Efficient GPU Implementation of Lucas-Kanade through OpenACC

Olfa Haggui[1,2], Claude Tadonki[1], Fatma Sayadi[3] and Bouraoui Ouni[2]
[1]*Centre de Recherche en Informatique (CRI), Mines ParisTech - PSL Research University, 60 boulevard Saint-Michel, 75006 Paris, France*
[2]*Networked Objects Control and Communications Systems (NOCCS), Sousse National School of Engineering, BP 264 Sousse Erriadh 4023, Tunisia*
[3]*Electronics and Microelectronics Laboratory,Faculty of Sciences,*

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Abstract: Optical flow estimation stands as an essential component for motion detection and object tracking procedures. It is an image processing algorithm, which is typically composed of a series of convolution masks (approximation of the derivatives) followed by 2×2 linear systems for the optical flow vectors. Since we are dealing with a stencil computation for each stage of the algorithm, the overhead from memory accesses is expected to be significant and to yield a genuine scalability bottleneck, especially with the complexity of GPU memory configuration. In this paper, we investigate a GPU deployment of an optimized CPU implementation via OpenACC, a directive-based parallel programming model and framework that ease the process of porting codes to a wide-variety of heterogeneous HPC hardware platforms and architectures. We explore each of the major technical features and strive to get the best performance impact. Experimental results on a Quadro P5000 are provided together with the corresponding technical discussions, taking the performance of the multicore version on a INTEL Broadwell EP as the baseline.

1 INTRODUCTION

Motion detection is an important topic in computer vision because of its central consideration in various real world applications. Related algorithms are used in *objects tracking*(S.A. Mahmoudi, 2014; V. Tarasenko, 2016), *video surveillance*(V. Tarasenko, 2016; Kalirajan and Sudha, 2015), *basic image processing*(E. Antonakos, 2015; S. N.Tamgade, 2009), *cars technology*(R. Allaoui, 2017), *robotics*(C. Ciliberto, 2011), to name a few. Motion estimation consists in extracting a motion vector from a sequence of consecutive images by assuming that the intensity is preserved during the displacement. Currently, among the methods available in the literature, the optical flow algorithm is one of the most commonly used approach for motion evaluation, which is a basic block of a vision process designed for a specific application. There are different methods for optical flow estimation, with a pioneer work by J.J. Gibson (Gibson, 1950) in 1950.

The computing of the optical flow is a subject that has been widely studied for several decades, with successful implementations in many interesting applications. Besides pure optical flow investigations, a combination with other techniques has been considered too, like the work of Horn and Schunck (K.P. Horn, 1981), that has led to multiple derived methods and improved optical flow algorithms. It introduces a global constraint of smoothness over the whole image to minimize distortions in the flow. However, in case of small motions, this method is impeded by its weak robustness. The so-called *Lucas-Kanade algorithm* by Lucas and Kanade (B.D. Lucas, 1981) is a local approach providing more accurate results for optical flow estimation. The algorithm is less sensitive to image noises, yields good quality results with moderate computational cost, and is capable of tracking even tiny motions. Considering all these factors and in comparison with other optical flow algorithms, Lucas-Kanade method is the most considered one for estimating the optical flow for all (or selected) pixels, assuming that the flow is constant in a local neighborhood. The results of the algorithm is more reliable if corner pixels (O. Haggui, 2018) are used.

Our work stands as another parallelization of Lucas-Kanade algorithm in the context of multicore and manycore processor. Beside our OpenACC im-

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plementation, which is not a novelty by itself, we study the impact of OpenACC directives considerations on the scalability and memory access for GPU and CPU processors. The remainder of paper is organized as follows. Section 2 provides a basic background of the optical flow method and describes the Lucas-kanade algorithm. we start with a baseline multicore implementation in section 3. Section 4 and 5 gives an overview of GPU architecture and OpenACC programming paradigms respectively. In Section 6, we describe our OpenACC parallelization and we provide a commented report of our experimental results . Section 7 concludes the paper and outline some perspectives.

2 RELATED WORK

Beside the quality of the estimation, the execution time is also important (A. Garcia-Dopico, 2014; S. Baker, 2004), especially with the consideration of the real-time constraint. Indeed, since the algorithm is likely to be applied on the consecutive frames of a live video, it should as fast as possible. Implementation of the Lucas-Kanade algorithm on the graphics processor Unit (GPU), in the GPGPU standpoint, is seriously considered. In (J.Marzat, 2009), Marzat, Dumortier and Ducroct propose a parallel implementation on a GPU to compute a dense and accurate velocity field using NVIDA Gt200 card, which achieved 15 velocity field estimations per second on 640x480 images. Another relevant contribution is presented in (S.A. Mahmoudi, 2014), in which the authors implemented the optical flow motion tracking using Lucas-kanade combined with Harris corner detector (only corner pixels are considered) on a Full HD video using multiple GPUs. A thorough implementation study is provided by Plyer, Guy and Champagnat in (A. Plyer, 2016) denoted by eFLOKI. It is a robust, accurate and high performance method even on large format images. Duvenhage, Delport and Jason(B. Duvenhage, 2010) also investigated a GPU implementation using the Open Graphics Library (OpenGL) and the Graphics Library Shading Language (GLSL), with a performance similar than a comparative CUDA implementation. Other authors have addressed the parallelization of optical flow computation on FPGA (A. Garcia-Dopico, 2014; R. Allaoui, 2017). They conclude that both have similar performance, although their FPGA implementation took much longer to develop. An implementation on the CELL processor (C66xDSP) is provided and discussed by Zhang and Cao (F. Zhang, 2014).

Regarding the multicore parallelization of the algorithm, the work by (Kruglov, 2016) for instance describes an updated method in order to speed up the objects movement between frames in a video sequence using OpenMP. Another multi-core parallelization is proposed in (N. Monz, 2012). Pal, Biemann and Baumgartner (I. Pal, 2014) discuss how the velocity of vehicles can be estimated using optical flow implementation parallelized with OpenMP. Moreover, another hybrid model mitigate the bottleneck of motion estimation algorithms with a small percentage of source code modification. In (N. Martin, 2015), Nelson and Jorge proposed the first implementation of optical flow of Lucas-kanade algorithm based on directives of OpenACC programming paradigms on GPU. Carlos and Guillerom (C. Garcia, 2015) evaluated also the directives of OpenACC with the GPU performance. In this context our work evaluate also a new OpenACC implementation but which processes and analyzes the bottlenecks of the accesses memory.

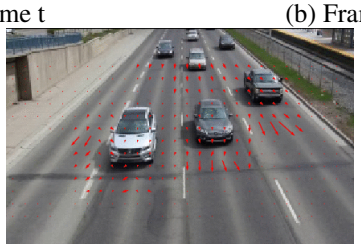
3 LUCAS-KANADE ALGORITHM

3.1 Optical Flow

The optical flow is a computer vision topic, where the main kernel is to calculate the apparent motion of features across two consecutive frames of a given video, thus estimating a global parametric transformation and local deformations. It is based mainly on local spatio-temporal convolutions that are applied consecutively. The optical flow has lots of uses, and it is an important clue for motion estimation, tracking, surveillance, and recognition applications. Different methods have been proposed for optical flow estimation (B.D. Lucas, 1981; K.P. Horn, 1981; Gibson, 1950; Adelson and Bergen, 1985; Fleet and Jepson, 1995; Kories and Zimmerman, 1986), and they can be grouped into *block-based* methods, *spatio-temporal* differential methods, *frequency-based* methods and *correlation-based* method. Each method has its advantages and its disadvantages, but the main drawback is the limited speed and the need of a large memory space. Over the years, Horn and Schunck algorithm(K.P. Horn, 1981) and Lucas-kanade algorithm (B.D. Lucas, 1981) have became the most widely used techniques in computer vision. We have focused on Lucas-kanade's approach because is the most adequate in terms of calculation complexity and requires less computing resources. The main principle of the Lucas-Kanade optical flow estimation is to assume the brightness constancy to find the velocity vector between two successive frames (t and t+1) as show in Figure 1, (a) and (b). The optical flow vectors

are drawn in Figure 1 (c). The accuracy of the estimation of the displacement from the video sequence is the main qualitative concern. Recalling that we have to analyze a (live) video, a real-time processing appears very important, thus justifying all efforts to reach a fast implementation.

(a) Frame t (b) Frame t+1



(c) Optical flow vectors

Figure 1: Optical Flow computation.

3.2 Description of Lucas-Kanade Algorithm

The idea is to focus on representative pixels (corner pixels for instance), which are then checked for motion across consecutive frames through intensity variations, that are perceived as relative motion between the scene and the camera. Consider a given 2D image, a small motion is approximated by a translation. Thus, if the current frame is represented by its intensity function I, then the intensity function H of the next frame is such that

$$H(x,y) = I(x+u, y+v), \tag{1}$$

where (u,v) is the displacement vector. For this purpose, we have to solve for every pixel the following so-called *Lucas-Kanade equation*:

$$\begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = - \begin{bmatrix} \sum I_x I_t \\ \sum I_y I_t \end{bmatrix} \tag{2}$$

where I_x, I_y and I_t are the derivatives of the intensity along x, y and t direction respectively. The system really implements a least-square approach to find the most likely displacement (u,v), since the original system is overdetermined. The summations within equation (2) are over the pixels inside the sampling window. If the condition number of the normal matrix is above a given threshold, then we compute the solution of the system (using Kramer method for instance) and thus obtain the components of the optical flow vector for the corresponding pixel. An schematic view of an algorithm for this computation can be stated as follows:

1. compute the derivatives I_x, I_y, and I_t
2. compute the products I_x^2, I_y^2, $I_x I_t$, $I_y I_t$, and $I_x I_y$
3. compute the matrix of the normal sub-matrices and the corresponding right and sides
4. solve the linear systems for the optical flow vectors

The derivatives (Step 1) are computed through their Taylor approximations using the corresponding convolution kernels. Then follows their point-wise products in step 2. Step 3 computes for each pixel the normal matrix and the right hand side of the linear system as described in equation (2). In the ultimate step where we solve the previous linear systems for each pixel, the computation of the condition numbers is implicit, they are indeed evaluated and compared with a the chosen threshold in order to decide whether we give up or we compute the solution of the system for the optical flow vector. Figure 2 displays a schematic view of the Lucas-Kanade computation chain.

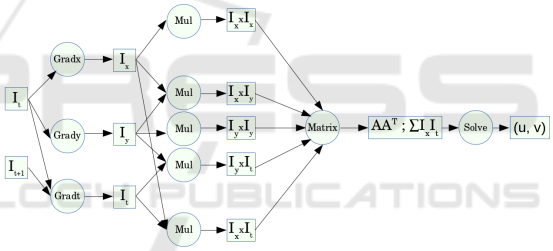


Figure 2: Workflow of Lucas-Kanade algorithm.

4 BASELINE MULTICORE IMPLEMENTATION

Our work start with a baseline sequential implementation where all operators involved in the Lucas-kanade algorithm are separable. We are apply operators clustering (O. Haggui, 2018) where the aims at merging all the operators into a single one, in order to reduce the number of floating point operations(flops) and reduce the intermediate storage. Furthermore, we are study the effect of array contraction technique (Y. Song, 2004), it is a program transformation which reduces the array size while preserving the correct output to perform the data reuse and cache locality. A special case of array contraction called array scalarization has been used in order to improve register utilization. At the same time, we use a shifting strategy which is the most well-known and fundamental

tool for matrix computations to resolve the memory alignment issues.

Table 1: Evaluation of the Multicore optimization.

# cores	1	2	4	8	10
	T(s)	Acc	Acc	Acc	Acc
2000^2	0.08	1.96	3.78	7.15	8.89
4000^2	0.34	1.95	3.86	7.53	9.28
6000^2	0.78	1.97	3.85	7.46	9.23
8000^2	1.38	1.95	3.88	7.58	9.35
12000^2	3.27	1.97	3.87	7.56	9.33

In order to evaluate our optimization strategies, we consider an Intel Xeon E5-2669 v4(Broadwell-EP) CPU having a total of 44 cores divided into 4 NUMA (Non-Uniform Memory Access) nodes. We chose to consider just one node NUMA (11 cores) with different size of images. Table 1 illustrates the effect of the optimization strategies with multicore using OpenMP programming language . we can notice that when increasing the image resolution, OpenMP does not provide a great improvement because it reaching the maximum parallelism that can be supplied. However, our speedups are good and can be improved by considering hardware accelerators like the GPU.

5 GPU ARCHITECTURE

Graphics Processor units (GPUs) stands as one of the most effective manycore hardware accelerator in the HPC landscape. GPUs are increasingly considered in the implementation of numerous scientific and commercial applications. Modern GPUs consist of multiple streaming multiprocessors (SMs or SMXs); each SM consists of many scalar processors (SPs, also referred to as cores). Each GPU supports a concurrent execution of hundreds to thousands of threads, and each thread is executed by a scalar core as shown in Figure 3. The elementary scheduling and execution unit is called a *warp*, which is composed of 32 threads. Warps of threads are grouped together into a *thread block*, and blocks are grouped into a *grid*. Both thread block and grid can be organized into a one, two or three-dimensional topology (A. Brodtkorb, 2013; T. Allen, 2016). The main advantage of GPUs is their ability to perform significantly more floating point operations(FLOPs) per unit of time than an ordinary CPU, and they well implement data parallelism. Memory system is quite different between CPUs and GPUs. A GPU has a more complex memory hierarchy and the related information are not usually provided with necessary details by the vendors. Analyzing the memory access pattern and the

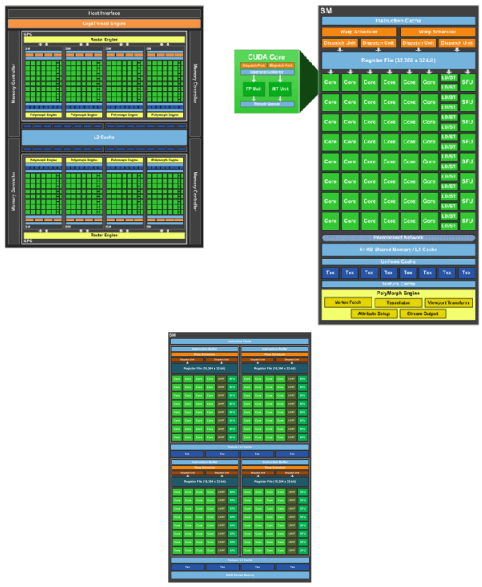


Figure 3: Processing units packaging within a GPU.

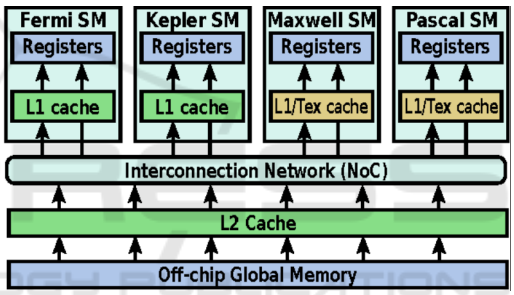


Figure 4: Overview of NVIDIA memory hierarchy.

associated costs on a GPU is an extremely challenging task, which is a very important optimization step as memory activity in this context is likely to be the main performance bottleneck. The memory of a GPU has different levels. The of-chip global memory resides in RAM of the host CPU. It is accessible by all threads in a grid, and this is the space where data exchanges occur. There are also other types of data storage units, namely *registers* and *shared memories*, which cannot be accessed directly by the host, but by the thread. However, shared memory subspace is allocated per thread block and is accessible by all of its threads. Because the shared memory is on-chip, latency is much lower than for global memory. It is frequently used as an optimization for applications where data are reused once inside a thread block. The L1 cache in the NVIDIA architecture is reserved only for local memory accesses by default. Global loads/stores are cached within the L2 cache only. Read-only Data Cache was introduced in the latest NVIDIA architecture. Texture memory and constant memory are allocated in the off-chip memory associated to global memory,

but is accessed via dedicated buses. Both memories have their own cache space and special features, and are accessible by all threads. Figure 4 shows an overview of the memory hierarchy in NVIDIA GPUs.

Memory accesses are commonly known to yield the performance bottleneck with GPUs, they have been the major focus of code analyses for performance improvements (N. K. Govindaraju, 2006; T. Allen, 2016). The most offending overhead comes from data transfers between the host and the device. These transfers must pass through peripheral components and the interconnect express bus. In addition, with the different levels of the GPU memory system and the large amount of data access, memory activity is globally a critical point for performance concerns. Accesses to global memory could get coalesced/uncoalesced. Hence,it is possible to reduce the number of global memory accesses as long as two conditions are met: *coalescence*, where the neighboring threads should access neighboring data and *alignment*, where the addresses should be a multiple of the segment's size. In addition, the accesses to shared memory could suffer from bank conflicts, accesses to texture memory could come with spatial locality penalty and accesses to constant memory could be broadcast. The use of GPUs is more suitable with highly regular applications.

6 OVERVIEW OF OPENACC PROGRAMMING MODEL

OpenACC(NVIDIA, 2015), (OpenACC, 2017) is an accelerator programming standard emerged in 2011 as a model that uses high-level compiler directives to expose parallelism in the code and generate parallel or accelerated versions for GPUs and multicore CPUs. This paradigm relies on compilers to generate efficient code and optimize for performance. In fact, the programmers use compiler directives to indicate which areas of code to accelerate, without any modification into the code itself. OpenACC uses *parallel* or *kernels* constructs to define a compute region that will be executed in parallel on the device, where the loop construct is used to specify the distribution of the iterations. In fact, the main program runs on the CPU and the parallel (child) tasks are offloaded to the GPUs. Moreover, the purpose of having both parallel and kernels constructs is that the parallel construct provides more control to the user while the kernels one offers more control to the compiler. OpenACC defines three levels of parallelism: *gang*, *worker* and *vector*. A schematic view of a standard OpenACC diagram is displayed in figure 5, Where a gang is composed of one or multiple workers. All workers within a gang can share resources such as cache memory or processor, and a worker can computes just one vector. A vector threads performs a single operation on multiple data (SIMD) in a single step.

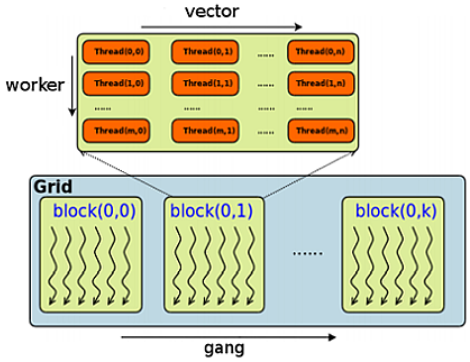


Figure 5: OpenACC working diagram.

In addition to the directives to express parallelism, the OpenACC API also contains data directives. To avoid unnecessary data exchanges between the local memory of the GPU and the main memory located on the host, the programmer can give some hint information to the OpenACC compilers through appropriate data directives. Generally, the OpenACC compiler is responsible for the correctness and optimization of data movement in both memories (GPU and CPU). OpenACC provides different types of data transfer directives, clauses and runtime. Listing 1 shows an example of a data directive to import the input from the host to the device using the *copyin* clause, and vice-versa with *copyout*.

```
#pragma acc data
copyin(I[0:sizeNt*sizeMt],
Itt[0:sizeNtt*sizeMtt])
copyout(F[0:sizeNt*sizeMt])
{
#pragma acc parallel loop
private(j,aIx,aIy,aIt)
gang num_gangs()
worker num_workers()
vector_length()
present(I[0:sizeNt*sizeMt],
Itt[0:sizeNtt*sizeMtt])
create(D[0:(2*z+1)*sizeNt])
 for(i = 0; i <2*z; i++)
 {
 #pragma acc loop gang, vector
  for(j = 0;j< sizeNt-2; j++)
   {
aIx = I[w((i+1),(j+1)+1)]-
      I[w((i+1),(j+1))];
aIy = I[w((i+1)+1,(j+1))]-
```

```
        I[w((i+1),(j+1))];
aIt  =  Itt[w((i+1),(j+1))] -
        I[w((i+1),(j+1))];
    }
  }
```

Listing 1: Generic code with data related directives

7 PARALLELIZATION AND EVALUATIONS

7.1 Hardware Configuration

To carry out the tests on the implementation developed in OpenACC, we have used a Quadro P5000 GPU accelerator from NVIDIA (Pascal architecture). It includes 2560 CUDA cores with 16 GB GDDR5 memory. The host is an Intel(R) Xeon(R) CPU E5-1620 v4 processors with 4 cores. We use PGI-pgcc, version 18.4.

7.2 Results of the Parallelization

In our experiments, we use different sizes of frame and run our Lucas-Kanade implementation for the optical flow vectors. We start with a baseline sequential implementation in C, enhanced with an OpenCV function to load the image frames, then we have the derived OpenACC version to parallelize the code without considering any data directives. The first step of the algorithm consists in loading the data from the CPU to the GPU's global memory. This step is yield a significant overhead. Then, we define which part will be accelerated with the device (kernel) using the basic directives (`#pragma acc kernel and/or #pragma acc Parallel`) as describe previously in listing 1.

Table 2: Evaluation of the GPU parallelization.

Image size	CPU (s)	GPU (s)
2000^2	0.09	0.018
4000^2	0.34	0.057
6000^2	0.78	0.13
8000^2	1.38	0.25
12000^2	3.27	0.64

We can see from table 2 that the OpenACC code on the GPU significantly outperforms the parallel CPU version. However, since the version at this stage does not contain any memory optimization directive, there is a *potential* room for improvement we at this stage. To evaluate this potential, we used the NVIDIA runtime profiler on our kernels to identify where memory accesses look too high. We can use also OpenACC flag `-Minfo=all,clff` to print all the information about how to optimize the code.

7.3 Data Movement Optimization

In this subsection, we analyze the behavior of the major data movement *directives* and *clauses* in order to reduce the overhead of data exchanges and get ride of intermediate data accesses whenever possible.

OpenACC allows an explicit control of data allocation together with the corresponding transactions through appropriates clauses (`copyin`, `copyout`, `present`, `create`). OpenACC provides the cache directive `#pragma acc cache`, which tells the compiler to seek the best cache performance for the indicated memory region.

Although NVIDIA provides the concept of *unified memory*, which allows the GPU and the host CPU to share the same global address space. This is made technically possible using the NVLink interconnect. The unified memory enables fast memory accesses with large data sets. In fact, OpenACC compiler provides the flag `-ta=tesla:managed` for the unified memory consideration, and the flag `-ta=tesla:pinned` for pinned memory. It is a memory allocated using the `cudaMallocHost` function, which prevents the memory from being swapped out and thereby provides improved transfer speeds, contrary to the non-pinned memory obtained with a plain `malloc`. In this context, the compiler relies on the CUDA runtime to migrate data automatically through Unified Memory, ensuring the coherence between data references on the GPU and the corresponding addresses on the main memory. The experimental results of our optimization investigation are summarized in Table 3.

Table 3: Evaluation of our GPU optimization.

	2000^2	4000^2	6000^2	8000^2	12000^2
(1)	0.018	0.057	0.130	0.250	0.640
(2)	0.007	0.024	0.056	0.091	0.174
(3)	0.007	0.025	0.057	0.095	0.181
(4)	0.006	0.023	0.055	0.088	0.174
(5)	0.006	0.020	0.052	0.074	0.147
(6)	0.005	0.018	0.047	0.074	0.145

- (1): Basic GPU parallelization
- (2): (1) + Data movement performance
- (3): (1) + Unified memory
- (4): (2) + cache directive
- (5): (2) + pinned
- (6): (4) + (5)

Figure 6 provides a global view of our incremental OpenACC optimization, while figure 7 displays a comparison between the baseline CPU implementation and the fully optimized GPU one. In both cases, the x-axis is for image sizes and the y-axis is for the overall execution timings in seconds.

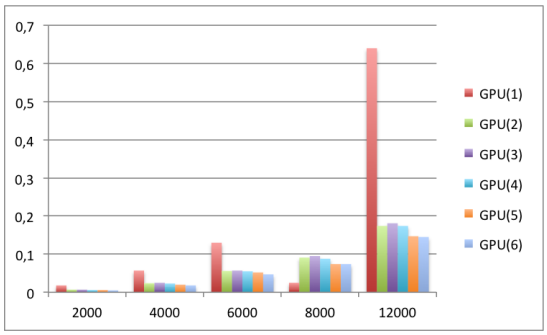


Figure 6: Incremental GPU optimization.

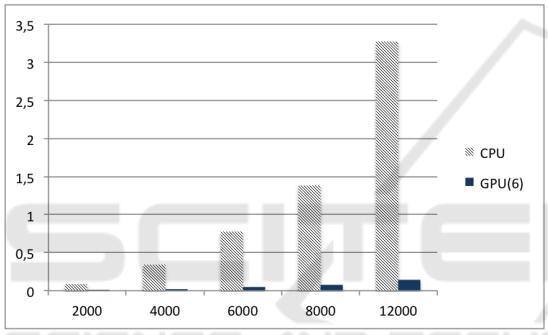


Figure 7: Basic CPU and fully optimized GPU.

Let summarize the steps of our work in this paper. We consider the Lucas-Kanade algorithm for optical flows computation. We start an optimized sequential version that we parallelize with OpenMP and we get decent speedups. Afterwards, looking at the absolute performance, we investigate what can be obtain with a GPU using OpenACC. Using the profile, we identify the major bottleneck of the kernel: memory transactions. We focus on efficient memory organization and movement of data, performing an incremental memory optimization to get the best performance, which, as expected, outperforms the parallel CPU implementation.

8 CONCLUSION

A fast and accurate estimation of the optical flow fields is a challenging task, both because of the stencil nature of the computation and the memory complexity of large-scale manycore accerelerator (GPU). In this work, we investigated an OpenACC parallelization of the Lucas-Kanade optical flow algorithm with GPUs and obtain better performance that a parallel version on a large multicore machine. OpenACC is a promising alternative to consider for a fast deployment on the GPU. It makes possible to migrate standard CPU code in a straightforward way without making too many modifications, and obtain a decent performance compared to other complex programming model like CUDA and OpenCL.

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