Final Project Report

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CSC 213: Operating Systems and Parallel Algorithms (Curtsinger)

I. Project Overview

We implement a variation of Conway's Game of Life – a cellular automaton simulation created by the mathematician John Conway. Scientific computing and large-scale simulations are incredibly useful across a variety of fields. However, many of these programs are prohibitively slow. Therefore the algorithms and design of these programs is crucial. Although Life was initially created as a tool to explore computability, Turing machines, and Von Neumann machines, the various types of optimization we explore in our project are applicable to a wide variety of graphics-intensive programs.

The Game of Life is a series of iterations of a rendering of a grid of cells. Each cell is either dead or alive, and there exists a simple deterministic algorithm that decides each cell's state at the next iteration. We implement a version of the Game of Life and render the simulation on an interactive graphical interface using the SDL framework, providing basic user controls such as pausing and unpausing the simulation, stepping through the simulation on iteration at a time,activating and deactivating cells, and clearing and quitting the application.

For each iteration, we use Conway's algorithm to determine the state (dead or alive) of every cell in our grid. Because this algorithm takes as input a cell along with the states of each of its eight immediate neighbors, this algorithm naturally lends itself to an "embarrasingly parallel" stencil computation on the GPU. We also have two threads running on the CPU in addition to the main update thread – one for recording and acting on user input from the mouse; the other from the keyboard.

To evaluate our system, we first vary the number of threads per block in our stencil function calls. Then, we implement a feature that allows us to find regions with no live cells in order to skip their calls to the update functions. We have two major findings: using the GPU significantly speeds up the update rate and the optimization actually slows down the update rate (compared to the unoptimized GPU). We hypothesize the optimization was ineffective because the costs of copying and extra evaluations outweigh the benefits of skipping some of the code.

II. Design and Implementation

The rules to Conway's Game of Life are simple. There exists a grid of cells in which every cell is either dead or alive. At each iteration of the simulation, Conway's algorithm is applied to every cell in order to determine its next state. The algorithm[1] is defined in Algorithm 1.

The repository for this report can be found at `https://github.com/blinderm/game-of-life`

[1]The details and history of which be found at `https://en.wikipedia.org/wiki/Conway's_Game_of_Life`.

Algorithm 1 How Conway's Game of Life updates the grid of cells Here, *Grid* is a 2-dimensional array of cells, which all have a *state* field. Two cells are neighbors if they are adjacent in the 2-dimensional array.

```
function UPDATE_GRID(Grid)
    for g ∈ Grid do
        N(g) ← {h ∈ Grid : h is a neighbor of g}
        s ← ∑_{h∈N(g)} h.state
        if s < 2 or s > 3 then
            g.state ← 0
        else
            if s = 2 and g.state = 0 then
                g.state ← 0
            else
                g.state ← 1
            end if
        end if
    end for
end function
```

Input	Behavior
Left click (or drag)	Toggle the cell enclosing the current mouse pointer's location to "alive."
Right click (or drag)	Toggle the cell enclosing the current mouse pointer's location to "dead."
Press `CTRL-Q`	Quits the simulation and closes the GUI.
Press `CTRL-C`	Clears the simulation game board.
Press `CTRL-P`	(Un)pauses the simulation.
Press `CTRL-SPACE`	Advances the simulation by one step (while paused).
Press `CTRL-G`	Populates the region around the mouse's current location with a glider.

TABLE I: User input options together with the resulting behavior.

With these baseline rules, we implement a system in which the user is able to click cells to switch their state, pause and run the simulation automatically, or step through various iterations. We also have features that go beyond the basic simulation, including reading boards from files, adding gilders to the board, and having cells change color as the age. The exact specifications for adjustable features are as follows:

- GUI (game board) display size
- cell size (thus adjusting the number of cells)
- delay between iterations while running simulation
- colors, including linear interpolation between start and end values
- can randomize a board
- can load board from file

During the simulation, the user's options are provided in Table I. Given that the update algorithm is itself simple to implement, most of our difficulties were centered around coordinating between the GUI display, the user input CPU threads, and the update algorithm on the GPU.

We start development with the GUI, which is responsible for displaying the board and updates with reasonable response time. We use the bitmap class from the Galaxies lab for the GUI because it offers high resolution for the display and easily adjustable parametes. Reusing the bitmap also follows Lampson's principle of "reuse good ideas" - we already have a class built for exactly what we want to do, so there's no need to reinvent the wheel. The GUI itself gave us no difficulties in our implementation.

Although both the bitmap class and The Game of Life are represented with grids, the bitmap provides a much higher resolution of squares than we wish to use for the representation of cells on the grid. Thus there are two options: use the bitmap and have multiple pixels refer to the same cell, or have a separate struct for the grid and translate between the grid struct and the bitmap. We opt for the latter. This separation allows us to more easily manipulate and update the representation and then simply update the visualization afterwards using Conway's original algorithm. The cells on the game board are initially populated from either a random starting configuration, one of some set of preset starting configurations, or by the user clicking squares on the board.

To handle user input, we intended to use a scheduler (as in the Worm lab) in order to split up listening for input and updating across processes. We quickly ran into problems with this approach, as the listeners would sometimes fail to register input if they weren't being executed by the scheduler at the exact moment the user clicked or pressed a button. Thus, we realized we needed complete concurrency on the CPU and switched to an implementation with threads: one for mouse input, one for keyboard input, and the main one to run updates. At this point, we applied Lampson's lesson of "Throw one away" and gave up on our scheduler-based approach. As we will discuss later, our listener threads handle user input perfectly. This switch from the scheduler to the listener threads on the CPU was integral in our building a working program.

In order for the threads to properly take in and act on user input, we have a struct which contains the information necessary for the various actions in the program to be taken – the location of the cell from which the user input was recorded, the state of the mouse (clicked or unclicked), and the `SDL_Event` which indicates the state of the user input devices to SDL. The mouse thread is then responsible for executing the first two of the above bullet points when appropriate; the keyboard thread is responsible for the other five. The main thread calls our update function. In any case, this struct of arguments is passed to the functions so that they may act appropriately.

We use SDL to register user input from both the mouse and the keyboard. Any mouseclick or button-presstriggers an update to the main `SDL_Event`, which is then sent to the mouse and keyboard event handler loops. Mouse events are handled by checking that the mouse state generated from `SDL_GetMouseState` on the current location is one of `SDL_BUTTON_LEFT` or `SDL_BUTTON_RIGHT`. A left press turns the cell in which the mouse event is located to "alive," and a right press turns the cell to "dead." Pressing down the left mouse button triggers the simulation to toggle the cell in which the mouse pointer is located to "alive," and similarly, pressing down the right mouse button triggers the simulation to toggle the cell to "dead." This feature allows the user to "click and drag" to toggle a series of adjacent cells.

Keyboard events are handled so that a full button press and release are required before the command is executed in the simulation. Upon receiving a new `SDL_Event`, the keyboard handler thread checks if the event type is `SDL_KEYDOWN` or `SDL_KEYUP`. If the type is `SDL_KEYDOWN` on a pre-specified command key, then a "tripwire" is set. If the type is `SDL_KEYUP` and the

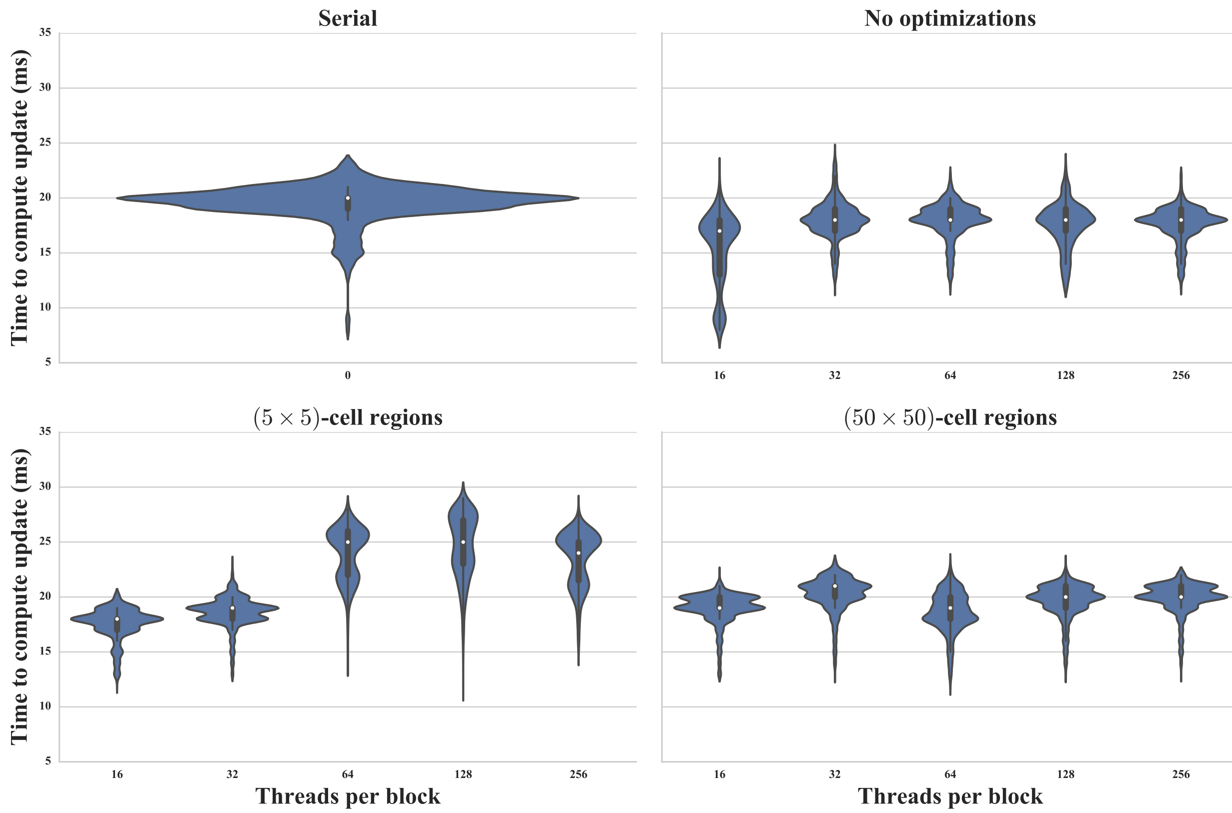
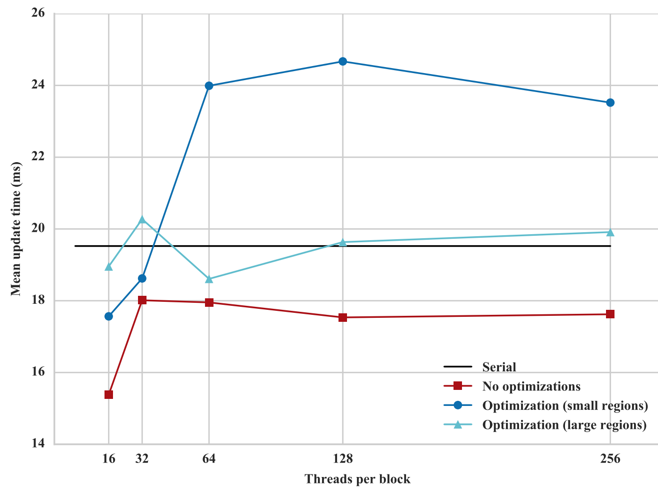


Fig. 1: Distribution of Update Times by Threads Per Block (T/B) and Optimization Region Dimension conditions

"tripwire" is active, then the command is executed. This feature prevents anything analogous to the "click and drag" from occurring with key presses. For the simulation itself to run, we must update all cells in our board according to Conway's original algorithm. As described above, this algorithm naturally lends itself to an "embarrassingly parallel" implementation. The update function progresses in two steps: first, we used a stencil pattern since a cell's next state depends on the states of its eight immediate neighbors, then use a map pattern to process whether or not a cell survives. We actually have two grids in the program: one that stores counts each cell's neighbors and one that stores the actual age of each cell. The steps are parallelizable because the state of a cell depends only on the states of the cells in the past iteration (i.e. not on any of the states of the other updated cells). Between each call of the update function, we copy the grid between the GPU and the CPU in order to account for user input.

III. Evaluation

The hardware needed to run our evaluations is the same as that which is needed to run our program in general: a computer with an Nvidia GPU and SDL. For our statistical analysis and production of graphs, we use `Python`, specifically with the `pandas` library to hold our data, the `numpy` package to run our analyses, and the `matplotlib` library to produce our figures.



(a) Comparing Mean Update Time (ms) to Thread Per Block (T/B)

T/B	Region Dimension 0	5	50
Serial	19.514	N/A	NA
16	15.402	17.589	18.981
32	18.040	18.646	20.290
64	17.963	24.019	18.633
128	17.565	24.675	19.660
256	17.644	23.528	19.919

(b) Mean Update Time (ms) by Threads Per Block (T/B) and Optimization Region Dimension

In addition to ensuring that our implementation properly reflects Conway's rules, we verify that the concurrent components of our system function properly. For our listener threads on the CPU, we notice from running many tests that the program's response to user input is both immediate and correct.

However, the speed of our program is our main focus in our evaluations. As a benchmark, we implement a serial version of each of our GPU kernel functions involved in the advancement of our simulation from one iteration to the next. In order to test the efficiency of our parallelized program against that of the serial version, we create a file and use `time_ms` to measure the running time of our update function and write that information to the file.

For our serial implementation, we loop over every cell in our grid to count the number of its neighbors that are alive. Then we apply Conway's algorithm to decide what its state will be at the next iteration. Finally, we loop over each pixel in our bitmap in order to correctly render these updates to the screen. Our parallel implementation is similar, although we count neighbors and update our cell grid using blocks of threads.

We run 1000 iterations of our serially-implemented simulation and collect the running time of each of the 1000 updates in a file. We do five similar runs for our parallel implementation, testing threads per block values of 16, 32, 64, 128, and 256.

Before proceeding to the experimental analysis, we remove a consistent outlier from the results of each configuration, which was always the first update. There is likely additional startup costs to the initial GPU setup which is captured in the first run of the update, which is true across each configuration. We perform a statistical test to decide the significance in the mean time to update between any two configurations. Since the populations appear to be, very roughly, approxmating a normal distribution, and because we have no prior information about the parameters of the distribution of the configuration we are sampling from, the 2-sample t-test is the appropriate statistical test. Our significance level is taken to be $\alpha = 0.01$. There are 128 such tests, the vast majority of which yield significant results. We record the insignificant results in Table II.

TABLE II: Statistically insignificant 2-sample t-test results ($p = 0.01$).

Configuration A		**Configuration B**			
Region Dimension	Threads/block	Region Dimension	Threads/block	t-statistic	p-value
5	16	0	128	-0.274335	0.783856
5	16	0	256	0.735564	0.462082
0	32	0	64	-0.969775	0.332276
5	32	50	64	-0.165566	0.868515
0	128	0	256	0.892050	0.372473
50	128	Serial	Serial	-1.870520	0.061558

For example, there is no significant difference between the configuration with small regions and 16 threads per block, and either configurations with no optimizations and 128 and 256 threads per block. This is evident in Figure 2a. The sample distributions from each configuration are displayed in Figure 1.

While running our simulations, we noticed a possible way to speed up our code further: because there are oftentimes large regions of the board in which there are no live cells, we can know that there is no need to check for updates in such regions. Thus, running the kernel function on those cells is computationally wasteful. In order to reduce the effects of this inefficiency, we overlay yet another grid onto our board. This "regions" grid, which is of lower dimension than our grid of cells, holds the a count of the number of live cells within its boundaries. We then modify our GPU kernels so that they only run the main body on cells that are in regions with at least one live cell. We again run 1000 iterations of this program, testing all ten combinations of the five threads per block values from above and a "region" dimension of either 5 or 50. In our current implementation, we ignore edge cases for simplicity (within a region, we must actually check the entirety of the region as well as another layer of cells surrounding it in order to ensure no cell within the region will be updated), so these tests report a lower runtime for our optimized runs than they would if our optimization were implemented completely. For the resulting means, see Table 2b and Figure 2a.

Our experiment shows that there is a negligible speedup in performing the region optimization. In fact, by comparing the mean update time in Table 2b, we observe that the optimizations actually worsen the overall performance of the simulations. Copying from the CPU to the GPU and vice versa is the likeliest cause for the added cost to the performance of the optimizations. The basic data model has an SDL bitmap and a lower-resolution game board which is represented on both the CPU and GPU. Both optimizations add an additional board which is again represented on both the CPU and GPU. The improvements in performance by ignoring inactive regions are more than offset by the memory copying between the CPU and GPU.

There is essentially no improvement in performance as the number of threads per block increases. This is likely because the total number of active threads running on the GPU does not change as the number of threads per block increases. Since the Game of Life update algorithm is an embarassingly parallel problem, there is likely no added benefit to the changing the structure of each block. This does not explain the apparent speed penalty for small regions incurred for 64, 128, and 256 threads per block (see Figure 1), which doesn't yield a simple interpretation.

Thus, we see that our parallelization of Conway's algorithm using GPU kernels is the optimization feature that consistently improves our program's efficiency.