GPU Accelerated Genetic Algorithm and Solver Information

Version 1.0

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<u>Algorithm Description</u>

The algorithm is outlined in the paper below:

Smith, M.R., Kuo, F.-A., Hsieh, C.-W., Yu, J.-P., Wu, J.-S. and Ferguson, A., Rapid optimization of blast wave mitigation strategies using Quiet Direct Simulation and Genetic Algorithm, Computer Physics Communications, 181[6], 2010.

A brief summary of the approach used is as follows: consider a parameter X which contributes in some unknown way to a fitness function F(X). A population of N children each store their own value of X - unique to each child. The N children together make up a single generation of children - the characteristics of each child (i.e. the values of X) are used in the creation of new generation of children, loosely based around the ideas of genetics.

In the case where we wish to maximize the value of the fitness, one of these children will have a higher value than the others - we shall call this X_1. When creating new children, we choose another parent randomly from the population - X_2 - and a third parent is chosen for the sake of measuring the populations' current variance (X_3). When combined, the value of the new child's X is:

$$X_c = GF\ X_1 + (1 - GF)X_2 + \sigma R_N(X_2 - X_3)$$

where GF is:

$$GF = FR * \max\left(R_f, 1 - R_f\right)$$

where Rf is a uniformly generated random fraction (between 0 and 1) and RN is a normally distributed random variable from a normal distribution with a mean of 0 and a variance of 1. The value of FR - normally equal to one - may be used to accelerate convergence by increasing its value, while sigma - attached to the mutation term - may be increased to increase stability of convergence.

The fitness is then computed for each child; if it is found to be an improvement over that parent previously occupying its space in memory, we choose its value of X and associated fitness and save them as part of the next generation information. Otherwise, the parent information is passed on. This process is repeated across all individuals from generation to generation, the result being generations of children which:

- Have higher measures of fitness (i.e. are better), and
- Demonstrate decreasing variation in X from generation to generation.

A benchmark is built-into the code for demonstration purposes - specifically Ackley's function, which is (for two variables):

$$f(x,y) = -20 \exp\left(-0.2\sqrt{0.5(x^2 + y^2)}\right) - \exp\left(0.5(\cos(2\pi x) + \cos(2\pi y))\right) + \exp(1) + 20$$

This function has many local minima which make it challenging to solve using conventional root finding algorithms. It may also be expanded to include multiple variables.

The graphics shown in Figure 1 show a contour plot of the two-variable Ackley's function as described above, while the convergence history for a 3 variable problem is also shown.
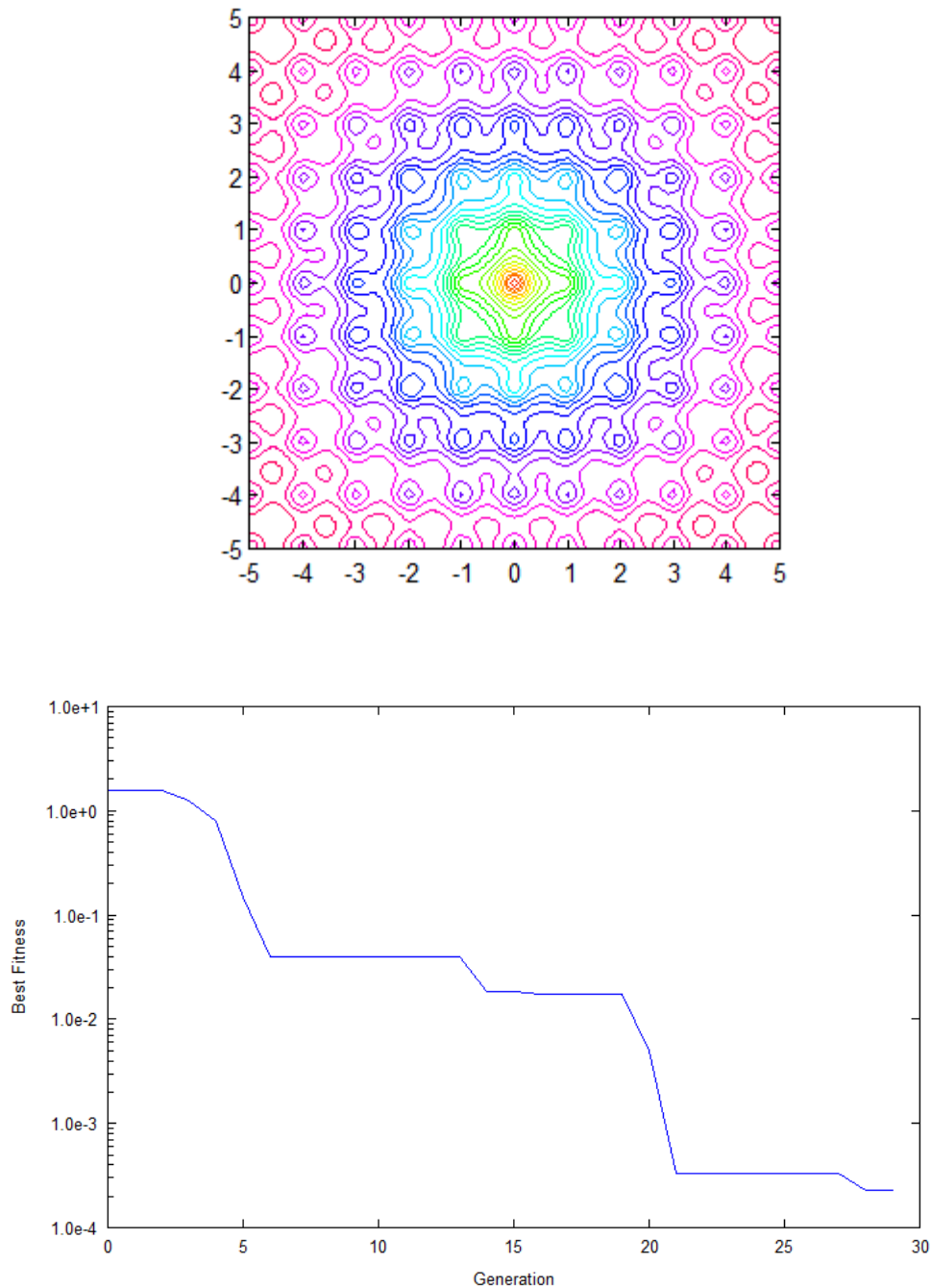

Figure 1: [Top] Contour function of the two-variable Ackley's function showing the single root (i.e. lowest value) at x,y = 0,0 where f(x,y) = 0. [Bottom] Fitness function vs generation for a three variable Ackley function using FR = 1.0 and SIGMA =

<u>Key Code Variables</u>

A brief description of key variables and constants is found below.

NOTE: In general,

- variables beginning with d_ are stored in GPU memory while h_ are stored in host (CPU) memory.
- UPPER_CASE constants are #defined values which are replaced at compile time.

config.h

NO_GEN   No. of Genetic Algorithm generations to run. Increase if problem is not converged.

TPB   Threads Per Block executed within each Streaming Multiprocessor on the GPU

BGP   The number of thread blocks to use on the device.

NO_KIDS   Number of children in each generation of the GA. Currently set such that each streaming processor in use on the GPU controls a single child.

NO_VAR   Number of parameters required to be solved in our optimization problem.

DEBUG   Set to 1 to turn on CUDA and debugging messages during runtime.

FR   Over-convergence parameter on crossover computation. Standard value is 1.0; can be increased to accelerate convergence, which also creates dangers.

SIG   Mutation parameter, larger values encourage larger mutations and prevent capture in local minima while also slowing convergence.

gpu_main.cu

_x   One dimensional arrays holding our solution parameters. (d_x for GPU, h_x for host)

_x_new   New (next generation) values of x. Computed and stored between generations.

_fitness   Current fitness as computed according to the values

_fitness_new   New (next generation) values of fitness, computed according to x_new.

x_min, m_max   Two arrays of length NO_VAR which contain the minimum and maximum values of x for each variable. These are only used during initialization; they are not used to enforce the ranges of x during computation.

_fitness_history   History of the best fitness, one dimensional array NO_GEN in length.

_x_history   History of the best values of x, one dimensional array of length NO_GEN*NO_VAR.

_BestKid   Index (i.e. name) of current best child in its generation. Integer.

_BestFitness   The fitness of the current best child in its generation.

_state   cuRAND random number generator state; each thread requires its own state.

The solver accommodates for NO_VAR variables / parameters in our optimization problem, which is stored across NO_KIDS children. This genetic information is stored inside a one dimensional array of length (NO_VAR*NO_KIDS). A figure demonstrating how each variable is stored for each child in the one dimensional array is shown below:
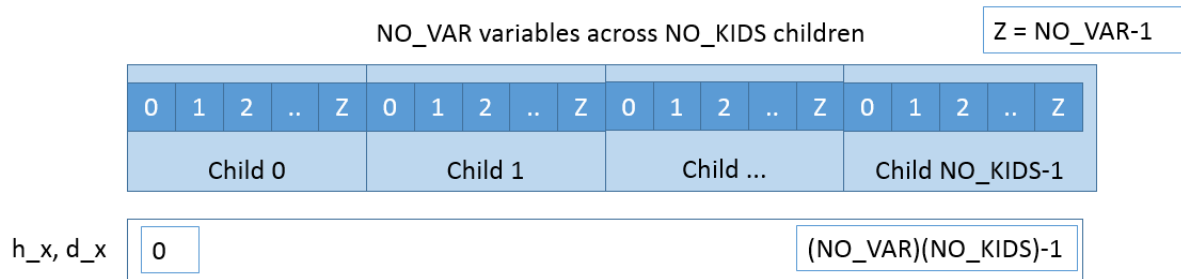

Figure 2: Picture describing how solution data is held in one-dimensional memory for NO_KIDS children and NO_VAR solution parameters.

The majority of other variables - d_fitness, for example - are one dimensional arrays of length NO_KIDS which hold single values for each child, i.e. the fitness for child j is held in the jth element of the fitness array (d_fitness[j]).

Function Descriptions

Host Functions / Wrapping Functions

Allocate_Memory()   Allocate memory on host and device. Perform prior to computation.

Free_Memory()   Free memory on host and device. Last step prior to exit() of program.

ComputeFitness(float *x, int N) Compute fitness on CPU using CPU held data.

ComputeNewGenCall()   Call GPU kernel (ComputeNewGenerationGPU) which computes the new fitness and new values of x.

UpdateNextGeneration()   Overwrites values of _x and _fitness on device with _x_new and _fitness_new.

FindBestGPUCall()   Calls GPU kernel (FindBestGPU) which uses a single block with MAX_TPB threads to find the current best child.

SetupRfGPUCall()   Calls GPU kernel (SetupRFGPU) which initializes the random number generator engine state for each thread.

SetupGPUCall()   Calls GPU kernel (SetupGPU) which primarily computes the fitness for each child in the starting (0th) generation.

Init()   Creates the initial values of x (solution parameters) for each child on the host, and saves them to file.

Randf()	Generate a random fraction between 0 and 1.
RandNf()	Generate a normally distributed random variable from a normal distribution with a mean of 0 and a variance of 1.
SaveFitness()	Saves the fitness data for each child after NO_GEN generations. Also saves to file the history data for analysis of its convergence.

GPU Kernels / Device Functions

MaxFrac()	Device function (single thread). Generates the maximum of A or (1-A).
ComputeFitnessGPU()	Device kernel (multi-thread). Computes the fitness for each thread using the parameters contained in d_x. Note: This is the part of the code which primarily needs to be modified in order to customize this code to specific applications. Note: The code currently solves minimization problems.

ComputeNewGenerationGPU()	Device kernel (multi-threaded). Compute the next generation value for each thread (i.e. child) in the current generation.
	
	Note: We assume here that a lower fitness value is optimal, i.e. minimization. In the event maximization is required, the line of code which reads:
	
	if (fabs(fitness_new[i] < fabs(fitness[i])) {
	
	should be changed to read:
	
	if (fabs(fitness_new[i]) > fabs(fitness[i])) {

SetupGPU()	Device kernel (multi-threaded). Computes the fitness for each child using d_x, and initializes the on-device generation counter (d_Step).
SetupRfGPU()	Device kernel (multi-threaded). Initializes the CUDA random number generator state for each thread.
FindBestGPU()	Device kernel (multi-threaded). Compute the best child in the current generation using info held in d_fitness. Also saves the fitness history for each generation and increments the d_Step variable.

Contact Information

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