University of Edinburgh

Programming Skills

Performance Testing Coursework

Performance Report

Author:
Jack Frankland

November 28, 2017

Abstract

This report provides the results and analysis of various performance tests which were carried out on the 2D Predator-Prey model that was written for the first coursework. A range of different tests are used to evaluate the program and in each case the tests results are analyzed and interpreted. A conclusion is then reached about the overall quality of the program in terms of performance.

List of Figures

List of Tables

Contents

1 Introduction

2 Performance Tests and Analysis

2.1 Effects of Compiler Optimization Flags

In this section we will investigate the performance effects of using different compilers with different optimization flags. To implement these tests we use a single 1000×1000 landscape given in figure **??** which consists of two large land masses separated by a river of water. This landscape was chosen since it is large enough and generic enough to provide results that could be scaled for any realistic landscape. The input parameters for all tests in this section were fixed as the values given in appendix C.

In order to get an accurate figure on the run time of the code under each compilation flag we initially planned to run the tests on the a single core on a Cirrus back end node. Because the traffic to Cirrus is fairly consistent, due to the fact is in constant use, this allows us to make performance measurements we know are reconstructible, and hence we can compare the run times with a good degree of confidence in their relative values. However, after some initial testing it was clear the code ran roughly 4-5 times faster on the cp-lab than it did on Cirrus. Further to this, we found that submitting several jobs to the Cirrus queue had the effect of slowing each job down by an amount

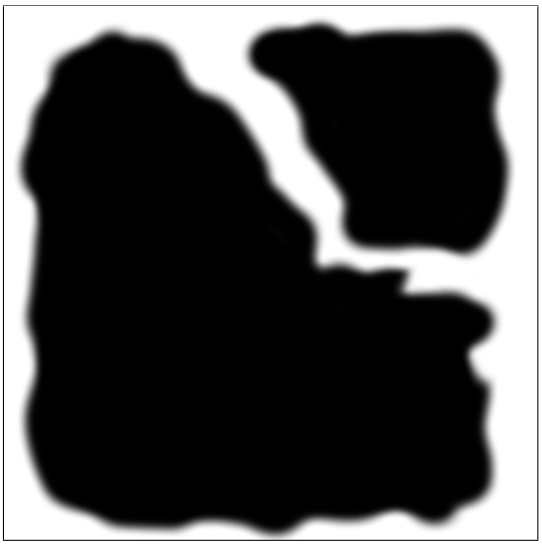

Figure 1: 1000×1000 Test Landscape for optimization flags.

proportional to the number of jobs submitted. The reason for this is not entirely clear; one possibility is that the different jobs were competing for memory on the front end node during output. This issue in particular made testing on Cirrus infeasible, since the run times were over ten minutes, and the jobs needed to be submitted one at a time, the total runtime would have been too large to get any results. Instead we decided to use the cp-lab, since the run times were faster we were able to submit jobs individually and since the cp-lab is in use most of the time we can assume our results accurately represent a standard job runtime. We ran 6 tests for each compiler flag and calculated the mean and standard error using equations 1 and 2.

Compiler	**Run Time(s)**					
	O0	**O1**	**O2**	**O3**	**Ofast**	**Os**
gcc	249.002 ± 0.765	181.647 ± 0.571	172.332 ± 0.912	174.978 ± 0.777	177.254 ± 1.127	190.362 ± 0.496

Table 1: Run times for the sample 1000×1000 grid running on the cp-lab.

From these results it is clear that under the gcc compiler the code runs fastest when compiled under the $\mathcal{O}2$ flag. This is slightly unexpected since one would expect the code to run fastest when compiled under the $\mathcal{O}3$ or $\mathcal{O}fast$ flags, however it is fairly common for different programs to run faster under different compiler flags due to the different optimisations the various

compiler flags employ, and the content of the code itself.

We were interested in how well the program would perform under a completely different compiler, which is one of the reason we initially chose to use Cirrus. However, due to the fact the the cp-lab only has the gnu gcc compiler installed this meant using a different machine to compile the code. We chose to carry out these extra experiments on a Cirrus back end node and a Macbook to see how they would compare. Due to the long runtime for each test we were only able to carry out one test in each case and have not performed any statistical averages.

Compiler	**Run Time(s)**					
	O0	**O1**	**O2**	**O3**	**Ofast**	**Os**
clang	529.025	457.535	395.897	415.884	383.270	399.656
intel	552.608	378.542	373.768	361.429	687.909	395.915

Table 2: Run times for the sample 1000×1000 grid running on mid 2014 Macbook Pro with 2.8GHz Intel i5 processor with 8 GB 1600 MHz DDR3.

Compiler	**Run Time(s)**					
	O0	**O1**	**O2**	**O3**	**Ofast**	**Os**
gcc	800.220	723.293	724.042	698.490	698.005	734.928
intel	871.976	751.004	728.728	718.015	723.325	731.965

Table 3: Run times for the sample 1000×1000 grid running on Cirrus back end node with 1 cpu.

2.2 Main Sources of Overhead

In order to identify the main sources of overhead in our program we used the Gnu gprof tool. The code was compiled under the gcc compiler with optimisation flags -O0 and without the debug flag -g. This is because compiling with optimizations turned on can lead to inlining of functions, which in turn causes them to disappear from the profiling tables, however since different

Figure 2: Flat profile page 1. for Gnu gprof profiler.

compilers and different flags may inline different functions in different places, the profiling data would be specific to the compiler case, and not a general profile of the code. By compiling with -O0 we can identify overheads that will be common to all compilers for the -O0 (no optimizations) optimization level. The input parameters and landscape are the same as in section 2.1. Since they are extensive and rather verbose we have included the first pages only since they contain the functions with the largest overheads.

The *flat profile* shows the total amount of time the program spent executing each function. From figure 2 we can see the program spent the most time executing the operator(). This is to be expected since the operator() function is used as a utility for accessing the landscape cells in the form (i,j). Due to the fact that internally the landscape is implemented as a 1-D array this function was introduced to make working with the landscape simple and intuitive, and any time access to the landscape is required in the program, the operator() will have been used. One way to reduce the number of function calls to operator() would be to access the elements of the landscape directly in the code using the operator[] on the array of cells. This would make the code for the various Grid methods significantly harder to write and read since all instances of operator(i,j) would become operator[[i + (rows + 1 - j) * (columns+2)]]. An alternative would be to implement the landscape as a 2D array, then the access would be implemented via operator[i][j], however it is likely the overhead of dynamically allocating a 2D array of a user defined

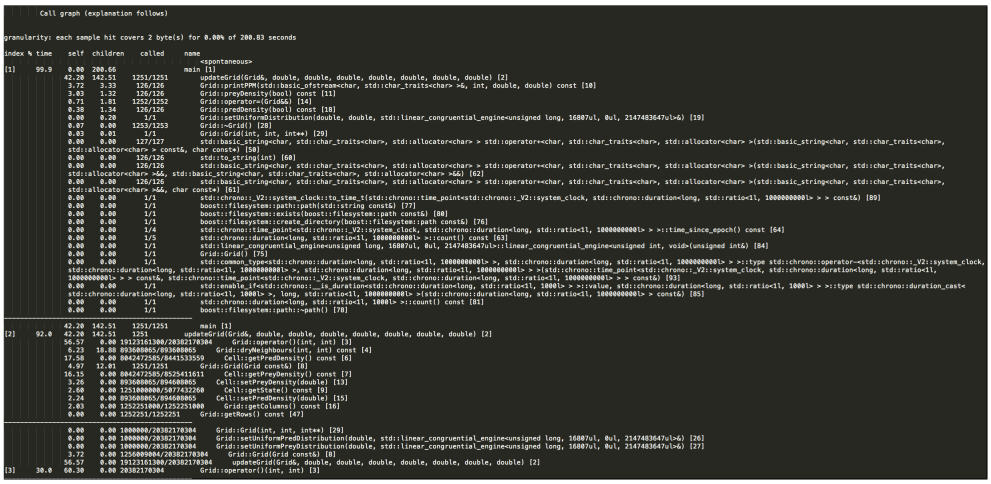

Figure 3: Call graph page 1. for Gnu gprof profiler.

type would outweigh the cost of the function we currently have.

The *call graph* shows how much time was spent in each function and its children. Form this information we are able to identify functions that themselves do not use much time, but call other functions that use exceptional amounts of time. From figure 3 line [2] we can see that 92% of the time was spent in the function updateGrid() and its subroutines, which is to be expected since this is the function that evolves the landscape and apart from printing output, most the remaining functions called from the main method perform one off tasks such as setting up initial conditions. Of the function calls from within updateGrid() we can see that operator() clocks in the highest with 56.57s spent within it when it is called from updateGrid(). This supports our above analysis that the function operator() is a serious overhead. From [3] and [5] (not shown in figure 3) we can see that 39.5% of the total time is spent in operator() or its constant equivalent. We can also see that it is the methods of the Grid class and the updateGrid() functions that call the operator(). Based on this analysis it would be a good idea to test giving these functions direct access to the grid cells through the operator[] instead of using the overloaded operator(). It may be that moving the functionality from operator() to operator[] means that the functions that call it inherit the overhead instead, however it is worth checking as a possible optimization.

2.3 Effects of Input/Output

2.4 Output Frequency

To begin the investigation into the effects of input we vary the number of time steps between the output of the plain .ppm files. The other input parameters are kept fixed at the same values as in section 2.1, however the number of steps between the output of the plain .ppm files is varied from 10 to 100 at intervals of 10 steps. The input landscape in figure 1 was used for the same reasons as in section 2.1. Since the program was shown to run fastest when compiled under the -O2 flag in section 2.1 we have used that option here.

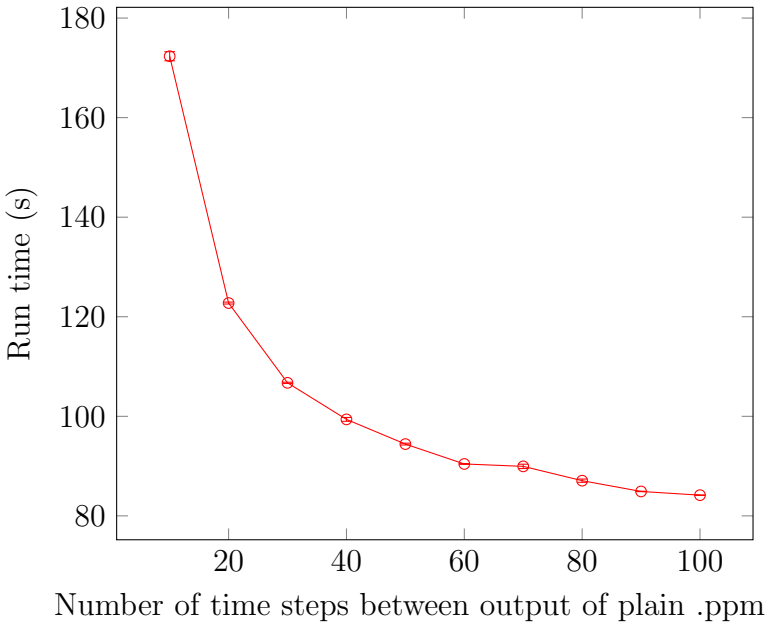

Figure 4: Output frequency of plain .ppm vs run time (s)

The error bars on the figure 4 have been included, however they are very small and hence difficult to see. As in section 2.1 we took six measurements for each output frequency and calculated the error using equations 1 and 2. It is clear from figure 4 that the runtime increases dramatically for higher frequencies, where as for lower frequencies the runtime increase is a lot slower. This relationship is perhaps made clearer in figure 5 where we have plotted the same run times against the total number of output files. The plot is

clearly linear, which is what we would expect; the total runtime should be directly proportional to the number of files it outputs. The total number of output files can be calculated by dividing the total number of time steps by the frequency and then flooring the number.

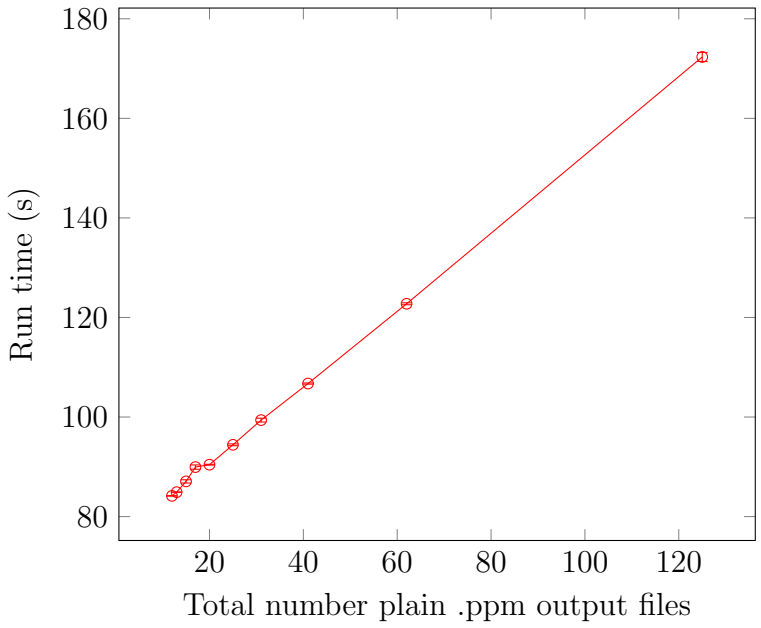

Figure 5: Number of output plain .ppm vs run time (s)

2.4.1 Landscape Water vs. Land

2.4.2 Landscape Size

To investigate the effects of varying landscape size for our program we scaled the square landscape of figure 1 using Gimp by increasing the width and height be equal amounts and recorded the time take to run in each case. From section 2.4 we know that the runtime scales linearly with the number of output files produced. Thus in order to run quicker tests for the landscape size we ran with a low output frequency of 100 and assumed that for any other output frequency the result would scale linearly. As above we recorded six measurements at each landscape size and calculated standard error using equations 1 and 2. The results plotted in 6 suggest a quadratic relationship between the size of the landscape and the run time, that is, run time =

a(landscape size)^k. This is to be expected, since the total area increases as the square of its sides for a square landscape, and we expect the run time to be proportional to the total area i.e. the number of squares in the landscape. Indeed, by taking the *log* of the data and plotting it in figure 7 we can approximate the parameters a and k above by measuring the y-intercept and the gradient respectively. We can read off figure 7 $a \approx 1$ and $k \approx 2$, so we get the relationship run time = (landscape size)^2, exactly as expected.

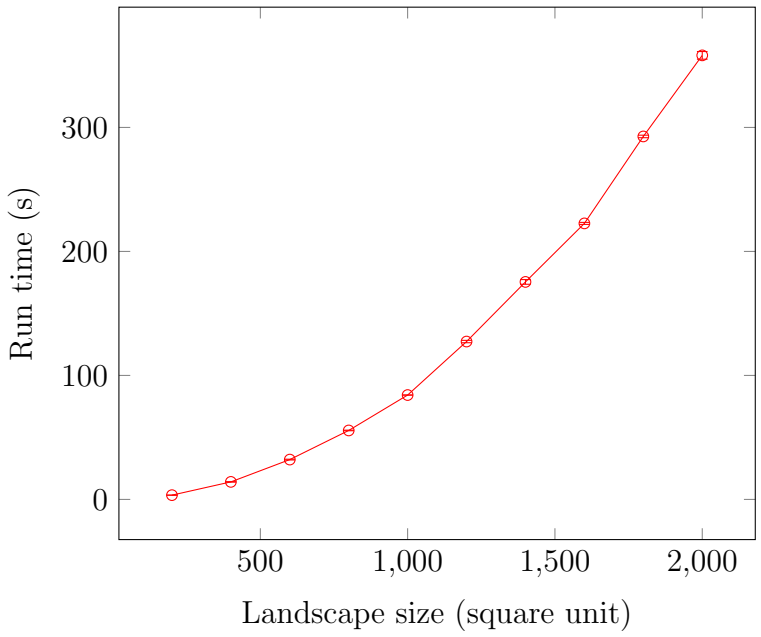

Figure 6: Size of square landscape vs run time (s)

3 Conclusion

A Complete Data Sets

B Statistical Equations and Calculations

Our data sets were small due to the fact jobs had to be submitted individually to stop them slowing each other down. Because of this, we choose to use the

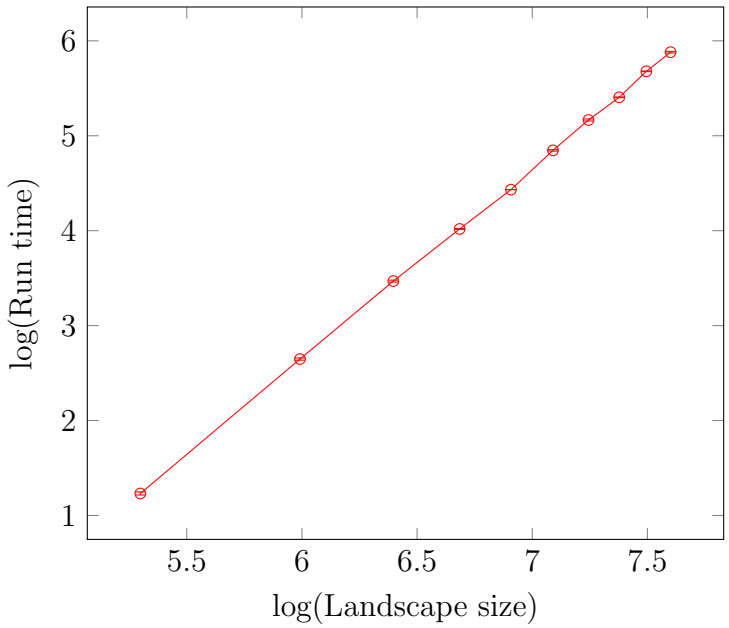

Figure 7: Log plot of size of square landscape vs run time (s)

Compiler	**Run Time(s)**					
	O0	O1	O2	O3	Ofast	Os
gcc	247.042	181.057	171.405	171.405	177.838	190.849
	247.466	181.326	171.641	175.660	176.470	190.547
	247.391	183.946	176.876	177.094	181.324	191.942
	250.712	182.675	171.137	175.355	179.191	190.994
	250.511	180.602	171.369	174.871	174.351	188.759
	250.888	180.273	171.561	175.481	174.350	189.081

Table 4: Complete data set for gcc optimisation tests on cp lab.

corrected sample standard deviation given by:

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{1}$$

Number steps	**Run Time(s)**					
10	171.405	171.641	176.876	171.137	171.369	171.561
20	122.466	122.400	123.026	122.703	123.573	122.341
30	106.718	106.978	106.254	106.518	106.862	107.034
40	100.035	98.694	98.721	101.000	98.802	99.043
50	94.207	94.208	93.995	94.274	94.611	95.233
60	90.761	90.289	90.335	90.298	90.570	90.307
70	89.597	89.076	91.979	89.224	90.130	89662
80	88.188	87.924	86.422	87.013	86.457	86.422
90	84.877	84.799	84.838	84.877	84.945	85.100
100	84.151	84.138	84.095	84.392	84.051	84.146

Table 5: Complete data set for varying number of steps between output of plain .ppm.

Landscape Size	**Run Time(s)**					
200×200	3.372	3.409	3.711	3.366	3.3379	3.373
400×400	14.431	13.768	14.803	14.029	13.848	13.881
600×600	33.229	32.582	31.024	31.608	32.466	31.779
800×800	55.585	56.726	55.295	55.303	54.997	55.709
1000×1000	84.151	84.138	84.095	84.392	84.051	84.146
1200×1200	126.580	131.212	125.095	127.586	124.953	128.426
1400×1400	182.386	177.712	174.942	176.624	170.565	170.154
1600×1600	222.399	220.579	221.788	222.024	222.322	226.443
1800×1800	290.897	291.087	291.301	291.407	294.728	296.894
2000×2000	359.388	360.973	360.214	367.307	356.216	344.524

Table 6: Complete data set for varying landscape size.

which compensates for the bias in standard deviation which occurs for a small data set. The **standard error** was then estimated in the usual way using:

$$\sigma_x \approx \frac{s}{\sqrt{N}} \tag{2}$$

C Input Parameters

- Birthrate of prey 0.08

- Predation rate at which predators eat prey 0.04
- Birth rate of predators per one prey eaten 0.02
- Predator mortality rate 0.06
- Diffusion rate of prey 0.2
- Diffusion rate of predators 0.2
- Size of time step 0.4
- Number of time steps between output of plain .pnm file 10