Sourcery VSIPL++

User's Guide

Sourcery VSIPL++: User's Guide

CodeSourcery

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Part I. Tutorial

The sections in Part I form a tutorial for using Sourcery VSIPL++, covering serial programming, parallel programming, and performance analysis. You can follow along with the tutorial to learn how to use VSIPL++, and you can adapt the examples for use in your own programs.

Chapter 1
Fast Convolution

This chapter describes how to create and run a serial VSIPL++ program with Sourcery VSIPL++ that performs fast convolution. You can modify this program to develop your own serial applications.

This chapter explains how to use Sourcery VSIPL++ to perform *fast convolution* (a common signal-processing kernel). First, you will see how to compute fast convolution using VSIPL++'s multiple FFT (Fftm) and vector-matrix multiply operations. Then, you will learn how to optimize the performance of the implementation.

1.1 Fast Convolution

Fast convolution is the technique of performing convolution in the frequency domain. In particular, the time-domain convolution f * g can be computed as F . G, where F and G are the frequency-domain representations of the signals f and g. A time-domain signal consisting of n samples can be converted to a frequency-domain signal in O(n log n) operations by using a Fast Fourier Transform (FFT). Substantially fewer operations are required to perform the frequency-domain operation F . G than are required to perform the time-domain operation f * g. Therefore, performing convolutions in the frequency domain can be substantially faster than performing the equivalent computations in the time domain, even taking into account the cost of converting from the time domain to the frequency domain.

One practical use of fast convolution is to perform the pulse compression step in radar signal processing. To increase the effective bandwidth of a system, radars will transmit a frequency modulated "chirp". By convolving the received signal with the time-inverse of the chirp (called the "replica"), the total energy returned from an object can be collapsed into a single range cell. Fast convolution is also useful in many other contexts including sonar processing and software radio.

In this section, you will construct a program that performs fast convolution on a set of time-domain signals stored in a matrix. Each row of the matrix corresponds to a single signal, or "pulse". The columns correspond to points in time. So, the entry at position (i, j) in the matrix indicates the amplitude and phase of the signal received at time j for the ith pulse.

The first step is to declare the data matrix, the vector that will contain the replica signal, and a temporary matrix that will hold the results of the computation:

```
// Parameters.
length_type npulse = 64; // number of pulses
length_type nrange = 256; // number of range cells

// Views.
typedef complex<float> value_type;
Vector<value_type> replica(nrange);
Matrix<value_type> data(npulse, nrange);
Matrix<value_type> tmp (npulse, nrange);
```

For now, it is most convenient to initialize the input data to zero. (In Section 1.3, “Performing I/O with User-Specified Storage”, you will learn how to perform I/O operations so that you can populate the matrix with real data.)

In C++, you can use the constructor syntax `T()` to perform "default initialization" of a type `T()`. The default value for any numeric type (including complex numbers) is zero. Therefore, the expression `value_type()` indicates the complex number with zero as both its real and imaginary components. In the VSIPL++ API, when you assign a scalar value to a view (a vector, matrix, or tensor), all elements of the view are assigned the scalar value. So, the code below sets the contents of both the data matrix and replica vector to zero:

```
data    = value_type();
replica = value_type();
```

The next step is to define the FFTs that will be performed. Typically (as in this example) an application performs multiple FFTs on inputs with the same size. Since performing an FFT requires that some set-up be performed before performing the actual FFT computation, it is more efficient to set up the FFT just once. Therefore, in the VSIPL++ API, FFTs are objects, rather than operators. Constructing the FFT performs the necessary set-up operations.

Because VSIPL++ supports a variety of different kinds of FFT, FFTs are themselves template classes. The parameters to the template allow you to indicate whether to perform a forward (time-domain to frequency-domain) or inverse (frequency-domain to time-domain) FFT, the type of the input and output data (i.e., whether complex or real data is in use), and so forth. Then, when constructing the FFT objects, you indicate the size of the FFT. In this case, you will need both an ordinary FFT (to convert the replica data from the time domain to the frequency domain) and a "multiple FFT" to perform the FFTs on the rows of the matrix. (A multiple FFT performs the same FFT on each row or column of a matrix.) So, the FFTs required are:

```
// A forward Fft for computing the frequency-domain version of
// the replica.
typedef Fft<const_Vector, value_type, value_type, fft_fwd, by_reference>
for_fft_type;
for_fft_type  for_fft (Domain<1>(nrange), 1.0);

// A forward Fftm for converting the time-domain data matrix to the
// frequency domain.
typedef Fftm<value_type, value_type, row, fft_fwd, by_reference>
  for_fftm_type;
for_fftm_type for_fftm(Domain<2>(npulse, nrange), 1.0);

// An inverse Fftm for converting the frequency-domain data back to
// the time-domain.
typedef Fftm<value_type, value_type, row, fft_inv, by_reference>
  inv_fftm_type;
inv_fftm_type inv_fftm(Domain<2>(npulse, nrange), 1.0/(nrange));
```

Before performing the actual convolution, you must convert the replica to the frequency domain using the FFT created above. Because the replica data is a property of the chirp, we only need to do this once; even if our radar system runs for a long time, the converted replica will always be the same. VSIPL++ FFT objects behave like functions, so you can just "call" the FFT object:

```
for_fft(replica);
```

Now, you are ready to perform the actual fast convolution operation! You will use the forward and inverse multiple-FFT objects you've already created to go into and out of the frequency domain. While in the frequency domain, you will use the `vmmul` operator to perform a vector-matrix multiply. This will multiply each row (dimension zero) of the frequency-domain matrix by the replica. The `vmmul` operator is a template taking a single parameter which indicates whether the multiplication should be performed on rows or on columns. So, the heart of the fast convolution algorithm is just:

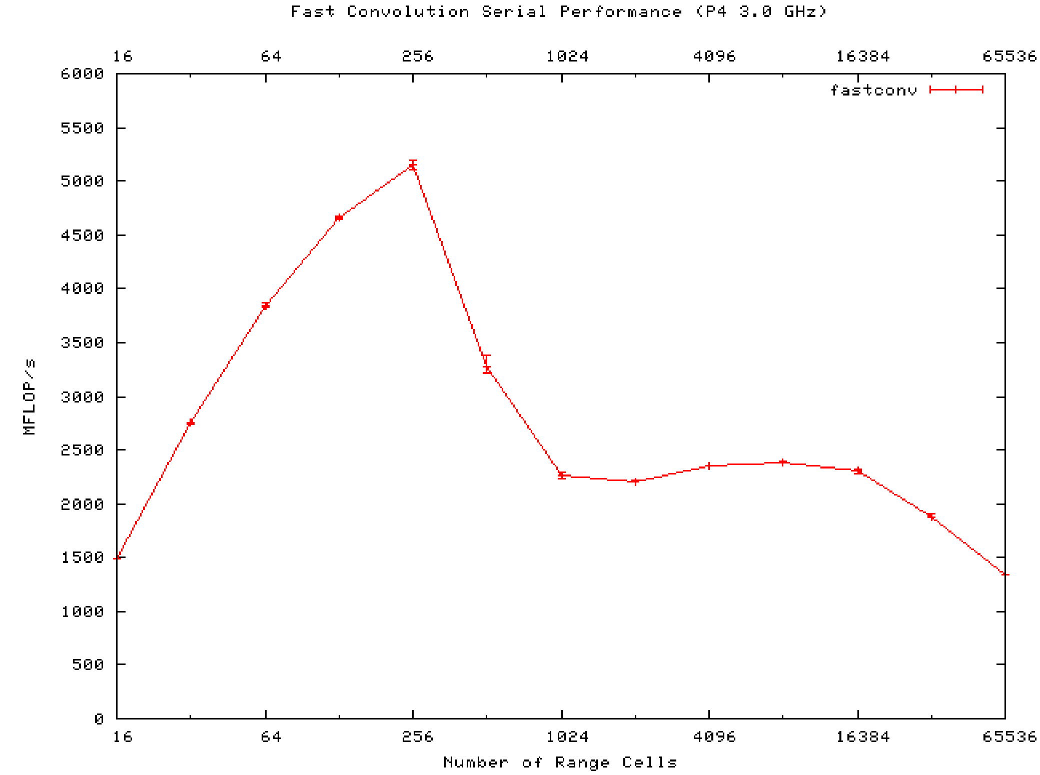
```
// Convert to the frequency domain.
for_fftm(data, tmp);

// Perform element-wise multiply for each pulse.
tmp = vmmul<0>(replica, tmp);

// Convert back to the time domain.
inv_fftm(tmp, data);
```

A complete program listing is show below. You can copy this program directly into your editor and build it. (You may notice that there are a few things in the complete listing not discussed above, including in particular, initialization of the library.)

```
/***********************************************************************
  Included Files
***********************************************************************/

#include <vsip/initfin.hpp>
#include <vsip/support.hpp>
#include <vsip/signal.hpp>
#include <vsip/math.hpp>

using namespace vsip;



/***********************************************************************
  Main Program
***********************************************************************/

int
main(int argc, char** argv)
{
  // Initialize the library.
  vsipl vpp(argc, argv);

  typedef complex<float> value_type;

  // Parameters.
  length_type npulse = 64; // number of pulses
  length_type nrange = 256; // number of range cells

  // Views.
  Vector<value_type> replica(nrange);
  Matrix<value_type> data(npulse, nrange);
  Matrix<value_type> tmp(npulse, nrange);

  // A forward Fft for computing the frequency-domain version of
  // the replica.
  typedef Fft<const_Vector, value_type, value_type, fft_fwd, by_reference>
  for_fft_type;
  for_fft_type  for_fft (Domain<1>(nrange), 1.0);

  // A forward Fftm for converting the time-domain data matrix to the
  // frequency domain.
  typedef Fftm<value_type, value_type, row, fft_fwd, by_reference>
    for_fftm_type;
  for_fftm_type for_fftm(Domain<2>(npulse, nrange), 1.0);

  // An inverse Fftm for converting the frequency-domain data back to
  // the time-domain.
  typedef Fftm<value_type, value_type, row, fft_inv, by_reference>
    inv_fftm_type;
  inv_fftm_type inv_fftm(Domain<2>(npulse, nrange), 1.0/(nrange));

  // Initialize data to zero.
  data    = value_type();
  replica = value_type();

  // Before fast convolution, convert the replica to the the
  // frequency domain
  for_fft(replica);


  // Perform fast convolution.

  // Convert to the frequency domain.
  for_fftm(data, tmp);

  // Perform element-wise multiply for each pulse.
```

```
  tmp = vmmul<0>(replica, tmp);

  // Convert back to the time domain.
  inv_fftm(tmp, data);
}
```

The following figure shows the performance in MFLOP/s of fast convolution on a 3.06 GHz Pentium Xeon processor as the number of range cells varies from 16 to 65536.



1.2 Serial Optimization: Temporal Locality

In this section, you will learn how to improve the performance of fast convolution by improving *temporal locality*, i.e., by making accesses to the same memory locations occur near the same time.

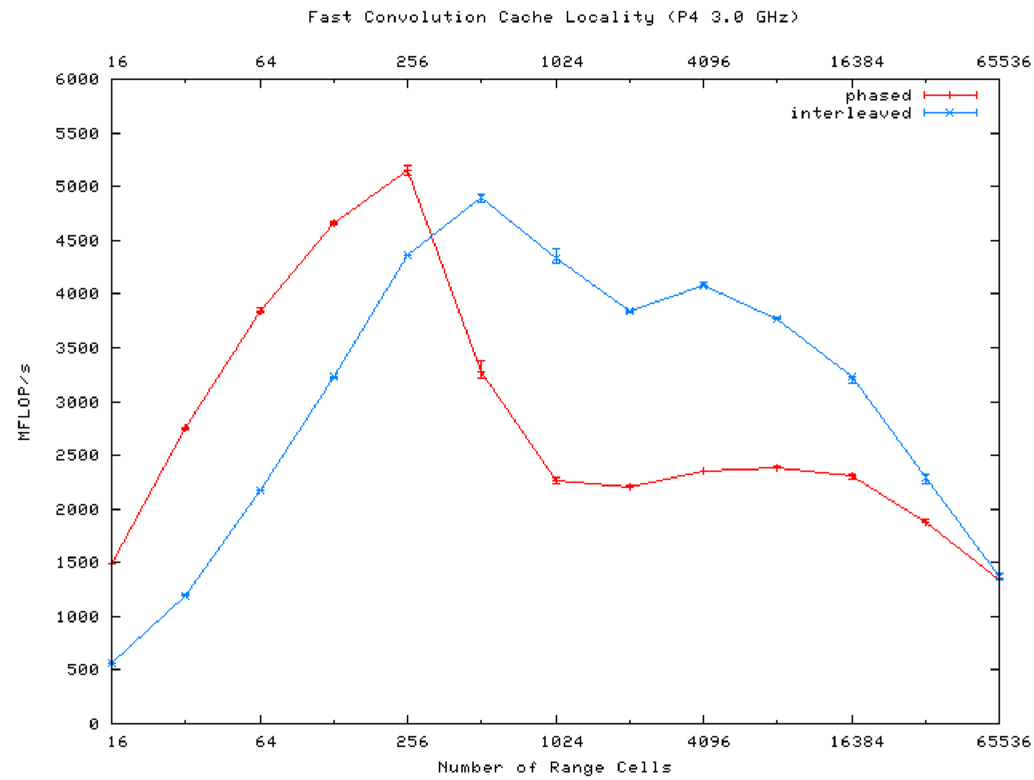
The code in Section 1.1, “Fast Convolution” performs a FFT on each row of the matrix. Then, after all the rows have been processed, it multiplies each row of the matrix by the `replica`. Suppose that there are a large number of rows, so that `data` is too large to fit in cache. In that case, while the results of the first FFT will be in cache immediately after the FFT is complete, that data will likey have been purged from the cache by the time the vector-matrix multiply needs the data.

Explicitly iterating over the rows of the matrix (performing a forward FFT, elementwise multiplication, and an inverse FFT on each row before going on to the next one) will improve temporal locality. You can use this approach by using an explicit loop, rather than the implicit parallelism of `Fftm` and `vmmul`, to take better advantage of the cache.

You must make a few changes to the application in order to implement this approach. Because the application will be operating on only a single row at a time, `Fftm` must be replaced with the simpler `Fft`. Similarly, `vmmul` must be replaced with `*`, which performs element-wise multiplication of its operands. Finally, `tmp` can now be a vector, rather than a matrix. (As a consequence, in addition to being faster, this new version of the application will require less memory.) Here is the revised program:

```
// Create the data cube.
Matrix<value_type> data(npulse, nrange);
Vector<value_type> tmp(nrange);            // tmp is now a vector

// Create the pulse replica
Vector<value_type> replica(nrange);

// Define the FFT typedefs.
typedef Fft<const_Vector, value_type, value_type, fft_fwd, by_reference>
for_fft_type;
typedef Fft<const_Vector, value_type, value_type, fft_inv, by_reference>
inv_fft_type;

// Create the FFT objects.
for_fft_type  for_fft(Domain<1>(nrange), 1.0);
inv_fft_type  inv_fft(Domain<1>(nrange), 1.0/(nrange));

// Initialize data to zero
data    = value_type();
replica = value_type();

// Before fast convolution, convert the replica into the
// frequency domain
for_fft(replica);

// Perform fast convolution:
for (index_type r=0; r < nrange; ++r)
{
  for_fft(data.row(r), tmp);
  tmp *= replica;
  inv_fft(tmp, data.row(r));
}
```

The following graph shows that the new "interleaves" formulation is faster than the original "phased" approach for large data sets. For smaller data sets (where all of the data fits in the cache anyhow), the original method is faster because performing all of the FFTs at once is faster than performing them one by one.



1.3 Performing I/O with User-Specified Storage

The previous sections have ignored the acquisition of actual sensor data by setting the input data to zero. This section shows how to initialize `data` before performing the fast convolution.

To perform I/O with external routines (such as posix `read` and `write` it is necessary to obtain a pointer to data. Sourcery VSIPL++ provides multiple ways to do this: using *user-defined storage*, and using *external data access*. In this section you will use user-defined storage to perform I/O. Later, in Section 1.4, “Performing I/O with External Data Access” you will see how to use external data access for I/O.

VSIPL++ allows you to create a block with user-specified storage by giving VSIPL++ a pointer to previously allocated data when the block is created. This block is just like a normal block, except that it now has two states: "admitted" and "released". When the block is admitted, the data is owned by VSIPL++ and the block can be used with any VSIPL++ functions. When the block is released, the data is owned by you allowing you to perform operations directly on the data. The states allow VSIPL++ to potentially reorganize data for higher performance while it is admitted. (Attempting to use the pointer while the block is admitted, or use the block while it is released will result in unspecified behavior!)

The first step is to allocate the data manually.

```
auto_ptr<value_type> data_ptr(new value_type[npulse*nrange]);
```

Next, you create a VSIPL++ `Dense` block, providing it with the pointer.

```
Dense<value_type, 2> data_block(Domain<2>(nrange, npulse), data_ptr.get());
```

Since the pointer to data does not encode the data dimensions, it is necessary to create the block with explicit dimensions.

Finally, you create a VSIPL++ view that uses this block.

```
  Matrix<value_type> data(block);
```

The view determines its size from the block, so there is no need to specify the dimensions again.

Now you're ready to perform I/O. When a user-specifed storage block is first created, it is released.

```
  ... setup IO ...
  read(..., data_ptr, sizeof(value_type)*nrange*npulse);
  ... check for errors (of course!) ...
```

Finally, you need to admit the block so that it and the view can be used by VSIPL++.

```
  data.block().admit(true);
```

The `true` argument indicates that the data values sould be preserved by the admit. In cases where the values do not need to preserved (such as admitting a block after outout I/O has been performed and before the block will be overwritten by new values in VSIPL++) you can use `false` instead.

After admitting the block, you can use `data` as before to perform fast convolution. Here is the complete program, including I/O to output the result after the computation.

```
/***********************************************************************
  Included Files
***********************************************************************/

#include <vsip/initfin.hpp>
#include <vsip/support.hpp>
#include <vsip/signal.hpp>
#include <vsip/math.hpp>

using namespace vsip;



/***********************************************************************
  Main Program
***********************************************************************/

int
main(int argc, char** argv)
{
  // Initialize the library.
  vsipl vpp(argc, argv);

  typedef complex<float> value_type;

  // Parameters.
  length_type npulse = 64; // number of pulses
  length_type nrange = 256; // number of range cells

  // Allocate data.
  auto_ptr<value_type> data_ptr(new value_type[npulse*nrange]);

  // Blocks.
  Dense<2, value_type> block(Domain<2>(npulse, nrange), data_ptr.get());

  // Views.
  Vector<value_type> replica(nrange);
  Matrix<value_type> data(block);
  Matrix<value_type> tmp(npulse, nrange);
```

```
  // A forward Fft for computing the frequency-domain version of
  // the replica.
  typedef Fft<const_Vector, value_type, value_type, fft_fwd, by_reference>
  for_fft_type;
  for_fft_type  for_fft (Domain<1>(nrange), 1.0);

  // A forward Fftm for converting the time-domain data matrix to the
  // frequency domain.
  typedef Fftm<value_type, value_type, row, fft_fwd, by_reference>
    for_fftm_type;
  for_fftm_type for_fftm(Domain<2>(npulse, nrange), 1.0);

  // An inverse Fftm for converting the frequency-domain data back to
  // the time-domain.
  typedef Fftm<value_type, value_type, row, fft_inv, by_reference>
    inv_fftm_type;
  inv_fftm_type inv_fftm(Domain<2>(npulse, nrange), 1.0/(nrange));

  // Initialize data to zero.
  data    = value_type();
  replica = value_type();

  // Before fast convolution, convert the replica to the the
  // frequency domain
  for_fft(replica);


  // Perform input I/O.
  view.block().release(false);
  size_t size = read(0, data_ptr.get(), sizeof(value_type)*nrange*npulse);
  assert(size == sizeof(value_type)*nrange*npulse));
  view.block().admit(true);

  // Perform fast convolution.

  // Convert to the frequency domain.
  for_fftm(data, tmp);

  // Perform element-wise multiply for each pulse.
  tmp = vmmul<0>(replica, tmp);

  // Convert back to the time domain.
  inv_fftm(tmp, data);

  // Perform output I/O.
  view.block().release(true);
  size_t size = read(0, data_ptr.get(), sizeof(value_type)*nrange*npulse);
  assert(size == sizeof(value_type)*nrange*npulse));
  view.block().admit(false);
}
```

The program also includes extra `release()` and `admit()` calls before and after the input and output I/O sections. For this example, they are not strictly necessary. However they are good practice because they make it clear in the program where the block is admitted and released. They also make it easier to modify the program to process data repeatedly in a loop, and to use separate buffers for input and output data. Because the extra calls have a `false` update argument, they incur no overhead.

1.4 Performing I/O with External Data Access

In this section, you will use *External Data Access* to get pointer to a block's data. External data access allows a pointer to any block's data to be taken, even if the block was not created with user-specified storage (or if the block is not a `Dense` block at all!) This capability is useful in context where you cannot control how a block is created. To illustrate this, you will create a utility routine for I/O that works with any view passed as a parameter.

To access a block's data with external data access, you create an `Ext_data` object.

```
Ext_data<block_type, layout_type> ext(block, SYNC_INOUT);
```

`Ext_data` is a class template that takes template parameters to indicate the block type `block_type` and the requested layout `layout_type`. The constructor takes two parameters: the block being accessed, and the type of syncing necessary.

The `layout_type` parameter is an specialized `Layout` class template that determines the layout of data that `Ext_data` provides. If no type is given, the natural layout of the block is used. However, in some cases it is necessary to access the data in a certain way, such as dense or row-major.

`Layout` class template takes 4 parameters to indicate dimensionality, dimension-ordering, packing format, and complex storage format (if complex). In the example below you will use the layout_type to request the data access to be dense, row-major, with interleaved real and imaginar values if complex. This will allow you to read data sequentially from a file.

The sync type is analgous to the update flags for `admit()` and `release()`. `SYNC_IN` indicates that the block and pointer should be synchronized when the `Ext_data` object is created (like `admit(true)`) `SYNC_OUT` indicates that the block and pointer should be synchronized when the `Ext_data` object is destroyed (like `release(true)`) `SYNC_INOUT` indicates that the block and pointer should be syncrhonized at both points.

Once the object has been created, the pointer can be accessed with the `data` method.

```
value_type* ptr = ext.data();
```

The pointer provided is valid only during the life of the object. Moreover, the block being accessed should not be used during that time.

Putting this together, you can create a routine to perform I/O into a block. This routine will take two arguments: a filename to read, and a view to put the data into. The amount of data read from the file will be determined by the view's size.

```
template <typename ViewT>
void
read_file(ViewT view, char* filename)
{
  using vsip::impl::Ext_data;
  using vsip::impl::Layout;
  using vsip::impl::Stride_unit_dense;
  using vsip::impl::Cmplx_inter_fmt;
  using vsip::impl::Row_major;

  dimension_type const dim = ViewT::dim;
  typedef typename ViewT::block_type block_type;
  typedef typename ViewT::value_type value_type;

  typedef Layout<dim, typename Row_major<dim>::type,
                 Stride_unit_dense, Cmplx_inter_fmt>
layout_type;

  Ext_data<block_type, layout_policy>
    ext(view.block(), SYNC_OUT);

  ifstream ifs(filename);
```

```
    ifs.read(reinterpret_cast<char*>(ext.data()),
             view.size() * sizeof(value_type));
  }
```

Chapter 2
Parallel Fast Convolution

This chapter describes how to create and run parallel VSIPL++ programs with Sourcery VSIPL++. You can modify the programs to develop your own parallel applications.

This chapter explains how to use Sourcery VSIPL++ to perform parallel computations. You will see how to transform the fast convolution program from the previous chapter to run in parallel. First you will convert the `Fftm` based version. Then you will convert the improved cache locality version. Finally, you will learn how to handle input and output when working in parallel.

2.1 Parallel Fast Convolution

The first fast convolution program in the previous chapter makes use of two implicitly parallel operators: `Fftm` and `vmmul`. These operators are implicity parallel in the sense that they process each row of the matrix independently. If you had enough processors, you could put each row on a separate processor and then perform the entire computation in parallel.

In the VSIPL++ API, you have explicit control of the number of processors used for a computation. Since the default is to use just a single processor, the program above will not run in parallel, even on a multi-processor system. This section will show you how to use *maps* to take advantage of multiple processors. Using a map tells Sourcery VSIPL++ to distribute a single block of data across multiple processors. Then, Sourcery VSIPL++ will automatically move data between processors as necessary.

The VSIPL++ API uses the Single-Program Multiple-Data (SPMD) model for parallelism. In this model, every processor runs the same program, but operates on different sets of data. For instance, in the fast convolution example, multiple processors perform FFTs at the same time, but each processor handles different rows in the matrix.

Every map has both compile-time and run-time properties. At compile-time, you specify the *distribution* that will be applied to each dimension. In this example, you will use a *block distribution* to distribute the rows of the matrix. A block distribution divides a view into continguous chunks. For example, suppose that you have a 4-processor system. Since there are 64 rows in the matrix `data`, there will be 16 rows on each processor. The block distribution will place the first 16 rows (rows 0 through 15) on processor 0, the next 16 rows (rows 16 through 31) on processor 1, and so forth. You do not want to distribute the columns of the matrix at all, so you will use a *whole distribution* for the columns.

Although the distributions are selected at compile-time, the number of processors to use in each dimension is not specified until run-time. By specifying the number of processors at run-time, you can adapt your program to the configuration of the machine on which your application is running. The VSIPL++ API provides a `num_processors` function to tell you the total number of processors available. Of course, since each row should be kept on a single processor, the number of processors used in the column dimension is just one. So, here is the code required to create the map:

```
typedef Map<Block_dist, Whole_dist>               map_type;
map_type map = map_type(/*rows=*/num_processors(),
                        /*columns=*/1);
```

Next, you have to tell Sourcery VSIPL++ to use this map for the relevant views. Every view has an underlying *block*. The block indicates how the view's data is stored. Until this point, you have been using the default `Dense` block, which stores data in a continguous array on a single processor. Now, you want to use a continguous array on *multiple* processors, so you must explicitly distribute the block. Then, when declaring views, you must explicitly indicate that the view should use the distributed block:

```
typedef Dense<2, value_type, row2_type, map_type> block_type;
typedef Matrix<value_type, block_type>            view_type;
view_type data(npulse, nrange, map);
view_type tmp(npulse, nrange, map);
```

Performing the vector-matrix multiply requires a complete copy of `replica` on each processor. An ordinary map divides data among processors, but, here, the goal is to copy the same data to multiple processors. Sourcery VSIPL++ provides a special `Replicated_map` class to use in this situation. So, you should declare `replica` as follows:

```
  Replicated_map<1> replica_map;
  typedef Dense<1, value_type, row1_type, Replicated_map<1> >
                                                    replica_block_type;
  typedef Vector<value_type, replica_block_type>    replica_view_type;
  replica_view_type replica(nrange, replica_map);
```

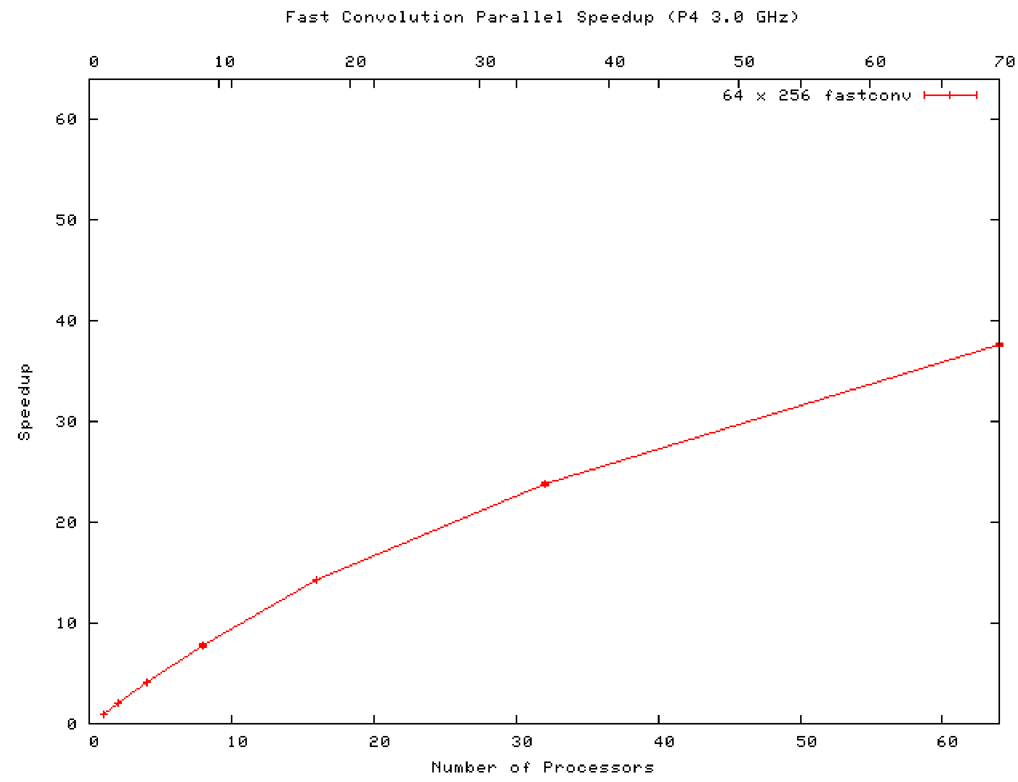
Because the application already uses implicitly parallel operators, no further changes are required. The entire algorithm (i.e., the part of the code that performs FFTs and vector-matrix multiplication) remains unchanged.

The complete parallel program is:

```
/***********************************************************************
  Included Files
***********************************************************************/

#include <vsip/initfin.hpp>
#include <vsip/support.hpp>
#include <vsip/signal.hpp>
#include <vsip/math.hpp>
#include <vsip/map.hpp>

using namespace vsip;



/***********************************************************************
  Main Program
***********************************************************************/

int
main(int argc, char** argv)
{
  // Initialize the library.
  vsipl vpp(argc, argv);

  typedef complex<float> value_type;

  typedef Map<Block_dist, Whole_dist>               map_type;
  typedef Dense<2, value_type, row2_type, map_type> block_type;
  typedef Matrix<value_type, block_type>            view_type;

  typedef Dense<1, value_type, row1_type, Replicated_map<1> >
                                                    replica_block_type;
  typedef Vector<value_type, replica_block_type>    replica_view_type;

  // Parameters.
  length_type npulse = 64; // number of pulses
  length_type nrange = 256; // number of range cells

  // Maps.
  map_type          map = map_type(num_processors(), 1);
  Replicated_map<1> replica_map;

  // Views.
  replica_view_type replica(nrange, replica_map);
  view_type         data(npulse, nrange, map);
  view_type         tmp (npulse, nrange, map);

  // A forward Fft for computing the frequency-domain version of
```

```
  // the replica.
  typedef Fft<const_Vector, value_type, value_type, fft_fwd, by_reference>
  for_fft_type;
  for_fft_type  for_fft (Domain<1>(nrange), 1.0);

  // A forward Fftm for converting the time-domain data matrix to the
  // frequency domain.
  typedef Fftm<value_type, value_type, row, fft_fwd, by_reference>
    for_fftm_type;
  for_fftm_type for_fftm(Domain<2>(npulse, nrange), 1.0);

  // An inverse Fftm for converting the frequency-domain data back to
  // the time-domain.
  typedef Fftm<value_type, value_type, row, fft_inv, by_reference>
    inv_fftm_type;
  inv_fftm_type inv_fftm(Domain<2>(npulse, nrange), 1.0/(nrange));

  // Initialize data to zero.
  data    = value_type();
  replica = value_type();

  // Before fast convolution, convert the replica to the the
  // frequency domain
  for_fft(replica);


  // Perform fast convolution:

  // Convert to the frequency domain.
  for_fftm(data, tmp);

  // Perform element-wise multiply for each pulse.
  tmp = vmmul<0>(replica, tmp);

  // Convert back to the time domain.
  inv_fftm(tmp, data);
}
```

The following graph shows the parallel speedup of the fast convolution program from 1 to 32 processors using a 3.0 GHz Pentium cluster system. As you can see, increasing the number of processors also increases the performance of the program.



2.2 Improving Parallel Temporal Locality

In the previous chapter, you improved the performance of the fast convolution program by exploiting temporary cache locality to process data while it was "hot" in the cache. In this section, you will convert that program to run efficiently in parallel.

If we apply maps (as in Section 2.1, “Parallel Fast Convolution”), but do not adjust the algorithm in use, the code in Section 1.2, “Serial Optimization: Temporal Locality” will not run faster when deployed on multiple processors. In particular, every processor will want to update `tmp` for every row. Therefore, all processors will perform the forward FFT and vector-multiply for each row of the matrix.

VSIPL++ provides *local subviews* to solve this problem. For a given processor and view, the local subview is that portion of the view located on the processor. You can obtain the local subview of any view by invoking its `local` member function:

```
  view_type::local_type      l_data     = data.local();)
```

Every view class defines a type (`local_type`) which is the type of a local subview. The `local_type` is the same kind of view as the view containing it, so, in this case, `l_data` is a matrix. There is virtually no overhead in creating a local subview like `l_data`. In particular, no data is copied; instead, `l_data` just refers to the local portion of `data`. We can now use the same cache-friendly algorithm from Section 1.2, “Serial Optimization: Temporal Locality”on the local subview:

```
rep_view_type::local_type l_replica = replica.local();

for (index_type l_r=0; l_r < l_data.size(0); ++l_r)
{
  for_fft(l_data.row(l_r), tmp);
```

```
   tmp *= l_replica;
   inv_fft(tmp, l_data.row(l_r));
 }
```

Because each processor now iterates over only the rows of the matrix that are local, there is no longer any duplicated effort. Applying maps, as in Section 2.1, “Parallel Fast Convolution” above, results in the following complete program:

```
/***********************************************************************
  Included Files
***********************************************************************/

#include <vsip/initfin.hpp>
#include <vsip/support.hpp>
#include <vsip/signal.hpp>
#include <vsip/math.hpp>
#include <vsip/map.hpp>

using namespace vsip;



/***********************************************************************
  Main Program
***********************************************************************/

int
main(int argc, char** argv)
{
  // Initialize the library.
  vsipl vpp(argc, argv);

  typedef complex<float> value_type;

  typedef Map<Block_dist, Whole_dist>               map_type;
  typedef Dense<2, value_type, row2_type, map_type> block_type;
  typedef Matrix<value_type, block_type>            view_type;

  typedef Dense<1, value_type, row1_type, Replicated_map<1> >
                                                    replica_block_type;
  typedef Vector<value_type, replica_block_type>    replica_view_type;

  // Parameters.
  length_type npulse = 64; // number of pulses
  length_type nrange = 256; // number of range cells

  // Maps.
  map_type          map = map_type(num_processors(), 1);
  Replicated_map<1> replica_map;

  // Views.
  replica_view_type  replica(nrange, replica_map);
  view_type          data(npulse, nrange, map);
  Vector<value_type> tmp(nrange);

  // A forward Fft for converting the time-domain data to the
  // frequency domain.
  typedef Fft<const_Vector, value_type, value_type, fft_fwd, by_reference>
  for_fft_type;
  for_fft_type  for_fft(Domain<1>(nrange), 1.0);

  // An inverse Fft for converting the frequency-domain data back to
  // the time-domain.
  typedef Fft<const_Vector, value_type, value_type, fft_inv, by_reference>
    inv_fft_type;
  inv_fft_type  inv_fft(Domain<1>(nrange), 1.0/nrange);
```

```
  // Initialize data to zero.
  data    = value_type();
  replica = value_type();

  // Before fast convolution, convert the replica into the
  // frequency domain
  for_fft(replica.local());

  view_type::local_type         l_data    = data.local();
  replica_view_type::local_type l_replica = replica.local();

  for (index_type l_r=0; l_r < l_data.size(0); ++l_r)
  {
    for_fft(l_data.row(l_r), tmp);
    tmp *= l_replica;
    inv_fft(tmp, l_data.row(l_r));
  }
}
```

2.2.1 Implicit Parallelism: Parallel Foreach

You may feel that the original formulation was simpler and more intuitive than the more-efficient variant using explicit loops. Sourcery VSIPL++ provides an extension to the VSIPL++ API that allows you to retain the elegance of that formulation while still obtaining the temporal locality obtained with the style shown in the previous two sections.

In particular, Sourcery VSIPL++ provides a "parallel foreach" operator. This operator applies an arbitrary user-defined function (or an object that behaves like a function) to each of the rows or columns of a matrix. In this section, you will see how to use this approach.

First, declare a `Fast_convolution` template class. The template parameter `T` is used to indicate the value type of the fast convolution computation (such as `complex<float>`):

```
template <typename T>
 class Fast_convolution
 {
```

This class will perform the forward FFT and inverse FFTs on each row, so you must declare the FFTs:

```
  typedef Fft<const_Vector, T, T, fft_fwd, by_reference> for_fft_type;
   typedef Fft<const_Vector, T, T, fft_inv, by_reference> inv_fft_type;

   Vector<T>    replica_;
   Vector<T>    tmp_;
   for_fft_type for_fft_;
   inv_fft_type inv_fft_;
```

Next, define a constructor for `Fast_convolution`. The constructor stores a copy of the replica, and also uses the replica to determine the number of elements required for the FFTs and temporary vector.

```
template <typename Block>
   Fast_convolution(
     Vector<T, Block> replica)
     : replica_(replica.size()),
       tmp_    (replica.size()),
       for_fft_(Domain<1>(replica.size()), 1.0),
       inv_fft_(Domain<1>(replica.size()), 1.0/replica.size())
   {
     replica_ = replica;
   }
```

The most important part of the `Fast_convolution` class is the `operator()` function. This function performs a fast convolution for a single row of the matrix:

```
  template <typename       Block1,
      typename       Block2,
      dimension_type Dim>
   void operator()(
     Vector<T, Block1> in,
     Vector<T, Block2> out,
     Index<Dim>        /*idx*/)
   {
     for_fft_(in, tmp_);
     tmp_ *= replica_;
     inv_fft_(tmp_, out);
   }
```

The `foreach_vector` template will apply the new class you have just defined to the rows of the matrix:

```
  Fast_convolution<value_type> fconv(replica.local());
   foreach_vector<tuple<0, 1> >(fconv, data);
```

The resulting program contains no explicit loops, but still has good temporal locality. Here is the complete program, using the parallel foreach operator:

```
/***********************************************************************
  Included Files
***********************************************************************/

#include <vsip/initfin.hpp>
#include <vsip/support.hpp>
#include <vsip/signal.hpp>
#include <vsip/math.hpp>
#include <vsip/map.hpp>
#include <vsip/parallel.hpp>

using namespace vsip;



/***********************************************************************
  Main Program
***********************************************************************/

template <typename T>
class Fast_convolution
{
  typedef Fft<const_Vector, T, T, fft_fwd, by_reference> for_fft_type;
  typedef Fft<const_Vector, T, T, fft_inv, by_reference> inv_fft_type;

public:
  template <typename Block>
  Fast_convolution(
    Vector<T, Block> replica)
    : replica_(replica.size()),
      tmp_    (replica.size()),
      for_fft_(Domain<1>(replica.size()), 1.0),
      inv_fft_(Domain<1>(replica.size()), 1.0/replica.size())
  {
    replica_ = replica;
  }

  template <typename       Block1,
     typename       Block2,
     dimension_type Dim>
  void operator()(
```

```
    Vector<T, Block1> in,
    Vector<T, Block2> out,
    Index<Dim>        /*idx*/)
  {
    for_fft_(in, tmp_);
    tmp_ *= replica_;
    inv_fft_(tmp_, out);
  }

  // Member data.
private:
  Vector<T>    replica_;
  Vector<T>    tmp_;
  for_fft_type for_fft_;
  inv_fft_type inv_fft_;
};



int
main(int argc, char** argv)
{
  // Initialize the library.
  vsipl vpp(argc, argv);

  typedef complex<float> value_type;

  typedef Map<Block_dist, Whole_dist>               map_type;
  typedef Dense<2, value_type, row2_type, map_type> block_type;
  typedef Matrix<value_type, block_type>            view_type;

  typedef Dense<1, value_type, row1_type, Replicated_map<1> >
                                                    replica_block_type;
  typedef Vector<value_type, replica_block_type>    replica_view_type;

  // Parameters.
  length_type npulse = 64; // number of pulses
  length_type nrange = 256; // number of range cells

  // Maps.
  map_type          map = map_type(num_processors(), 1);
  Replicated_map<1> replica_map;

  // Views.
  replica_view_type replica(nrange, replica_map);
  view_type         data(npulse, nrange, map);
  view_type         tmp (npulse, nrange, map);

  // A forward Fft for computing the frequency-domain version of
  // the replica.
  typedef Fft<const_Vector, value_type, value_type, fft_fwd, by_reference>
  for_fft_type;
  for_fft_type  for_fft (Domain<1>(nrange), 1.0);

  Fast_convolution<value_type> fconv(replica.local());

  // Initialize data to zero.
  data    = value_type();
  replica = value_type();

  // Before fast convolution, convert the replica into the
  // frequency domain
  for_fft(replica.local());

  // Perform fast convolution.
  foreach_vector<tuple<0, 1> >(fconv, data);
```

```
}
```

2.3 Performing I/O

The previous sections have ignored the acquisition of actual sensor data by setting the input data to zero. This section shows how to extend the I/O techniques introduced in the previous chapter to initialize `data` before performing the fast convolution.

Let's assume that all of the input data arrives at a single processor via DMA. This data must be distributed to the other processors to perform the fast convolution. So, the input processor is special, and is not involved in the computation proper.

To describe this situation in Sourcery VSIPL++, you need two maps: one for the input processor (`map_in`), and one for the compute processors (`map`). These two maps will be used to define views that can be used to move the data from the input processor to the compute processors. Let's assume that the input processor is processor zero. Then, create `map_in` as follows, mapping all data to the single input processor:

```
  typedef Map<> map_type;
  Vector<processor_type> pvec_in(1);  pvec_in(0)  = 0;
  map_type map_in (pvec_in,  1,  1);
```

In contrast, `map` distributes rows across all of the compute processors:

```
  // Distribute computation across all processors:
  map_type map    (num_processors(), 1);
```

Because the data will be arriving via DMA, you must explicitly manage the memory used by Sourcery VSIPL++. Each processor must allocate the memory for its local portion of `data_in_block`. (All processors except the actual input processor will allocate zero bytes, since the input data is located on a single processor.) The code required to set up the views is:

```

  block_type data_in_block(npulse, nrange, NULL, map);
  view_type data_in(data_in_block);
  view_type data   (npulse, nrange, map);
  size_t size = subblock_domain(data_in).size();
  auto_ptr<value_type> buffer(new value_type[size]);
  data_in.block()->rebind(buffer);
```

Now, you can perform the actual I/O. The I/O (including any calls to low-level DMA routines) should only be performed on the input processor. The `subblock` function is used to ensure that I/O is only performed on the appropriate processors:

```
  if (subblock(data_in) != no_subblock)
   {
     data_in.block().release(false);
     // ... perform IO into data_in ...
     data_in.block().admit(true);
   }
```

Once the I/O completes, you can move the data from `data_in` to `data` for processing. In the VSIPL++ API, ordinary assignment (using the = operator) will perform all communication necessary to distribute the data. So, performing the "scatter" operation is just:

```
  data = data_in;
```

The complete program is:

```
/***********************************************************************
  Included Files
***********************************************************************/

#include <vsip/initfin.hpp>
#include <vsip/support.hpp>
#include <vsip/signal.hpp>
#include <vsip/math.hpp>
#include <vsip/map.hpp>
#include <vsip/parallel.hpp>

using namespace vsip;



/***********************************************************************
  Main Program
***********************************************************************/

template <typename       ViewT,
   dimension_type Dim>
ViewT
create_view_wstorage(
  Domain<Dim> const&                          dom,
  typename ViewT::block_type::map_type const& map)
{
  typedef typename ViewT::block_type block_type;
  typedef typename ViewT::value_type value_type;

  block_type* block = new block_type(dom, (value_type*)0, map);
  ViewT view(*block);
  block->decrement_count();

  if (subblock(view) != no_subblock)
  {
    size_t size = subblock_domain(view).size();
    value_type* buffer = vsip::impl::alloc_align<value_type>(128, size);
    block->rebind(buffer);
  }

  block->admit(false);

  return view;
}



template <typename ViewT>
void
cleanup_view_wstorage(ViewT view)
{
  typedef typename ViewT::value_type value_type;
  value_type* ptr;

  view.block().release(false, ptr);
  view.block().rebind((value_type*)0);

  if (ptr) vsip::impl::free_align((void*)ptr);
}



template <typename ViewT>
ViewT
create_view_wstorage(
  length_type                                 rows,
  length_type                                 cols,
```

```
  typename ViewT::block_type::map_type const& map)
{
  return create_view_wstorage<ViewT>(Domain<2>(rows, cols), map);
}



template <typename ViewT>
ViewT
create_view_wstorage(
  length_type                                 size,
  typename ViewT::block_type::map_type const& map)
{
  return create_view_wstorage<ViewT>(Domain<1>(size), map);
}




int
main(int argc, char** argv)
{
  // Initialize the library.
  vsipl vpp(argc, argv);

  typedef complex<float> value_type;

  typedef Map<Block_dist, Block_dist>               map_type;
  typedef Dense<2, value_type, row2_type, map_type> block_type;
  typedef Matrix<value_type, block_type>            view_type;

  typedef Dense<1, value_type, row1_type, Replicated_map<1> >
                                                    replica_block_type;
  typedef Vector<value_type, replica_block_type>    replica_view_type;

  typedef Dense<1, value_type, row1_type, Map<> >   replica_io_block_type;
  typedef Vector<value_type, replica_io_block_type> replica_io_view_type;

  // Parameters.
  length_type npulse = 64; // number of pulses
  length_type nrange = 256; // number of range cells

  length_type np = num_processors();

  // Processor sets.
  Vector<processor_type> pvec_in(1);  pvec_in(0)  = 0;
  Vector<processor_type> pvec_out(1); pvec_out(0) = np-1;

  // Maps.
  map_type          map_in (pvec_in,  1, 1);
  map_type          map_out(pvec_out, 1, 1);
  map_type          map_row(np, 1);
  Replicated_map<1> replica_map;

  // Views.
  view_type data(npulse, nrange, map_row);
  view_type tmp (npulse, nrange, map_row);
  view_type data_in (create_view_wstorage<view_type>(npulse, nrange, map_in));
  view_type data_out(create_view_wstorage<view_type>(npulse, nrange, map_out));
  replica_view_type    replica(nrange);
  replica_io_view_type replica_in(
    create_view_wstorage<replica_io_view_type>(nrange, map_in));

  // A forward Fft for computing the frequency-domain version of
  // the replica.
  typedef Fft<const_Vector, value_type, value_type, fft_fwd, by_reference>
  for_fft_type;
```

```
  for_fft_type  for_fft (Domain<1>(nrange), 1.0);

  // A forward Fftm for converting the time-domain data matrix to the
  // frequency domain.
  typedef Fftm<value_type, value_type, row, fft_fwd, by_reference>
    for_fftm_type;
  for_fftm_type for_fftm(Domain<2>(npulse, nrange), 1.0);

  // An inverse Fftm for converting the frequency-domain data back to
  // the time-domain.
  typedef Fftm<value_type, value_type, row, fft_inv, by_reference>
    inv_fftm_type;
  inv_fftm_type inv_fftm(Domain<2>(npulse, nrange), 1.0/(nrange));

  // Perform input IO
  if (subblock(data_in) != no_subblock)
  {
    data_in.block().release(false);
    // ... perform IO ...
    data_in.block().admit(true);

    replica_in.block().release(false);
    // ... perform IO ...
    replica_in.block().admit(true);

    data_in    = value_type();
    replica_in = value_type();

    // Before fast convolution, convert the replica into the
    // frequency domain
    for_fft(replica_in.local());
  }

  // Scatter data
  data    = data_in;
  replica = replica_in;

  // Perform fast convolution.
  for_fftm(data, tmp);  // Convert to the frequency domain.
  tmp = vmmul<0>(replica, tmp); // Perform element-wise multiply.
  inv_fftm(tmp, data);  // Convert back to the time domain.

  // Gather data
  data_out = data;

  // Perform output IO
  if (subblock(data_out) != no_subblock)
  {
    data_out.block().release(true);
    // ... perform IO ...
    data_out.block().admit(false);
  }

  // Cleanup
  cleanup_view_wstorage(data_in);
  cleanup_view_wstorage(data_out);
  cleanup_view_wstorage(replica_in);
}
```

The technique demonstrated in this section extends easily to the situation in which the sensor data is arriving at multiple processors simultaneously. To distribute the I/O across multiple processors, just add them to `map_in`'s processor set `pvec_in`:

```
  Vector<processor_type> pvec_in(num_io_proc);
  pvec_in(0)              = 0;
```

```
...
pvec_in(num_io_proc-1)  = ...;
```

Chapter 3
Performance

3.1 Library Profiling

Sourcery VSIPL++ provides library profiling features that speed application development by locating and quantifying the expensive computations in your algorithm. These profiling capabilities provide timing data for signal processing functions (such as FFTs), linear algebra computations (such as matrix multiply), and elementwise expressions (such as vector addition). Profiling is enabled by defining a macro when compiling and linking your application. For complete instructions, see Section 3.1.1, “Enabling Profiling” below. A full listing of functions covered is shown in Table 3.1, “Operations Supporting Profiling”.

The profiler operates in two modes. If you want to know how particular types of computations (such as all FFTs of a given size) are performing, then you can use the "accumulate" mode. In this mode, Sourcery VSIPL++ will keep track of the total amount of time spent performing the computation of interest and will report the average runtime and average MFLOP/s for that computation. In contrast, if you want complete information about all of the individual computations performed by your application, you can use "trace" mode. In this mode, Sourcery VSIPL++ will produce a log showing the time used and MFLOP/s for each individual computation.

In addition to the accumulate and trace modes, which have pre-defined output formats, Sourcery VSIPL++ exposes a profiling API that you can use to gather data directly on individual objects, such as FFTs. If you need finer control of what operations are profiled, or if you want to record the profiling data in a custom format, you may wish to use this API directly. See Section 3.1.4, “Performance API” for more details.

Section	Operations
signal	`Convolution, Correlation, Fft, Fir and Iir`
math.matvec	`dot, dotcvj, trans, herm, kron, outer, gemp, gems, cumsum and modulate`
fns	`1-D, 2-D and 3-D Loop Fusion, Copy, Transpose, Dense Block, SIMD and vendor libraries`

See the file `profiling.txt` for a detailed explanation of the profiler output for each of the functions above. See the file `profiling.txt` for a detailed explanation of the profiler output for each of the functions above. For information about how to configure the library for profiling, see the Quickstart also.

3.1.1 Enabling Profiling

To enable profiling, define `-DVSIP_IMPL_PROFILER=`*`mask`* on the command line when compiling your program. On many systems, this option may be added to the CXXFLAGS variable in the project makefile.

This macro enables profiling operations in several different areas of the library, depending on the value of *`mask`*. To profile all operations, use the value `15`. See Table 5.1, “Profiling Configuration Mask” for other possible values.

Note

Profiling support requires that you link with a version of Sourcery VSIPL++ that supports profiling. If you have received a binary distribution of Sourcery VSIPL++ from CodeSourcery, you probably already have an appropriate version of the library. If you are building Sourcery VSIPL++ yourself, see the Quickstart guide for more information about the requirements for building Sourcery VSIPL++ with profiling enabled.

3.1.2 Accumulating Profile Data

To use the accumulate mode, you must declare a `Profile` object. Sourcery VSIPL++ will collect profiling data throughout its lifetime. When the object goes out of scope, the data collected by profiling will be written to a log file. For example, to profile your entire program, with all data written to the file `profile.txt`, you would add this line:

```
Profile profile("profile.txt", pm_accum);
```

to the beginning of your `main` function, after initializing Sourcery VSIPL++. Then, when the program exits, this object will go out of scope and profiling data will be written to the output file. For this reason, only one object of this type may be in scope at any given time.

If you are profiling your entire program, you may specify options on the command line that perform the equivalent of the above two steps:

```
--vsipl++-profile-mode=accum --vsipl++-profile-output=profile.txt
```

Using this technique on the example program `fce-serial.cpp` from Section 1.1, “Fast Convolution”, the profiler gives following output:

```
# mode: pm_accum
# timer: x86_64_tsc_time
# clocks_per_sec: 3591375104
#
# tag : total ticks : num calls : op count : mops
Expr_Dense 2D *(C,s) 64x256 : 687285 : 1 : 32768 : 171.228
Expr_Loop 1D *(C,s) 16384 : 653265 : 1 : 32768 : 180.145
Expr_Loop_Vmmul 2D vmmul(C,C) 64x256 : 1539531 : 1 : 98304 : 229.321
Expr_SIMD_VV-simd::vmul 1D *(C,C) 256 : 316674 : 64 : 1536 : 1114.86
Fft 1D Fwd C-C by_ref     256x1 : 142119 : 1 : 10240 : 258.767
Fftm 2D Fwd C-C by_ref      64x256 : 1188144 : 1 : 1146880 : 3466.65
Fftm 2D Inv C-C by_ref      64x256 : 1559304 : 1 : 1146880 : 2641.48
```

The log file contains a line corresponding to each computation (or "event"). The first column gives a name for the event. The second column is the total amount of time spent in this operation in "ticks". (You can convert ticks to seconds by dividing by the value given by the "clocks_per_sec" value in the profiling header.) The third column indicates the number of times this operation was performed. The fourth column indicates the number of mathematical operations performed during the computation. (This is the number of operations required to perform the computation once, not the total. Multiply by the third column to obtain the total.) The last column gives the achieved throughput for the computation in Millions of Operations per Seconds (MOP/s).

3.1.2.1 Analyzing Profile Data

Having collected the data, you can use it to see how efficiently the program is using the available hardware. Although the lines in the profiling output are sorted alphabetically, it is often more useful to consider the events in the order they occur in your program. The following sections use this methodology to analyze the performance in the four phases of the fast-convolution computation.

3.1.2.1.1 Setup

The only computation performed in the setup phase is a forward FFT that maps the pulse replica into the frequency domain. This computation corresponds to the following line of the profiling data:

```
Fft Fwd C-C by_ref 256 : 142119 : 1 : 10240 : 258.767
```

The "Fft Fwd C-C by_ref 256" tag indicates that this computation is a 256-element forward FFT with complex, single-precision inputs and outputs, returning its result by reference. The notation used for data types (e.g., "C-C" in this example) is given in Table 5.2, “Data Type Names”.

3.1.2.1.2 Convert to frequency domain

The next step of the computation is to convert from the time domain to the frequency domain. In particular, an FFT is applied to a data cube of 64 pulses, each containing 256 range cells:

```
Fftm Fwd row_type C-C by_ref 64x256 : 1188144 : 1 : 1146880 : 3466.65
```

For this FFT, the size is reported differently (rows x columns) because this is a two-dimensional FFT. The operation count (1.1 million) far outweighs that of any other step, except the inverse FFT. The performance measured was 3.5 GFLOPS/s on a 3.6 GHz Xeon. Since the theoretical peak performance on such a machine is about 14.4 GFLOP/s, the program has achieved an a very good 24% of peak. Other example programs measure in-cache FFT perfomance on vectors of the same size at 4.9 GFLOP/s. Therefore, considering that the 3.5 GFLOP/s includes cache overheads, the result is still good.

3.1.2.1.3 Convolution

The actual convolution consists of a vector-matrix multiplication. The corresponding profiling output is:

```
Expr_Loop_Vmmul 2D vmmul(C,C) 64x256 : 1539531 : 1 : 98304 : 229.321
```

Sourcery VSIPL++ chose to evaluate this expression by performing a row-wise vector-vector multiplication on each of the rows of the matrix. Therefore, there is a second line:

```
Expr_SIMD_VV-simd::vmul 1D *(C,C) 256 : 316674 : 64 : 1536 : 1114.86
```

The tag used for this expression is "*(C,C)". The profiling tag for many operations is shown using a prefix notation; the operation performed is followed by the types of the arguments. The "simd" tag indicates that VSIPL++ used the Single Instruction Multiple Data (SIMD) facilities on the Xeon architecture for maximum performance.

The tick count for the vector-matrix multiplication (vmmul) includes the time spent in the multiple row-wise scalar-vector multiplications. Therefore the total number of time used by the program is *not* the sum of the tick counts given for each line.

3.1.2.1.4 Convert back to time domain

The last step of the algorithm is to convert back to the time domain by using an inverse FFT. An inverse FFT is computationally equivalent to a forward FFT, except that an additional multiplication is performed to handle scaling. The lines corresponding to the inverse FFT are:

```
Expr_Dense 2D *(C,s) 64x256 : 687285 : 1 : 32768 : 171.228
Expr_Loop 1D *(C,s) 16384 : 653265 : 1 : 32768 : 180.145
Fftm Inv row_type C-C by_ref 64x256 : 1559304 : 1 : 1146880 : 2641.48
```

The first line describes a evaluation of a "dense" two- dimensional multiplication between a single-precision complex view (a matrix) and a single-precision scalar. Note that scalars are represented using lower-case equivalents for the data types in the table above.

A "dense" matrix is one in which the values are packed tightly in memory with no intervening space between the rows or columns. Therefore, the two-dimensional multiplication can be thought of as a 1-dimensional multiplication of a long vector. The evaluation of the 2-D operation includes the time required for the 1-D operation, together with a small amount of overhead. You can tell that this is the case as the time shown on the first line is slightly greater than the time shown on the second. Both show the same number of operations because they are referring to the same calculation.

Similarly, the time required for the inverse FFT includes both the time spent actually computing the FFT as well as the time required for the scaling multiplication. Because the multiplication is not included in the theoretical operation count, the MOP/s count shown is somewhat smaller than than for the forward FFT.

The analysis presented in this section is only a portion of what one would do to verify an algorithm is performing as desired. Core routines utilizing techniques such as the fast convolution method comprise only a portion of larger programs whose performance is also of interest. The profiling capabilities utilized here can be extended to cover those areas of the application as well. See Section 3.2, “Application Profiling” for more details.

3.1.3 Trace Profile Data

By passing an additional parameter to the 'Profile' constructor, you can switch from "accumulate" mode to "trace" mode. This line:

```
Profile profile("profile.txt", pm_trace);
```

will cause Sourcery VSIPL++ to enter trace profiling mode. All computations performed by your program while `profile` is in scope will be traced. This mode is useful for investigating the execution sequence of your program. The profiler records each library call as a pair of events, allowing you to see where each call was made and when it returned. This provides two time stamps per call, showing not only which functions were executed, but how they were nested with respect to one another. Long traces can result when profiling in this mode, so be sure to avoid gathering more data than you have memory to store (and have time to process later). The output is very similar to the output in accumulate mode.

Here is a sample of the output obtained by running the fast convolution example in trace mode, which can also be run with the options

```
--vsipl++-profile-mode=trace --vsipl++-profile-output=profile.txt
```

```
# mode: pm_trace
# timer: x86_64_tsc_time
# clocks_per_sec: 3591375104
#
# index : tag : ticks : open id : op count
1 : Fft Fwd C-C by_ref 256 : 2996724026993517 : 0 : 10240
2 : Fft Fwd C-C by_ref 256 : 2996724027053115 : 1 : 0
3 : Fast Convolution : 2996724027065535 : 0 : 2424832
4 : Fftm Fwd row_type C-C by_ref 64x256 : 2996724027068541 : 0 : 1146880
5 : Fftm Fwd row_type C-C by_ref 64x256 : 2996724028229361 : 4 : 0
6 : Expr_Loop_Vmmul 2D vmmul(C,C) 64x256 : 2996724028324626 : 0 : 98304
7 : Expr_SIMD_VV-simd::vmul 1D *(C,C) 256 : 2996724028378509 : 0 : 1536
8 : Expr_SIMD_VV-simd::vmul 1D *(C,C) 256 : 2996724028384656 : 7 : 0
9 : Expr_SIMD_VV-simd::vmul 1D *(C,C) 256 : 2996724028414761 : 0 : 1536
10 : Expr_SIMD_VV-simd::vmul 1D *(C,C) 256 : 2996724028422465 : 9 : 0
...
130 : Expr_SIMD_VV-simd::vmul 1D *(C,C) 256 : 2996724029681025 : 129 : 0
131 : Expr_SIMD_VV-simd::vmul 1D *(C,C) 256 : 2996724029698458 : 0 : 1536
132 : Expr_SIMD_VV-simd::vmul 1D *(C,C) 256 : 2996724029701833 : 131 : 0
133 : Expr_SIMD_VV-simd::vmul 1D *(C,C) 256 : 2996724029717412 : 0 : 1536
134 : Expr_SIMD_VV-simd::vmul 1D *(C,C) 256 : 2996724029721111 : 133 : 0
135 : Expr_Loop_Vmmul 2D vmmul(C,C) 64x256 : 2996724029722893 : 6 : 0
136 : Fftm Inv row_type C-C by_ref 64x256 : 2996724029724846 : 0 : 1146880
137 : Expr_Dense 2D *(C,s) 64x256 : 2996724030603048 : 0 : 32768
138 : Expr_Loop 1D *(C,s) 16384 : 2996724030622578 : 0 : 32768
139 : Expr_Loop 1D *(C,s) 16384 : 2996724031260696 : 138 : 0
```

```
140 : Expr_Dense 2D *(C,s) 64x256 : 2996724031262739 : 137 : 0
141 : Fftm Inv row_type C-C by_ref 64x256 : 2996724031264422 : 136 : 0
142 : Fast Convolution : 2996724031265574 : 3 : 0
```

For each event, the Sourcery VSIPL++ outputs an event number, an indentifying tag, and the current timestamp (in "ticks"). The next two fields differ depending on whether the event marks the entry point of a library function or its return. At the start of a call, a zero is shown followed by the estimated count of floating point operations for that function. When returning from a call, the profiler displays the event number created when the function was called, followed by a zero. In all cases, the timestamp (and intervals) may be converted to seconds by dividing by the 'clocks_per_second' constant in the log file header.

In the break shown by the ellipses, the program is in the middle of performing the vector-matrix multiply, which has been broken down into 64 separate vector-multiplies. The first two FFT's are completed, as shown by the fact that each have two entries, one for where the computation began and one for where it ended. The Vmmul function has started, but not yet finished, so it only has one entry as of yet.

3.1.4 Performance API

An additional interface is provided for getting run-time profile data. This allows you to selectively monitor the performance of a particular instance of a VSIPL class such as Fft, Convolution or Correlation.

Classes with the Performance API provide a function called `impl_performance` that takes a std::string parameter and returns a single-precision floating point number.

The following call shows how to obtain an estimate of the performance in number of operations per second:

```
float mops = fwd_fft.impl_performance("mops");
```

The definition of "operation" varies depending on the object and type of data being processed. For example, a single-precison Fft object will return the number of single-precison floating-point operations performed per second while a complex double-precision FFT object will return the number of double- precision floating-point operations performed per second.

The table below lists the current types of information available.

Parameter	Description
`mops`	performance in millions of operations per second
`count`	number of times invoked
`time`	total time spent performing the operation, in seconds
`op_count`	number of floating point operations per invocation
`mbs`	data rate in millions of bytes per second (not applicable in for all operations)

3.2 Application Profiling

Sourcery VSIPL++ provides an interface that allows you to instrument your own code through the `Scope_event` class.

To create a `Scope_event`, call the constructor, passing it a std::string that will become the event tag and, optionally, an integer value expressing the number of floating point operations that will be performed by the time the `Scope_event` object is destroyed. For example, to measure the time taken to compute the main portion in the fast convolution example, modify the source as follows:

```
#include <vsip/initfin.hpp>
#include <vsip/support.hpp>
#include <vsip/impl/profile.hpp>

using namespace vsip;
using namespace impl;

int
main()
{
  vsipl init;

  int data[1024];
  for (int i = 0; i < 1024; ++i)
    data[i] = i;

  profile::Scope_enable scope("/dev/stdout" );

  // This computation will be timed and included in the profiler output.
  {
    profile::Scope_event user_event("sum of squares", 2 * 1024);

    int sum = 0;
    for (int i = 0; i < 1024; ++i)
      sum += data[i] * data[i];
  }

  return 0;
}
```

The operation count passed as the second parameter is the sum of the two FFT's and the vector-matrix multiply. This resulting profile data is identical in format to that used for profiling library functions.

```
# mode: pm_accum
# timer: x86_64_tsc_time
# clocks_per_sec: 3591375104
#
# tag : total ticks : num calls : op count : mops
Expr_Dense 2D *(C,s) 64x256 : 669627 : 1 : 32768 : 175.743
Expr_Loop 1D *(C,s) 16384 : 637974 : 1 : 32768 : 184.462
Expr_Loop_Vmmul 2D vmmul(C,C) 64x256 : 1470033 : 1 : 98304 : 240.162
Expr_SIMD_VV-simd::vmul 1D *(C,C) 256 : 332109 : 64 : 1536 : 1063.04
Fast Convolution : 4256109 : 1 : 2424832 : 2046.11
Fft Fwd C-C by_ref 256 : 81261 : 1 : 10240 : 452.562
Fftm Fwd row_type C-C by_ref 64x256 : 1152891 : 1 : 1146880 : 3572.65
Fftm Inv row_type C-C by_ref 64x256 : 1535049 : 1 : 1146880 : 2683.22
```

Now the output has a new line that represents the time that the `Scope_event` object exists, i.e. only while the program executes the three main steps of the fast convolution.

```
Fast Convolution : 4256109 : 1 : 2424832 : 2046.11
```

This technique can also be used to determine the overall performance of a critical piece of code, even if an accurate operation count is not known. By knowing the amount of time consumed when executing a section of code, you can quickly obtain the "latency" of the operation, and thereby determine the number of times the operation can be performed in a given unit of time. This technique can be used to estimate the percent system utilization for single processor systems and/or determine the number of nodes needed in a multi-processor system.

Combining both application and library profiling is possible in either trace or accumulate modes. Performance events can be nested to help identify points of interest in your program. Events can be used to label different regions, such as the different steps in the fast convolution example. When examining the trace output, profile events for library functions, such as FFTs, will be nested within profile events for application regions.

Part II. Reference

The sections in Part II form a reference manual for Sourcery VSIPL++.

Chapter 4
API overview

4.1 Views

VSIPL++ defines a number of mathematical types for linear algebra: vectors, matrices, and (3D) tensors. They provide a high-level interface suitable for solving linear algebra equations. All these types give an intuitive access to their elements. They are collectively referred to as views as the actual data they provide access to is sharable among views.

```
// create an uninitialized vector of 10 elements
Vector<float> vector1(10);

// create a zero-initialized vector of 10 elements
Vector<float> vector2(10, 0.f);

// assign vector2 to vector1
vector1 = vector2;

// set the first element to 1.f
vector1(0) = 1.f;

// access the last element
float value = vector1(9);
```

Every view has an associated Block, which is responsible for storing or computing the data in the view. More than one view may be associated with the same block.

Depending on how a view is constructed it may allocate the block, or refer to a block from another view. All views created via copy-construction will share the blocks with the views they were constructed with.

```
// copy-construct a new vector from an existing one
Vector<float> vector3(vector1);

// modify the original vector
vector1.put(1, 1.f);

// the new vector reflects the new value
assert(vector3(1) == 1.f);
```

4.1.1 Domains

A domain represents a logical set of indices. Constructing a one-dimensional domain requires a start index, a stride, and a length. For convenience an additional constructor is provided that only takes a length argument, setting the starting index to 0 and the stride to 1.

```
// [0...9]
vsip::Domain<1> all(10);

// [0, 2, 4, 6, 8]
vsip::Domain<1> pair(0, 2, 5);

// [1, 3, 5, 7, 9]
vsip::Domain<1> impair(1, 2, 5);
```

Two- and three-dimensional domains are composed out of one-dimensional ones.

```
// [(0,0), (0,2), (0,4),...,(1,0),...]
vsip::Domain<2> dom(Domain<1>(10), Domain<1>(0, 2, 5));
```

Views provide convenient access to subviews in terms of subdomains. For example, to assign new values to every second element of a vector, simply write:

```
// assign 1.f to all elements in [0, 2, 4, 6, 8]
vector1(pair) = 1.f;
```

All complex views provide real and imaginary subviews:

```
// a function manipulating a float vector in-place
void filter(Vector<float>);

// create a complex vector
Vector<complex> vector(10);

// filter the real part of the vector
filter(vector.real());
```

4.1.2 Elementwise Operations

VSIPL++ provides elementwise functions and operations that are defined in terms of their scalar counterpart.

```
Vector<float> vector1(10, 1.f);

Vector<complex<float> > vector2(10, complex<float>(2.f, 1.f));

// apply operator+ elementwise
Vector<complex<float> > sum = vector1 + vector2;

// apply conj(complex<float>) elementwise
Vector<complex<float> > result = conj(sum);
```

For binary and ternary functions VSIPL++ provides overloaded versions with mixed view / scalar parameter types:

```
// delegates to operator*=(complex<float>, complex<float>)
result *= complex<float>(2.f, 0.f);

// error: no operator*=(complex<float>, complex<double>)
result *= complex<double>(5., 0.);
```

4.1.3 Vectors

4.1.4 Matrices

Matrices provide a number of additional subviews. All of them

```
Matrix<float> matrix(10, 10);
//...

// return the first column vector
Matrix<float>::col_type column = matrix.col(0);

// return the first row vector
Matrix<float>::row_type row = matrix.row(0);

// return the diagonal vector
Matrix<float>::diag_type diag = matrix.diag();

// return the transpose of the matrix
Matrix<float>::transpose_type trans = matrix.trans();
```

4.1.5 Tensors

Tensors are three-dimensional views. In addition to the types, methods, and operations defined for all view types, they provide additional methods to access specific subviews:

```
// a 5x6x3 cube initialized to 0.f
Tensor<float> tensor(5, 6, 3, 0.f);

// a subvector
Vector<float> vector1 = tensor(0, 0, whole_domain);
```

The symbolic constant `whole_domain` is used to indicate that the whole domain the target view holds in a particular dimension should be used. In the example above that not only provides a more compact syntax compared to explicitely writing Domain<1>(6) but it also enables better optimization opportunities.

```
// a submatrix
Matrix<float> plane = tensor(whole_domain, 0, whole_domain);

Tensor<float> upper_half = tensor(whole_domain, Domain<1>(3), whole_domain);
```

4.2 Blocks

The data accessed and manipulated through the View API is actually stored in blocks. Blocks are reference-countable, allowing multiple views to share a single block. However, blocks may themselves be proxies that access their data from other blocks (possibly computing the actual values only when these values are accessed). These blocks are thus not modifiable. They aren't allocated directly by users, but rather internally during the creation of subviews, for example.

4.2.1 Dense Blocks

The default block type used by all views is Dense, meaning that Vector<float> is actually a shorthand notation for Vector<float, Dense<1, float> >. As such Dense is the most common block type directly used by users. Dense blocks are modifiable and allocatable. They explicitely store one value for each index in the supported domain:

```
// create uninitialized array of size 3
Dense<1, float> array1(Domain<1>(3));

// create array of size 3 with initial values 0.f
Dense<1, float> array2(Domain<1>(3), 0.f);

// assign array2 to array1
array1 = array2;

// access first item
float value = array1.get(0);

// modify first item
array1.set(0, 1.f);
```

4.2.1.1 Layout

Beside the two template parameters already discussed above, Dense provides an optional third parameter to specify its dimension ordering. Using this parameter you can explicitely control whether a 2-dimensional array should be stored in row-major or column-major format:

```
// array using row-major ordering
Dense<2, float, tuple<0, 1> > rm_array;
```

```
// array using column-major ordering
Dense<2, float, tuple<1, 0> > cm_array;
```

Row-major arrays store rows as contiguous chunks of memory. Iterating over its columns will thus access close-by memory regions, reducing cache misses and thus enhancing performance:

```
length_type size = rm_array.size(0);
for (index_type i = 0; i != size; ++i)
  rm_array.set(i, 1.f);
```

4.2.1.2 User Storage

They also allow user-storage to be provided, either at construction time, or later via a call to `rebind`:

```
float *storage = ...;

// create array operating on user storage
Dense<1, float> array3(Domain<1>(3), storage);

// create uninitialized array...
Dense<1, float> array4(Domain<1>(3));

// ...and rebind it to user-storage
array4.rebind(storage);
```

However, special care has to be taken in these cases to synchronize the user storage with the block using it. While the storage is being used via the block it was rebound to, it has to be *admitted*, and *released* in order to be accessed directly, i.e. outside the block.

```
// grant exclusive access to the block
array3.admit();

// modify it
array3.set(0, 1.f);

// force synchronization with storage
array3.release();

// access storage directly
assert(storage == 1.f);
```

Chapter 5
Profiling

This reference explains how to compile a program with profiling statements enabled, how to use the profiling functions in order to investigate the execution timing of a program and finally, how to interprete the resulting profiler data.

5.1 Enabling Profiling

5.1.1 Configure and Compile Options

There are no configure options for profiling, instead it is enabled via compile-time options. However, to use profiling it is necessary to configure the library with a suitable high-resolution timer (refer to the Quickstart for details on this and other configuration options). For example,

```
--enable-timer=x86_64_tsc
```

Pre-built versions of the library enable a suitable timer for your system.

To enable profiling, define `VSIP_IMPL_PROFILER=` *`mask`* on the command line when compiling your program. On many systems, this option may be added to the CXXFLAGS variable in the project makefile.

This macro enables profiling operations in several different areas of the library, depending on the value of *`mask`*.

Section	Description	Value
signal	Signal Processing	1
matvec	Linear Algbra	2
fns	Elementwise Functions	4
user	User-defined Operations	8

Determine the mask value by summing the values listed in the table for the areas you wish to profile. For example, if you wish to gather performance data on your own code as well as for FFT's, you would enable 'user' and 'signal' from the table above. The value you would choose would be 1 + 8 = 9.

5.1.2 Command Line Options

For programs that have been compiled with profiling enabled, the profiling mode and output file can be controlled from the command line. You may profile programs without modifying your source files using this method. Use this to choose the profiler mode:

```
--vsipl++-profile-mode=mode
```

where *`mode`* is either `accum` or `trace`.

Specify the path to the log file for profile output using:

```
--vsipl++-profile-output=/path/to/logfile
```

The second option defaults to the standard output on most systems, so it may be omitted.

The profiling command line options control profiling for the entire program execution. For finer grain control, such as enabling profiling during a specific portion of the program, or to mix different profiling modes, explicit Profiling objects can be created.

5.2 Using the Profiler

5.2.1 Profiling Objects

The `Profile` object is used to enable profiling during the lifetime of the object. When created, it takes arguments to indicate the output file and the profiling mode (trace or accumulate). When destroyed (i.e. goes out of scope or is explicitly deleted), the profile data is written to the specified output file. For example:

```
impl::profile::Profile profile("profile.txt", impl::profile::accum)
```

During the lifetime of the Profile object, timing data is stored through a simple interface provided by the `Scope_event` object. These objects are used to profile library operations for the different areas mentioned in Table 5.1, “Profiling Configuration Mask” above. Any `Scope_event` objects defined in user programs falls into the 'user' category of events.

The declaration of an instance of this object starts a timer and when it is destroyed, the timer is stopped. The timing data is subsequently reported when the `Profile` object is destroyed. For example:

```
impl::profile::Scope_event event("Event Tag", op_count);
```

The first parameter is the tag that will be used to display the event's performance data in the log file (Section 5.3.2, “Event Tags” describes the event tags used internally by the library.) The second parameter, `op_count`, is an optional unsigned integer specifying an estimate of the total number of operations (floating point or otherwise) performed. This is used by the profiler to compute the rate of computation. Without it, the profiler will still yield useful timing data, but the average rate of computation will be shown as zero in the log.

Creating a Scope_event object on the stack is the easiest way to control the region it will profile. For example, from within the body of a function (or the as the entire function), use this to define a region of interest:

```
{
  impl::profile::Scope_event event("Main computation:");

  // perform main computation
  //
  ...
}
```

The closing brace causes 'event' to go out of scope, logging the amount of time spent doing the computation.

5.2.2 Profiler Modes

In `trace` mode, the start and stop times where events begin and end are stored as profile data. The log will present these events in chronological order. This mode is preferred when a highly detailed view of program execution is desired.

In `accum` (accumlate) mode, the start and stop times are subtracted to compute the duration of an event and the cumulative sum of these durations are stored as profile data. The log will indicate the total amount of time spent in each event. This mode is desirable when investigating a specific function's average performance.

5.3 Profiler Output

5.3.1 Log File Format

The profiler outputs a small header at the beginning of each log file which is the same accumulate and trace modes. The data that follows the header is different depending on the mode. The header describes the profiling mode used, the low-level timer used to measure clock ticks and the number of clock ticks per second.

5.3.1.1 Accumulate mode

```
# mode: pm_accum
# timer: x86_64_tsc_time
# clocks_per_sec: 3591375104
#
# tag : total ticks : num calls : op count : mops
```

The respective columns that follow the header are:

tag	A descriptive name of the operation. This is either a name used internally or specified by the user.
total ticks	The duration of the event in processor ticks.
num calls	The number of times the event occurred.
op count	The number of operations performed per event.
mops	The calculated performance figure in millions of operations per second. (num_calls * op_count * 10^{-6}) / (total_ticks / clocks_per_sec)

5.3.1.2 Trace mode

```
# mode: pm_trace
# timer: x86_64_tsc_time
# clocks_per_sec: 3591375104
#
# index : tag : ticks : open id : op count
```

The respective columns that follow the header are:

index	The entry number, beginning at one.
tag	A descriptive name of the operation. This is either a name used internally or specified by the user.
ticks	The current reading from the processor clock.
open id	If zero, indicates the start of an event. If non-zero, this indicates the end of an event and refers to the index of corresponding start of the event.
op count	The number of operations performed per event, or zero to indicate the end of an event.

Note that the timings expressed in 'ticks' may be converted to seconds by dividing by the 'clocks_per_second' constant in the header.

5.3.2 Event Tags

Sourcery VSIPL++ uses the following tags for profiling objects and functions within the library. These tags are readable text containing information that varies depending on the event, but generally they follow this format:

```
OPERATION [DIM] DATATYPE SIZE
```

OPERATION gives the object or function name.

DIM is the number of dimensions (when needed).

DATATYPE describes the data types involved in the operation. See Table 5.2, “Data Type Names” below.

SIZE is expressed by giving the number of elements in each dimension.

Tags used for signal processing and matrix-vector operations are as follows:

```
Convolution [1D|2D] T SIZE
Correlation [1D|2D] T SIZE
Fft 1D [Inv|Fwd] I-O [by_ref|by_val] SIZE
Fftm 2D [Inv|Fwd] I-O [by_ref|by_val] SIZE
Fir T SIZE
Iir T SIZE
dot T SIZE
cvjdot T SIZE
trans T SIZE
herm T SIZE
kron T SIZE A SIZE B
outer T SIZE
gemp T SIZE
gems T SIZE
cumsum T SIZE
modulate T SIZE
```

In all cases, data types (`T, I and O` above) are expressed using a notation similar to the BLAS/LAPACK convention as in the following table:

	Views	**Scalars**
single precision real	`S`	`s`
single precision complex	`C`	`c`
double precision real	`D`	`d`
double precision complex	`Z`	`z`

Element-wise expression tags use a slightly different format:

```
EVALUATOR DIM EXPR SIZE
```

The EVALUATOR indicates which VSIPL++ evaluator was dispatched to compute the expression.

`Expr_Loop` - generic loop-fusion evaluator.
`Expr_SIMD_Loop` - SIMD loop-fusion evaluator.
`Expr_Copy` - optimized data-copy evaluator.
`Expr_Trans` - optimized matrix transpose evaluator.

`Expr_Dense` - evaluator for dense, multi- dimensional expressions. Converts them into corresponding 1-dim expressions that are re-dispatched.
`Expr_SAL_*` - evaluators for dispatch to the SAL vendor math library.
`Expr_IPP_*` - evaluators for dispatch to the SAL vendor math library.
`Expr_SIMD_*` - evaluators for dispatch to the builtin SIMD routines (with the exception of Expr_SIMD_Loop, see above).

DIM indicates the dimensionality of the expression.

EXPR is mnemonic of the expression shown using prefix notation, i.e.

```
operator(operand, ...)
```

Each operand may be the result of another computation, so expressions are nested, the parenthesis determining the order of evaluation.

SIZE is expressed by giving the number of elements in each dimension.

Glossary

Block
: A block is an interface to a logically contiguous array of data. Blocks provide a means to organize the access to the data. They may store the data themselves, or access the data through other blocks. This abstraction provides important latitude for optimizations such as expression templates, or parallelism.

  Block types have to fulfill the requirements outlined in table 6.1 of the specification.

Dense Block
: Dense blocks are modifiable, allocatable blocks that explicitely store one value for each index in its domain. The data layout is specified in terms of a template parameter, allowing storage to be optimized for particular operations (see dimension ordering).

  Dense blocks allow users to supply data storage, either at construction time, or later, in which case the block is 'rebound' to an alternate user storage.

Dimension Ordering
: Dimension ordering refers to the layout of data in a multi-dimensional block, such as row-major or column-major. Dimension ordering has an impact on performance in operations involving loops over the data, as adjacent reads / writes may require a new cache-line to be fetched first.

Domain
: A domain represents a logical set of indices for which views provide data. It may be a contiguous set of indices for dense matrices, or a non-contiguous set of indices for subviews.

Expression Block
: Expression blocks are used to store mathematical expressions, allowing optimized evaluation. Conventionally, in an equation 'View A = B + C * D' the computation of A would require at least two temporaries, representing the results of the two binary operations. Additionally, the evaluation of each of these subexpressions implies a loop, resuling in suboptimal performance.

  With expression blocks, the above expression will generate a block representing 'B + C * D', which is evaluated when assigned to 'A'. Specializations of expression blocks may use highly optimized functions to be called, depending on the specific types and subexpressions involved.

Map
: A map specifies how a block can be devided into subblocks for the purpose of parallel execution. It defines how subblocks are to be assigned to processors.

  Map types have to fulfill the requirements outlined in table 3.1 of the parallel specification.

View
: A view represents the base for mathematical linear algebra operations, such as vectors, matrices, tensors. It has a dimension, a value_type, and a number of accessors to access and manipulate

its values. The actual data are stored in blocks, to which views hold references internally.

Multiple views may share the same data, making copy operations for those views an inexpensive operation. All views are parametrized for two types: the view's value_type, as well as the underlaying block type.

View types have to fulfill the requirements outlined in table 6.3 of the specification.