REAL-TIME DENSE DISPARITY ESTIMATION USING CUDA'S API

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Keywords: Stereovision, Real-time, Range map, Depth map, Dense matching, Beliefs propagation, General purpose calculations on graphic processors.

Abstract: In this paper, we present a real-time dense disparity map estimation based on beliefs propagation inference algorithm. While being real-time, our implementation generates high quality disparity maps. Despite the high complexity of the calculations beliefs propagation involves, our implementation on graphics processor using CUDA API makes more than 100 times speedup compared to CPU implementation. We tested our experimental results in the Middlebury benchmark and obtained good results among the real-time algorithms. We use several programming techniques to reduce the number of iterations to convergence and memory usage in order to maintain real-time performance.

1 INTRODUCTION

Stereo matching is a fundamental computer vision problems with a wide range of applications, and hence it has been extensively studied in the computer vision field for decades. This paper describes a programmable graphics hardware implementation of hierarchical beliefs propagation algorithm for stereo vision within Markov Random Field framework. MRF formulations of stereo and other early vision problems have existed for some time, but the computational and storage complexity make exact solutions infeasible; exact solutions to MAP estimator are NP-complete, hence the need for approximation algorithms such as graph cuts and beliefs propagation. As processing power has increased, the approximation algorithms have become practical for real-time stereo applications. Beliefs propagation is well suited for parallel execution and hardware implementation. Graphics processing units (GPUs) are highly parallel single -instruction-multiple-data (SIMD) processors built into modern graphics cards along with up to 512 MB or more of high-speed memory. GPUs and their programmable interface have become so versatile that much research has been done on performing general purpose computation in graphics hardware (GPGPU). GPU computing with CUDA is a new approach to computing where hundreds of on-chip processor cores simultaneously communicate and cooperate to solve complex computing problems up to 100 times faster than traditional approaches.

Section 2 describes state-of-the-art stereo matching algorithms. Section 3 describes parallel computing on GPUs using CUDA API. In section 4, we describe our implementation of the hierarchical beliefs propagation. Section 6 draws some conclusions based on our results exposed in section 5.

2 STEREO MATCHING ALGORITHMS

Stereo matching is a crucial step in the depth map estimation. Despite the simplification brought by the epipolar geometry, the problem of matching remains difficult to solve due to occlusion, luminosity changes between viewpoints and non textured areas. To overcome these difficulties, several methods have been proposed. A state of the art of different existing methods is presented by (Scharstein and Szeliski, 2002). Stereo matching algorithms are generally classified into two classes, local algorithms and global algorithms based on the cost computation method.

2.1 Local Methods

Local approaches are based on a correlation criterion over a local window containing the element to match. The choice of the appropriate size and shape is crucial

Boufarguine M., Baklouti M., Guitteny V. and Couvet S.
REAL-TIME DENSE DISPARITY ESTIMATION USING CUDAâĂŹS API.
DOI: 10.5220/0001773204170422
In *Proceedings of the Fourth International Conference on Computer Vision Theory and Applications (VISIGRAPP 2009)*, page
ISBN: 978-989-8111-69-2

to ensure the efficiency of these methods. The choice of a fixed size is not very wise because it does not fit all areas of the image. The principle of more efficient methods is to vary the size (Kanade and Okutomi, 1994) and/or the shape (Veksler, 2002) of the correlation windows. In (Yoon and Kweon, 2005), instead of finding the optimal correlation window, the authors adjust the weight of each pixel in the window.

2.2 Global Methods

Global approaches minimize an overall cost function that involves all the pixels of the image. It is generally expressed as an objective energy function

$$E(d) = E_{data}(d) + E_{prior}(d) \quad (1)$$

E_{prior} is a regularization term. The formulation of this term depends heavily on the scene and chosen constraints. Most algorithms use smoothness constraint. In this case, the function penalizes the difference of disparity of neighbouring pixels.

E_{data} encodes knowledge about forward image formation. It assigns a high cost for the functions of disparity that are not consistent with the data.

In the global methods, calculating the disparity field is led to minimize the objective function of energy. Several optimization methods have been proposed such as dynamic programming (Kim et al., 2005), graph cuts (Roy and Cox, 1998) and beliefs propagation.

3 BELIEFS PROPAGATION

We model the problem of stereo matching with a Markov random Field (MRF). We refer the reader to (Sun et al., 2003). Let P be the set of pixels in an image and L be a finite set of labels. The labels correspond to disparities that we want to estimate at each pixel. A labeling d assigns a label $d_p \in L$ to each pixel $p \in P$. To measure the quality of a labeling d, we consider the global energy function

$$E(d) = \sum_{p \in P} D_p(d_p) + \sum_{(p,q) \in N} U_{p,q}(d_p, d_q) \quad (2)$$

D_p and $U_{p,q}$ are the *data cost* and *smooth cost* respectively. The data cost encodes the log-likelihood function. The smooth cost encodes the prior distribution. N is the set of neighboring pixels couples.

3.1 Data and Smooth Costs

To compute the data cost, we use a truncated absolute difference as the matching cost. We aggregate this cost over a square window with constant disparity.

$$D_p(d_p) = \sum_{(x,y) \in N(p)} min(|I_{ref}(x,y) - I_{match}(x-d,y)|, T) \quad (3)$$

The smooth cost is also computed using a truncated absolute difference.

$$U_{p,q}(d_p, d_q) = min(|d_p - d_q|, \lambda) \quad (4)$$

$N(p)$ is a p-centered square window, I_{ref} is the reference image and I_{match} is the target image. T and λ are thresholds.

3.2 BP Algorithm

In the min-sum form of the BP algorithm, we minimize the global energy function in equation 2.

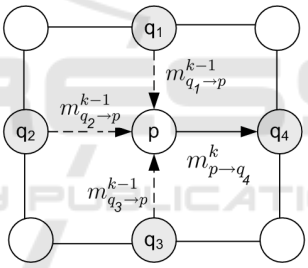


Figure 1: Messages Updates scheme.

BP estimates a MAP labelling for the MRF by sending messages between nodes (Figure 1). A node p sends to each of its four neighboors $q_i, i \in \{1,2,3,4\}$ a message $m^k_{p \to q_i}$ at every iteration k. Each message is a vector of length $|L|$, with each component being proportional to how likely node p "believes" that node q_i will have the corresponding disparity. In the min-sum algorithm, messages are updated in the following way

$$m^k_{p \to q_i}(d_{q_i}) = \min_{d_p}(D_p(d_p) + U_{p,q_i}(d_p, d_{q_i}) + \sum_{j \in \{1,2,3,4\}, j \neq i} m^{k-1}_{q_j \to p}(d_p)) \quad (5)$$

After K iterations, we compute the "beliefs" vector for each node p

$$b_p(d_p) = D_p(d_p) + \sum_{i \in \{1,2,3,4\}} m^K_{q_i \to p}(d_p) \quad (6)$$

Finally, for each node p we select the label d_p^* that corresponds to the component of b_p with the minimum value

$$d_p^* = arg\min_{d_p \in L} b_p(d_p) \quad (7)$$

3.3 Complexity Analysis

A standard implementation of the algorithm will be at best a complexity of $O(4 \times W \times H \times |L|^2 \times K)$. Where W and H are the image dimensions, L the set of disparity values and K the number of iterations. The factor 4 is due to the fact that four messages are updated per pixel and per iteration. we notice that the complexity is a quadratic function of the disparity range ($|L|$). In fact, to compute each of the $|L|$ values of the message, we do a minimization through the disparity values of equation 6. Moreover, the number of iterations to convergence (K) has a complexity of $O(\sqrt{W \times H})$ in order to propagate information over all the pixels. Thus, the complexity of computation is not linear according to the image dimensions.
In addition to its complexity, the beliefs propagation algorithm has the disadvantage to need a fairly large memory space. Indeed, we need to save in the memory, at least for two successive iterations and for each pixel, the four vectors of $|L|$ components representing messages.

3.4 Proposed Solution and Algorithm

In this section, we describe how to reduce the complexity of the algorithm. To reduce the complexity of the algorithm, we propose three solutions :

- reduce the complexity related to the disparity range from O($|L|^2$) to O($|L|$), by exploiting the properties of the chosen $U_{p,q}$ function (eq 4);
- reduce by half the memory space by exploiting the fact that our graph is bipartite;
- reduce the number of iterations needed for the convergence of the algorithm, using an hierarchical approach to update messages.

3.4.1 Reducing the Complexity Related to the Disparity Range

We can rewrite the equation 6 in the following form:

$$m^k_{p \to q_i}(d_{q_i}) = \min_{d_p \in [d_{min}, d_{max}]} (U_{p,q_i}(d_p, d_{q_i}) + h(d_p)) \quad (8)$$

where $h(d_p) = D_p(d_p) + \sum_{j=1, j \neq i}^{4} m^{k-1}_{q_j \to p}(d_p)$.
The usual approach to compute this message, explicitly minimizes this term throughout all the possible values of d_p. This needs $O(|L|^2)$ operations ($|L|$ is the number of disparity values). Using the properties of the function U_{p,q_i} (equation 4), we will demonstrate how to reduce the complexity to $O(|L|)$.
To simplify the demonstration, let's consider a non-truncated function. The update message function is done then as in equation 9.

$$m'(u) = \min_{d_p \in [d_{min}, d_{max}]} (\rho.min(|d_p - u| + h(d_p)) \quad (9)$$

for each $u \in [d_{min}, d_{max}]$. The minimisation of equation 9 can be seen as the convex hull of L cones defined by the parametric equation 10. Figure 2 shows and example of the convex hull.

$$\mathcal{C}_{d_p} : x \mapsto \rho\,|d_p - x| + h(d_p); d_p \in [d_{min}, d_{max}] \quad (10)$$

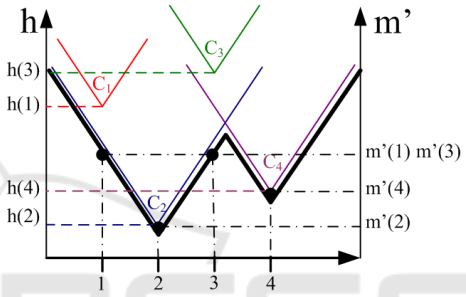


Figure 2: Convex hull of an example of 4 cones.

To compute this hull, we use an algorithm of distance transformation introduced by (Borgefors, 1986). The algorithm to compute the messages is detailed below.

Algorithm 1: Algorithm of computation of m' in O($|L|$).

for $u = d_{min}$ d_{max} **do**
  $m'(u) \leftarrow h(u)$
end for
for $u = d_{min} + 1$ d_{max} **do**
  $m'(u) \leftarrow \min(m'(u), m'(u-1) + \rho)$
end for
for $u = d_{max} - 1$ d_{min} **do**
  $m'(u) \leftarrow \min(m'(u), m'(u+1) + \rho)$
end for

Hence, for the truncated function we obtain :

$$m^k_{p \to q_i}(d_{q_i}) = \min\left(m'(d_{q_i}), \min_{d \in [d_{min}, d_{max}]} h(d) + \lambda\right) \quad (11)$$

3.4.2 Reducing the Memory Usage

The propagation of messages have the property of bipartite graph (figure 1). A bipartite graph is a graph

whose vertices can be divided into two disjoint sets A and B such that every edge connects a vertex in A to one in B. We notice that in the case of a bipartite graph, to update the messages sent by the pixels of A, we only need the messages sent by the pixels of B. As a result, to compute messages sent by a pixel of A at iteration $k+1$, we need only half of the messages of the iteration k unlike the classical algorithm. In addition to the gain in memory space, this technique can reduce by half the number of operations, since only half of the messages will be updated at each iteration.

3.4.3 Reduce the Number of Iterations a Hierarchical Approach

In our implementation, we use a multi-scale grid as described in (Felzenszwalb and Huttenlocher, 2006) to reduce the number of iterations to convergence. The basic idea is to perform BP in different scales from a coarset scale to a finest one. This technique allows long range interactions between pixels with a minimum number of iterations. The messages of a coarser scale are used to initialise the messages in a finer scale allowing to dramatically reduce the number of iterations in that scale.

4 PARALLEL COMPUTING ON GPUS WITH CUDA API

Graphics processing units (GPUs) have evolved to performances surpassing 500 GFLOPS. CUDA is a technology for GPU computing from NVIDIA. It exposes the hardware as a set of SIMD multiprocessors, each of which consists of a number of multiprocessors. These multiprocessors have arbitrary read/write access to a global memory region called the device memory, but also share a memory region known as shared memory. Access times to the device memory are long, but it is large enough (up to 1.5 GB on some cards) to store entire data sets. The shared memory, on the other hand, is small (16 KB) but has much shorter access times. It acts as an explicitly-managed cache. Traditional textures can also be stored in the device memory and accessed in a read-only fashion through the multiprocessor's texture cache. In addition, a limited amount of read-only memory is available for constants used by all the processors. This is accessed through the constant cache.

A schematic overview of the hardware model is shown in Figure 3. In a CUDA program, the developer sets up a large number of threads that are grouped into thread blocks. A CUDA thread has a set of registers and a program counter associated with

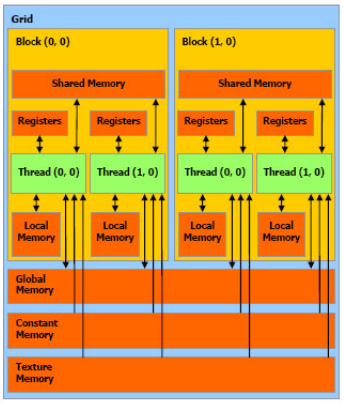


Figure 3: CUDA Execution Model.

it. Each thread block is executed on a single multiprocessor. It is possible to synchronize the threads within a block, allowing the threads to share data through the shared memory. Communication between all threads, however, require the use of global memory. Given that a thread block can consist of more threads than the number of processors in a multiprocessor, the hardware is responsible for scheduling the threads. This allows it to hide the latency of fetches from device memory by letting some threads perform computations while others wait for data to arrive.

5 CUDA IMPLEMENTATION STRATEGY

The implementation strategy has a great impact on the overall performance of the implementation. It deals with the allocation of threads to the problem and the usage of the different types of onboard memory. The approach chosen uses a thread to process a single pixel. The reference image is then divided into blocks having the same dimensions. Threads within a same threads block can communicate through the low latent shared memory. The next step is to determine what types of memory to use. Texturing from a CUDA Array is used for both the reference and target images. Using texturing provides several advantages mainly a cached access. Global memory is used to save the data costs and the messages. While using global memory is bandwidth limiting because of its latency (400 to 600 clock cycles), the use of shared memory is inadequate since the treatement of one block of pixels is dependent on its neighbouring blocks. Figure 4 shows the instruction flow (single arrows) and the data flow (double arrows) of our implementation.

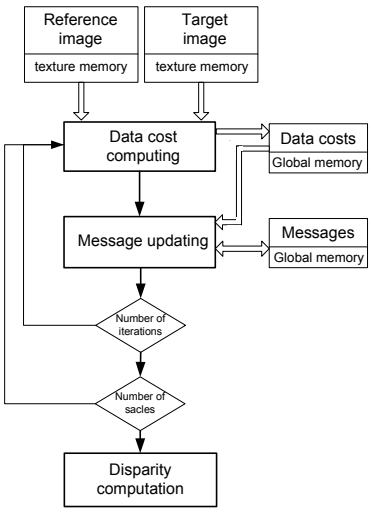
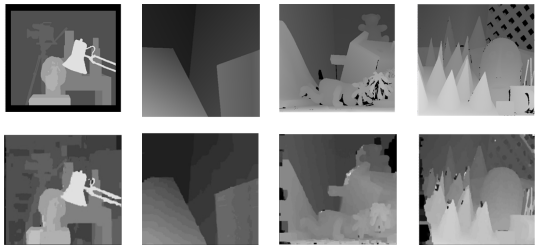


Figure 4: CUDA implementation details.

6 EXPERIMENTAL RESULTS

We tested our real-time BP algorithm on a 3 GHz PC equipped with a Geforce 8800 GTS graphics card with 512M video memory. In the proposed algorithm, we have two parameters T and λ used in the data and smooth costs computation modules (equations 3 and 4).

All kernels are implemented using CUDA API. The same parameter settings were used throughout the experiments with the following parameters $T = 20$, $\lambda = 3.0$. We implement hierarchical BP in GPU with three scales, and the typical iterations for each scale are (4,5,5), from coarse-to-fine scale.
Figure 5 shows the results we obtained for sequences of the benchmark Middlebury. The table 1 reproduces the classification by the benchmark Middlebury of our results compared to some algorithms listed. It is noteworthy that our algorithm is the 23^{rd} place in the overall standings, and 2^{nd} in the ranking algorithms real time.



(a) Tsukuba (b) Venus (c) Teddy (d) Cones

Figure 5: Disparity map estimation on sequences from Middlebury database.

Table 1: Classification by the benchmark Middlebury.

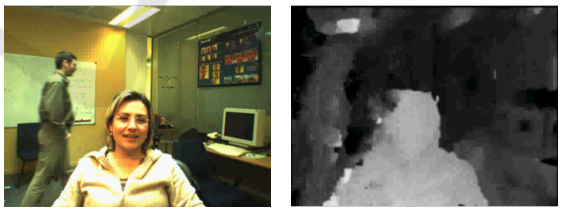
Algorithm	Rank	% false matching			
		Tsukuba	Venus	Teddy	Cones
AdaptingBP (Klaus et al., 2006)	2.8	1.11	0.10	4.22	2.48
RealtimeBP (Yang et al., 2006)	21.9	1.49	0.77	8.72	4.61
Our implementation	**23.2**	**1.59**	**1.13**	**12.6**	**6.27**
RealTimeGPU (Wang et al., 2006)	26.8	2.05	1.92	7.23	6.41
BP+MLH (Scharstein and Szeliski, 2002)	32.5	4.17	1.96	10.2	4.93

The implementation of the non-hierarchical algorithm takes approximately 14 ms per iteration (70 iterations per second). The choice of the number of iterations is empirical and depends on the desired quality of the disparity map.
The hierarchical approach of the algorithm reduces the number of iterations required. In our implementation, we used three scales. At each level, the image is downscaled by two from a scale to another. In our implementation, we chose to take one pixel on two to move from a scale to another.

Table 2: Comparaison between CPU and GPU computing times (Tsukuba sequence).

	Computing Time (ms)	FPS (fps)
CPU	4542	0.22
GPU	37	27

We obtained a frame rate of 27 FPS. To estimate the acceleration of the algorithm done with the GPU, we implemented the same algorithm on CPU and we used the same settings (table 2). The CPU takes 4.54 seconds to calculate a disparity map, which corresponds to 0.22fps. We have thus obtained an acceleration of 122 times compared to CPU.

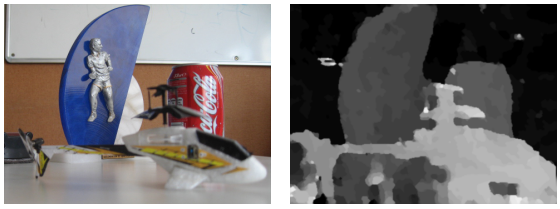


(a) Refernece image (b) Disparity map

Figure 6: Disparity map estimation on videos from Microsoft Research.

Figure 6 shows the estimated disparity map of a stereo sequence of 320x240 from Microsoft Research. Our implementation computes 25 frames per second to estimate a 40 levels disparity map.

Figure 7 shows the estimated disparity map of a stereo images of 320x240 taken by two DALSA cameras. Our implementation computes 26 frames per second to estimate a 35 levels disparity map.



(a) Reference image (b) Disparity map

Figure 7: Disparity map estimation on our own sequence.

7 CONCLUSIONS

Algorithms achieving high frame rates must have strong limitations in image size and disparity search range, whereas high quality results often need several minutes per image pair. We have presented in this paper a real time dense disparity estimation using CUDA API. GPU computing with CUDA is a new approach for parallel computing that supports the parallel data cache and thread execution manager for higher efficiency. We have presented in this paper a new parallel implementation of the efficient belief propagation algorithm. This allows real time computation and robustness is clearly demonstrated on the dedicated Middleburry benchmark.
We reduced the complexity of the algorithm using a distance transformation to minimize the convex hull for message computation. We reduced then the memory usage using bipartite graph properties. Finally, we used a multi-scale grid to reduce the number of iterations to convergence. In our implementation, we performed parallelized message updates thanks to CUDA progamming.
We tested our real-time BP algorithm on a 3 GHz PC equipped with a Geforce 8800 GTS graphics card with 512M video memory. We implemented hierarchical BP in GPU with three scales, and the typical iterations for each scale are (4,5,5), from coarse-to-fine scale. We used the Tsukuba data set with 16 disparity levels and we obtained 27 fps.

REFERENCES

Borgefors, G. (1986). Distance transformations in digital images. *Comput. Vision Graph. Image Process.*, 34(3):344–371.

Felzenszwalb, P. F. and Huttenlocher, D. P. (2006). Efficient belief propagation for early vision. *Int. J. Comput. Vision*, 70(1):41–54.

Kanade, T. and Okutomi, M. (1994). A stereo matching algorithm with an adaptive window. *IEEE Trans. Pattern Anal. Mach. Intell.*, 16(9):920–932.

Kim, J. C., Lee, K. M., Choi, B. T., and Lee, S. U. (2005). A dense stereo matching using two-pass dynamic programming with generalized ground control points. In *CVPR05*, pages 1075–1082.

Klaus, A., Sormann, M., and Karner, K. (2006). Segment-based stereo matching using belief propagation and a self-adapting dissimilarity measure. In *ICPR06*, pages 15–18.

Roy, S. and Cox, I. J. (1998). A maximum-flow formulation of the n-camera stereo correspondence problem. In *ICCV98*, page 492.

Scharstein, D. and Szeliski, R. (2002). A taxonomy and evaluation of dense two-frame stereo correspondence algorithms. *Int. J. Comput. Vision*, 47(1-3):7–42.

Sun, J., Shum, H., and Zheng, N. (2003). Stereo matching using belief propagation. *IEEE Trans. Pattern Anal. Mach. Intell.*, 25(7):787–800.

Veksler, O. (2002). Stereo correspondence with compact windows via minimum ratio cycle. *IEEE Trans. Pattern Anal. Mach. Intell.*, 24(12):1654–1660.

Wang, L., Liao, M., Gong, M., Yang, R., and Nister, D. (2006). High-quality real-time stereo using adaptive cost aggregation and dynamic programming. In *3DPVT06*, pages 798–805.

Yang, Q., Wang, L., and Yang, R. (2006). Real-time global stereo matching using hierarchical belief propagation. In *BMVC06*, page III:989.

Yoon, K.-J. and Kweon, I.-S. (2005). Locally adaptive support-weight approach for visual correspondence search. In *CVPR05*, pages 924–931.