Concurrent Cuba

T. Hahn
Max-Planck-Institut für Physik
Föhringer Ring 6, D–80805 Munich, Germany

August 28, 2014

Abstract

The parallel version of the multidimensional numerical integration package Cuba is presented and achievable speed-ups discussed.

1 Introduction

Cuba is a library for multidimensional numerical integration written in C99 with interfaces for Fortran, C/C++, and Mathematica. Cuba offers a choice of four independent routines for multidimensional numerical integration, Vegas, Suave, Divonne, and Cuhre, with very different characteristics [1, 2, 3].

Numerical integration is perfectly suited for parallel execution, which can significantly speed up the computation as it generally incurs only a very small overhead. Several features for concurrent sampling were added in Cuba versions 3 and 4, for both parallelization and vectorization. The objective was to make parallel use of Cuba very easy, ideally automatic, and led to the following design decisions:

1. No kind of Message Passing Interface is used, as that requires extra software to be installed. That is, the parallelization is restricted to one computer, using operating-system functions only. A standard setup these days is a single CPU with a number of cores, say 4 or 8. Utilizing many more compute nodes, as one could potentially do with MPI, is more of a theoretical option anyway since the speed-ups cannot be expected to grow linearly, see Sect. 4.2 on Performance.

2. Cuba uses fork/wait rather than the pthread* functions. The latter are slightly more efficient because parent and child share their memory space, but for the same reason they also require a reentrant integrand function, and the programmer may not have control over reentrancy in all languages (e.g. Fortran’s I/O is typically non-reentrant). fork on the other hand creates a completely independent copy of the running process and thus works for any integrand function.

3. Changing the number of cores to use should not require a re-compile, in particular as the program image should be able to run on several computers (with possibly differ-
ent numbers of cores) simultaneously. This is solved through an environment variable \texttt{CUBACORES}, which defaults to the number of idle cores on the present system.

The present note describes the concurrent features of Cuba 4 and discusses their performance. For installation and usage details not related to parallelization, the user is referred to the Cuba manual.

## 2 Parallelization model

Cuba uses a master–worker model. The master process orchestrates the parallelization but does not count towards the number of cores, e.g. \texttt{CUBACORES = 4} means four workers and one master. Very importantly, the samples are generated by the master process only and distributed to the workers, such that random numbers are never used more than once.

### 2.1 ‘Simple’ parallelization

The parallelization of Cuba naturally focusses on the main sampling routine \texttt{DoSample}, called by all Cuba integrators, which has been abstracted since the very first Cuba version simply because it is implemented very differently in Fortran/C/C++ and in Mathematica. \texttt{DoSample} in principle parallelizes straightforwardly on \(N\) cores:

- Serial version: sample \(n\) points.
- Parallel version: sample \(n/N\) points on core 1,
  
  \[\vdots\]
  
  sample \(n/N\) points on core \(N\).

The actual distribution strategy is somewhat more involved and is described in Sect. 3.2.4.

One appealing aspect of the parallelization through \texttt{DoSample} is that changes are made at a conceptually ‘low’ level of the integration, i.e. parallelization can be dealt with without modifying the integration algorithm itself.

### 2.2 Parallelization in Divonne

The speed-ups achieved with Divonne by parallelizing \texttt{DoSample} alone were generally unsatisfactory and significantly below those of the other integrators, e.g. \(\lesssim 1.5\) on four cores.

The Divonne algorithm works in three phases:

- **Partitioning Phase**: Split the integration region into subregions with approximately equal spread, defined as

  \[
  \text{Spread}(r) = \frac{1}{2} \operatorname{Vol}(r) \left( \sup_{\vec{x} \in r} f(\vec{x}) - \inf_{\vec{x} \in r} f(\vec{x}) \right),
  \]

  where the minimum and maximum of the integrand \(f\) are sought using methods from numerical optimization.
Sampling Phase: Sample the subregions independently with the same number of points each. That number is extrapolated from the results of the Partitioning Phase.

Refinement Phase: Further subdivide or sample again if results from the Partitioning and Sampling Phase do not agree within their estimated errors.

It turned out that the Partitioning Phase was crucial for attaining reasonable speed-ups and needed special treatment: Firstly, the original partitioning algorithm divided the regions recursively (and with a minimum recursion depth, too) and had to be ‘un-recursed’, mainly by better bookkeeping of the subregions.

Secondly, the Partitioning Phase was modified such that each core receives an entire region to subdivide, not just a list of points (as DoSample does). In particular the minimum/maximum search, during which only one point at a time is sampled, is distributed much more efficiently this way. The other two phases were not so critical precisely because they sample more points per region.

By moving the parallelization one level ‘up’ as it were, i.e. no longer at the ‘lowest’ (sampling) level of the integration, the genuine Divonne algorithm becomes more entwined with the parallelization, of course, and also the master–worker communication becomes more complex.

3 User Guide

The parallelization procedure is rather different in Fortran/C/C++ and in Mathematica. We shall deal with the latter first because it needs only a short explanation. The remainder of this chapter is then devoted to the Fortran/C/C++ case.

3.1 Parallelization in Mathematica

The Mathematica version of Cuba performs its sampling through a function MapSample. By default this is identical to Map, i.e. the serial version, so to parallelize one merely needs to redefine MapSample = ParallelMap (after loading Cuba).

If the integrand depends on user-defined symbols or functions, their definitions must be distributed to the workers beforehand using DistributeDefinitions and likewise required packages must be loaded with ParallelNeeds instead of Needs; this is explained in detail in the Mathematica manual.

3.2 Parallelization in Fortran and C/C++

In Fortran and C/C++ the Cuba library can (and usually does) automatically parallelize the sampling of the integrand. It parallelizes through fork and wait which, though slightly less performant than pthreads, do not require reentrant code. (Reentrancy may not even be under full control of the programmer, for example Fortran’s I/O is usually non-reentrant.) Worker processes are started and shut down only as few times as possible, however, so the
performance penalty is really quite minor even for non-native fork implementations such as Cygwin’s. Parallelization is not available on native Windows for lack of the fork function.

The communication of samples to and from the workers happens through IPC shared memory (shmget and colleagues), or if that is not available, through a socketpair (two-way pipe). Remarkably, the former’s anticipated performance advantage turned out to be hardly perceptible. Possibly there are cache-coherence issues introduced by several workers writing simultaneously to the same shared-memory area.

### 3.2.1 Invocation in Fortran

For reference, the prototypes of the integrators in Cuba 4 are repeated here; their detailed description is left to the Cuba manual. Only the underlined arguments are relevant for the following discussion.

```fortran
subroutine vegas(ndim, ncomp, integrand, userdata, nvec, 
  epsrel, epsabs, flags, seed, mineval, maxeval, 
  nstart, nincrease, nbatch, gridno, statefile, spin, 
  neval, fail, integral, error, prob)

subroutine suave(ndim, ncomp, integrand, userdata, nvec, 
  epsrel, epsabs, flags, seed, mineval, maxeval, 
  nnew, flatness, statefile, spin, 
  nregions, neval, fail, integral, error, prob)

subroutine divonne(ndim, ncomp, integrand, userdata, nvec, 
  epsrel, epsabs, flags, seed, mineval, maxeval, 
  key1, key2, key3, maxpass, 
  border, maxchisq, mindeviation, 
  ngiven, ldxgiven, xgiven, nextra, peakfinder, 
  statefile, spin, 
  nregions, neval, fail, integral, error, prob)

subroutine cuhre(ndim, ncomp, integrand, userdata, nvec, 
  epsrel, epsabs, flags, mineval, maxeval, 
  key, statefile, spin, 
  nregions, neval, fail, integral, error, prob)
```

The external function which computes the integrand is expected to be declared as

```fortran
integer function integrand(ndim, x, ncomp, f, userdata, nvec, core, ...) 
integer ndim, ncomp, nvec, core 
double precision x(ndim,nvec), f(ncomp,nvec)
```
The integrand receives \( nvec \) \( ndim \)-dimensional samples in \( x \) and is supposed to fill the array \( f \) with the corresponding \( ncomp \)-component integrand values. The return value is irrelevant unless it is \(-999\), in the case of which the integration will be aborted immediately. Note that \( nvec \) indicates the actual number of points passed to the integrand here and may be smaller than the \( nvec \) given to the integrator.

The dots represent optional arguments provided by Vegas, Suave, and Divonne (see manual). Also \texttt{userdata}, \( nvec \), and \texttt{core} are optional and may be omitted if unused, i.e. as in former Cuba versions the integrand may minimally be declared (for \( nvec = 1 \) as

\begin{verbatim}
integer function integrand(ndim, x, ncomp, f)
    integer ndim, ncomp
    double precision x(ndim), f(ncomp)
end function integrand
\end{verbatim}

### 3.2.2 Invocation in C/C++

The C/C++ prototypes are contained in \texttt{cuba.h}. They are reproduced here for reference. Again, only the underlined arguments are relevant for the present discussion.

\begin{verbatim}
typedef int (*integrand_t)(const int *ndim, const double x[],
                           const int *ncomp, double f[], void *userdata);

typedef void (*peakfinder_t)(const int *ndim, const double b[],
                             int *n, double x[]);

void Vegas(const int ndim, const int ncomp,
           integrand_t integrand, void *userdata, const int nvec,
           const double epsrel, const double epsabs,
           const int flags, const int seed,
           const int mineval, const int maxeval,
           const int nstart, const int nincrease, const int nbatch,
           const int gridno, const char *statefile, void *spin,
           int *neval, int *fail,
           double integral[], double error[], double prob[])

void Suave(const int ndim, const int ncomp,
           integrand_t integrand, void *userdata, const int nvec,
           const double epsrel, const double epsabs,
           const int flags, const int seed,
           const int mineval, const int maxeval,
           const int nnew, const double flatness,
           const char *statefile, void *spin,
           int *nregions, int *neval, int *fail,
           double integral[], double error[], double prob[])
\end{verbatim}
void Divonne(const int ndim, const int ncomp,
  integrand_t integrand, void *userdata, const int nvec,
  const double epsrel, const double epsabs,
  const int flags, const int seed,
  const int mineval, const int maxeval,
  const int key1, const int key2, const int key3,
  const int maxpass, const double border,
  const double maxchisq, const double mindeviation,
  const int ngiven, const int ldxgiven, double xgiven[],
  const int nextra, peakfinder_t peakfinder,
  const char *statefile, void *spin,
  int *nregions, int *neval, int *fail,
  double integral[], double error[], double prob[])

void Cuhre(const int ndim, const int ncomp,
  integrand_t integrand, void *userdata, const int nvec,
  const double epsrel, const double epsabs,
  const int flags,
  const int mineval, const int maxeval,
  const int key, const char *statefile, void *spin,
  int *nregions, int *neval, int *fail,
  double integral[], double error[], double prob[])

The integrand_t type intentionally declares only a minimalistic integrand type (and even the userdata argument could be omitted further). A more complete declaration is

typedef int (*integrand_t)(const int *ndim, const double x[],
  const int *ncomp, double f[], void *userdata,
  const int *nvec, const int *core, ...);

where the dots stand for extra arguments passed by Vegas, Suave, and Divonne (see manual) not needed in the following. In the presence of an nvec argument, x and f are actually two-dimensional arrays, x[*nvec][*ndim] and f[*nvec][*ncomp].

The integrand receives *nvec *ndim-dimensional samples in x and is supposed to fill the array f with the corresponding *ncomp-component integrand values. The return value is irrelevant unless it is −999, which signals immediate abortion of the integration. Note that *nvec indicates the actual number of points passed to the integrand here and may be smaller than the *nvec given to the integrator.

3.2.3 Starting and stopping the workers

The workers are usually started and stopped automatically by Cuba’s integration routines, but the user may choose to start them manually or keep them running after one integration and shut them down later, e.g. at the end of the program, which can be slightly
more efficient. The latter mode is referred to as ‘Spinning Cores’ and must be employed with certain care, for running workers will not ‘see’ subsequent changes in the main program’s data (e.g. global variables, common blocks) or code (e.g. via dlsym) unless special arrangements are made (e.g. shared memory).

The spinning cores are controlled through the ‘spin’ argument of the Cuba integration routines (Sect. 3.2.1):

- A value of −1 or %VAL(0) (in Fortran) or NULL (in C/C++) tells the integrator to start and shut down the workers autonomously. This is the usual case. No workers will still be running after the integrator returns. No special precautions need to be taken to communicate e.g. global data to the workers. Note that it is expressly allowed to pass a ‘naive’ -1 (which is an integer, not an integer*8) in Fortran.

- Passing a zero-initialized variable for spin instructs the integrator to start the workers but keep them running on return and store the ‘spinning cores’ pointer in spin for future use. The spinning cores must later be terminated explicitly by cubawait, thus invocation would schematically look like this:
  
  ```fortran
  integer*8 spin
  spin = 0
  call vegas(..., spin, ...)  Vegas(..., &spin, ...);
  ...
  call cubawait(spin)  cubawait(&spin);
  ```

- A non-zero spin variable is assumed to contain a valid ‘spinning cores’ pointer either from a former integration or an explicit invocation of cubafork, as in:
  
  ```fortran
  integer*8 spin
  call cubafork(spin)  cubafork(&spin);
  call vegas(..., spin, ...)  Vegas(..., &spin, ...);
  ...
  call cubawait(spin)  cubawait(&spin);
  ```

### 3.2.4 Accelerators and Cores

Based on the strategy used to distribute samples, Cuba distinguishes two kinds of workers.

Workers of the first kind are referred to as ‘Accelerators’ even though Cuba does not actually send anything to a GPU or Accelerator in the system by itself – this can only be done by the integrand routine. The assumption behind this strategy is that the integrand evaluation is running on a device so highly parallel that the sampling time is more or less independent of the number of points, up to the number of threads $p_{accel}$ available in hardware. Cuba tries to send exactly $p_{accel}$ points to each core – never more, less only for the last batch. To sample e.g. 2400 points on three accelerators with $p_{accel} = 1000$, Cuba sends batches of 1000/1000/400 and not, for example, 800/800/800 or 1200/1200. The number of accelerators $n_{accel}$ and their value of $p_{accel}$ can be set through the environment variables
CUBAACCEL = \( n_{\text{accel}} \) (default: 0)
CUBAACCELMAX = \( p_{\text{accel}} \) (default: 1000)

or, superseding the environment, an explicit

\[
\text{call cubaaccel}(n_{\text{accel}}, p_{\text{accel}})
\]

CPU-bound workers are just called ‘Cores’. Their distribution strategy is different in that all available cores are used and points are distributed evenly. In the example above, the batches would be 800/800/800 thus. Each core receives at least 10 points, or else fewer cores are used. If no more than 10 points are requested in total, Cuba uses no workers at all but lets the master sample those few points. This happens during the partitioning phase of Divonne, for instance, where only single points are evaluated in the minimum/maximum search. Conversely, if the division of points by cores does not come out even, the remaining few points \( (< n_{\text{cores}}) \) are simply added to the existing batches, to avoid an extra batch because of rounding. Sampling 2001 points on two cores with \( p_{\text{cores}} = 1000 \) will hence give two batches 1001/1000 and not three batches 1000/1000/1.

Although there is typically no hardware limit, a maximum number of points per core, \( p_{\text{cores}} \), can be prescribed for Cores, too. Unless the integrand is known to evaluate equally fast at all points, a moderate number for \( p_{\text{cores}} \) (10000, say) may actually increase performance because it effectively load-levels the sampling. For, a batch always goes to the next free core so it doesn’t matter much if one core is tied up with a batch that takes longer.

The number of cores \( n_{\text{cores}} \) and the value of \( p_{\text{cores}} \) can be set analogously through the environment variables

CUBACORES = \( n_{\text{cores}} \) (default: no. of idle cores)
CUBACORESMAX = \( p_{\text{cores}} \) (default: 10000)

If CUBACORES is unset, the idle cores on the present system are taken (total cores minus load average), which means that a program calling a Cuba routine will by default automatically parallelize on the available cores. Again, the environment can be overruled with an explicit

\[
\text{call cubacores}(n_{\text{cores}}, p_{\text{cores}})
\]

Using the environment has the advantage, though, that changing the number of cores to use does not require a re-compile, which is particularly useful if one wants to run the program on several computers (with potentially different numbers of cores) simultaneously, say in a batch queue.

The integrand function may use the ‘core’ argument (Sect. 3.2.1) to distinguish Accelerators (\( \text{core} < 0 \)) and Cores (\( \text{core} \geq 0 \)). The special value \( \text{core} = 32768 \) \( (2^{15}) \) indicates that the master itself is doing the sampling.

3.2.5 Worker initialization

User subroutines for (de)initialization may be registered with
call cubainit(initfun, initarg)
call cubaexit(exitfun, exitarg)

and will be executed in every process before and after sampling. Passing a null pointer (%VAL(0) in Fortran, NULL in C/C++) as the first argument unregisters either subroutine. The init/exit functions are actually called as

call initfun(initarg, core)
call exitfun(exitarg, core)

where initarg and exitarg are the user arguments given with the registration (arbitrary in Fortran, void * in C/C++) and core indicates the core the function is being executed on, with (as before) core < 0 for Accelerators, core ≥ 0 for Cores, and core = 32768 for the master.

On worker processes, the functions are respectively executed after fork and before wait, independently of whether the worker actually receives any samples. The master executes them only when actual sampling is done. For Accelerators, the init and exit functions are typically used to set up the device for the integrand evaluations, which for many devices must be done per process, i.e. after the fork.

3.2.6 Concurrency issues

By creating a new process image, fork circumvents all memory concurrency, to wit: each worker modifies only its own copy of the parent’s memory and never overwrites any other’s data. The programmer should be aware of a few potential problems nevertheless:

- Communicating back results other than the intended output from the integrand to the main program is not straightforward because, by the same token, a worker cannot overwrite any common data of the master, it will only modify its own copy.

  Data exchange between workers is likewise not directly possible. For example, if one worker stores an intermediate result in a common block, this will not be seen by the other workers.

  Possible solutions include using shared memory (shmget etc., see App. A) and writing the output to file (but see next item below).

- fork does not guard against competing use of other common resources. For example, if the integrand function writes to a file (debug output, say), there is no telling in which order the lines will end up in the file, or even if they will end up as complete
lines at all. Buffered output should be avoided at the very least; better still, every worker should write the output to its own file, e.g. with a filename that includes the process id, as in:

```fortran
character*32 filename
integer pid
data pid /0/
if( pid .eq. 0 ) then
  pid = getpid()
  write(filename,'("output.",I5.5)') pid
  open(unit=4711, file=filename)
endif
```

- Fortran users are advised to flush (or close) any open files before calling Cuba, i.e. call `flush(unit)`. The reason is that the child processes inherit all file buffers, and each of them will write out the buffer content at exit. Cuba preemptively flushes the system buffers already (`fflush(NULL)`) but has no control over Fortran’s buffers.

For debugging, or if a malfunction due to concurrency issues is suspected, a program should be tested in serial mode first, e.g. by setting `CUBACORES = 0` (Sect. 3.2.4).

### 3.2.7 Vectorization

Vectorization means evaluating the integrand function for several points at once. This is also known as Single Instruction Multiple Data (SIMD) paradigm and is different from ordinary parallelization where independent threads are executed concurrently. It is usually possible to employ vectorization on top of parallelization.

Vector instructions are commonly available in hardware, e.g. on x86 platforms under acronyms such as SSE or AVX. Language support varies: Fortran 90’s syntax naturally embeds vector operations. Many C/C++ compilers offer auto-vectorization options, some have extensions for vector data types (usually for a limited set of mathematical functions), and even hardware-specific access to the CPU’s vector instructions. And then there are vectorized libraries of numerical functions available.

Cuba cannot automatically vectorize the integrand function, of course, but it does pass (up to) `nvec` points per integrand call (Sect. 3.2.1). This value need not correspond to the hardware vector length – computing several points in one call can also make sense e.g. if the computations have significant intermediate results in common. The actual number of points passed is indicated through the corresponding `nvec` argument of the integrand.

A note for disambiguation: The `nbatch` argument of Vegas is related in purpose but not identical to `nvec`. It internally partitions the sampling done by Vegas but has no bearing on the number of points given to the integrand. On the other hand, it it pointless to choose `nvec > nbatch` for Vegas.
4 Performance

4.1 Test setup

Parallelization entails a certain overhead as usual, so the efficiency will depend on the ‘cost’ of an integrand evaluation, i.e. the more ‘expensive’ (time-consuming) it is to sample the integrand, the better the speed-up will be.

The timing measurements in the following figures were made with the 11 integrands of the demo code included in the Cuba distribution, which were originally chosen to highlight different aspects of the integrators. These are simple one-liners and for timing purposes ‘infinitely’ fast. To tune the cost of the integrands, a calibrated delay loop was inserted into the integrand functions.

The calibration was necessary because the system time resolution was visibly imprinted on the first versions of the plots. In a separate program, the delay loop was executed with no upper bound but with the timer set to interrupt at 10 seconds. The number of cycles performed per second was recorded in a file and in subsequent timing measurements was used to compute the upper bound of the delay loop. This guaranteed that, for a prescribed delay, each integrand was slowed down by the same number of delay-loop turns, with a µsec precision of the delay.

The number of repetitions of each integration was moreover adjusted for each integrator to make the serial version run for 240 sec. That leaves at least 30 sec run-time per invocation even for the ideal speed-up of 8 (on an i7), long enough to make time-measurement errors negligible.

To exclude systematic effects, all measurements were done on the same i7-2600K Linux machine, idle except for the timing program. The i7 processor has four real and eight virtual (hyperthreaded) cores, i.e. eight register sets but only four arithmetic units. Beyond four cores, indicated by a line in the plots, CPU effects are thus expected on top of Cuba’s ‘pure’ scaling behavior.

4.2 Timing measurements

Fig. 1 shows the speed-ups for an ‘easy’ and a ‘hard’ one of the 11 integrands of the demo program included in the Cuba package for two different integrand delays. Also in the one-core case the parallel version was deployed (one master, one worker), which explains why the timings normalized to the serial version are below 1, in the top row visibly so.

The first, expected, observation is that parallelization is worthwhile only for not-too-fast integrands. This is not a major showstopper, however, as many interesting integrands fall into this category anyway. What appears to be a drastic underperformance of Cuhre in the ‘easy’ case can in fact be attributed to Cuhre’s outstanding efficiency: it delivers a result correct to almost all digits with around 300 samples. In such a case, Cuba may for efficiency choose not to fill all available cores and relative to the full number of cores this shows up as a degradation.
The second observation is that parallelization works best for ‘simple-minded’ integrators, e.g. Vegas. This is showcased even better in Fig. 2. The ‘intelligent’ algorithms are generally much harder to parallelize because they don’t just do mechanical sampling but take into account intermediate results, make extra checks on the integrand (e.g. try to find extrema), etc. This is particularly true for Divonne, see Sect. 2.2. Then again, the ‘intelligent’ algorithms are usually faster to start with, i.e. converge with fewer points sampled, which compensates for the lack of parallelizability.

5 Summary

The Cuba library for multidimensional numerical integration now features concurrent sampling and thereby achieves significant speed-ups. No extra software needs to be installed since only operating-system functions are used. No reentrancy is required for the integrand function since fork/wait is applied. Parallelization is usually switched on automatically but can be controlled through API calls or the environment.

Cuba is available from http://feynarts.de/cuba and licensed under the LGPL. The download contains a manual which gives full details on installation and usage.

Acknowledgments

The author thanks Alexander Smirnov for valuable suggestions and comments and the MIAPP Workshop ‘Challenges, Innovations and Developments in Precision Calculations for the LHC’ for hospitality during the preparation of this work.

References

[1] T. Hahn, Comput. Phys. Commun. 168 (2005) 78–95 [hep-ph/0404043].

[2] S. Agrawal, T. Hahn, E. Mirabella, J. Phys. Conf. Ser. 368 (2012) 012054 [arXiv:1112.0124].

[3] B. Chokoufe Nejad, T. Hahn, J.-N. Lang, E. Mirabella, J. Phys. Conf. Ser. 523 (2014) 012050 [arXiv:1310.0274].
Figure 1: Cuba speed-ups for three-dimensional integrals with $10^{-4}$ requested accuracy. Left: ‘easy’ integrand, right: ‘hard’ integrand. Top: ‘fast’ integrand (10 µsec), bottom: ‘slow’ integrand (1000 µsec per evaluation). Solid: shared memory, dashed: socketpair communication (two curves each to show fluctuations in timing).

Figure 2: Comparison of the parallelization efficiency for all 11 integrands.
A Shared Memory in Fortran

IPC shared memory is not natively available in Fortran, but it is not difficult to make it available using two small C functions `shmalloc` and `shmfree`:

```c
#include <sys/shm.h>
#include <assert.h>

typedef long long int memindex;
typedef struct { void *addr; int id; } shminfo;

void shmalloc_(shminfo *base, memindex *i, const int *n, const int *size) {
    base->id = shmget(IPC_PRIVATE, *size*(*n + 1) - 1, IPC_CREAT | 0600);
    assert(base->id != -1);
    base->addr = shmat(base->id, NULL, 0);
    assert(base->addr != (void *)-1);
    *i = ((char *)(base->addr + *size - 1) - (char *)base)/(long)*size;
}

void shmfree_(shminfo *base) {
    shmdt(base->addr);
    shmctl(base->id, IPC_RMID, NULL);
}
```

The function `shmalloc` allocates (suitably aligned) \(n\) elements of size \(size\) and returns a mock index into \(base\), through which the memory is addressed in Fortran. The array \(base\) must be of the desired type and large enough to store the struct `shminfo`, e.g. two doubles wide. Be careful to invoke `shmfree` after use, for the memory will not automatically be freed upon exit but stay allocated until the next reboot (or explicit removal with `ipcs`).

The following test program demonstrates how to use `shmalloc` and `shmfree`:

```fortran
program test
    implicit none
    integer*8 i
    double precision base(2)

    call shmalloc(base, i, 100, 8) ! allocate 100 doubles

    base(i) = 1 ! now use the memory
    ...  
    base(i+99) = 100

    call shmfree(base) ! don’t forget to free it
end
```

14