A Pilot Study to Evaluate Development Effort for High Performance Computing

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ABSTRACT

The ability to write programs that execute efficiently on modern parallel computers has not been fully studied. In a DARPA-sponsored project, we are looking at measuring the development time for programs written for high performance computers (HPC). To attack this relatively novel measurement problem, our goal is to initially measure such development time in student programming to evaluate our own experimental protocols. Based on these results, we will generate a set of feasible experimental methods that can then be applied with more confidence to professional expert programmers.

This paper describes a first pilot study addressing those goals. We ran an observational study with 15 students in a graduate level High Performance Computing class at the University of Maryland. We collected data concerning development effort, developer activities and chronology, and resulting code performance, for two programming assignments using different HPC development approaches. While we did not find strong correlations between the expected factors, the primary outputs of this study are a set of experimental lessons learned and 12 well-formed hypotheses that will guard future study.

Keywords

High performance computing, development effort, parallel computing performance, programmer productivity

1. INTRODUCTION

As in other types of software development, the usual goal of developing codes in High Performance Computing (HPC) is to arrive at the solution of a problem with minimal effort and time. Thus, an important metric for evaluating various approaches to code development in HPC is "time to solution," encompassing both the effort required to understand and develop a solution as well as the amount of computer time it takes to execute that solution and arrive at an answer.

Metrics and even predictive models have already been developed for measuring the code performance part of that equation, under various constraints (e.g. [Hoisie00, Snavely02]). However, little empirical work has been done to date to study the human effort required to implement those solutions. As a result, many of the practical decisions about development language and approach are currently made based on anecdote, "rules of thumb," or personal preference. Researchers in the HPC community associated with DARPA's High Productivity

Computing System (HPCS) project[1] have decided that it is important to begin to understand empirically whether or not the general assumptions that are guiding decision-making are true.

Specifically, HPCS will study:

- Differences among development approaches, languages, etc. in terms of how they affect the time to solution of various problems.
- Differences between novice and expert developers, especially in regard to the level of expertise necessary in order to effectively create HPC codes of various types. A current assumption, which should be verified, is that the solutions produced by novices will not execute as fast as solutions produced by experts and may take slightly longer to build. However, there is also the issue of whether different combinations of development approaches and languages make it more difficult for developers to reach the "expert" level. If only a few experts can effectively develop HPC codes, then the number of problems that can be solved is greatly limited.
- The workflows (i.e. series of distinct activities) used to effectively produce HPC codes. Understanding different types of workflows allows us to give better guidance to novice developers as well as identify the significant bottlenecks in the process.

As a first step in this direction the members of HPCS are executing a series of empirical studies. The overall goal is to study the human effort required to develop solutions to various problems using different HPC approaches and languages. As data is collected about the implementation of various solutions, the amount of effort necessary for various applications and various approaches can be characterized. This data will allow heuristics to be developed to decide which approach(es) should be used in a given environment. These heuristics will provide a more rigorous basis for making the decisions that are currently being made without empirical evidence.

This type of empirical research is novel for the HPC community, so we will begin by conducting some pilot studies to debug the experimental methods and techniques. The eventual goal is to run a large study in multiple HPC classes at universities across the country. The study described in this paper is a pre-pilot study aimed at understanding the issues involved and debugging our methods. The results of this pre-pilot study will allow us to better design the pilot studies so that the results of the pilots can be used to develop well formed hypotheses to be tested in the full study. The setting for the pre-pilot study is a graduate level High Performance Computing class at the University of Maryland. The students in this class for the most part have no previous experience developing HPC codes but are being taught the basic concepts of HPC code development, so it is an ideal place to begin evaluating the performance of novice HPC developers.

2. BACKGROUND

2.1 Time to Solution

In developing HPC software, *time to solution* is an important metric. For many applications, the value of a result goes down considerably if it cannot be obtained by a deadline. Two main components make up the time to solution metric. The first component is the human

[1] [http://www.darpa.mil/ipto/programs/hpcs/index.htm]

effort/calendar time required to develop and tune the software. The second component is the amount of machine time required to execute the software to produce the desired result.

Currently in the HPC community, human effort is often not empirically measured as rigorously as execution time. Both development time and execution time play crucial roles in the overall time to solution, so we believe that empirically measuring development time is important. This study was an initial attempt at understanding the effort required to develop HPC software.

2.2 Tradeoff between execution time and development time

An important goal in HPC research is to reduce the time to solution, by reducing either the development time or the execution time or both. One of the major differences between HPC software development and traditional software development is the amount of effort devoted to tuning HPC code for performance. It is widely believed that more time spent tuning the code will result in shorter execution times. Therefore, understanding the tradeoff between time spent in development and execution time is crucial. For large-scale systems, the extra development time can lead to orders of magnitude reduction in execution time.

The overall idea is to determine the optimal values for development time and execution time, such that time to solution is minimized. These values will differ based on the circumstances of use for the software. If the code will be executed many times, then the cost of increased development time can be amortized across multiple runs of the software and balanced against the cumulative reduced execution time. Conversely, if the code will only be used once, the benefit of increased effort tuning the code may not be as large.

3. GOALS AND DESIGN OF EXPERIMENT

3.1 Goals

As a pre-pilot study, the goal of this study was to debug the experimental protocols and data collection mechanisms for later studies.

> **G1 – Analyze the experimental protocols and data collection mechanisms with respect to usability from the point of view of the researcher.**
>
> **G2 – Characterize the code development workflows of the subjects from the point of view of the researcher.**
>
> **G3 – Characterize the performance of the code from the point of view of the developer.**

3.2 Objects of Study

The goals stated above are related to two very different types of object of study: G1 aims at improving future studies by focusing on the experimental protocols themselves, while G2 and G3 focuses on the results of using specific HPC development approaches.

3.2.1 Empirical Research Object of Study

When we talk about studying "experimental protocols," we specifically mean:

- The set of information measured about subjects and the HPC codes they produce (e.g. subjects' amount of background in HPC development, amount of speedup achieved by the code compared to the serial version);

- The metrics used to quantify that information (e.g. number of HPC-related courses taken by a subject or number of years with development experience, number of seconds taken by the program to return with a correct solution to the given problem);
- The mechanisms used to collect that information (e.g. a form with open-ended questions, interviews with subjects, automatically-generated compiler logs).

3.2.2 HPC Research Object of Study

In this study, two different programming approaches were compared, MPI and OpenMP. For MPI the subjects used the C programming language. For OpenMP the subjects used Fortran. This arrangement means that effects due to differences in programming language will be confounded with the differences between programming approaches.

Message Passing Interface (MPI)

MPI [MPIForum] is a portable, scalable programming approach that can be used on both distributed-memory multicomputers and shared-memory multiprocessors. The MPI standard specifies various aspects of the communication patterns among a set of processes operating together as a unit. MPI specifies the format of the messages passed between processes as well as defining process groups to allow for more powerful functionality [Dongarra96].

The subjects used MPI for the first assignment. This approach involves understanding the problem, developing a serial (one processor) solution to the problem, modifying that solution to work on multiple processors in parallel, and tuning the solution to improve its performance (execution time).

OpenMP

OpenMP is a shared-memory programming model. OpenMP takes advantage of the ability to directly access shared memory throughout the system along with fast shared-memory locks improve on the complexity of the MI approach. OpenMP is useful for quickly parallelizing existing code and for developing a broad set of new applications. OpenMP uses compiler directives and callable runtime libraries to implement the necessary control structure, data environment and synchronization [Dagum98].

3.3 Research Questions

We refined the experimental goals in Section 3.1 into more specific research questions as follows:

For G1 (analyzing experimental protocols):
- Q1: Are the tasks given to subjects in the experiment adequate for providing the necessary information about the development approaches used?
- Q2: Is the data accurate?
- Q3: Is all of the necessary data collected?

For G2 (characterizing development workflows):
- Q4: What is the order of the activities performed by the subjects?
- Q5: How much effort was expended in performing each activity?
- Q6: Is there a relationship between a subject's background and his/her workflow?

For G3 (characterizing code performance):

- Q7: What is the performance of the code?
- Q8: Is there a relationship between a subject's background and the performance of his/her code?
- Q9: Is there a relationship between the workflow used and the performance of the code?

3.4 Metrics

In order to help answer the questions above, metrics were collected concerning the background of subjects, the effort expended by the subjects, the work processes used, and the execution time of the resulting codes. Metrics are described here according to the means by which they were collected, since the data collection mechanisms used are expected to affect the feasibility of the experimental protocols (studied in G1).

3.4.1 Manually collected metrics

We developed a series of forms that subjects can use to report their effort and background information. Some key variables we asked for include:

- Educational background (related to HPC development);
- Native language;
- Prior development experience (overall software experience as well as parallel-specific experience);
- Problem domain experience.

A copy of the full background questionnaire can be found in Appendix A.

Perhaps most importantly, we created a log form that subjects are asked to use to keep track of the effort spent on the project over time and the various tasks they performed with that effort:

- Thinking/planning
- Coding a serial implementation/Reading and understanding the serial code
- Parallelizing the serial implementation
- Tuning the parallel code
- Testing the code
- Other

In one of the treatments, the subjects started from an existing serial implementation rather than developing their own. Thus option 2 varied slightly between the two treatments. The form the subjects were asked to complete can be found in Appendix B.

3.4.2 Automatically collected metrics

To have a more objective way to collect data about effort and activities, we created a wrapper for the compiler (two versions were necessary with slight tailoring, to take into account different programming languages and different file structures) and for the job submission program. When either the compiler or the job submission program is invoked, the wrapper logs a timestamp, the user's name, and any flags sent, before passing execution to the intended program. Additionally, when the compiler is invoked the wrapper logs the entire source file, and the user must choose the reason for compilation from a short menu consisting of:

1. Adding functionality (serial code)

2. Parallelizing code
3. Improving performance (tuning)
4. Debugging: Compile-time error on previous compile
5. Debugging: Crashed on previous run (segmentation fault)
6. Debugging: Hung on previous run (deadlock, infinite loop, etc.)
7. Debugging: Incorrect behavior on previous run (logic error)
8. Restructuring/cleanup (no change in behavior or performance)
9. Other

The reason chosen is stored along with the other information captured for that compile. Post-hoc questionnaires and interviews with subjects confirmed most subjects did not perceive the instrumentation as notably onerous.

Aside from being asked to choose the reason for compilation, the behavior of the wrapped programs is indistinguishable to the user from their normal operation.

We are currently experimenting with ways to incorporate the automatic collection tools into a package that will be available for other researchers to use with minimal tailoring required.

3.4.3 Execution Time

At the conclusion of the assignments, the subjects were required to execute their final code on clusters of size 1, 4 and 8 and report the execution time for each configuration. In addition to these numbers, because we captured the intermediate source code versions, execution time numbers could be computed for any intermediate versions.

3.4.4 Post-study Follow-up

An important source of data is the qualitative feedback that subjects can provide upon completion of the study. This data was collected through two methods, questionnaires and interviews. The questionnaire was distributed to every subject at the completion of the study. Some subjects volunteered to participate in an interview with the researchers where their answers could be explored in more depth.
A copy of the post-experiment questionnaire can be found in Appendix C.

4. THE EXPERIMENT

4.1 Experimenters

This experiment was a collaboration between researchers who were experienced in empirical studies in software engineering, from the University of Maryland and the Fraunhofer Center Maryland, and researchers in the area of High Performance Computing, also from the University of Maryland.

4.2 Subjects

The 15 subjects were students in a graduate level High Performance Computing class (CMSC 714) in the Fall semester of 2003 at the University of Maryland.

As there were important pedagogical goals to be met in this environment, one of our constraints in designing this study was to cause as little interruption as possible to the normal classroom activities and material.

4.3 Materials

In this study, two approaches to developing HPC software were used, MPI and OpenMP (described in Section 2.3). Two development problems were selected for the application of those approaches. All subjects used MPI on the Game of Life problem and OpenMP on the SWIM benchmark.

The actual assignment descriptions given to the students (including problem description, grading criteria, etc.) are included in Appendix D.

4.3.1 The Game of Life

The game of life is a simulation of cellular automata. The game is played on a rectangular board containing cells. At the beginning of the game, some cells are occupied and the rest are empty. The game consists of constructing successive generations of the game board. The rules for constructing the next generation from the previous generation are:

1. *Death*: cells with 0,1,4,5,6,7, or 8 neighbors die (0,1 of loneliness and 4-8 of overpopulation)
2. *Survival*: cells with 2 or 3 neighbors survive to the next generation
3. *Birth*: an unoccupied cell with 3 neighbors becomes occupied in the next generation.

The game board has a fixed size, and the subjects were given the layout of the first generation and instructed on how many generations to iterate through. The subjects were given the specification for this problem and required to develop a parallel solution from scratch.

4.3.2. SWIM Benchmark

This is a benchmark weather prediction program for comparing the performance of current supercomputers. The model is based on a paper by Sadourny [Sadourny75]. The subjects were given a sequential version of the program and instructed to parallelize it.

4.4 Procedure

4.4.1 Collection of Background Information

At the beginning of the study, the subjects were given a survey to collect their background and prior experiences in relevant HPC fields. This data was used during the data analysis process. The questionnaire can be found in Appendix B.

4.4.2 First assignment

The subjects were next trained in the first method for developing HPC software, MPI. This study was conducted as part of an existing HPC class, so the training was done at the normal lecture time by the course instructor, Dr. Jeffrey K. Hollingsworth. The training lectures were similar to those given in previous semesters of this class. In addition to this training in the HPC approach, another member of the research team trained the subjects on how to fill out the forms for the study and the types of information that must be provided.

After the training, the subjects were given the Game of Life problem to implement as a homework assignment. As part of the homework assignment, the subjects were required to keep track of their effort on the form described in Section 3.3.1. In addition, some information was recorded each time the subjects submitted their program to the compiler, as noted in Section 4.4.2. Subjects were given approximately two weeks to develop the solution. As part of the assignment, the subjects were required to run their solution on machines with varying numbers of processors (1, 2, 4 and 8) and record execution time metrics for submission with their code.

4.4.3 Second assignment

After completion of the first homework assignment, the subjects were trained in the second HPC technique, OpenMP. This training was very similar to the training for the first method and took one class period. The subjects were then given a second homework assignment containing a description of the SWIM problem. The subjects were given a serial solution to the problem and required to add OpenMP directives to the code to parallelize it and improve the performance. As in the first assignment, the subjects completed a form to track their activities and had information collected automatically at compile time. Subjects were also given approximately two weeks to develop the solution. Also similar to assignment 1, the subjects were required to submit execution metrics for various numbers of processors.

4.4.4 Post-hoc analysis

After the completion of the two homework assignments, the subjects were given a questionnaire to discuss their experiences with the assignments and with the study in general. The goal of this questionnaire was to allow the researchers to collect some qualitative data from the subjects. The subjects were asked about their experiences using the techniques and given a chance to provide feedback to the researchers. A sample of the questionnaire can be found in Appendix C. Finally, some of the subjects agreed to be interviewed by the researchers. These interviews allowed us to better understand some of the responses to the questionnaire and explore the issues in more depth.

5. Results

5.1 Results about experimental protocols

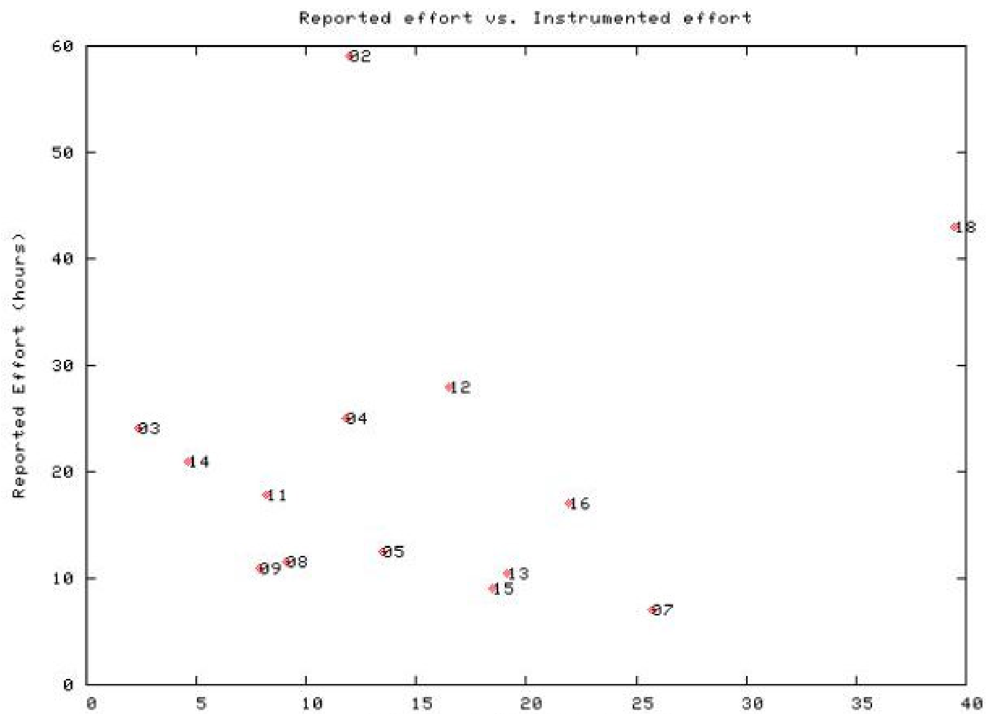
Recall that our first experimental goal G1 was decomposed into three specific research questions:

- Q1: Are the tasks given to subjects in the experiment adequate for providing the necessary information about the development approaches used?
- Q2: Is the data accurate?
- Q3: Is all of the necessary data collected?

To validate the accuracy of the data (Q2), we tried to correlate the results from the manual and automatic collection methods. Unfortunately, in doing so we found wide discrepancies. The correlation was done initially by making estimates about the total effort spent by subjects based upon the timestamps recorded in the automatically-generated logs. For each subject, the time between any two events (either compiles or runs) in the log was calculated. If the time interval was less than a specific threshold (in this analysis we used 45 minutes), that interval was added to the subject's effort total. As shown in Figure 1, no correlation between this estimate and the manually-reported data is detectable.

Furthermore, no such correlation was detected even after we accounted for the fact that significant amounts of work might have been done off of the instrumented cluster. To make the estimate more accurate, emails were sent to students after the experiment asking them to estimate what percentage of their development effort had been spent on the instrumented machine. Based

Figure 1: Manually reported total effort vs. automatically-collected total effort



on these percentages, the instrumented effort was adjusted, but there was still no correlation detected with the manually-reported effort.

Puzzled by this discrepancy, we investigated whether the *days on which effort was spent,* reported in the manual data, matched the days recorded in the timestamp logs. We found several discrepancies, which were not consistently associated with particular subjects and which did not have a consistent duration. Also, there were no obvious "holes" in the timestamp logs when no data was recorded for any subject. The only remaining explanation seems to be that subjects were simply inconsistent in their effort reporting.

This lack of accuracy and our inability to provide a clearer picture of subject activities seems to indicate that a different method of subject interaction and a different set of data to be collected may be necessary (Q1 and Q3). This answer has led us to hypothesize some improvements to experimental protocols necessary in future studies:

- One possibility will be to investigate whether we can develop mechanisms for better process conformance to the data collection procedures (for example, by not letting subjects submit their program until all previous data has been submitted).
- Another possible solution is to analyze the activity data in greater detail, incorporating assumptions about chronological order in order to make better estimates about the task being undertaken. For example, a lot of compiles in rapid succession would suggest debugging, while alternating between compile and execution or multiple executions in quick succession might suggest testing of the code. More ambitiously, if we can pinpoint the differences between successive versions of the code, we can develop heuristics about the activity that was ongoing in that time period. For example, if the delta contains no

editing on statements involving parallel operations, then we can infer that the subject was doing serial coding.

- It may also be the case that we simply need to collect more or different data. Philip Johnson's tool HackyStat [Johnson] is one possible answer we are exploring. It can be tailored to work with a number of different editors, and reports the amount of time an editor is "live," providing a better baseline of overall effort. However, we haven't found a way to cross-index this with specific tasks yet (e.g. to know when a subject is parallelizing vs. tuning code). We are also considering the use of an extensible IDE, like Eclipse [Eclipse], that would allow us to collect more accurate data.

A second major issue that we discovered regarding the completeness of data collection (Q3) is the need to distinguish between the final serial version and the beginning of parallelization. In this study, the students were only asked to submit the final (parallel) version of their code. While we did capture intermediate versions via the compiler instrumentation, we could not definitively determine which version was the final serial version. There were two types of desirable data analyses that could not be accurately performed because of the lack of this separation of serial activities and parallel activities.

First, the execution time (performance) of a subject's serial code needed to be compared to the execution time of his or her parallel code run on various numbers of processors. This analysis is used to determine the amount of speedup achieved by the subject. Because we did not have a serial version of the code, we had to approximate this metric by using the performance number of the parallel code run on only 1 node.

Second, in our analysis, we often wished to separate out the effort expended during serial coding from the effort expended during parallel coding. The manually reported effort data, which did separate the serial and parallel activities, was not very reliable. So, in order to have an accurate separation, we needed to be able to separate the effort captured via the compiler instrumentation into serial effort and parallel effort. Because the serial code was not submitted, giving us a definitive end date for serial coding, we had to develop an algorithm to approximate the point at which serial coding stopped and parallel coding began.

Based on the above observations from this study, we formulated our provisional results as a series of lessons learned to increase the ease with which we can plan future studies:

Lesson 1 – Separate the serial coding and parallel coding into two assignments.

For future studies, we suggest splitting the coding assignments into parts. In the first part, the subjects are instructed to solve the problem by writing a serial program. Once the serial program is completed and submitted, then the subjects can begin working on parallelizing the serial code already created.

Lesson 2 – Account for uncollected data when subjects work on uninstrumented machines.

As we began to analyze the automatically collected data, it became obvious that many of the subjects did some of their work on machines that were not instrumented to collect data automatically. In hindsight this occurrence is not surprising but it is something that was not accounted for during the planning and design of the study. The automatically collected data indicated that many of the subjects did not begin working on the instrumented machines until they needed either the MPI compiler or the use of multiple processors to test their parallel code. To make matters more complex, an MPI version of the C compiler is standard on most Linux implementations, so a student with access to a Linux machine could effectively finish the project before submitting a final run on the instrumented HPC system. This observation means that the automatically collected data was not collected for much of the serial development step and potentially for the parallel tuning effort.

There are two possible solutions to this problem for future studies. First we can ask the subjects to work only on the instrumented machines, thereby allowing us to automatically collect data for all of their development work. Secondly, we can develop a small script that subjects can install on any other machine on which they work that will collect the same data as the script on the main machine. Neither of these solutions is ideal, so we are continuing to pursue other solutions to this problem.

Lesson 3 – Manually reported data is suspect.

Because we were unable to correlate the manual and automatic data collection in a meaningful way, we treat the automatically collected data as more accurate, since this data was objective (not reliant upon subjective reporting by humans), unobtrusive (not interfering with normal work processes) and automatable (not dependent upon active reporting by human). Subjects were aware they were being monitored, but not aware of what was being observed or why. This included not only the log of compilation and execution activities, but also a database that was created containing captured source code and test data used throughout the development process.

Following from Lesson 3,

Lesson 4 – Data collection and analysis should be as automated as possible.

Of course, a central weakness of automated collection is that while the data can tell us what was done on the computer, it doesn't provide information about how those activities contribute to the decision making process in code development. A key research goal is to increase the usefulness of the data collected from automated mechanisms without making it more obtrusive to the developer.

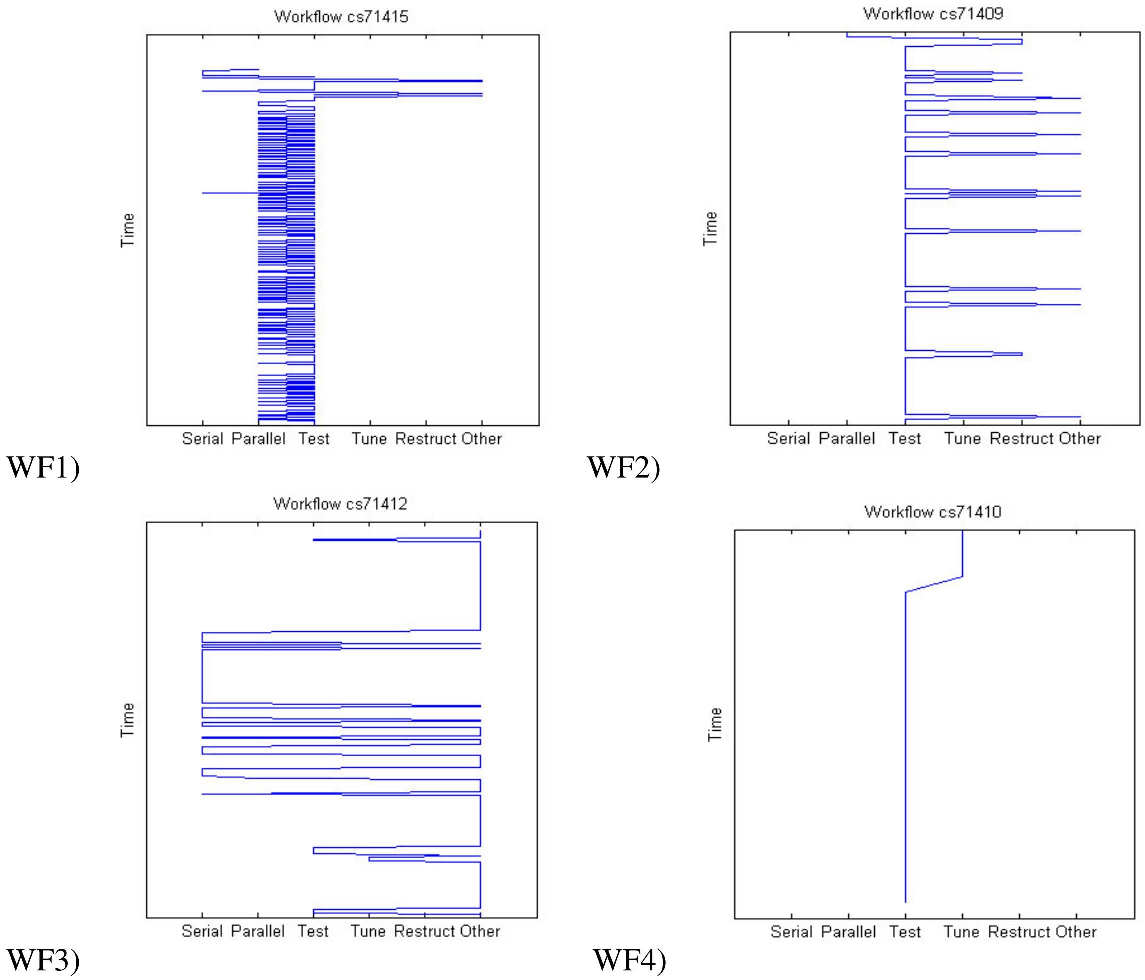
5.2 Results about development workflows

For G2 (characterizing development workflows) we can address each of the research questions separately.

5.2.1 What is the order of the activities performed by the subjects?

To analyze the order of the activities performed by the subjects (Q4) we looked first at the automatically-collected data. The timestamp data allowed us to understand the chronological series of events and look for various workflow patterns in how subjects attacked the problem. Specifically, we wanted to see the relation between the effort spent on serial versus parallel coding, and on functional development versus performance tuning. To do this, we mapped the data recorded in the log (especially focusing on the "reason for compilation," whose possible values were described in Section 3.4.2) to a smaller set of activity types: If the user explicitly gave "serial", "parallel", "tuning", restructuring", or "other" as the reason for compiling, then that was simply used as the activity category. Runs were classified as "testing". If the user was

Figure 2: Chronological sequence of development activities (serial development, parallel development, testing, tuning, restructuring, other) over time. WF1 shows a pattern of developing and testing in small increments; WF2 shows development in small increments followed by a long sequence of testing; WF3 shows development in large increments followed by testing of each; WF4 shows development in large increments followed by a long sequence of testing after each.



debugging, then the event was classified based on the previous event (e.g. if the previous event had been serial, then the debugging was classified as serial work, if the previous event had been parallel, then the debugging was classified as parallel work, etc.).

The data does show some high-level patterns. For example, Figure 2 illustrates each of four different styles of iteration through the key tasks of adding serial functionality, adding parallel code, testing, and performance tuning.

By categorizing similar workflows based on data from the study, we formulate the hypothesis:

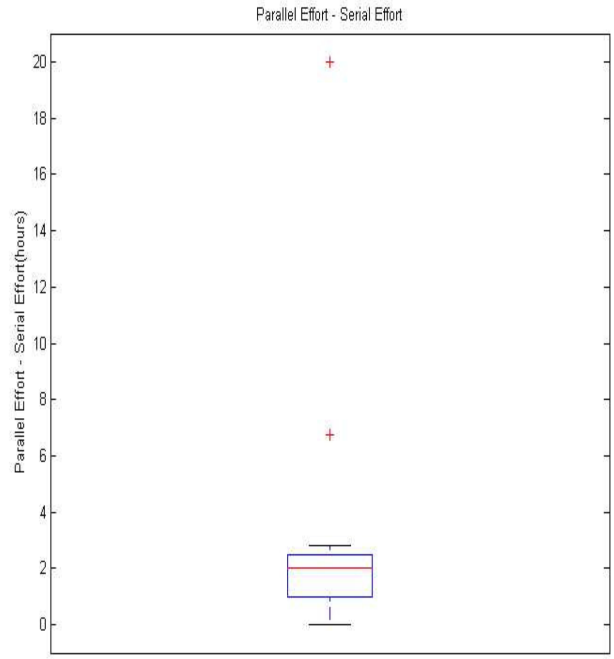
H1: There are four workflows for parallel programming:

- ***WF1: develop and test in small increments,***
- ***WF2: develop in small increments with a long sequence of tests after that,***

- *WF3: develop in large chunks and test after each large development,*
- *WF4: develop in large chunks with a long sequence of tests after each large development*

All subjects in the study were categorized according to the workflow he/she exhibited (see Table 2, Appendix E). Some subjects who appeared to switch back and forth between multiple workflows had to be grouped in multiple categories. Because the majority of subjects used workflows WF1 and WF2, analysis of contrasts among the workflows was difficult.

Figure 3: Box plot of ADDITIONAL effort (in person-hours) each subject spent on parallel than on serial development.



Interestingly, there was a weak relation between the workflow used and the amount of effort used overall. Because the majority of subjects used either workflow WF1 or WF2, we tested for a significant difference between those two groups. "Hybrid" subjects using workflow WF1/2 were removed from the analysis, leaving 9 subjects. Due to the small sample size we set $\alpha=0.10$, and found that the difference between the amount of effort required for parallel development using WF1 (15 hours on average) and using WF2 (6.6 hours on average) was statistically significant ($p=0.1$).

5.2.2 How much effort was expended in performing each activity?

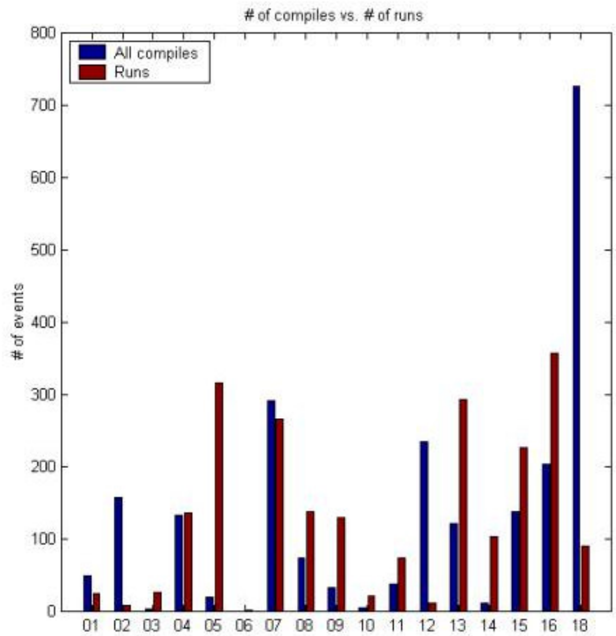
At the highest level of generality, we used the manual data from assignment 1 to describe how much effort subjects spent on the serial development versus the parallel development parts of the assignment. Expecting that the parallel development effort would be greater, we plotted the differential of (parallel effort – serial effort) for all subjects (Figure 3). A one-tailed test was sufficient to show that the average value for all subjects was significantly greater than zero (i.e., that parallel effort was significantly greater than serial effort for each subject; $z=3.18$).

Based on data from assignment 1 and a statistical test for significance, we hypothesize: H6: The parallel development effort on an HPC solution is greater than the serial effort.

To analyze the relative and absolute effort expended in performing more specific development activities (e.g. developing, testing, executing), we first summarized the *automatically collected* data from the compiler and job submit instrumentation for each subject, as shown in Figure 4. Although we had at first expected to see a rough parity between the number of compiles and the number of times the code was run, the data show that there is not necessarily any such clear relationship. In the current study we were not able to explore the reasons for this, but some possible explanations do exist:

- A larger number of runs than compiles may indicate:
  - Subjects exhaustively tested their code at various points during development, on multiple data sets, perhaps as part of performance tuning.
  - A significant amount of development was done off the cluster, and the cluster was used mainly for accurately measuring code performance.
  - Subjects had difficulty with the syntax of the job scheduler and repeatedly sent jobs that immediately came back as errors.
- A larger number of compiles than runs may indicate:
  - Subjects were "thrashing," i.e. were trying to develop the code quickly to turn in the assignment rather than optimizing performance or correctness of output.
  - Subjects spent an inordinate amount of time on debugging, responding to compiler errors.

Figure 4: Number of compiles and number of runs logged for each subject.



Regardless of the explanation, the data from this study allows us to hypothesize:
H7: There will be a large variation in the ratio of compiles to executions for novice developers.

We also used the manually-completed time and activity logs to investigate a fuller picture of development effort, including time spent off of the computer. Results are shown in Figure 5. Most interestingly, although the total effort reported by subjects through the manual logs varied widely in its absolute value, the relative distribution among the activities was similar across all of the subjects.

Thus based on the data from this study, we hypothesize:

H8: There is a large variation in the overall amount of effort among developers, but the distribution among the various activities is similar.

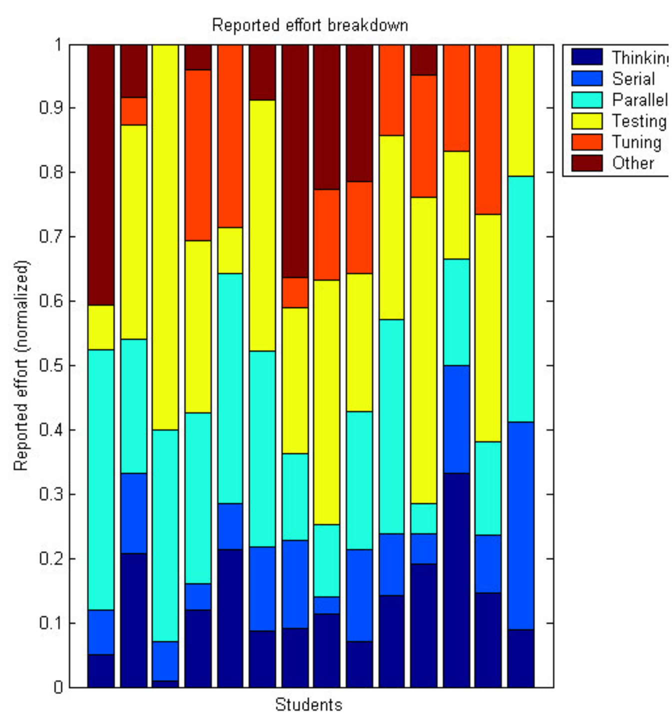
5.2.3 *Is there a relationship between a subject's background and his/her workflow?*

Using our classification of subject workflows, we investigated whether there were any patterns between a subject's background and his/her workflow (Q6). Because we had no prior experience with the best way to measure these variables, we looked for relationships among a number of different metrics. Specifically,

- Subject background was measured as:
    - Current major (Computer Science, Electrical Engineering, or Electrical & Computer Engineering)
    - Prior (undergraduate) major
    - Degree of software development experience (rated on a 5-point scale: 1 = never developed; 2 = developed on own; 3 = developed as part of a team on a course project; 4 = developed once in industry; 5 = developed multiple industry projects)
- Subject workflow was measured:
    - Using the four workflows described in Section 5.2.1, or some combination therefore.
    - Based on the size of an increment of production code, where WF1, WF2, and WF1/2 map to "small," and WF3, WF4, and WF3/4 map to "large."

We looked for any correlation between each of the above metrics, but due to the small number of data points and the tendency toward homogeneous value, there were no strong results from the data in this study.

Figure 5: Percent of effort spent on each development activity, per subject.



However, we did augment our quantitative data collection with a poll of HPC experts at the HPCS project meeting in January 2004, sponsored by DARPA, in order to better plan future studies.

Based on expert consensus, we hypothesize:
H2: Workflows will be different for students from different programs.
H3: Workflows will be different for developers with less programming experience than for developers with more programming experience.
H4: Developers with less programming experience will be more likely to work in small increments, testing with small data sets to ensure that each increment is correct.
H5: Developers with more programming experience will be more likely to work in larger chunks, coding

more functionality before testing.

Formal testing of these hypotheses awaits further study.

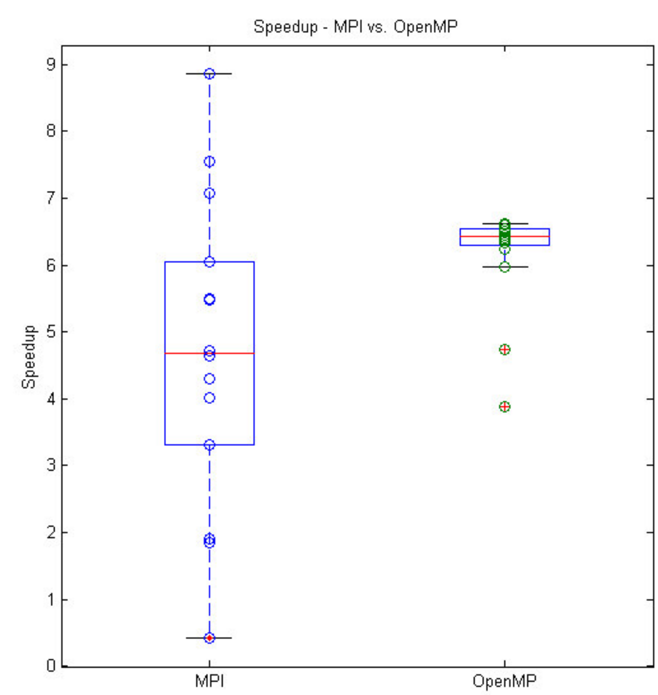
5.3 Results about code performance

Our experimental protocols did allow us to accurately measure the performance of the code (Q7), using a number of different metrics including both the absolute time to solution, speedup achieved by the parallel version.

Figure 6 does show that there were characteristic differences in the amount of speedup achievable using OpenMP and MPI in this study. However, it is necessary to recall that the use of each of these HPC approaches is entirely confounded with factors such as the programming assignment given and the programming language used – each of which is at least an equally plausible explanation for any observed differences. Therefore we draw no conclusions from this analysis, but include it as an example of the type of analysis that is feasible and desirable from future studies.

Based on the expert opinion poll of HPC researchers (described in Section 5.2.3), we formulate the following hypotheses to help focus such future studies:
H9: For a specific problem, the mean performance of MPI programs will be higher than the mean performance of OpenMP programs
H10: For a specific problem, the median MPI performance will be lower than the median OpenMP performance
H11: For a specific problem, the max MPI performance will be higher than the max OpenMP performance
H12: For a specific problem, the amount of effort required to parallelize the MPI code will be greater than the amount of effort required to parallelize the OpenMP code, but the speedup of the MPI code will be greater than the speedup of the OpenMP code

Figure 6: Degree of speedup achieved for MPI and OpenMP development assignments.



Next, using the data from assignment 1 only, we segmented the subjects based on experience levels, and then analyzed the mean level of performance for each sub-group to investigate whether there was a relationship between subjects' backgrounds and performance they were able to achieve (Q9). We examined several ways of measuring each of those variables, including:

- For subject experience:

    - Experience in C development (industrial experience, no industry experience)
    - Experience with general software development (industrial experience, no industry experience)
    - Experience with parallel programming (some, none)
    - Experience with MPI (some, none)
    - Experience with the problem domain, the Game of Life (some, none)
    - Whether the subject had taken a class in operating systems (yes, no)
- For performance:
    - Time for serial program to produce a solution
    - Speedup on 2 processors
    - Speedup on 8 processors

In no case did we find a clear and compelling pattern of different results for the two groups. Therefore, we recognize the identification of useful ways of measuring experience as an open question for future work, possibly requiring more data points and a more heterogeneous population.

We also looked for correlations between the workflow used and the performance of the resulting code (Q9). As in Section 5.2.3, workflow was measured alternately as WF1-WF4, or as "small" or "large" increments. As above, performance was measured as serial time, speedup achieved on 2 processors, and speedup on 8 processors. No correlation was found between any measure of workflow and any measure of performance.

6. Threats to Validity

As has been discussed earlier, the overriding threat to the validity of our results concerning the HPC development approaches lies in the design of the experiment itself: Because we did not systematically vary the various factors in the experiment, we cannot determine whether any difference in performance on the two treatments was do to the development approach, the programming language, or the order of treatments. For this reason, our analysis of results has been careful to avoid drawing conclusions about any of these factors, focusing instead on our analysis of the experimental protocols. We do hope, however, that the data collected in this study can be the beginning of a larger baseline built up about HPC approaches, and can provide points of comparison against future data collection.

Even within these constraints, however, we identified various threats to internal validity that we made an effort to control:

- Learning effects – Especially as they were novices, there is a danger that subjects may behave differently on treatment 2 than on treatment 1 due to learning more about HPC development and hence changing their approaches. We did our best to minimize this danger by not giving subjects their grades or other feedback on treatment 1 before they had completed treatment 2.

- Instrumentation – There is the additional danger that, if the development environment differed from one subject to the next, results concerning code performance and development effort may have also been impacted by this. Some of the potential sources of variation we could control – for example, because the final submitted code had to be run by the course instructor, all codes (at least in their final versions) called the same HPC libraries and used the same development language. On the other hand, as we discussed in Section 5.1, it became apparent that it was quite easy to recreate the same development environment on hardware outside our control, a potentially more threatening problem especially with respect to completeness of data collection. Mitigation strategies for this problem are considered in Section 5.1.

7. CONCLUSIONS

The specific output of this pilot study consisted of 4 lessons learned for HPC study design and 12 well-formulated hypotheses (based on a mix of data collected from this study and expert opinion), both of which will be used to guide future experimentation in this program. Incorporating these results, we have already begun running a set of new studies in classroom environments, the expected result of which will be data well suited to exploring the effects of different HPC development approaches on different problem types. Some data will come from the same subjects performing different types of tasks; others will reflect the same task addressed by subjects in different environments and with different backgrounds and skill levels. These data sets will form the basis of future data needed to explore the relationships among our phenomena of interest.

The ultimate goal of this work is to run full fractional factorial experiments with HPC code development professionals, to investigate specific hypotheses resulting from our earlier pilot studies with the most rigor. In such an experiment, we envision that subjects will use two or more parallel programming approaches to implement different benchmark applications. The order of the approaches and benchmarks can be varied to combat the effects of subjects learning from one assignment to the next. Such an experiment will help us to better quantify the tradeoffs between the different approaches for different types of benchmarks.

To do that, we will be able to reuse the refined instrumentation and our experience with empirical study designs and HPC environment data collection mechanisms, which we have been experimenting with in the meantime.

The end result of such studies will be well-formulated and tested heuristics concerning the aspects of human developers, HPC architectures, and code development practices that work together to influence the time to solution of problems being tackled using HPC approaches. That knowledge, in turn, is necessary to be able to plan and meet the current and increasing challenges in a number of important scientific fields.

8. ACKNOWLEDGEMENTS

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Appendix A – Experience Questionnaire

Experience Questionnaire
CMSC 714

Name ____________________
Current Major ____________________
Undergraduate Major ____________________

General Background
Please estimate your English language background:
_____I am a native speaker
_____I am not a native speaker [Please complete the following]
TOEFL Score __________ Year ______________
My English reading comprehension skills are:
_____Low _____Medium _____High

My English listening and speaking skills are:
_____Low _____Medium _____High

How many courses have you taken at Maryland? __________

Please indicate if you received a grade of A or B in the following classes (or equivalent) at the undergraduate and graduate level. [This information will be used for classification purposes only].

	Passed Undergraduate Class with an A or B (Y/N)	**Passed Graduate Class with an A or B (Y/N)**
Computer Architecture		
Operating Systems		
High Performance Computing		
Software Engineering		

What is your previous experience with software development in practice? (Check the bottom-most item that applies)
_____I have never developed software
_____I have developed software on my own
_____I have developed software as part of a team, as part of a course
_____I have developed software as part of a team **one time** in industry
_____I have developed software as part of a team **more than one time** in industry

Please explain your answer. Include the number of projects you have worked on. Include the approximate size and duration of each project and the type of project. (E.g. "I worked on a 100,000 line telecommunication project for 5 years"; "I developed a 1000 line class project"; "I worked on a 5000 line parallel software project for 1 year"; etc.)

High Performance Computing Experience

Please rate your experience in the following activities. For **Experience Level** use the following scale:

0 = No experience (Leave Extra Information blank)
1 = Classroom experience only
Extra Information should indicate whether you:
a) only learned the concept in class
b) used the concept on a homework
c) used the concept on a project
2 = Professional experience
Extra Information should indicate the number of projects on which you performed the activity

	Experience Level	Extra Information
Parallel Programming		
Developing software in C		
Developing software in C++		
Developing software in Fortran		
Developing software in other languages		
Developing software on a Unix platform		
Using MPI		
Using OpenMP		
Tuning code for parallel performance		

Experience in Problem Domains

We will use answers in this section to understand how familiar you are with various systems we may use as examples or for assignments during the class.

Have you ever implemented solutions to the following problem:

	Y/N
The Game of Life	

Appendix B – Effort Collection Forms

CMSC 714
Effort Report Form – Assignment 1

Each time you work on the homework assignment, please have this form with you and record the time spent (round to nearest 15 minutes) and the activity that you were doing. Place a check or an X in the appropriate column to describe your activites. For example, if you spent 30 minutes thinking about the solution and then 1 hour writing serial code, you would make two entries. The first would be .5 hours of thinking. The second would be 1 hour of Serial Coding.

Remember that the information provided on this form will in no way affect your grade and will not be seen by Dr. Hollingsworth. The purpose of this information is to help understand what processes you use, not to evaluate you.

Date	Effort (hours)	Thinking/ Planning	Serial Coding	Parallelizing the Code	Testing Code	Tuning Parallel Code	Other
[ex] 8/18/03	0.5	X					
[ex] 8/18/03	1		X				

Name: ______________________ Login ID: ____________________

CMSC 714
Effort Report Form – Assignment 2

Each time you work on the homework assignment, please have this form with you and record the time spent (round to nearest 15 minutes) and the activity that you were doing. Place a check or an X in the appropriate column to describe your activites. For example, if you spent 30 minutes thinking about the solution and then 1 hour coding, you would make two entries. The first would be .5 hours of thinking. The second would be 1 hour of coding.

Remember that the information provided on this form will in no way affect your grade and will not be seen by Dr. Hollingsworth. The purpose of this information is to help understand what processes people use, not evaluate them.

Date	Effort (hours)	Reading Serial Code	Thinking/ Planning	Parallelizing the Code	Testing Code	Tuning Parallel Code	Other
[ex] 8/18/03	0.5	X					
[ex] 8/18/03	1		X				

Appendix C – Post study questionnaire

CMSC 714
Post Study Questionnaire

Name: ___________________________________ LoginID: ____________________________

Please note that your answers on this questionnaire will ***not*** affect your grade in any way. These questions will help us correctly interpret and make the most effective use of the data from this study.

1. Assignment 1 (MPI)

1.1 What was the most difficult aspect of MPI to understand from the class discussions?

1.2 What was the most difficult aspect of using MPI on the assignment?

1.3 Which type (based on the compiler menu) of debugging was the most difficult with MPI?

1.4 What would have made this assignment easier?

2. Assignment 2 (OpenMP)

2.1 What was the most difficult aspect of OpenMP to understand during the class discussion?

2.2 What was the most difficult aspect of using OpenMP on the assignment?

2.3 Which type (based on the compiler menu) of debugging was the most difficult with OpenMP?

2.4 What would have made this assignment easier?

3. Comparing MPI to OpenMP

3.1 Which programming model was easier to use overall? Why?

3.2 Which programming model was easier to use when parallelizing the code?

3.3 Which programming model was easier to use for tuning the code to increase performance?

3.4 Compare C and FORTRAN as languages for developing parallel programs. Which is better and why?

4. General Questions

4.1 Was the effort form easy to understand and fill out? If not, please let us know what problems you found, and how the form could be improved.

4.2 Did categories on the effort form accurately capture the different stages of *your* development process? If not, what categories should be added, removed or changed?

4.3 Did it require too much effort for you to complete the forms?

4.4 What could have been done to improve the forms (both the effort form and the background form)?

4.5 Did the choices for recompilation accurately capture the reasons why you were compiling? If not, what options should be added, removed or changed?

4.6 Did you mind being asked by the compiler why you were recompiling?

4.7 Did the question by the compiler interfere with your normal work habits? If so, how?

4.8 Can you suggest a less-intrusive method for collecting this compile time information?

4.9 Did completing the effort form interfere with your normal work habits? (E.g. Did it change the amount of time you spent on the assignments? Did it change how early you started working? Etc…?)

4.10 Did you think there were any problems with how this experiment was carried out?

Appendix D – Problem Descriptions

Assignment 1 – Game of Life

The purpose of this programming assignment is to gain experience in parallel programming and MPI. For this assignment you are to write a parallel implementation of a program to simulate the game of life.

The game of life simulates simple cellular automata. The game is played on a rectangular board containing cells. At the start, some of the cells are occupied, the rest are empty. The game consists of constructing successive generations of the board. The rules for constructing the next generation from the previous one are:

1. *death*: cells with 0,1,4,5,6,7, or 8 neighbors die (0,1 of loneliness and 4-8 of over population)
2. *survival*: cells with 2 or 3 neighbors survive to the next generation.
3. *birth*: an unoccupied cell with 3 neighbors becomes occupied in the next generation.

For this project the game board has finite size. The x-axis starts at 0 and ends at *X_limit*-1 (supplied on the command line). Likewise, the y-axis start at 0 and ends at *Y_limit*-1 (supplied on the command line).

INPUT

Your program should read in a file containing the coordinates of the initial cells. Sample files are located life.data.1 and life.data.2. You can also find many other sample patterns on the web (use your favorite search engine on "game of life" and/or "Conway").

Your program should take five command line arguments: the name of the data file, the number of processes to invoke (including the initial one), the number of generations to iterate, *X_limit*, and *Y_limit*.

OUTPUT

Your program should print out one line (containing the x coordinate, a space, and then the y coordinate) for each occupied cell at the end of the last iteration.

HINTS

The goal is not to write the most efficient implementation of Life, but rather to learn parallel programming with MPI.

Figure out how you will decompose the problem for parallel execution. Remember that MPI (at least the mpich implementation) does not have great communication performance and so you will want to make message passing infrequent. Also, you will need to be concerned about load balancing.

One you have decided how to decompose the problem, write the sequential version first.

WHAT TO TURN IN

You should submit your program and the times to run it on the input file final.data (for 1, 2, 4, and 8 processes).

You also must submit a short report about the results (1-2 pages) that explains:

- what decomposition was used
- how was load balancing done
- what are the performance results, and are they what you expected

Using MPICH

To compile MPI, run the program usr/local/stow/mpich/bin/mpicc as your C compiler

To run MPI, you need to set a few environment variables:

```
setenv MPI_ROOT /usr/local/stow/mpich
setenv MPI_LIB  $MPI_ROOT/lib
setenv MPI_INC  $MPI_ROOT/include
setenv MPI_BIN $MPI_ROOT/bin
# add MPICH commands to your path (includes mpirun and mpicc)
set path=($MPI_BIN $path)
# add MPICH man pages to your manpath
if ( $?MANPATH ) then
    setenv MANPATH  $MPI_ROOT/man:$MANPATH
else
    setenv MANPATH  $MPI_ROOT/man
endif
```

COMMAND LINE ARGUMENTS

The command line arguments should be:

```
life < input file> <# of generations> < x limit> < y limit>
```

The number of processes is specified as part of the mpirun command.

GRADING

The project will be graded as follows:

Item	Pct
Correctly runs on 1 processor	15 %
Correctly runs on 8 processors	40%
Performance on 1 processor	15%
Speedup of parallel version	20%
Writeup	10%

In addition, extra credit of 5% is available if you complete and turn-in the log for the study.

ADDITIONAL RESOURCES

For additional MPI information, see http://www.mpi-forum.org/ (MPI API) and http://www-unix.mcs.anl.gov/mpi (for MPICH)

For more information about using the Maryland cluster PBS scheduler, see http://umiacs.umd.edu/labs/LPDC/plc/user-manual.html .
This page needs to be updated (path names are not correct for the current Linux environment), which should happen soon.

Assignment 2 – Swim Benchmark

The purpose of this programming assignment is to gain experience in writing openMP programs. You will start with a working serial program (swim.f) and add openMP directives to create a parallel program.

HINTS

The goal is be systematic in figuring out how to parallelize this program. You should start by using the gprof command to figure out what parts of the program take the most time. From there you should exam the loops in the most important subroutines and figure out how to add openMP directives.

The programs will be run on a Sparc SMP (called tau.umiacs.umd.edu). Your account names will be the same as on the Linux cluster.

WHAT TO TURN IN

You should submit your program and the times to run it on the input file swim.in (for 1, 4, 8 and 16 processors).

You also must submit a short report about the results (1-2 pages) that explains:

- what directives were used
- what are the performance results, and are they what you expected

Using openMP

To compile openMP you use the Fortran90 (/opt/SUNWhpc/bin/mpf90) compiler and supply the additional command line argument -xopenmp=parallel.

The environment variable OMP_NUM_THREADS controls the number of processors that will run the program. Set this value in the shell window you are about to run the program from.

RUNNING THE PROGRAM

Swim reads the input file swim.in from standard input that describes various aspects of how the program should run.

GRADING

The project will be graded as follows:

Item	Pct
Correctly runs on 1 processor	15 %
Correctly runs on 8 processors	40%
Performance on 1 processor	15%
Speedup of parallel version	20%
Writeup	10%

In addition, extra credit of 5% is available if you complete and turn-in the log for the study.

Appendix E – Raw Data

Table1: Subject background and experience data (related to treatment 1)

Subject ID	Current Major	Undergrad Major	Software Dev. Experience	Experience in C Dev	Exp. with Parallel Prog.	Class in OS?	Exp. With MPI	Exp. With Game of Life
02	CS	CS	3	1	2	0	0	1
03	CS	CS	3	2	0	1	0	0
04	CS	CS	3	1	1	1	0	0
05	CS	Business/Appl.Sci.	5	2	1	1	0	1
07	CS	EE	5	1	0	1	0	0
08	CS	CS	3	1	0	0	0	0
09	CS	MATH	5	2	0	0	0	0
10		CS	4	2	0	0	1	0
11	CS	Aero&Astro	5	2	1	0	0	0
12	CS		3	0	0	1	0	0
13	EE	E&COMM.	4	2	0	1	0	0
14	EE	EE	2	1	1	1	1	1
15	CS	CS	3	1	0	1	0	0
16	ECE	EE	3	1	1	1	0	0
18	CS	Physics	5	1	0	0	0	0

- **Subject ID** is a unique identified used to label each subject.
- **Current major** is the subject's major program at the time of the study; CS = Computer Science, EE = Electrical Engineering, ECE = Electrical and Computer Engineering.
- **Undergrad major** is the subject's undergraduate degree program.
- **Software Dev Experience** describes the subject's level of experience with software development, rated on a 5-point scale: 1 = never developed; 2 = developed on own; 3 = developed as part of a team on a course project; 4 = developed once in industry; 5 = developed multiple industry projects.
- **Experience in C Dev** describes whether or not the subject has experience programming in C in industry.
- **Exp with Parallel Prog** indicates whether the subject has any previous experience with parallel programming.
- **Class in OS?** Indicates whether the subject has had a class in operating systems.
- **Exp with MPI** indicates whether the subject has any previous experience with the MPI HPC approach used in treatment 1.
- **Exp with Game of Life** indicates whether the subject has any previous experience with the "Game of Life" programming assignment given in treatment 1.

Table2: Workflow data for treatment 1

Subject ID	Workflow	Total Effort (Instrument)	Total Effort (Manual)	Instrumented Parallel Effort(Hrs)	No. of Runs	No. of Compiles
02	WF3/4	11.96	59	8.33	8	157
03	WF2	2.32	24	2.13	26	84
04	WF1/2	11.78	25	9.92	136	132
05	WF2	13.44	12.5	13.16	317	20
07	WF1/2	25.68	7	20.36	266	292
08	WF1	9.09	11.5	3.84	138	73
09	WF2	7.90	11	5.95	129	32
10	WF4	1.09	N/A	1.09	21	5
11	WF2	8.14	17.75	7.28	74	38
12	WF3	16.47	28	0.84	11	234
13	WF1/2	19.16	10.5	15.63	294	122
14	WF2	4.63	21	4.28	104	12
15	WF1	18.47	9	17.63	227	138
16	WF1	21.91	17	17.63	357	203
18	WF1/3	39.47	43	20.67	90	727

- **Subject ID** is a unique identified used to label each subject.
- **Workflow** corresponds to the four distinct workflows identified in Section 5.2.1. Subjects who switched between workflows at different points in development are labeled with all workflows applied, e.g. "WF1/2."
- **Total Effort (Instrument)** is the total effort estimated for the serial and parallel parts of the development assignment, based on the automatic data collection built into the compiler and job submitter.
- **Total Effort (Manual)** is the total effort figure reported manually by each subject.
- **Instrumented Parallel Effort** is a measure of the number of person-hours required to complete the parallel development part of the assignment, as measured by the *automatic* data collection mechanisms. (We argue in Section 5.1 that instrumented effort is more accurate than manual.)
- **No. of Runs** is the number of run events captured by the automatic data collection.
- **No. of Compiles** is the number of compile events captured by the automatic data collection.

Table3: Performance data for treatment 1

Subject ID	Serial Time	2 Proc. Speedup	8 Proc. Speedup
02	0.00	0.00	0.00
03	173.20	1.99	6.04
04	40.76	1.00	0.00

05	114.90	2.10	5.49
07	62.80	1.79	4.71
08	94.89	3.23	5.48
09	77.29	1.47	1.90
10	15.46	2.27	8.87
11	17.50	1.67	1.86
12	185.70	1.95	4.30
13	59.66	1.82	4.02
14	59.66	2.03	7.55
15	120.24	1.84	4.64
16	80.16	2.00	7.08
18	175.42	1.26	3.31

- **Subject ID** is a unique identified used to label each subject.
- **Serial time** is a measure of the time required for the serial program to produce a solution (in seconds)
- **2 Proc Speedup** is the degree of speedup achieved on 2 parallel processors
- **8 Proc Speedup** is the degree of speedup achieved on 8 parallel processors