, it is almost the same as in the previous section.

An exploiting agents is a simple asynchronous channel definition that repeatedly calls the function `render_image` of page 14.

```
def render_images() =
  render_image (buffer.get()) ;
  render_images()
```

It remains to start several such agents, how many depending on some user setting a_{max}.

```
let () =
  for _k = 1 to $a_{\mathsf{max}}$ do
    spawn render_images()
  done
```

An alternative is unconstrained concurrency: an exploiting agent is spawned as soon as an image is available.

```
def render_images() =
  let sc = buffer.get() in
  spawn begin render_image (sc) ; 0 end ;
  render_images()

let () = spawn render_images()
```

Notice that, with respect to the previous definition of `render_images`, the function `render_image` is called asynchronously. Now, we have three versions of `RenderMaster.render`, that respectively control the rendering of one image at a time, of at most a_{max} images at a time, and of as many images as possible at a time. Preliminary experiments show that setting a_{max} to be 2 or 3 is a reasonable choice. However, we list all these possibilities to demonstrate the flexibility of JoCaml. In particular, master termination is controlled by the same counting monitor (see page 14) in all cases.

8 Results

The performance of parallel programs is best illustrated by speedup measures. Speedup is the ratio of sequential execution time by parallel execution time. By sequential, we here mean the sequential ray tracer, not the concurrent ray tracer with one slave running. Of course, the measured times are wall-clock time. So as to minimize noise, any data we present is the median of three measures.

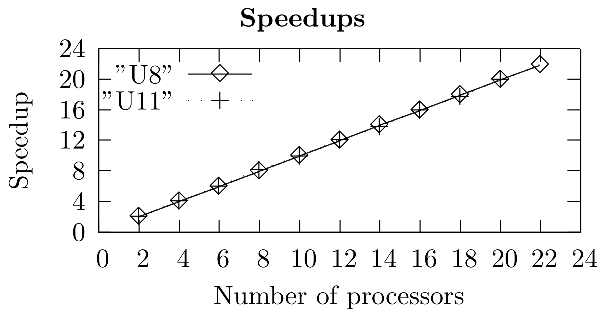
We perform most of our experiments on a cluster machine, the machine has 11 nodes, each node being a 2 $\times$ 2GHz AMD-64 bi-processor. Each node has 6 Gb of physical memory and the nodes are connected by a fast Gigabit dedicated network. Our main experiment consists in running two instances of the slave program on 1, 2, ..., 11 nodes, yielding 2, 4, ..., 22 participating slaves. Expressing speedup as a function of the number of slaves involved here makes sense, since cluster nodes are identical.

We also perform the additional experiment of running one slave per processor on 111 processors from the students computer lab at École polytechnique — we use 68 machines, some of which are bi-processors. The machines involved are of various CPU model and memory size, but all are rather modern. By contrast with the cluster, speedup as a function of the number of slaves involved does not make sense on such an heterogeneous network. Instead, we introduce *processing power*, a crude estimate computed by considering running times for a small image. We take one processor of the cluster as a base (1.0), cluster power is thus 22.0, while the local network power is about 80.0. Network conditions are standard for such a local network. All machines involved run Linux of one kind or another.

In all experiments, we run the master program on a distinct, “front-end”, machine, from which we launch the slave programs on the other machines by the means of `ssh`. More precisely, we start slaves in advance and measure the running time of the master.

We perform two sets of experiments, “urchin” (U) and “Sierpinski” (S) — see Appendix A. In both experiments, inputs to the ray tracer are scenes of identical structure and increasing complexity. By contrast, rendering parameters do not change: images are of size 1000 × 1000, the subimage unit is the default setting of one line, and adaptive antialiasing [?] is enabled, yielding between 2 and 27 primary rays per pixel.

Figure 3: Stylized sea urchin.



Running times, in seconds

	Seq	x22	x111
U8	768	35	20.3
U11	9120	416	127

Experiments U yield excellent results: here, we basically achieve linear speedup on the cluster (left of Figure 3). To provide an idea of the concrete benefits of concurrency, we also give some execution times (columns “Seq” and “x22” at the right of Figure 3). For instance, in the case of `U11`, image production time is reduced from more of 2 hours and a half to less than 7 minutes. It is still possible to go faster by using the local network (column “x111”), with a better result for the most difficult test U11.

Indeed, we here achieve a speedup of 71.8, which is surprisingly good, considering that the estimated processing power the network is 80.0 and that some of the machines involved are not idle at the time we use them. We shall thus assume that experiment U11 somehow validates our crude estimate of processing power. Namely, the (relatively) poor performance of U8 originates in the important setup times we observe while 111 slaves attempt their first connection to the master. The setup of `ssh` tunnels may partly explain this delay, but we cannot reject the hypothesis of a master overflow here.

We think that the good performance of experiment U stems from two main factors.

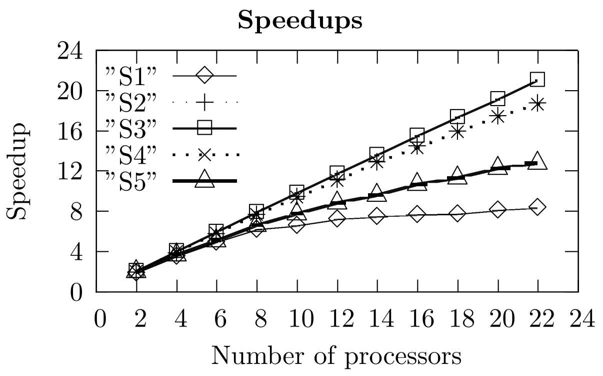
1. Rendering operations account for the vast majority of computations, almost the totality. They literally dwarf other operations which, by contrast, are executed sequentially by the master (parsing and image saving) or are executed once by every slave (scene building).

2. The subimage unit of one line is adequate.

   (a) It is large enough. That is, due to scene complexity and antialiasing, most of the 1000 lines computed represent sufficient work for messaging and task management costs to remain unnoticed. In particular, by observing instantaneous CPU load, we had the confirmation that slaves are seldom idle because they are waiting for the master to allocate a subimage to them.

   (b) It is small enough. Obviously, dividing the images into 1000 subimages to be computed by no more than 22 (or even 111) slaves allows a distribution of tasks that adapts well to varying task complexity and slave load. Besides, near the end, image completion is delayed by no more than a small fraction of the total work to be performed.

Figure 4: Decaying Sierpinski cube



Running times, in seconds

	Seq	x22	x111
S1	7.2	0.86	– [a]
S2	36.6	1.95	– [a]
S3	190	9.10	10.9
S4	759	40.6	32.05
S5	2620	204	262

[a]Unstable results

Our second series (Figure 4) illustrates some of the limitations inherent to concurrent ray tracing. Series S includes simple scenes (S1 is made of a few cubes) and scenes that take time to compute (S5 is made of almost 580,000 cubes).

Experiments S1 and S2 are here for completeness, there is little point in attempting to compute such simple images faster than 7 s and 36 s. However, we achieve decent speedups, at least for S2. As regards the other experiments, significant sequential running times make relevant the idea of distributed execution. And indeed, we achieve good speedups on the cluster for experiments S3 and S4. However, the most demanding S5 experiment yields poor speedups. Those are easily explained once one knows that the sequential ray tracer starts to cast rays after about 100 s of computing time, which is mostly devoted to the interpretation of the Gml program. About 100 s is a small fraction (3.8%) of the sequential running time of 2620 s, but a significant fraction of

204 s. More precisely, we can approximate the expected speedup for N slaves as $N/(0.038 \times N + 0.962)$ (Amdahl's law). For $N = 22$ we have a theoretical speedup of 12.2, which is rather close to the observed speedup of 12.8.

Experiments S on the local network are not very rewarding. In particular, computing image S5 on the local network of 111 processors is actually slower than on the cluster. Here also, poor performance originates from non-parallelized work dominating parallelized work, but on a more dramatic scale. Direct measures showed us that slaves engage in computing subimages no sooner than 200 s after they start. The expected delay inferred from processing powers should be about 140–160 s. Obviously, the computers at École polytechnique are not as fast as we expect them to be, perhaps due to significant memory traffic. Furthermore, about 20 processors are so slow that they do not take any part to the concurrent computation. This is mostly due to the presence of other users[6].

In spite of those unfavorable results, we claim to have demonstrated the efficiency of our concurrent ray tracer. Namely, for complex images of reasonable memory footprint and building time, we achieve dramatic speedups. Additionally, in a less favorable situation, we still make a decent profit out of the cluster.

9 Related works and conclusion

We are not computer graphics specialists and cannot claim that our work is a contribution to the study of parallel ray tracing. The survey [?] cites the humorous quote that "*the more experience the writer of the parallel algorithm has in sequential algorithms, the less parallelism that algorithm is likely to exhibit*". Thus, as novices, we are likely to discover a lot of parallelism.

Rather, our contribution resides in the design and implementation of a concurrent language. Since the pioneering languages of the eighties (*e.g.* [?]) there have been many such languages. We restrict our attention to recent works that are close to ours as regards design and availability. We directly compare with Cω [?] that extends C$^\sharp$ with join-definitions. In numerous aspects, the Cω design and development effort is similar to ours. Some differences exist though, most of which reflect the differences in the language extended. For instance, C$^\sharp$ being an object language, channels appear as methods of the objects that define the join-patterns (called *chords*). This often leads to a natural and concise style, more than our technique of explicitly bundling channels in records. As to JoCaml, OCaml being a functional language, JoCaml offers pattern-matching of channel arguments, a feature that we use in several occasions here. Another extension inspired by the join-calculus is Join Java [?]. Finally, it is to be noticed that the principles of the join-calculus also inspire recent concurrency libraries: `Joins` [?] for .NET, and `Boost.Join` [?] for C++. On the one hand such libraries provide an easier approach to the high-level abstractions of the join-calculus than the linguistic approach, both on the psychic (no need to try a new language) and technical level (no need to install a new compiler). On the other hand, they offer less static checks and integrated features, such as convenient syntax.

A recent extension of (standard) ML is Alice [?]. As regards distributed programming, Alice component model allows one program to transmit a module to another in a type-safe manner, and for the receiver to link the received

[6]Other causes are possible though: in one case, the machine was over-heating. . .

module in a controlled manner. This comes in sharp contrast with our type-less name server, and with our renunciation of code migration. As regards the basic concurrency primitives, Alice relies on explicit threads and support for data-flow synchronization. Scala is a language in its own right, not an extension, which is both object-oriented and functional. Support for concurrency in Scala is library based and using actors as the basic abstraction is encouraged [**?**]. The language Erlang [**?**] primarily targets the concurrent and distributed systems of the telecommunications industry. Its model for concurrency is reminiscent of actors, with provisions for fault tolerance; while its functional core language is rather simple. Erlang is being used for industrial developments of important size.

Clearly, there is a steady trend in programming language design: mature implementations are released that offer serious support for concurrency and distribution. The systems we have cited are based upon a variety of models. It certainly does not belong to us to claim that the join-calculus is the best amongst those models. Rather, we hope that our presentation of JoCaml at work demonstrate its elegance and expressive power.

A Scenes used during experiments

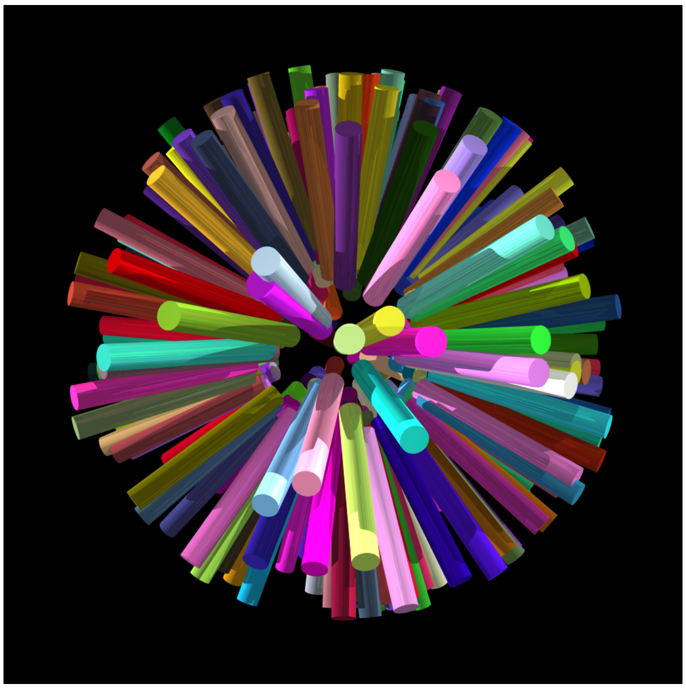
A.1 Urchin

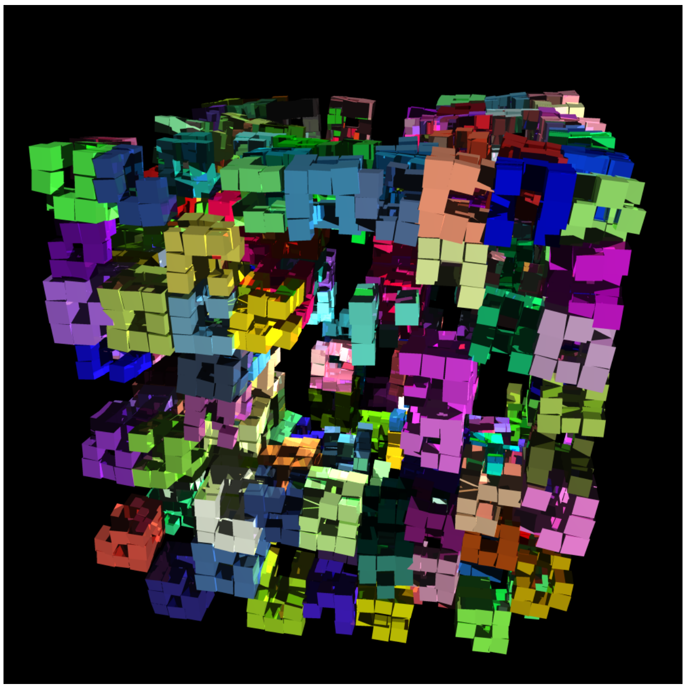
The scenes in experiments U are made of small cylinders arranged into a spheric shape, yielding a stylized sea urchin — see the first image of Figure 5. At order n, there are 2^n cylinders. The "urchin" scenes achieve a reasonably high level of complexity in rendering, since there are many intersections to compute, still at a moderate price in memory and scene building time.

A.2 Decaying Sierpinski cube

The scenes in experiments S are decaying Sierpinski cubes of increasing order — see the second image of Figure 5. The Sierpinski cube of order n normally contains 20^n small cubes. In our "decaying" version we erase 2 sub-elements out of 7 at every induction step, and apply pseudo-random rotation and scaling As a result, we obtain a slightly chaotic image made of approximatively 14.2^n elementary cube.

Figure 5: Images "urchin (8)" and "Sierpinski (3)"





Éditeur
INRIA - Domaine de Voluceau - Rocquencourt, BP 105 - 78153 Le Chesnay Cedex (France)
http://www.inria.fr
ISSN 0249-6399