



Universidade Estadual de Campinas  
Instituto de Computação



Eder Maicol Gomez Zegarra

Support for Parallel Scan in OpenMP

Suporte de Parallel Scan em OpenMP

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**Eder Maicol Gomez Zegarra**

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Dissertação apresentada ao Instituto de Computação da Universidade Estadual de Campinas como parte dos requisitos para a obtenção do título de Mestre em Ciência da Computação.

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**Supervisor/Orientador: Prof. Dr. Guido Costa Souza de Araujo**  
**Co-supervisor/Coorientador: Dr. Marcio Machado Pereira**

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**Banca Examinadora:**

- Prof. Dr. Guido Costa Souza de Araujo (Supervisor/*Orientador*)  
IC/UNICAMP
- Prof. Dr.
- Prof. Dr.

A ata da defesa com as respectivas assinaturas dos membros da banca encontra-se no processo de vida acadêmica do aluno.

Campinas, 10 de fevereiro de 2018

# Agradecimientos

# Resumo

Abstract in Portuguese

# Abstract

Prefix Scan (or simply scan) is an operator that computes all the partial sums of a vector. A scan operation results in a vector where each element is the sum of the preceding elements in the original vector up to the corresponding position. Scan is a key operation in many relevant problems like sorting, lexical analysis, string comparison, image filtering among others. Although there are libraries that provide hand-parallelized implementations of the scan in CUDA and OpenCL, no automatic parallelization solution exists for this operator in OpenMP. This work proposes a new clause to OpenMP which enables the automatic synthesis of the parallel scan. By using the proposed clause a programmer can considerably reduce the complexity of designing scan based algorithms, thus allowing he/she to focus the attention on the problem and not on learning new parallel programming models or languages. Scan was designed in AClang ([www.aclang.org](http://www.aclang.org)), an open-source LLVM/Clang compiler framework that implements the recently released OpenMP 4.X Accelerator Programming Model. AClang automatically converts OpenMP 4.X annotated program regions to OpenCL. Experiments running a set of typical scan based algorithms on NVIDIA, Intel, and ARM GPUs reveal that the performance of the proposed OpenMP clause is equivalent to that achieved when using OpenCL library calls, with the advantage of a simpler programming complexity.

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# Chapter 1

## Introduction

Parallelizing loops is a well-known research problem that has been extensively studied. The most common approach to this problem uses DOALL [22] algorithms to parallelize the iterations of loops which do not have loop-carried dependencies. Although there are approaches such as DOACROSS [13], DSWP [27] and BDX [14] that can be used to parallelize loop-carried dependent loops, these algorithms can not be directly applied to loops that are sequential in nature. One example of such loop can found in the implementation of the scan operation.

Cumulative sum, inclusive scan, or simply *scan* [8] is a key operation that has for goal to compute the partial sums of the elements of a vector. The scan operation results in a new vector where each element is the sum of the preceding elements of the input vector up to its corresponding position. Scan is a central operation in many relevant problems like sorting, lexical analysis, string comparison, image filtering, stream compaction, histogram construction as well as in many data structure transformations [9].

Scan is a very simple operation that can be generalized in two flavors (*inclusive* and *exclusive*) as follows. Given a binary associative operator  $\oplus$  and a vector of  $n$  elements  $x = [x_0, x_1, \dots, x_{n-1}]$ , an *inclusive scan* produces the vector  $y = [x_0, x_0 \oplus x_1, \dots, x_0 \oplus x_1 \oplus \dots \oplus x_{n-1}]$ .

$$\begin{aligned} y[0] &= 0 \\ y[1] &= x[0] \\ y[2] &= x[0] + x[1] \\ y[3] &= x[0] + x[1] + x[2] \\ &\dots \\ y[i] &= \sum_{j=0}^{i-1} x[j] \end{aligned} \tag{1.1}$$

Similarly, the *exclusive scan* operation results in vector  $y = [I, x_0, x_0 \oplus x_1, \dots, x_0 \oplus x_1 \oplus \dots \oplus x_{n-2}]$ , where  $I$  is the identity element in the binary associative operator  $\oplus$ . The parallel scan clause proposed in this work is based on the exclusive scan operation which will be called *scan* from now on. It is trivial to compute inclusive scan from the result of its exclusive version. This can be done by: (i) computing the exclusive scan of  $y$ ; (ii)

Listing 1.1: The prefix sum implementation

```

1  (a) Sequential implementation
2
3  y[0] = 0;
4  for(int i = 1; i < n; i++)
5      y[i] = y[i-1] + x[i-1];
6
7  (b) Parallel implementation using the new clause
8
9  y[0] = 0;
10 #pragma omp parallel for scan(+: y)
11 for(int i = 1; i < n; i++)
12     y[i] = y[i-1] + x[i-1];
13

```

shifting the elements of  $y$  to the left; and (iii) storing the operation  $y[n-2] \oplus x[n-1]$  into  $y[n-1]$ .

The scan of a sequence is trivial to compute using an  $\mathcal{O}(n)$  algorithm that sequentially applies the recurrence formula  $y[i] = y[i-1] \oplus x[i-1]$  to the  $n$  elements of  $x$ . For example, when the binary operator  $\oplus$  is the addition (Equation 1.1), the scan operation stores in  $y$  all partial sums of array  $x$ , an algorithm named *Prefix Sum*. As shown in Listing 1.1a, the loop that implements prefix sum is intrinsically sequential due to the loop-carried dependence on  $y$  which makes the value of  $y[i]$  depend on the value of  $y[i-1]$  from the previous iteration. Hence, the loop body in Listing 1.1a forms a single *strongly connected component* in the program control-flow graph [6] and thus typical DOACROSS based algorithms like [31, 11] cannot be used to parallelize the loop iterations of prefix sum.

There are many other scan based operations that use various associative binary operators like product, maximum, minimum, and logical AND, OR, and XOR to parallelize some very relevant algorithms [26, 12, 7]. Given the relevance of scan in computing, library based parallel implementations of scan have been proposed in the past [16, 8] and designed as library calls in languages like OpenCL and CUDA [29, 10]. Unfortunately, most of these implementations are problem specific leaving the programmer with the task of mastering the complexity of OpenCL and CUDA in order to handle the design of a scan based operation to a specific problem.

This work proposes a new OpenMP `scan` clause that enables the automatic synthesis of parallel scan. The programmer can use the new clause to design algorithms in OpenMP C/C++ code thus eliminating the need to deal with the complexity of OpenCL or CUDA. The new scan clause was integrated into *ACLing*, an open-source LLVM/Clang compiler framework ([www.aclang.org](http://www.aclang.org)) that implements the recently released *OpenMP 4.X Accelerator Programming Model* [24]. ACLing automatically converts OpenMP 4.X annotated program regions to OpenCL/SPIR kernels, including those regions containing the new scan clause.

A careful reader might think that such new scan clause is a trivial extension of the reduction clause already available in OpenMP. As a matter of fact, the reduction of the elements of a sequence  $x$  can be obtained by computing the scan of  $x$  into  $y$  as shown in Listing 1.1b and returning the value of  $y[n-1] + x[n-1]$ . In other words, reduction is a simpler version of scan in which the values of all intermediate partial sums are not exposed, and only the total sum of the elements of  $x$  is returned. Reduction can be performed in  $\mathcal{O}(\log n)$  complexity using a tree-based [5] or a butterfly-based [20] parallel

algorithm. Moreover, both reduction and scan are operations that handle loop-carried dependent variables. In the reduction case, a single variable accumulates the value from the previous iterations, while in scan the accumulation occurs for all elements of  $y[i]$  each depending on elements from the previous iterations. This makes the implementation of parallel scan much harder than the implementation of reduction.

The rest of the work is organized as follows. Chapter 2 details some concepts of programming for GPU and AClang compiler. Chapter 3 describes scan algorithm evolution until that is used to implement the new scan clause, in Section 2.2 gives an outline of the structure of the AClang compiler and describes the details of the implementation and integration of the clause into the OpenMP library and in Section 4 describes some examples of scan use. Chapter 5 discusses related work and Chapter 6 provides performance numbers and analyzes the results when programs are compiled with the new scan clause. Finally, Chapter 7 concludes the work.

# Chapter 2

## Background

### 2.1 Introduction to GPUs

#### 2.1.1 A Brief History of GPUs

In the early 1990s, users began purchasing 2D display accelerators for their computers. These display accelerators offered hardware-assisted bitmap operations to assist in the display and usability of graphical operating systems.

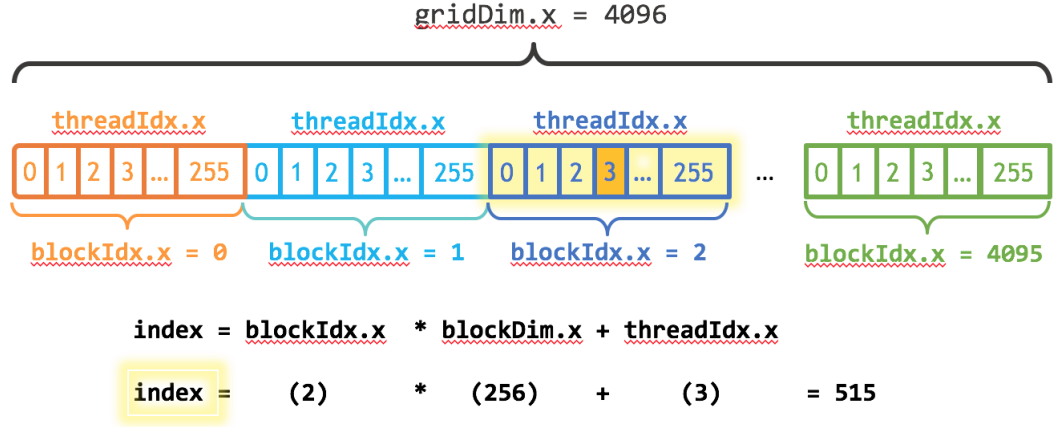
Around the same time, the company Silicon Graphics popularized the use of three-dimensional graphics. In 1992, Silicon Graphics opened the programming interface to its hardware by releasing the OpenGL library they wanted that OpenGL was used as a standardized.

By the mid-1990s, the demand of applications that were using 3D graphics increase considerably growing one stage of development. PC gaming was affected for those devices to create progressively more realistic 3D environments. At the same time, companies such as NVIDIA, ATI Technologies, and 3dfx Interactive began releasing graphics accelerators that were affordable enough to attract widespread attention. These developments cemented 3D graphics as a technology that would figure prominently for years to come.

In 1999 was created the first GPU GeForce 256 that was marketed as "the world's first GPU" or Graphic Processing Unit, enhancing the potential for even more visually interesting applications. Since transform and lighting were already integral parts of the OpenGL graphics pipeline, the GeForce 256 marked the beginning of a natural progression where increasingly more of the graphics pipeline would be implemented directly on the graphics processor.

In 2001 was introduced the GeForce 3 that is the first programmable GPU that means for the first time, developers had some control over the exact computations that would be performed on their GPUs.

Figure 2.1: CUDA parallel thread hierarchy



## 2.1.2 GPU Architecture Overview

### 2.1.3 Programming for GPUs

This section presents some important concepts of GPU programming that will be used throughout the work.

## 2.2 The AClang Compiler

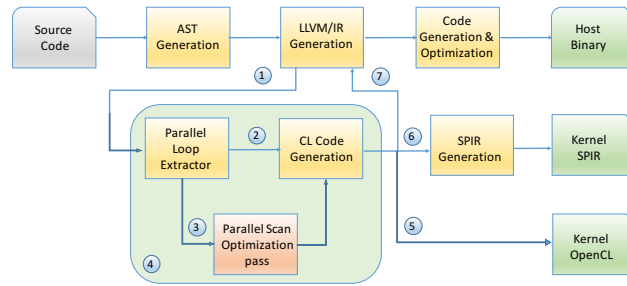
Although OpenCL provides a library that eases the task of offloading kernels to devices, its function calls are complex, have many parameters and require the programmer to have some knowledge of the device architecture's features (e.g. block size, memory model, etc.) in order to enable a correct and effective usage of the device. Hence, OpenCL can still be considered a somehow low-level language for heterogeneous computing.

Introduced through OpenMP 4.0 the new *OpenMP Accelerator Model* [23] proposes a number of new clauses aimed at speeding up the task of programming heterogeneous architectures. This model extends the concept of offloading and enables the programmer to use dedicated directives to define offloading target regions that control data movement between host and devices. Although most OpenMP directives used for multicore hosts can also be used inside target regions, the new accelerator model eases the tasks of identifying data-parallel computation.

AClang is an open source ([www.aclang.org](http://www.aclang.org)) LLVM/Clang based compiler that implements the OpenMP Accelerator Model. It adds an *OpenCL runtime library* to LLVM/Clang that supports OpenMP offloading to accelerator devices like GPUs and FGPAs. The kernel functions are extracted from the OpenMP region and are dispatched as OpenCL [2] or SPIR [3] code to be loaded and compiled by OpenCL drivers, before being executed by the device. This whole process is transparent and does not require any programmer intervention.

Figure 2.2 shows the AClang execution flow pipeline with emphasis on the *Parallel Scan Optimization* pass. The LLVM IR generation phase handles the conversion of the

Figure 2.2: AClang compiler pipeline.



AST nodes generated by the Semantic phase into LLVM Intermediate Representation<sup>1</sup>. In this phase, the annotated loops are extracted from the AST ①, optimized ③, and/or transformed ② into OpenCL kernels in source code format ⑤ (see Section 3.2 for more details on the Parallel Scan optimization pass). Kernels can also go through the SPIR generation pass ⑥ to produce kernel bit codes in SPIR format. AClang’s transformation engine ④ provides information to the LLVM IR generation phase ⑦ to produce intermediate code that calls AClang runtime library functions. These functions are used to perform data offloading and kernel dispatch to the OpenCL driver.

---

<sup>1</sup>Historically, this was referred to as *codegen*

# Chapter 3

## The Parallel Scan

### 3.1 The Scan algorithm

During the 80's Hillis and Steele [16] developed approaches to parallelize many serial algorithms. Although at that time these algorithms seemed to have only sequential solutions, by using The Connection Machine [17] they managed to achieve execution times in  $\mathcal{O}(\log n)$ . One of these algorithms was the sum of the elements of an array, also known as reduction. With a slight modification of reduction Hillis and Steele proposed a solution to compute *All Partial Sums* of an array, a problem that is currently known as prefix sum or simply scan.

The generalization that scan is an important primitive for parallel computing was presented by Guy E. Blelloch in [8]. In that work scan was defined as a *unit time* primitive under the PRAM (Parallel Random Access Machine) model and Blelloch presented a new technique to perform the scan operator. That technique was implemented using a binary balanced tree and was explained in Section ?? . Scan was then used to parallelize some very relevant algorithms like: Maximum-Flow, Maximal Independent Set, Minimum Spanning Tree, K-D Tree and Line of Sight, thus improving their asymptotic running time to  $\mathcal{O}(\log n)$ .

In [18] Horn proposed an efficient implementation of scan in GPUs. That algorithm was based in Hillis and Steele's work and was used to solve the problem of extracting the undesired elements of a set. Scan was used to determine the undesired elements, and this was followed by a search and gather operation to compact the set. This problem is known as *Stream Compaction*, and has a running time of  $\mathcal{O}(n \log n)$ .

In [15] Mark Harris et al. implemented in GPUs the scan operator based on the work of Blelloch [8]. That implementation proved to be better than the solution proposed by Horn [18]. The main difference between those two approaches is the number of operations executed to solve the problem. In the case of [18], the total number of operations is  $n \log n$ , and in the case of [15] the total number of operations is  $n$ , the same number as in the serial version.

Also in [15], Harris presented a solution to treat large input vectors in GPUs. It is well known that the size of one GPU block is limited and thus the computation of scan for larger input sizes is done in two scan steps: (i) a first step inside each block; and (ii) a second step among the blocks. The approach proposed in Section 3.2 uses [15] to deal



with large input vectors and the work in [8] to perform the individual scan steps.

In [28] Sengupta and Harris presented several optimizations for the implementation proposed in [15]. Those optimizations were designed to deliver maximum performance for regular execution paths via a *Single-Instruction, Multiple-Thread* (SIMT) architecture and regular data access patterns through memory coalescing. That work was the base for the widely used CUDPP library [1], which presents an easy and efficient but limited use of the scan operator.

In [19] Bell and Hoberock designed a library called Thrust. That library resembles the C++ Standard Template Library (STL). Thrust parallel template library allows to implement high-performance applications with minimal programming effort. The library offers an implementation of the scan operator that eases the task of the programmer. Thrust was used to implement the CUDA version of the benchmarks described in Section ??.

Shengen Yan et. al. [32] implemented the scan operator in OpenCL based on [15], He improved the performance by reducing the number of memory accesses from  $3n$  to  $2n$  and eliminating global barrier synchronization completely.

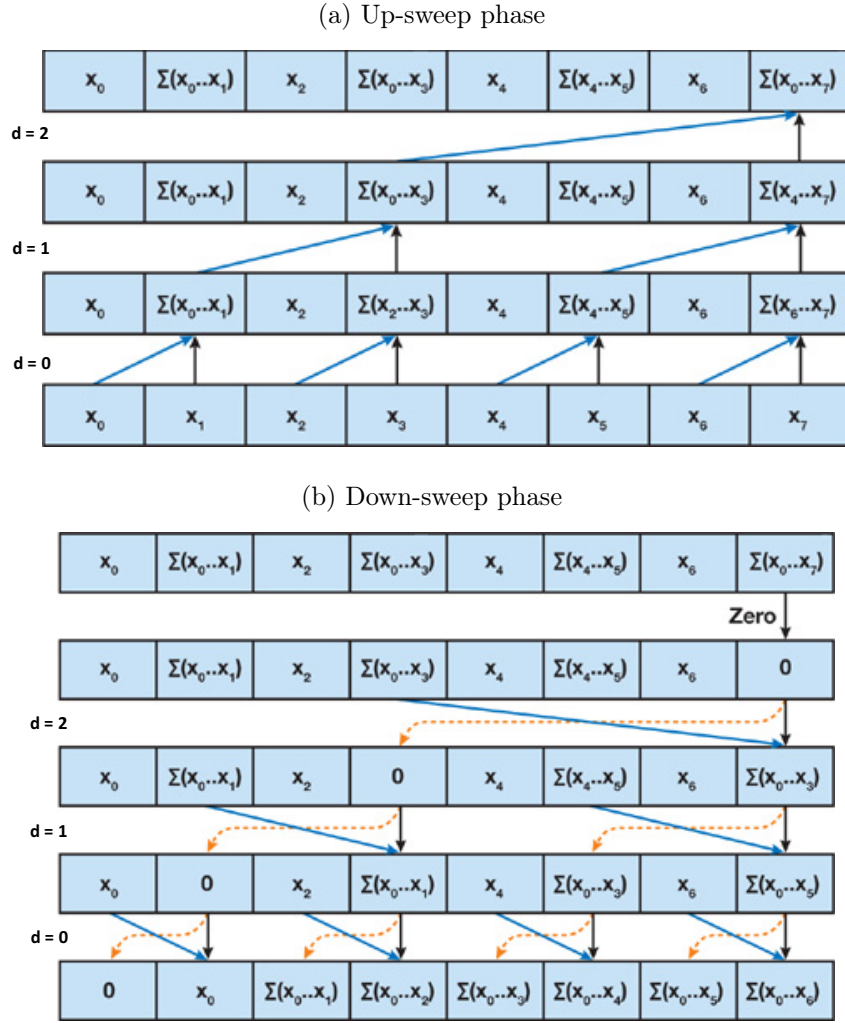
In 2015, Wiefferink [30] implemented other version of the scan operation in OpenCL. This work improved the branch divergence of the algorithm in [8] [15]. As expected, this implementation works in NVIDIA and AMD GPU platforms, unlike most previous versions that just worked in NVIDIA GPUs.

This section describes the parallel scan algorithm used in the design of the proposed scan clause. The algorithm is based on the work of Mark Harris et al. [29] and is currently known as the best approach to the parallel computation of scan.

For the sake of simplicity and without any loss of generality please consider the loop in Listing 3.1a (lines 3–10) which contains a sequential scan operation that will be parallelized with the scan clause. Notice that unlike the code of Listing 1.1a (line 5) the current example stores the result of the scan operation into the array  $x$  itself (line 8 of Listing 3.1a).

The key idea in [29] is to build a balanced binary tree on the input data  $x$  and sweep it to and from the root, scanning at each phase half of the elements of the array. The tree is not an actual data structure, but a concept used to determine what each thread does at each one of the two phases of the traversal. The tree representation is shown in Figures 3.1a – 3.1b where blue and black arrows represent read operations of the elements of  $x$  that will be added, and orange arrows represent copy statements.

As shown in Listings 3.1b – 3.1c, the algorithm consists of two phases: *up-sweep* and *down-sweep*. In the up-sweep phase, described in Listing 3.1b the tree is traversed bottom-up computing the scan of half of the internal nodes of the tree in Figure 3.1a. As described in Listing 3.1b at each level (iteration)  $d$  of the tree neighbors at distance  $2^d$  are accumulated into the elements at index  $k + 2^{(d+1)} - 1, k = 0 \dots \lfloor n/2 \rfloor$  of the array (line 18). For example, at level  $d = 0$  of Figure 3.1a neighbors at distance  $2^{(0+1)} - 1 = 1$  are accumulated into the elements at index  $k + 1$ , at the next level of the tree. The distance of the neighbors that are accumulated doubles as the tree level is incremented (e.g. the distance is 2 at level  $d = 1$ ) until the partial sum at  $x[i - 1]$  is computed. This phase is also known as *parallel reduction*, because after this phase, the root node (the last node in the array) holds the sum of all nodes in the array.

Figure 3.1: Parallel scan in  $\mathcal{O}(\log n)$ 

In the down-sweep phase, the tree is traversed top-down and the partial sums computed in the previous phase are propagated downward to accumulate with the entries which did not have their partial sums computed previously in the up-sweep phase. The phase starts by inserting zero at the root of the tree. Then at each step, each node at the current tree level will: (i) sum its value to the former value of its left child and store the result into its right child; and (ii) copy its own value to its left child. For example, consider the node at index 7 level  $d = 1$  of the tree in Figure 3.1a. That node has two children, a left child at index 5 and a right child at index 7. Hence, during the down-sweep phase two operations will occur: (i) the value at index 7 is summed to the value at index 5 (left child of index 7) and is stored into the right child of index 7 (index 7 itself); and (ii) the value at index 7 is copied to index 5 to be used in the next level  $d = 0$  (orange arrow to left child of index 7).

**Maicol: REVIEW 2: "complexity" and parallel compute time** The algorithm performs  $\mathcal{O}(n)$  operations in the first phase (*up-sweep*) and for every level of this phase is computed in  $\mathcal{O}(1)$  hence the total time is computed in  $\mathcal{O}(\log n)$ , similarly for the second phase (*down-sweep*) the total of operations is  $\mathcal{O}(n)$  between adds  $(n - 1)$  and swaps  $(n - 1)$

Listing 3.1: The parallel scan implementation

```

1  (a) Modified sequential implementation
2
3  aux = x[0];
4  x[0] = 0;
5  #pragma omp parallel for scan(+: x)
6  for(int i = 1; i < n; i++) {
7      temp = x[i];
8      x[i] = x[i-1] + aux;
9      aux = temp;
10 }
11
12 (b) Up-sweep phase of scan parallel implementation
13
14 x[0] = 0;
15 for(d = n >> 1; d > 0; d >>= 1){
16     // We parallelize this section
17     for(k = 0 ; k < n ; k += (1<<(d+1)) ){
18         x[k + (1<<(d+1)) - 1] = x[k + (1<<d) - 1] +
19         x[k + (1<<(d+1)) - 1];
20     }
21 }
22
23 (c) Down-sweep phase of scan parallel implementation
24
25 x[n-1] = 0;
26 for(d = log2(n); d >= 0 ; d--){
27     // We parallelize this section
28     for(k = 0 ; k < n ; k += (1<<(d+1))){
29         t = x[k + (1<<d) - 1];
30         x[k + (1<<d) - 1] = x[k + (1<<(d+1)) - 1];
31         x[k + (1<<(d+1)) - 1] = t + x[k + (1<<(d+1)) - 1];
32     }
33 }
34

```

moreover the computed time is  $\mathcal{O}(\log n)$ . So the total number of operation of parallel scan is  $\mathcal{O}(n)$  and computed time is  $\mathcal{O}(\log n)$  time.

## 3.2 Scan clause implementation in AClang

The Parallel Scan Optimization pass ❸ shown in Figure 2.2 is responsible for implementing the scan clause. This implementation is based on the best parallel scan algorithm known today [29] and is detailed in Section 3.1. Nevertheless, the effectiveness of that algorithm is increased when it runs within a thread block within which it can leverage on data locality.

In order to apply the parallelized scan from Section 3.1 to data sets larger than a single thread block, an extended four step method was proposed [15] which applies twice the scan algorithm described in Listings 3.1b – 3.1c to spread the scan of each block to all blocks of the array. Such method is shown in the block diagram of Figure 3.2 where each number corresponds to one step of the method. In the first step, the method divides the large input array into blocks that are scanned each by a single thread block ❶ using the algorithm from Section 3.1. During the second step, the total sum of all elements of each block (i.e. the value in the last element of the scanned block) is transferred to the corresponding entry of an auxiliary array ❷. In the third step, using again the algorithm in Section 3.1, the method scans the auxiliary array, and writes the output at another

array of block sums ❸. At the end of this third step each entry of the array of block sums contains the partial sums of all elements of the blocks up to that entry (inclusive). Finally in the fourth step, for each block the method adds the previous block sums to the elements of the current block ❹.

In more detail, we show how aclang implements the scan algorithm, so we will explain a resumed code of the process. Just to remind, this process prepare an intern OpenCL environment and fill the template with the needs of the programmer (variable type, operation type, output vector).

Our first step that we need to do is about get the information from the omp scan clause as we detail in Listing 3.2a from the line 3 to 20.

In the line 3 and 4, from all clauses, we obtained the kind of clause the it represents. From line 5 to 7, is ensured that was found a Scan clause, so in this case we get all the information from this clause(data and needs of the programmer).

In the part Listing 3.2b, is processed how the programmer used the clause, it means, as we can see in Listings 3.4a – 3.4b was defined two ways to write the scan clause, the first one is a standard, using 3 components, one of them is the input data, the second refers to the accumulate sum until one position before that we are analyzing at the moment from the accumulate vector and the third component is the currently position which is filled. For the second way to write the scan clause, it is not necessary the use of one auxiliary vector of the accumulate, we can modified the input vector to convert it in the result vector, in this case to don't lose information from the input data that will be used, it's necessary save some information as we can see in the Listing 3.4b.

From the line 24 to 33 is prepared the scan parameters and the OpenCL environment. The line 24 computes the number of threads per block and the number of blocks than we will use to call the functions of the parallel scan algorithm, this step is important because as was mentioned before, the algorithm just work if the size of the input data is a power of two it means some like  $(2^k)$  so when the size is not a power of two we can't solve the problem, to solve this, we find the closest higher number that is a product of two number power of two, for the number of blocks ( $B$ ) and the number threads ( $T$ ) per block, for example if the size of input is 12, the closest number with that properties is 16 where we found more of one solution  $B : 1 - T : 16$ ,  $B : 2 - T : 8$ ,  $B : 4 - T : 4$  and so on. Attention, in some cases we can find some solution with  $T$  bigger than the threads provides for our architecture so, we limited  $T$  according the computer programmer features, same way for  $B$ , thus the maximum size to compute the scan algorithm is limited for the resources provided, later in 7 it will show a proposal to extend the limit.

In line 25 is found the type of variable with which the programmer is working, could be *int*, *double*, *float* and so on, nevertheless remember that we provide the possibility to define a new type of variable as a struct.

For the next line 26 is found the operator that the programmer defined to use in the scan algorithm, attention with this, as mentioned before this operator should be a binary associative operator, the more common are:  $(+, *, \&, ||, \max, \min)$  besides of these operator usually for primitive variables we can define our binary associative operator if we are working with other variably type.

From the line 28 to 34 is customized the OpenCL environment to execute the scan parallel algorithm, for example to execute the algorithm is necessary create a auxiliary buffer as we can see in 3.2 ②, the creation of the buffer is made in the line 28. Attention, Aclang provides a class CGM that has functions to facilitate the use of OpenCL, those function have as structure *get.MPtoGPURuntime().”operation”* those functionalities allow a friendlier use of OpenCL code. The line 29 sets the initial parameter for the OpenCL program only the standard process.

From the line 31 to 33 are executed the kernels necessities to compute the scan algorithm, for example in the line 31 is computed the scan for every single block thread independently we can see this in 3.2 ①, for the next line 32 is execute the second kernel in charge to computed the sum of accumulates from the auxiliary vector about himself as we can see in 3.2 ③ and for the line 33 is executed that distributes the corresponding accumulates to all the positions of the solution vector 3.2 ④.

Finally, the line 34 sends the solution vector to the desired vector of the programmer, as we mentioned before, the programmer has two options to get the answer, he could create a new vector o replace the input data to convert in a result vector.

### 3.2.1 The Template

This section aims to explain how we build the parallel scan algorithm, as the first step we have to remember that the algorithm is based on the best algorithm known today [29]. To summarize this section, we can say that the algorithm only has three parameters that could be changed for different applications, the first is about type of variable, the second is the operator used for that variable and the third case is when the programmer needs to use another struct as a variable, so he has to define the new variable and its operator. Additionally, the programmer has the option to choose if he needs a new vector for the results or he can convert the input data into a result. Thereby, as we mentioned before, all this information is recovered in the compilation phase and is used to generate the final kernel to execute the parallel scan algorithm when the programmer executes the program. In Listing 3.3a is defined the header for every kernel, in this example, we show the header of the first kernel, we can see that we need to define the variable *dataType*, and as was mentioned before, that information is extracted from the clause scan. As expected, every kernel or for every operation that involves creation or the use of the variable type we have to replace *dataType* for the real variable type.

In Listing 3.3b is defined how the algorithm performs the operations, it means if the programmer is using a overloaded operation of the programming language is possible to operate two variable in a simple way, for example for two variables *x* and *y* of type *int* we will use the line 10 to compute the result, remember that we need to replace the word "operation" for the operation that the programmer is using, and that information was extracted from the scan clause.

On other hand, when the programmer defined defined another type of variable, he must define also its binary associative operator to be able to use the scan algorithm, so in this case, the operation can't be computed in a simple way, for example for integer variables

( $a = b + c$ ), that operation has to be overloaded for the programmer and its information is recovered from the scan clause, thereby the way to use this new operation was defined in the line 11.

Finally, the last main component of the template Listing 3.3c refers to where the programmer wants to save the result vector, the line 16 represents that the programmer needs a new vector to save the result of the computed in the algorithm, in the second case, line 17 refers to the programmer wants the result vector in input data vector.

Now, returning to Listing 3.2d, the line 38 is only filling a standard header, from the line 39 to 42 is analyzed if previously the programmer defined a new type of variable with its operator, in the case it's true, that information is placed immediately after the header mentioned before.

From the line 43 to 52 is defined the neutral value according of the operation, a neutral value is defined by the operation ( $a = a \oplus \text{neutralValue}$ ) where  $a$  is any variable  $\oplus$  is an operator, as we can see, when we operate any variable with the neutral, the result is the same variable, in the case of the sum, this neutral value is 0, for the multiplication is 1 and so on. This information is necessary because the scan algorithm need of this information, when we are working with a basic operation, for default this neutral is initialized internally however when the programmer defined a new type of variable, he has to defined its neutral value to send this information.

The line 54 is defined the word *dataType* that represents what type of variable is using the programmer, and finally the line 55 closes the file that will perform the scan parallel algorithm, these is a very summarized code of the total process, the aims to explain this code is to show the mainly components to understand the process to pass from the omp clause to OpenCL version, many informations have been left aside because is not relevant information. For more details that how is generated this template could be seen in Section 4.

Listing 3.2: Pseudocode of Scan Parallel implementation in Aclang

```

1  (a) Get information from omp scan clause
2
3  I = S.clauses().begin(), E = S.clauses().end();
4  OpenMPClauseKind ckind = ((*I)->getClauseKind());
5  if (ckind == OMPC_scan){ //Checking if the clause extracted is our Scan clause.
6      OMPVarListClause<OMPScanClause> *list = cast<OMPVarListClause>cast<OMPScanClause>(*I);
7  }
8
9  (b) Detecting programmer needs
10  if (num_mapped_data == 1) {
11      ...
12  }
13  else {
14  if (num_mapped_data > 2) {
15      llvm_unreachable("Unsupported scan clause with more than two mapped data");
16  }
17  if (MapClauseTypeValues[0] == OMP_TGT_MAPTTYPE_TO ||
18      MapClauseTypeValues[0] == OMP_TGT_MAPTTYPE_TOFROM) {
19      ...
20  }
21  }
22
23  (c) Preparing the scan algorithm parameters and openCL environment
24
25  ThreadBytes = EmitRuntimeCall(CGM.getMPtoGPURuntime().cl_get_threads_blocks(), KArg);
26  Q = dyn_cast<ArrayType>(Q.getTypePtr())->getElementType();
27  OpenMPScanClauseOperator op = cast<OMPScanClause>(*I)->getOperator();
28
29  Status = EmitRuntimeCall(CGM.getMPtoGPURuntime().cl_create_read_write(), Size);
30  Status = EmitRuntimeCall(CGM.getMPtoGPURuntime().cl_create_program(), FileStrScan);
31
32  Status = EmitRuntimeCall(CGM.getMPtoGPURuntime().cl_create_kernel(), FunctionKernel_0);
33  Status = EmitRuntimeCall(CGM.getMPtoGPURuntime().cl_create_kernel(), FunctionKernel_1);
34  Status = EmitRuntimeCall(CGM.getMPtoGPURuntime().cl_create_kernel(), FunctionKernel_2);
35  Status = EmitRuntimeCall(CGM.getMPtoGPURuntime().cl_release_buffer(), Aux);
36
37  (d) Customing the scan generator
38
39  CLOS << "#pragma OPENCL EXTENSION cl_khr_fp64 : enable\n\n";
40  std::string includeContents = CGM.OpenMPSupport.getInclStr();
41  if (includeContents != "") {
42      CLOS << includeContents;
43  }
44  switch (op) {
45      case OMPC_SCAN_add:
46      case OMPC_SCAN_sub:
47          initializer = "0";
48      ...
49  }
50  if (initializer == "") {
51  } else {
52      CLOS << "\n#define _initializer " << initializer;
53  }
54
55  CLOS << "\n#define _dataType_ " << scanVarType.substr(0, scanVarType.find_last_of(' '))
56      << "\n";
57  CLOS.close();
58

```

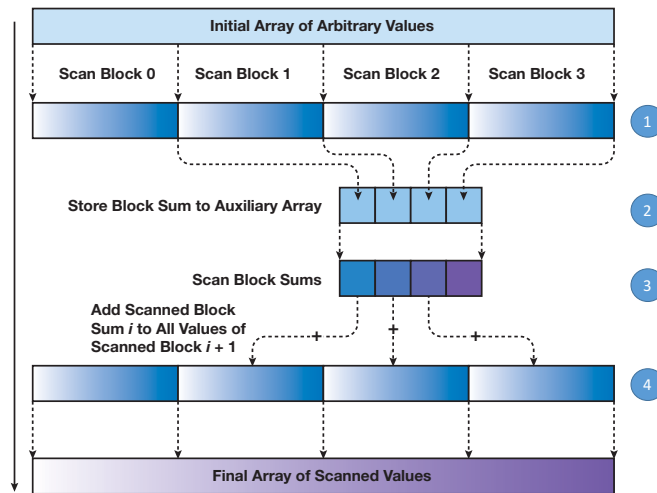
Listing 3.3: Template to generate the final kernel of scan parallel algorithm

```

1  (a) Header for every kernel
2  Header_kernel = ""
3  __kernel void kernel_0 (__global __dataType_ *input ,
4  __global __dataType_ *S,
5  const int n) {
6  ""
7
8  (b) Kind of Operation
9
10  Oper_0_basic = "" block[bi] = block[bi] _operation_ block[ai]; ""
11  Oper_0_user = "" block[bi] = _operation_(block[bi], block[ai]); ""
12
13  (c) Vector result
14
15  Tail_input_basic = "" input[gid] = input[gid] _operation_ S[bid]; ""
16  Tail_output_basic = "" output[gid] = input[gid] _operation_ S[bid]; ""
17
18
19

```

Figure 3.2: Algorithm to perform a block sum scan



Listing 3.4: Pseudocode of Scan Parallel implementation in Aclang

```

1  (a) Standard way to write scan algorithm
2  y[0] = 0;
3  for(i = 1 ; i < n ; i++){
4  y[i] = y[i-1] + x[i-1];
5
6
7  (b) Alternative way saving memory to write scan algorithm
8  int aux1 = x[0], aux2;
9  x[0] = 0;
10  for(i = 0 ; i < n ; i++){
11  aux2 = x[i];
12  x[i] = x[i-1] + aux;
13  aux = aux2;
14  }
15
16

```



# Chapter 4

## Using Scan

### 4.1 Radix Sort

A sorting algorithm puts elements of a list in certain order. This section presents Radix Sort algorithm parallelized through of scan operator. It is well know how Radix Sort algorithm works. For this reason, the section focused on explaining the parallelized version.

The basic idea is to considerer each element to be sorted digit by digit, from least to most significant. For every digit the elements will be rearranged. Let's take a simple example of 4 elements with 4 binary digits in its representation. Listing 4.1 shows a visual representation of how the algorithm works.

**Maicol:** Os itens abaixo precisam ser reescritos. Não está claro a explicação do algoritmo But, How can Listing 4.1 do parallel? The next steps show how to do it.

1. Generate a vector of the list (bit in common, starting form the least significant bit) where every bit that is 0 in the new vector is 1 else the value is 0.
2. Scan the vector, and record the sum of the predicate in the process. Notice, Scan algorithm works for arrays of arbitrary size instead of  $2^n$  size, however as how was explained before the propose resolves for any arbitrary size.
3. Flips bits of the predicate, and scan that.
4. Move the values in the vector with the following rule:
  - (a) For the  $i^{th}$  element in the vector:
  - (b) If the  $i^{th}$  predicate (vector generate in the step 1) is TRUE, move the  $i^{th}$  value to the index in the  $i^{th}$  element of the predicate scan.
  - (c) Else, move the  $i^{th}$  value to the index in the  $i^{th}$  element of the opposite array of the Predicate Scan plus the sum of the original Predicate.
5. Move to next significant bit (NSB).

In the code Listing 4.2, the line 7 indicates the analyze for every bit, depending of the type of variable could be 15, 31 or 63. The line 9 is an auxiliary variable to heps to work the current bit. Next lines (10 – 14) generated the vector mentioned above in the

Listing 4.1: Radix Sort algorithm basic idea

```

1  1) Elements representation
2  Element #   1       2       3       4
3  Value:      7       14      4       1
4  Binary:     0111    1110    0100    0001
5
6  2) At first step, Radix sort algorithm rearranges the elements by the values of
7     the bit analyzed (bit 0):
8  Element #   2       3       1       4
9  Value:      14      4       7       1
10 Binary:     1110    0100    0111    0001
11 bit 0:      0       0       1       1
12
13 3) Finalized the first step, it is necessary analyze the next bit (bit 1):
14 Element #   3       4       2       1
15 Value:      4       1      14       7
16 Binary:     0100    0001    1110    0111
17 bit 1:      0       0       1       1
18
19 4) And so on (bit 2):
20 Element #   4       3       2       1
21 Value:      1       4      14       7
22 Binary:     0001    0100    1110    0111
23 bit 2:      0       1       1       1
24
25 5) And move them again:
26 Element #   4       3       1       2
27 Value:      1       4       7      14
28 Binary:     0001    0100    0111    1110
29 bit 3:      0       0       0       1
30
31

```

step 1 also generate the opposite vector of the first one. The following lines (17 – 25) compute scan operator for the to vector mentioned before. The final lines (27 – 32) move the elements in accordance of the vectors generated in the previous step.

In Listing 4.3 is presented the kernel generated for the framework AClang, the kernel has 3 main components which were detailed before.

## 4.2 Sequence alignment

Sequence alignment is an important tool for researchers in molecular biology in their efforts to relate the molecular structure and function to the underlying sequence. Biological sequence data mainly consists of DNA and protein sequences, which can be treated as strings over a fixed alphabet of characters. Usually, is considered the comparison of two biological sequences. This comparison is done by aligning the two sequences, which refers to stacking one sequence above the other with the intention of matching characters from the two sequences that lie in the same position. To deal with missing characters and extraneous characters, gaps may be inserted into either sequence. A scoring mechanism is designed for each possible alignment and the goal is to find an alignment with the best possible score.

Let  $m$  and  $n$  be the lengths of the two sequences to be compared. Sequence alignment algorithms typically use dynamic programming in which a table, or multiple tables of size  $(m + 1) \times (n + 1)$  are filled.

Listing 4.2: Fragment of Radix Sort benchmark

```

1 int main(){
2     ...
3     predicateTrueScan = ( unsigned int* )malloc( numElem * sizeof(unsigned int) );
4     predicateFalseScan = ( unsigned int* )malloc( numElem * sizeof(unsigned int) );
5     ...
6     unsigned int max_bits = 31; //Unsigned int type
7     for (unsigned int bit = 0; bit < max_bits; bit++){
8
9         nsb = 1<<bit;
10        for(int i = 0 ; i < N ; i++){
11            int r = ((inputVals[i] & nsb) == 0);
12            predicateTrueScan[i] = r;
13            predicateFalseScan[i] = predicate[i] = !r;
14        }
15
16
17        #pragma omp target device(GPU) map(tofrom: predicateTrueScan [:N])
18        #pragma omp parallel for scan(+:predicateTrueScan)
19        for(int i = 1 ; i < N ; i++){
20            predicateTrueScan[i] += predicateTrueScan[i-1];
21        }
22        #pragma omp target device(GPU) map(tofrom: predicateFalseScan [:N])
23        #pragma omp parallel for scan(+:predicateFalseScan)
24        for(int i = 1 ; i < N ; i++){
25            predicateFalseScan[i] += predicateFalseScan[i-1];
26        }
27
28        for(int i = 0 ; i < N ; i++){
29            if ( predicate[i] == 1 )
30                newLoc = predicateFalseScan[i] + numPredicateTrueElements;
31            else
32                newLoc = predicateTrueScan[i];
33            outputVals[newLoc] = inputVals[i];
34        }
35    }
36 }
37

```

### 4.3 Polynomial Evaluation

Given a Polynomial  $P$  with coefficients  $a_n, a_{n-1} \dots a_0$ , the *polynomial evaluation*  $P_{(x)}$  is an operation that performs the value of  $P$  when  $x$  takes some value. The use of polynomials appears in settings ranging from basic chemistry and physics to economics and social science; they are used in calculus and numerical analysis to approximate other functions.

$$P(x) = a_n x^n + a_{n-1} x^{n-1} + a_{n-2} x^{n-2} + \dots + a_1 x + a_0 \quad (4.1)$$

Polynomial evaluation is used in many problems as was mentioned above, this section shows how to use a non primitive variable (int, long, float, double, bool, char) using the scan clause to solve this problem, from the programmer perspective and how AClang works when is used the proposed. Listing 4.6 presents a part of the code to perform the value of the polynomial. Equation 4.1 is the basic representation of a polynomial.

Before of describe the code of for the problem, in this section is showed how can solve the problem using Scan operator.

The trick to solve the problem is to replace each element (Coefficient) of the Polynomial to became a pair. In this case, was changed element  $a_i$  to become the pair  $(a_i, x)$  that created an array of pairs. To perform scan operator on the new array of pairs, the  $\oplus$

Listing 4.3: Fragment of Radix Sort kernel generated

```

1  __kernel void kernel_0 (__global unsigned int *input,
2  __global unsigned int *S,
3  const int n) {
4      ...
5  }
6
7  __kernel void kernel_1 (__global unsigned int *input,
8  const int n) {
9      ...
10 }
11
12 __kernel void kernel_2(__global unsigned int *input,
13 __global unsigned int *S) {
14     ...
15 }
16
17

```

Listing 4.4: Fragment of Sequence alignment

```

1  int main() {
2  int *h;
3  int *t;
4
5
6  t = (int *)malloc(N * sizeof(int));
7  w = (int *)malloc(N * sizeof(int));
8  h = (int *)malloc(N * sizeof(int));
9
10 ...
11
12 #pragma omp target device(GPU) map(from : t[:N]) map(to : h[:N])
13 #pragma omp parallel for scan(max : t)
14 for (int i = 1; i < N; i++)
15     t[i] = max(t[i - 1], h[i - 1]);
16
17

```

operator defined as follows:

$$(p, y) \oplus (q, z) = (pz + q, yz) \quad (4.2)$$

Where does it come from? It's a little difficult to understand at first, but each such pair is meant to summarize the essential knowledge needed for a segment of the array. This segment itself represents a polynomial. The first number in the pair is the value of the segment's polynomial evaluated for  $x$ , while the second is  $x^n$ , where  $n$  is the length of the represented segment of the polynomial.

To use scan operator, it's necessary first confirm that the operator is indeed associative.

$$\begin{aligned}
 ((a, x) \oplus (b, y)) \oplus (c, z) &= (ay + b, xy) \oplus (c, z) \\
 ((a, x) \oplus (b, y)) \oplus (c, z) &= ((ay + b)z + c, xyz) = (ayz + bz + c, xyz) \\
 (a, x) \oplus ((b, y) \oplus (c, z)) &= (a, x) \oplus (bz + c, yz) = (ayz + bz + c, xyz)
 \end{aligned} \quad (4.3)$$

In Equation 4.3 is demonstrated that the operator is associative. Now let's look at an example to see how it works. Suppose that it's necessary to evaluate

Listing 4.5: Fragment of Radix Sort kernel generated

```

1  __kernel void kernel_0 (__global unsigned int *input ,
2  __global unsigned int *S,
3  const int n) {
4  ...
5  }
6
7  __kernel void kernel_1 (__global unsigned int *input ,
8  const int n) {
9
10 ...
11 }
12
13 __kernel void kernel_2(__global unsigned int *input ,
14 __global unsigned int *S) {
15 ...
16 }
17

```

the polynomial  $x^3 + x^2 + 1$  when  $x$  is 2. In this case, the coefficients of the polynomial can be represented using the array  $\langle 1, 1, 0, 1 \rangle$ . The first step of the algorithm is to convert it into an array of pairs.

$$\langle (1, 2), (1, 2), (0, 2), (1, 2) \rangle$$

Now, is possible to apply the  $\oplus$  operator defined above to get the result.

$$\begin{aligned}
 (1, 2) \oplus (1, 2) \oplus (0, 2) \oplus (1, 2) &= (1.2 + 1, 2.2) \oplus (0, 2) \oplus (1, 2) \\
 (1, 2) \oplus (1, 2) \oplus (0, 2) \oplus (1, 2) &= (3, 4) \oplus (0, 2) \oplus (1, 2) \\
 (1, 2) \oplus (1, 2) \oplus (0, 2) \oplus (1, 2) &= (3.2 + 0, 4.2) \oplus (1, 2) = (6, 8) \oplus (1, 2) \\
 (1, 2) \oplus (1, 2) \oplus (0, 2) \oplus (1, 2) &= (6.2 + 1, 8.2) = (13, 16)
 \end{aligned}$$

So the result of the operation is  $(13, 16)$ , which has the desire value to compute 13 as its first element:  $2^3 + 2^2 + 1 = 13$  of the pair. In the computation above, we proceeded in left-to-right order as would be done on a single processor. In fact, parallel scan algorithm would combine the first two elements and last two elements in parallel:

$$\begin{aligned}
 (1, 2) \oplus (1, 2) &= (1.2 + 1, 2.2) = (3, 4) \\
 (0, 2) \oplus (1, 2) &= (0.2 + 1, 2.2) = (1, 4)
 \end{aligned}$$

And then it would combine these two results to get the final result  $(3.4 + 1, 4.4) = (13, 16)$ .

Now in the code, the **target** clause (lines 27–28 in Listing 4.6) defines the part of the code that will be executed by the device (lines 31–32). The **map** clauses control the direction of the data flow between the host and the target device. All definitions of data structures or functions that can be used by the **scan** clause, i.e., the **Polynomial** data structure and the **Operator** multiply function (`operator*`), must be enclosed in the **declare target** directives. This is done by lines 1–13 in Listing 4.6. Attention, in this example is presented the use of the operator overloading construct that it's necessary to solve the problem.

Listing 4.7 shows the header and signatures of the kernel functions generated by the compiler for the example showed at Listing 4.6 (Polynomial evaluation).

As shown in Listing 4.7, the first lines (1 – 11) is the information about the structure and operator used. The lines (16 – 20) kernel\_0 represented the first part of the algorithm

Listing 4.6: Fragment of the Polynomial Evaluation benchmark

```

1  #pragma omp declare target
2  typedef struct tag_my_struct {
3      int x;
4      int y;
5  } Pair;
6
7  Pair op(Pair A, Pair C) {
8      Pair ans;
9      ans.x = A.x * C.y + C.x;
10     ans.y = A.y * C.y;
11     return ans;
12 }
13 #pragma omp end declare target
14
15 #pragma omp declare scan(op
16 : Pair
17 : omp_out = op(omp_out, omp_in))
18 initializer(omp_priv = (Pair){0, 1})
19
20 int main() {
21     Pair *h;
22     Pair *t;
23
24     t = (Pair *)malloc(N * sizeof(Pair));
25     h = (Pair *)malloc(N * sizeof(Pair));
26     ...
27     #pragma omp target device(GPU) map(from : t[:N]) map(to : h[:N])
28     #pragma omp parallel for scan(op : t)
29     for (int i = 1; i < N; i++)
30         t[i] = op(t[i - 1], h[i - 1]);
31
32

```

who applies scan operator of the whole problem into blocks, The lines (22 – 25) `kernel_1` represented the second who applies scan operator over the vector filled in the previous step to get the cumulative sums for all the blocks. The lines (27 – 31) `kernel_2` is the final step who fixes cumulative sums for every element to get the final vector.

## 4.4 Parallelizing matrix exponentiation

Given a square matrix  $A$  the *Matrix Exponentiation*  $A^k$  is an operation that performs the iterative multiplication of  $A$   $k$  times.  $A^k$  is a central operation in many scientific problems like finding multiple recurrent sequences, solving dynamic programming with fixed linear transitions, finding strings under constraints, among others [25].

$$\begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}^n = \begin{bmatrix} fib_{n+1} & fib_n \\ fib_n & fib_{n-1} \end{bmatrix} \quad (4.4)$$

Among all problems solved through matrix exponentiation, finding the first  $n$  numbers of the Fibonacci sequence is the most well-known [21]. This section shows, from the programmer perspective, how AClang works when using the proposed scan clause to solve this problem. Listing 4.8 presents a fragment from the calculation of the Fibonacci series using matrix exponentiation<sup>1</sup>. The algorithm is based on Equation 4.4, which can

<sup>1</sup>Note that in real applications, this is counted in terms of the number of *bigint* arithmetic operations, not primitive fixed-width operations.

Listing 4.7: Fragment of Polynomial Evaluation kernel generated

```

1  struct Pair{
2      int x;
3      int y;
4  };
5
6  Point op(Pair A, Pair C) {
7      Point ans;
8      ans.x = A.x * C.y + C.x;
9      ans.y = A.y * C.y;
10     return ans;
11 }
12
13
14 #define omp_priv (Pair){ 0, 1 }
15
16 __kernel void kernel_0 (__global Pair *input,
17 __global Pair *S,
18 const int n) {
19     ...
20 }
21
22 __kernel void kernel_1 (__global Pair *input,
23 const int n) {
24     ...
25 }
26
27 __kernel void kernel_2(__global Pair *output,
28 __global Pair *input,
29 __global Pair *S) {
30     ...
31 }
32

```

be proven by mathematical induction.

The **target** clause (lines 28–29 in Listing 4.8) defines the portion of the program that will be executed by the accelerator device (lines 30–32). The **map** clauses control the direction of the data flow between the host and the target. All definitions of data structures or functions that can be used by the **scan** clause, i.e., the **Matrix** data structure and the **Matrix** multiply function (operator\*), must be enclosed in the **declare target** directives. This is done by lines 1–18 in the example. The **declare target** construct will result in the extraction of the appropriate code to be stored inside the kernel.

Notice that the implementation of the scan clause proposed in this work is powerful enough to handle the operator overloading construct already available in OpenMP (lines 20–22). This construct was previously defined in OpenMP for the **reduction** clause and was extend in the AClang compiler to enable the usage in the **scan** clause as well. Listing 4.8 shows how a programmer can use the **scan** clause with the user-defined matrix multiplication operator (\*). This operator and its neutral value (the identity matrix, in this case) are defined by the **declare scan** directive (lines 20–22). The AClang transformation engine (see Figure 2.2 ④) gathers this piece of information and through pattern matching techniques builds the kernel that will be dispatched to the target device so as to perform the scan operation.

Listing 4.9 shows the header and signatures of the kernel functions generated by the compiler for the example showed at Listing 4.8 (Fibonacci series). Notice that this example uses the new OpenCL 2.2 for which the kernel language is a static subset of the C++14

Listing 4.8: Fragment of the Fibonacci series benchmark

```

1  #pragma omp declare target
2  struct Matrix {
3      long x00, x01, x10, x11;
4      // default constructor:
5      Matrix() { x00 = 1; x01 = 1; x10 = 1; x11 = 0; }
6      // constructor:
7      Matrix(long x00_, long x01_, long x10_, long x11_) {
8          x00 = x00_; x01 = x01_; x10 = x10_; x11 = x11_;
9      }
10 };
11
12 Matrix operator*(Matrix A, Matrix C) {
13     return Matrix(A.x00 * C.x00 + A.x01 * C.x10,
14                  A.x00 * C.x01 + A.x01 * C.x11,
15                  A.x10 * C.x00 + A.x11 * C.x10,
16                  A.x10 * C.x01 + A.x11 * C.x11);
17 };
18 #pragma omp end declare target
19
20 #pragma omp declare scan( * : Matrix:          \
21     omp_out = omp_out * omp_in) \
22     initializer(omp_priv = Matrix(1,0,0,1))
23
24 int main() {
25     Matrix *x = new Matrix[N];
26     Matrix *y = new Matrix[N];
27     ...
28     #pragma omp target device(GPU) map(tofrom: y[:N]) map(to: x[:N])
29     #pragma omp parallel for scan( * : y)
30     for (int i = 1; i < N; i++)
31         y[i] = y[i - 1] * x[i - 1];
32     ...
33 }
34

```

standard which includes classes, templates, lambda expressions, function overload, etc. The OpenCL kernel language of any version older than 2.2 is an extended subset of C99, which does not feature operator overloading.

As shown in Listing 4.9, the data type and the user-defined functions in Listing 4.8 are passed to the kernel file as is, and the `omp_priv` variable that represents the identity matrix in the example (neutral element) is transformed to a `#define`. The size ( $N$ ) of the input matrix  $x$  is divided, according to the target device capacity in  $nt$  threads and  $nb$  blocks. The `kernel_0` function (lines 18–22) is responsible for executing the up-sweep and down-sweep phases for each block of the input array  $x$ , and to store into the auxiliary matrix  $sb$  (scan block) the cumulative user-defined operation (matrix multiply) of each block. The `kernel_1` function (lines 24–27) is responsible for executing the up-sweep and down-sweep phases of the auxiliary matrix  $sb$  that was generated in the `kernel_0` function. Finally, `kernel_2` (lines 29–33) is responsible for applying the user-defined operation (matrix multiply) of element  $i$  of the scanned block  $sb$  (`kernel_1`) to all values of the scanned block  $i + 1$  of the input array  $x$ , thus producing as result the output matrix  $y$ .

The current offloading mechanism in AClang implements the OpenMP 4.X `target data`, `target` and `declare target` constructs. This is done through the *AClang runtime library* which has two main functionalities: (i) it hides the complexity of OpenCL code from the compiler; and (ii) it provides a mapping from OpenMP directives to the OpenCL



Listing 4.9: Fragment of Fibonacci Series kernel generated

```

1  struct Matrix {
2  long x00, x01, x10, x11;
3  Matrix() { x00 = 1; x01 = 1; x10 = 1; x11 = 0; }
4  Matrix(long x00_, long x01_, long x10_, long x11_) {
5      x00 = x00_; x01 = x01_; x10 = x10_; x11 = x11_;
6  }
7  };
8
9  Matrix operator*(Matrix A, Matrix C) {
10     return Matrix(A.x00 * C.x00 + A.x01 * C.x10,
11                 A.x00 * C.x01 + A.x01 * C.x11,
12                 A.x10 * C.x00 + A.x11 * C.x10,
13                 A.x10 * C.x01 + A.x11 * C.x11);
14 };
15
16 #define omp_priv Matrix(1, 0, 0, 1)
17
18 __kernel void kernel_0 (__global Matrix *x,
19 __global Matrix *sb,
20 const int nt) {
21     ...
22 }
23
24 __kernel void kernel_1 (__global Matrix *sb,
25 const int nb) {
26     ...
27 }
28
29 __kernel void kernel_2(__global Matrix *y,
30 __global Matrix *x,
31 __global Matrix *sb) {
32     ...
33 }
34

```

API, thus avoiding the need for device manufacturers to build specific OpenMP drivers for their accelerator devices.

The AClang compiler generates calls to the AClang runtime library whenever a **target data** or **target** directive is encountered. As shown in the Fibonacci Series example (Listing 4.8), the **declare target** construct will result in the extraction of the appropriate code to be stored inside the kernel. Also, the AClang runtime library is responsible to initialize the data structures that handle the devices and the context and command queues for each device. In addition, it creates the necessary data structures to store the handlers for the kernels and the buffers and to offload data to the accelerator device memory. In AClang, it is responsibility of the compiler to generate the code needed to manage all the phases required by the scan algorithm. Therefore, no changes were made to the runtime library.

# Chapter 5

## Related Works

During the 80's Hillis and Steele [16] developed approaches to parallelize many serial algorithms. Although at that time these algorithms seemed to have only sequential solutions, by using the **The Connection Machine** [17] they managed to achieve execution times in  $\mathcal{O}(\log n)$ . One of these algorithms was the sum of the elements of an array, also known as reduction. With a slight modification of reduction Hillis and Stelle proposed a solution to compute *All Partial Sums* of an array, a problem that is currently known as prefix sum or simply scan.

The generalization that scan is an important primitive for parallel computing was presented by Guy E. Blelloch in [8]. In that work scan was defined as a *unit time* primitive under the PRAM (**P**arallel **R**andom **A**ccess **M**achine) model and Blelloch presented a new technique to perform the scan operator. That technique was implemented using a binary balanced tree and was explained in Section ?? . Scan was then used to parallelize some very relevant algorithms like: Maximum-Flow, Maximal Independent Set, Minimum Spanning Tree, K-D Tree and Line of Sight, thus improving their asymptotic running time to  $\mathcal{O}(\log n)$ .

In [18] Horn proposed an efficient implementation of scan in GPUs. That algorithm was based in Hillis and Steele's work and was used to solve the problem of extracting the undesired elements of a set. Scan was used to determine the undesired elements, and this was followed by a search and gather operation to compact the set. This problem is known as *Stream Compaction*, and has a running time of  $\mathcal{O}(n \log n)$ .

In [15] Mark Harris et al. implemented in GPUs the scan operator based on the work of Blelloch [8]. That implementation proved to be better than the solution proposed by Horn [18]. The main difference between those two approaches is the number of operations executed to solve the problem. In the case of [18], the total number of operations is  $n \log n$ , and in the case of [15] the total number of operations is  $n$ , the same number as in the serial version.

Also in [15], Harris presented a solution to treat large input vectors in GPUs. It is well known that the size of one GPU block is limited and thus the computation of scan for larger input sizes is done in two scan steps: (i) a first step inside each block; and (ii) a second step among the blocks. The approach proposed in Section 3.2 uses [15] to deal with large input vectors and the work in [8] to perform the individual scan steps.

In [28] Sengupta and Harris presented several optimizations for the implementation

proposed in [15]. Those optimizations were designed to deliver maximum performance for regular execution paths via a *Single-Instruction, Multiple-Thread* (SIMT) architecture and regular data access patterns through memory coalescing. That work was the base for the widely used CUDPP library [1], which presents an easy and efficient but limited use of the scan operator.

In [19] Bell and Hoberock designed a library called Thrust. That library resembles the C++ Standard Template Library (STL). Thrust parallel template library allows to implement high-performance applications with minimal programming effort. The library offers an implementation of the scan operator that eases the task of the programmer. Thrust was used to implement the CUDA version of the benchmarks described in Section ??.

Shengen Yan et. al. [32] implemented the scan operator in OpenCL based on [15], He improved the performance by reducing the number of memory accesses from  $3n$  to  $2n$  and eliminating global barrier synchronization completely.

In 2015, Wiefferink [30] implemented other version of the scan operation in OpenCL. This work improved the branch divergence of the algorithm in [8] [15]. As expected, this implementation works in NVIDIA and AMD GPU platforms, unlike most previous versions that just worked in NVIDIA GPUs.

# Chapter 6

## Experimental Evaluation

This section presents an experimental evaluation using a prototype implementation of the OpenMP scan clause in the AClang compiler. The experiments in this section use three heterogeneous CPU-GPU architectures: (i) a desktop with 2.1 GHz 32 cores Intel Xeon CPU E5-2620, NVIDIA Tesla K40c GPU with 12GB and 2880 CUDA cores running Linux Fedora release 23; (ii) a laptop with 2.4 GHz dual-core Intel Core i5 processor integrated with an Intel Iris GPU containing 40 execution units, and running MacOS Sierra 10.12.4; and (iii) a mobile Exynos 8890 Octa-core CPU (4x2.3 GHz Mongoose & 4x1.6 GHz Cortex-A53) integrated with an ARM Mali-T880 MP12 GPU (12x650 Mhz), and running Android OS, v6.0 (Marshmallow)

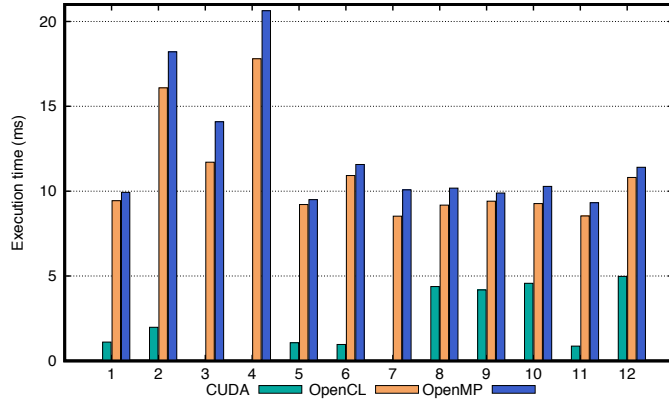
The experiments were carried out by a set of micro-benchmarks shown on Table ?? that were specially selected to evaluate the proposed scan clause and to provide significant insight on the strengths and weaknesses of its implementation in OpenMP. This set of micro-benchmarks was designed to enable the exploration of the parallel scan algorithms of representative applications in scientific computing. For each micro-benchmark used in the evaluation three versions were developed: (i) a CUDA based version, using the Trust C++ template library [4]. Thrust provides a rich collection of data parallel primitives such as scan, sort, and reduce, allowing the implementation of high performance parallel applications with minimal programming effort through a high-level interface that is fully interoperable with CUDA C. However, the parallel scan implementation only allows vectors of primitive data types, i.e. it does not allow the use of structures (compound data types); (ii) an OpenCL version using the same algorithms used in the implementation of the OpenMP scan clause in AClang; and, (iii) a C/C++ version using the proposed OpenMP parallel scan clause which enables a higher level of abstraction when compared to the OpenCL and CUDA versions.

The results presented in all experiments of this section are average over ten executions. Variance is negligible; hence, we will not provide error intervals.

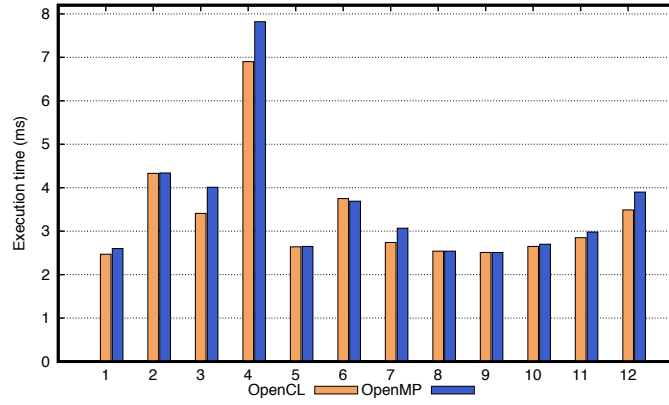
To evaluate the performance of the implementation of the proposed OpenMP scan clause, three experiments were performed. In first hardware platform (NVIDIA Tesla) three versions of parallel scan were tested for each benchmark program: (i) CUDA; (ii) OpenCL; and (iii) OpenMP. The other two hardware platforms (Intel Iris and ARM Mali) do not support (CUDA) and thus only the OpenCL and OpenMP implementations were used.

Figure 6.1: Analysis of parallel scan using a set of micro-benchmarks

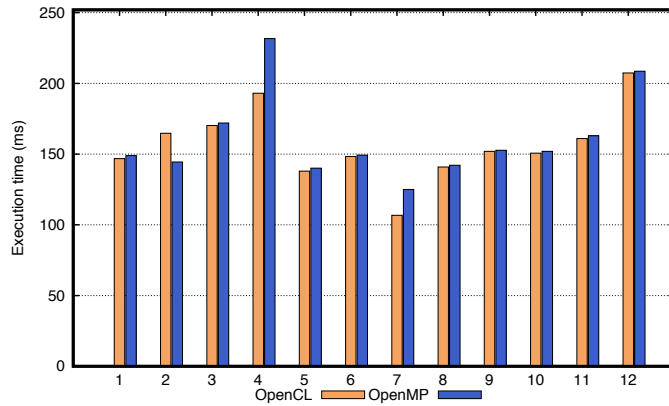
(a) The execution on Intel Xeon CPU E5-2620 with NVIDIA Tesla K40c



(b) The execution on Intel Core i5 with Intel Iris GPU

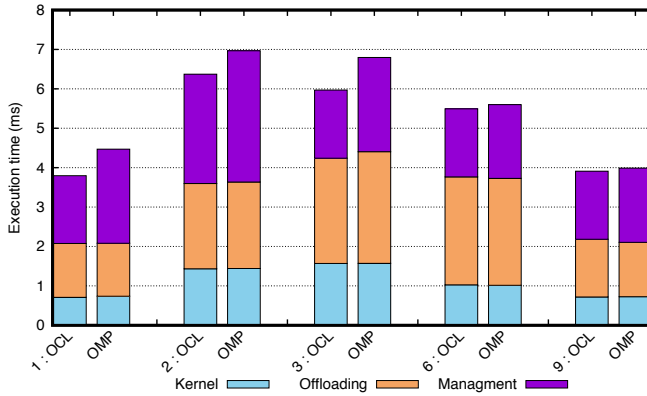


(c) The execution on Exynos 8890 Octa-core with ARM/Mali-T880



The graphs in Figures 6.1a, 6.1b & 6.1c display the results. The horizontal axis of the graphs denote the number of the benchmark as in Table ?? and the vertical axis the execution time. In order to provide a minimum fair load for the GPUs and to minimize the influence of the data offloading latency appropriate data sizes were used for each input data. In other words, input sizes of  $1M$  elements were used for the NVIDIA platform and inputs of  $512K$  elements were used for the other two (smaller) hardware platforms (Intel

Figure 6.2: Analysis of the performance difference between the OpenCL and OpenMP implementations



and ARM) .

The graph in Figure 6.1a do not show the results for the CUDA version of experiments 3 (Polynomial Evaluation), 4 (Linear Recurrences) and 7 (Adding Big Integers) due to the lack of support to structured inputs in the CUDA Thrust library.

As shown in Figure 6.1a for all programs the CUDA version performed much better than the OpenCL and OpenMP versions. This is expected, given that the Trust library is optimized and specialized to NVIDIA devices. On the other hand, the focus of this work is to enable a generic scan implementation that could run on a broad range of heterogeneous devices and not only NVIDIA devices. For this reason, our implementation synthesizes generic OpenCL. Of course this does not preclude us from synthesizing CUDA in the future.

In order to better compare the performance of the proposed OpenMP scan clause to the performance of OpenCL code, we measured their percentage difference in all three hardware platforms. The experiments revealed a maximum 20.3%, an average 6.2%, and a standard deviation 7.4% difference in performance. This strongly suggests that the proposed clause can result in a similar performance as when directly programming in OpenCL with the advantage of a smaller programming complexity.

Although small, the performance difference between the OpenCL code and the new OpenMP scan clause is puzzling given that they use the exact same algorithm. After a thorough analysis, we observed that the performance difference was likely due by the AClang runtime library. To evaluate that, a new set of experiments with profile enabled was performed. Figure 6.2 shows the total execution time for some micro-benchmarks. On the x-axis of the figure are benchmark programs identified by their numbers as listed in Table ?? followed by a label OCL (OpenCL) or OMP (OpenMP) to indicate the corresponding implementation. On the y-axis are program execution times. Each bar in the figure is broken down according to the following tasks performed during program execution: (i) kernel computation (Kernel bar); (ii) kernel data offloading (Offloading bar) and (iii) runtime tasks like context creation, queue management, kernel objects creation and GPU dispatch (Managment bar). The analysis reveals that 80% to 90% of the slowdown over the OpenCL implementation are due to the AClang runtime library, not the algorithm itself. In fact, the runtime library does not have specific routines to handle

the scan operation data management. This was implemented using existent offload and dispatch operations in the library. We believe that it is possible to reduce this performance difference significantly by slightly adapting the runtime library to provide routines specific to the new scan clause.

**Maicol: REVIEW 3: Scalability** About large inputs, the algorithm computes of scan operator in accordance of user's resources, it means that the algorithm will divide the input size in slices of total threads available in the GPU, for example if the threads available are 1M and the size of the input is 10M, the algorithm will run 10 times slices of 1M and then will merge the partials slices to obtain the final answer.

## Chapter 7

# Conclusions and Future Works

The scan operation is a simple and powerful parallel primitive with a broad range of applications. This work presented an efficient implementation of a new scan clause in OpenMP which exhibits a similar performance as direct programming in OpenCL at a much smaller design effort. The main findings are:

- It is possible to improve the performance of the scan clause by providing specific routines to handle scan (and reduction) operations into the AClang runtime library.
- Based on the evaluated benchmarks, and after investigating the reasons for the differences in performance between the OpenMP and OpenCL versions, it is concluded that the use of the scan clause is perfectly acceptable due to the ease of programming given the high level of abstraction of OpenMP when compared to CUDA and OpenCL.



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