Intelligent Vehicle Perception: Toward the Integration on Embedded Many-core

Tiana Rakotovao, Diego Puschini, Julien Mottin, Lukas Rummelhard, Amaury Nègre, Christian Laugier

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Tiana Rakotovao[1,2], Diego Puschini[1], Julien Mottin[1],
Lukas Rummelhard[2], Amaury Negre[3], Christian Laugier[2]

[1]CEA-LETI MINATEC Campus
17 rue des Martyrs
38000 Grenoble
surname.name@cea.fr

[2]INRIA Grenoble Rhône-Alpes
655 Av. de l'Europe
38334 Saint Ismier cedex
surname.name@inria.fr

[3]CNRS, LIG Laboratory
110 Av. de la chimie
38041 Grenoble cedex 9
surname.name@imag.fr

ABSTRACT

Intelligent vehicles (IVs) need a perception system to model the surrounding environment. The Hybrid Sampling Bayesian Occupancy Filter (HSBOF) is a perception algorithm monitoring a grid-based model of the environment called "occupancy grid". It is a highly data-parallel algorithm and requires a high computational performance to be executed in reasonable time. It is currently implemented in CUDA on a NVIDIA GPU. However, the GPU is power consuming and its purchase cost is too high for the embedded market. In this paper, we prove that, the couple embedded many-core/OpenCL is a feasible hardware/software architecture for replacing the GPU/CUDA. Our OpenCL implementation and experimental results on a testing hardware showed that a many-core can produce an occupancy grid every $168ms$ while consuming 40 times less power than the GPU. The results are promising for a future integration into IVs.

Categories and Subject Descriptors

C.3 [**SPECIAL-PURPOSE AND APPLICATION-BASED SYSTEMS**]: Real-time and embedded systems

Keywords

Many-core,OpenCL,perception system

1. INTRODUCTION

The research on Intelligent Vehicles (IVs) has gained an increasing focus during the last decades. Currently, IVs are equipped with Advance Driver Assistance Systems (ADAS) for performing security features (obstacle detection, collision avoidance, mobile object tracking, autonomous cruise control, automatic braking, etc.). Motivated by the improvement of car safety, road safety, lives saving and for a better driving, the development of ADAS institutes a main step toward fully-autonomous car. For realizing the features cited above, various technologies of sensors (stereo-vision, radar, Light Detection and Ranging (LIDAR), etc) are embedded on IVs for observing the surrounding environment. Regarding the sensor readings, the ADAS dispose a block called *perception system*, for building a computational model of the surrounding that the vehicle can interpret. For this purpose, the Hybrid Sampling Bayesian Occupancy Filter (HSBOF) [7] is a perception algorithm that builds a grid-based model of the environment. As shown in figure 1, the HSBOF maps the surroundings into a fixed size 2-dimension (2D) spatial grid divided into regular spatial cells. For each cell, the HSBOF computes the occupancy probability, that is, the probability that the cell is occupied, and estimates the velocity of the content of the cell. The nature of the obstacle occupying the cell does not matter. The occupancy probability is then updated according to new sensor readings. The output grid is called *occupancy grid*.

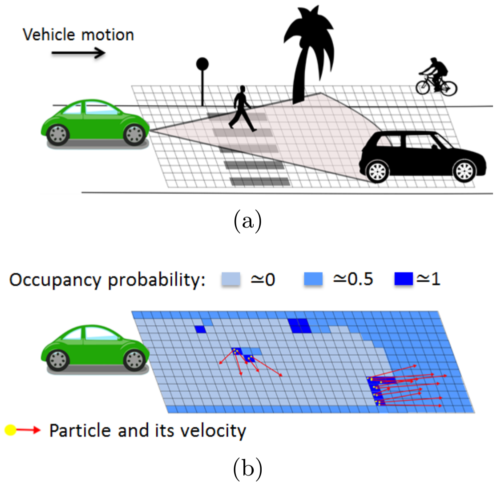


Figure 1: Principle of HSBOF. (a) the surrounding environment is mapped into a 2D grid. (b) Occupancy Grid and Velocity estimation

The grid-representation of the internal data implies that HSBOF is a highly data-parallel problem where the same set of operations is applied to each cell. A rectangular grid with given width and height, and squared cells, is used. The cell sides define the resolution of the grid. Thus, in one hand, a lower resolution implies a more accurate estimation of the spatial position of the obstacles. In the other hand, when the resolution decreases, the number of cells increases, and the number of computation follows on. Consequently, to be embedded on IVs, HSBOF should run on a hardware that provides enough computation performance to get an accurate result.

Choosing the right hardware architecture for integrating HSBOF into IVs remains a challenge. First, the hardware has to provide enough computational performance. Second, its purchase cost has to be low for being adopted for the mass production in the automotive industrie. Third, the limited energy resource on vehicle imposes that the hardware has to consume an electrical power as low as possible. Currently, the HSBOF is implemented on a Graphics Processing Unit (GPU) from NVIDIA [7], using the Compute Unified Device Architecture (CUDA) as a programming model. While providing a high computational performance, the GPUs consume a lot of energy. High-end GPUs consume easily a hundreds of watts, which represents a significant charge for the electrical batteries on IVs. Moreover, the GPUs are too expensive for the embedded market. They were not designed for an embedded use. On the software point of view, CUDA belongs to NVIDIA and is implemented only on their GPUs. Thus, the question arises: *which hardware/software architecture can be used for replacing the GPU/CUDA architecture?*

Concerning the hardware architecture, the first existing solution is the multi-core Central Processing Unit (CPUs) which were already used for executing perception systems in [4, 8]. Embedded multi-core CPUs, mainly designed by ARM, outperform on generic tasks. But with their dual, quad or octa-core, they are optimized for multi-threading, thus for task-parallel problems, not for data-parallel algorithms. Further more, embedded CPUs do not provide enough computational performance for executing highly data-parallel algorithms such as the HSBOF.

The second solution is the embedded Multi-Processor System on Chip (MPSoCs) which are initially designed for embedded uses and have more computational cores than CPUs but less than those of GPUs. The advent of MPSoCs relates the convergence of the hardware toward a more heterogeneous architecture composed of a host and one or more hardware accelerators. The host is generally made of a multi-core CPU. Existing MPSoCs are generally equipped with one of the following hardware accelerator: 1) an embedded GPU as in the processor Tegra K1 from NVIDIA, 2) one or more Digital Signal Processors (DSPs) as the in the Keystone II designed by Texas Instrument, 3) a many-core accelerator as in the Parallela board or the MPPA many-core from Kalray. The architecture of these accelerators are very different. They all might be an alternative to the GPU but in the present work, we focus first on many-core architecture. On a software point of view, we need a parallel programming model which is, first, adapted to the data-parallel nature of HSBOF. Second, the programming model must allow the developer to take advantage of the parallelism in the many-core architecture and the heterogeneity of the MPSoC. The OpenCL standard [1], a priori meets the two criterion. It was specifically designed for programming task-parallel and data-parallel algorithms on heterogeneous systems.

In this paper, we present a case-study on the feasibility of the utilization of the couple many-core/OpenCL as a hardware/software architecture for replacing the GPU/CUDA. Through our OpenCL implementation and experiments, we prove that the many-core disposes enough computational performance for producing an occupancy grid in a reasonable time while consuming a lesser energy compared to GPU. On our testing hardware, the computation time of one iteration of HSBOF can reach $168ms$, that is, about the double of the computation time on GPU. However, the many-core accelerator consumes only $1W$, which is **40 times** less than the GPU.

The current paper is organized as follow. Section 2 explains the principle of the perception algorithm HSBOF. Section 3 presents the hardware/software platform. The OpenCL implementation is detailed in section 4. Experimental results are presented and discussed in section 5. Finally, Section 6 concludes the paper.

2. THE PERCEPTION ALGORITHM

As shown in figure 1, the Hybrid Sampling Bayesian Occupancy Filter (HSBOF) [7] models the environment as a 2D grid. The algorithm produces an **occupancy grid**. It estimates also the **velocity** of the occupant of each cell and computes another grid called **static grid**. In contrast to the occupancy grid, the static grid contains the probability that each cell is occupied by a static obstacle (a non-moving obstacle). HSBOF is a mix of a classic Bayesian grid-filtering and a particle-based approach. According to the state of each cell at time t_{n-1}, that is, its occupancy probability, static probability and estimated velocity, the algorithm predicts the state at time t_n, and updates this prediction with new sensor observations. By assuming that cell states are independent, the HSBOF can be seen as a data-parallel problem because the same set of operations are independently applied on each cell.

Concerning the velocity estimation, an obstacle can have theoretically an infinite possibility of velocity. Because, the algorithm cannot consider all of these possibilities, it focuses only on some samples of velocity. A **set of particles** represents the samples. Actually, a particle is interpreted as a fictive point having a spatial coordinates, a velocity and a weight. The particle weight represents the probability that the speed of the content of the cell in which the particle is located, is actually the speed of the particle. We assume that unoccupied cells and cells occupied by static obstacles have a null velocity. Thus, HSBOF propagates the particles so that they follow the motion of the content of cells occupied by dynamic obstacles. For the sake of simplicity, these cells are called "dynamic cells".

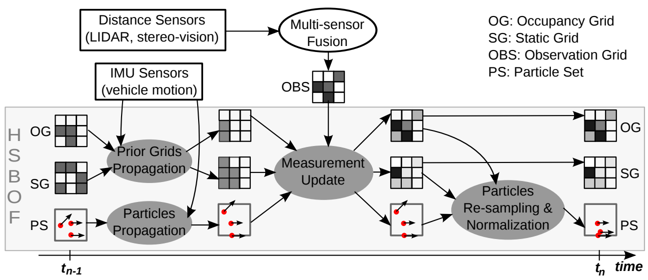
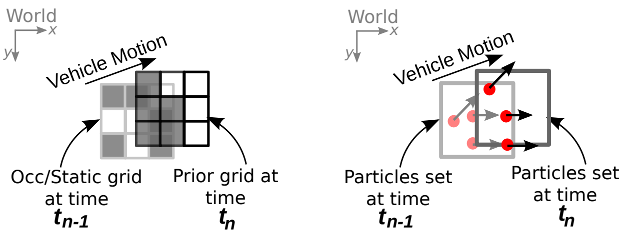


Figure 2: Overview of the HSOF algorithm

Figure 2 presents an overview of the main steps of HSBOF. The static grid, the occupancy grid, a set of particles at time t_{n-1} and an observation gird build from sensor measurements constitute the inputs. The outputs are composed by the same elements but at time t_n. The static grid and the occupancy grid at time t_{n-1} are called *prior grids*. The algorithm follows a particle filter approach with three steps: 1) particles and prior propagation, 2) measurement update, and 3) particles re-sampling and normalization.

2.1 Particles and prior propagation

The motion of the ego-vehicle is tracked by Inertial Measurement Unit (IMU) sensors such as odometer, accelerometer and gyroscopes. The 2D grid on figure 1(a) is fixed in the front of the vehicle. When the ego-vehicle moves, the grid is also displaced. The priors have then to be propagated in the new spatial placement of the 2D grid. The priors propagation is shown on figure 3(a). The prior grid at time t_n is computed by applying a linear interpolation on the cells in the occupancy and static grids t_{n-1}. Concerning the particles, they are propagated in the space according to a motion model. Their position are updated depending on their speed and the duration $\Delta t = (t_n - t_{n-1})$ (see figure 3(b)).



(a) (b)

Figure 3: (a) Prior grids propagation. (b) Particles propagation.

2.2 Measurement update

As explained on figure 2, the measurement update is for updating the occupancy probability, and the static probability of each cell regarding the sensor observation. The weight of every particles in a given cell is also updated according to the static and occupancy probability of that cell. It applies a bayesian program which mathematical formulation is detailed in [7]. We notice that an additional process called **multi-sensor fusion** processes the sensor readings and produces an *observation grid*. In simple words, the observation grid is closely related to the probability that each cell is occupied, regarding to the sensor readings [2].

2.3 Particle re-sampling and normalization

A re-sampling process is necessary for avoiding particles degeneracy, that is, for cell having particles, all but one particle will have negligible weight. A new set of particles is sampled from the previous set regarding their weights [7]. This step changes the local number of particles per cell by affecting more particles to dynamic cells. Particles with high weights are duplicated while particles with low weights are removed. After re-sampling, particle weights are normalized so that their sum per cell equals to 1.

3. HW/SW PLATFORM

As HSBOF computes and updates probabilities for each cell of the 2D grid, an instinctive way to store the probabilities is using arrays of floating points. For an implementation on a parallel platform, the arrays can be seen as shared resources among the processing cores. OpenCL [1] is an appropriate standard for a parallel-shared memory programming model. OpenCL can be mapped on many-core SoCs. It was initially designed for parallel heterogeneous systems.

3.1 OpenCL platform model on many-core

The OpenCL platform model is devided into two parts : one *host* as a central processing unit (CPU) and one or many *compute devices* which are hardware accelerator. A *compute device* is composed by one or many Compute Units. The latter is further divided into one or more *processing elements (PE)*. Figure 4 shows an example of how the OpenCL platform is mapped on a many-core SoCs. The compute device is the actual many-core platform while the host is mapped to more general CPUs such as an ARM processors and runs traditional operating system (linux, android, etc.).

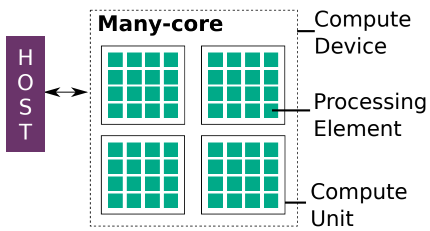


Figure 4: OpenCL platform model on many-core SoC.

3.2 OpenCL memory and execution model

In the OpenCL execution model, the parallelized tasks executed on compute devices are called *kernels*. An instance of a kernel is called *work-item*. Work-items are grouped within a *work-group*. A set of work-groups forms an *NDRange*. Consequently, kernels are executed accross an NDRange. A work-group is affected to a compute unit. Then, processing elements execute the work-items.

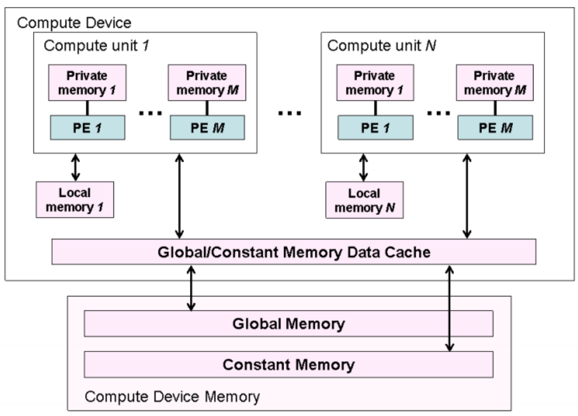


Figure 5: OpenCL Memory model [1]

The figure 5 shows the OpenCL hierarchical Memory Model in a compute device. Each PE has its own *private* and fast memory. *Local memories* are shared memory for compute units. Work-items in a work-group can share data through local memories. *Global and constant memory* are accessible by all work-items. They are slower and might be cached depending on the capabilities of the device. For improving the memory bandwidth, OpenCL exposes the control of DMA blocks to the developer if they are available on the hardware.

4. IMPLEMENTATION

For implementing the HSBOF on an embedded many-core SoC using OpenCL, four points are interesting to be detailed: 1) how to schedule the different steps of the algorithm, 2) how to utilize the memory model in order to improve the performance, 3) how to map them on on the OpenCL platform, 4) what NDRange size is suitable for the algorithm.

4.1 Tasks and Scheduling

The HSBOF and the multi-sensor fusion form our perception system. The overall can be divided into five main tasks : 1) *Particles Propagation* , 2) *Priors Propagation*, 3) *Measurement Update*, 4) *Particles Re-sampling and Normalization* and 5) *Multi-sensor Fusion*. After that, the re-sampling and the particles normalization are separated into two subtasks. Furthermore, the particles propagation contains also two subtasks : *Propagate Particles* and *Reorder Particles*. The first actually propagates the particles as described above. The second subtask is explained in section 4.3.

Two scheduling policies can be explored. First, a *sequential scheduling* policy executes all tasks sequentially, one after the other. An executed task can then utilize all the computing resource and memory available on the hardware. It allows us to tune tasks separately and improve their individual performance. Second, by exploiting the input/output dependency on figure 6, a *parallel scheduling* policy can be implemented for reducing the overall execution time.

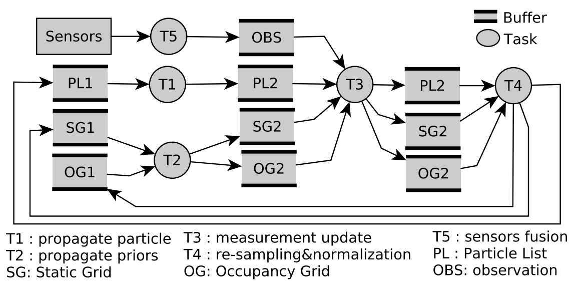


Figure 6: Perception system task level parallelism and buffers read/write

4.2 Memory mapping

As shown on figure 6, the occupancy prior at time t_{n-1} and the occupancy grid at t_n are stored in two buffers $OG1/2$. The buffers $SG1/2$ are for storing the static prior and the newly computed static grid. The particles are placed into the buffer $PL1/2$. All these buffers are shared resources for work-items. They should be stored in global or local memory. However, due to the limited size of local memories, the global memory is preferred. The **data locality** is preponderant in OpenCL. For a fast access, data processed by PEs should be placed in private or local memories.

For improving the memory bandwidth, OpenCL provides special Application Programming Interfaces (APIs) for handling DMA. It is used for transferring a block of data between the local and global memory. Moreover, it allows us to use a *double buffering* technique for improving the memory bandwidth. While working on a first rectangular portion of an input/output grid placed in the local memory, a second portion is DMA-transfered from global into a reserved region of the local memory. It will be processed when the first portion is treated. The double-buffering technique with DMA transfer allows to overlap the computations and the memory access.

4.3 Platform mapping

Two main computation resources can be used on the OpenCL platform: the host and the compute device. All tasks and subtasks of HSBOF can be parallelized except the subtask *Reorder Particles*. The smallest or "native" data granularity is a cell for grid-related tasks, and a particle for particle-related tasks. For the sake of performance, the **computation should be aggregated** by matching the number of work-items to the number of PEs. Thus, the granularity of a work-item becomes coarser in the sense that it has now to process several "native" data instead of only one.

Concerning the subtask *Reorder Particles*, for a given cell, the weight of every particles in that cell is updated in the *Measurement Update* step. The subtask *Reorder Particles* arranges the particle buffer $PL2$ so that the particles in the same cell are stored in contiguous memory. In this way, the particles can be DMA-transfered and processed on the local memories. The subtask *Reorder Particles* uses a sequential sort algorithm. It can be then implemented on the OpenCL host which is more optimized for sequential operations.

5. EXPERIMENTAL RESULTS

The HSBOF has two global parameters : the grid resolution and the number of particles. For a given width and length of the 2D grid, the value of the resolution determines the number of cells. We realized experiments and measured performance by changing the values of the algorithm parameters.

5.1 Experimental Setup

For a testing purpose, we implemented the HSBOF on an off-the-shelf embedded low-power MPSoC [6], composed of a host and a many-core compute device. A dual core ARM Cortex A9 running at 800MHz serves as a host. The compute device comprises four compute units. A compute unit features a block made of 16 processing elements (PEs) and a 256 KBytes shared L1 and a DMA block. The L1 memory serves as the private and local memories for the PEs. For the sake of performance, the number of work-items in a work-group is limited to 16. The compute device disposes a fast global memory L2 of 1MBytes. It can also share data with the host through a 1GByte of DRAM. But the later is slower compared to the L2. Data on real scenarios from eight LIDARs and IMUs are stored in files and are used as input for the multi-sensor fusion. These data were collected through the experiments realized in [7].

5.2 Performance measurement and validation

For quantifying the performance, two criterion are analyzed: the computation time and the power consumption. The overall computation time consists of the average duration of the execution of one iteration of the algorithm. We also measure the computation time of individual tasks. The power consumption concerns only the compute device (the many-core). It is deduced from voltage and current measurements on oscilloscope.

Validation: An implementation of HSBOF on an GPU from NVIDIA already exists [7] and will serve as reference. Between the occupancy grids produced by the GPU and the many-core, the average relative error of the occupancy probabilities is 2%. It can be explained by the difference in the design of the two hardware and the random nature of the particle filter. This low difference confirms that the many-core implementation behaves as expected.

5.3 Overall Computation Time

For a $30m \times 50m$ grid, we tested two resolutions : $0.1m$ and $0.2m$, which respectively correspond to two cell numbers : 150000 and 375000. The table 1 shows the overall computation time regarding the particle number and the cell number. The size of the global memory on the compute device limits the maximum of particle number to 19000. By changing the algorithm parameters, the overall computation time on the many-core varies between $487ms$ and $168ms$ which is in the state of the art [5].

Part. Num.	Res.(m)	Cell Num.	Comp. Time.(ms)
19000	0.1	150000	487
19000	**0.2**	**37500**	**325**
10000	0.1	150000	387
10000	0.2	37500	168

Table 1: Overall Computation Time

5.4 Individual Tasks Performance

This paragraph presents an analysis of the effect of the HSBOF parameters and OpenCL parameters on the individual performance of each task.

Number of particles: For a $30m \times 50m$ grid, the figure 7 plots the tasks computation time when changing the number of particles. The *Prior Propagation* does not depend on particles, its computation time remains constant. We notice the same behavior for the *Measurement Update*. In opposite, the duration of the *Re-sampling* and *Particles Propagation* increases linearly with the number of particles. This behavior is normal because these tasks process only particles.

Number of cells: While the grid width and length remain constant ($30m \times 50m$), the number of cell changes depending on the resolution of the grid. On figure 8, the number of particles equals to 19000. When increasing the resolution, the computation time of the *Priors Propagation*, the *Measurement Update* and the *Multi-sensor Fusion* are subject to exponential decay. Indeed, they apply the same set of operations for each cell, which make their duration very sensitive to the cell number. Table **??** and figure 8 shows that passing from a resolution of $0.1m$ to $0.2m$ reduces the overall computation time by more than $150ms$. Besides, we notice that the *Particle Propagation* performs

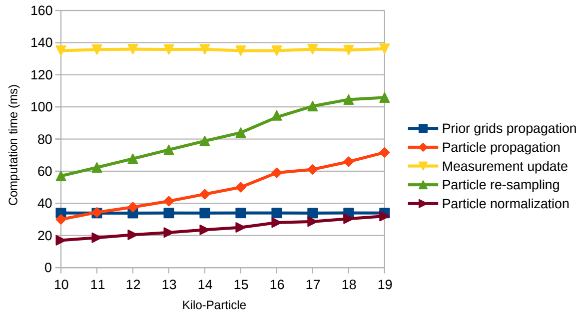


Figure 7: Computation time vs number of particles

slower when the resolution increases. Actually, the parallel subtask *Propagate Particles* processes only particles and does not depend on cell number. However, the sequential subtask *Reorder Particles* becomes slower due to a collateral effect of the *Re-sampling* process.

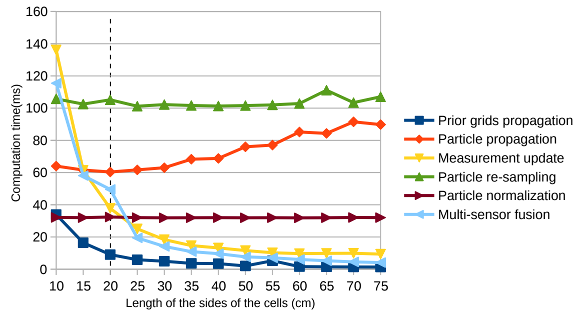


Figure 8: Computation time vs grid resolution

Scalability: Scaling an application on OpenCL implies changing the number of the running work-items. We chose the *Measurement update* to prove the effect of scalability since it process a high number of input/outputs and has a higher computation time. The figure 9 shows that the *Measurement update* scales in a sub-linear fashion. A speedup gain is observed with a number of work-item between 1 and 14. Beyond this number, using more work-items does not bring any improvement. This result can be exploited to minimize the energy consumption. For instance, in our testing hardware, the many-core disposes a hardware component that can be software programmed to reduce the clock frequency of the unused compute units. A fine grained energy management can be then implemented.

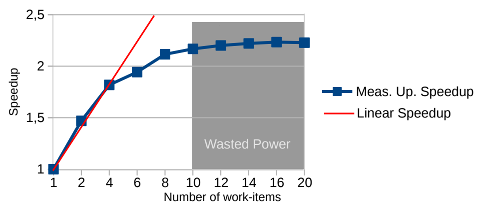


Figure 9: Measurement update speedup

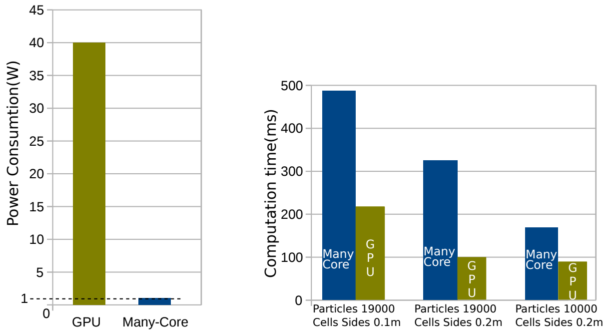
DMA transfer size: The probability distribution processed by the algorithm are stored in buffers of floating point.

For a $30m \times 50m$ grid with a resolution of $0.1m$ and 19000 particles, the buffers consumes about 6MBytes of memory. In our implementation on the testing hardware, a particle buffer is placed in the L2 global memory, the other buffers are stored in the DRAM which is slower. The memory bandwidth can be improved by using a the double buffering technique with a DMA transfer as explained above. We notice in our tests that the more data are coalesced into a DMA block, the less the computation time is. On our testing hardware, a speedup of $\times 7$ can be achieved by choosing the right size of the DMA block transfer.

5.5 Discussions

An implementation of HSBOF in CUDA already exists [7]. We run it on a GPU Quadro FX 1700 from NVIDIA for a comparison to our many-core/OpenCL implementation. The results are shown on figure 10. By increasing the resolution from $0.1m$ to $0.2m$, the overall computation time on the many-core is significantly reduced. By also decreasing the number of particles to 10000, the many-core performs at $168ms$ while $90ms$ for the GPU. In the three configurations, it is clear that the GPU beats the many-core concerning the computation time (see figure 10(b)).

However, as shown on figure 10(a) ,the GPU consumes typically $40W$, while the many-core power consumption is less than $1W$ (actually between $883mW$ and $967mW$). The many-core consumes then **40 times less power** than the GPU.



(a) (b)

Figure 10: Many-core vs GPU. (a) Power Consumption. (b) Computation Time

Is the result promising for a future integration into IVs? The choice of the value of the particle number and the grid resolution depends on the observed environment. Resolutions between $0.1m$ and $0.2m$ were tested in [7][3]. Furthermore, the particle number depends also on the number of cells, thus, on the resolution. While currently, we do not dispose yet a formal method for estimating the correct number of particles, we assume that fewer cells implies fewer particles. Thus, the algorithm parameters can be adapted to the street scenario. For instance, in cities, the obstacles are numerous and their nature are diversified. It can vary from a vehicle to an animal. Consequently, a lower resolution with a high number of particles is then needed. However, on highway, obstacles are mainly vehicles running at high speed. A higher resolution with few particles are then acceptable.

We deduce then that the performances (computation time and power consumption) we get on the many-core are promising. On the one hand, even if the GPU beats the testing hardware in term of computation time, the many-core performs an interesting **computation time** of **168ms** by finding a trade-off on the algorithm parameters to get values that can be adapted to certain scenarios. On the other hand, the **power consumption** on the many-core is **40 times lower** than on the GPU. The result in the second line on table 1 represents an example of trade-off between the number of particles (19000) and the resolution ($0.2m$). The power consumption remains low (less than $1W$) and the computation time lasts $325ms$ which is still in the state of the art navigation requirements according to [5].

6. CONCLUSION

The HSBOF needs a high computational performance to be executed in a reasonable duration. It is currently implemented in CUDA on a NVIDIA GPU that is power consuming. In this paper, we proved that, the couple embedded many-core/OpenCL is a feasible hardware/software architecture for replacing the couple GPU/CUDA. The experimental results are promising. They were validated by a low average relative error compared to the results produced by the GPU. While consuming a lesser power, the many-core can produce an occupancy grid within a reasonable time. On our testing hardware, the many-core consumes less than $1W$ which is 40 times less power consmption than the GPU. Though, the many-core can output an occupancy grid every $168ms$. These results are obtained by tuning the implementation parameters provided by OpenCL: the mapping of the algorithm on the available computing resources, the scalability, the data locality and the DMA for improving the memory bandwidth. We conclude that the many-core/OpenCL is a promising hardware/software architecture for integrating HSBOF into intelligent vehicles.

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