

UNIVERSITY OF CALGARY

Title of Thesis

Second Thesis Title Line

by

Student's name

A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE
DEGREE OF NAME OF DEGREE IN FULL

DEPARTMENT OF NAME OF DEPARTMENT

CALGARY, ALBERTA

monthname, year

© Student's name year

Abstract

Acknowledgements

Table of Contents

Abstract	i
Acknowledgements	ii
Table of Contents	iii
List of Tables	iv
List of Figures	v
List of Symbols	vi
1 Introduction	1
1.1 The Task Allocation Problem	1
1.2 Related Work	1
1.3 Statement of Results	2
2 The Model and Problem Statement	3
2.1 Standard Model	3
2.2 Problem Statement	3
2.3 The Dynamic Adaptive To-Do Tree	4
3 Analysis	7
3.1 Correctness	7
3.1.1 Definitions and Terminology	7
3.1.2 Analysis and Proofs	9
3.2 Performance	13
3.2.1 DoTask Analysis	13
3.2.2 InsertTask Analysis	13
3.3 Competitive Analysis	13
4 Conclusions	14
4.1 Contributions	14
4.2 Future Work	14
A First Appendix	15

List of Tables

List of Figures and Illustrations

List of Symbols, Abbreviations and Nomenclature

Symbol

Definition

U of C

University of Calgary

Chapter 1

Introduction

In this chapter, we will introduce the task allocation problem as well as its dynamic version and survey the past work related to it.

1.1 The Task Allocation Problem

Task allocation problem, also called do-all problem, is already a foundational problem in distributing computing domain. During the last two decades, significant research was dedicated to studying the task allocation problem in various models of computation, including message passing, shared memory, etc. under specific assumption about the asynchrony and failures.

In this thesis, we consider the dynamic and shared memory version of the task allocation problem. The dynamic task allocation via asynchronous shared memory problem could be described as follows:

p processes must cooperatively perform a set of tasks in the presence of adversity. The tasks are injected by the adversary dynamically over time.

1.2 Related Work

The task allocation via shared memory was firstly discussed by Kanellakis and Shavartsmann[1]. In their paper about PRAM algorithm, they gave a robust parallel solution to the task allocation problem. The data structures they used are four full binary trees and tasks are abstracted as registers in an array. Each cell of the array is initialized with 0, and when it is turned to be 1 implies the abstracted task is performed successfully.

Up to now, there have been many research results focus on the topic. ..

Dan Alistarh and Michael, etc.

However, the above papers about the task allocation problem all focus on the static version, or called one-shot version, where the tasks are available at the beginning, and the execution is done when all these tasks are performed successfully. Dan Alistarh and Michael, etc. considered the dynamic version of task allocation problem, i.e. given p asynchronous processes that cooperate to perform tasks while the tasks are not available but inserted dynamically by the adversary during the execution. In that paper, they gave the first asynchronous shared memory algorithm for the dynamic task allocation, and proved that their algorithm is optimal within logarithmic factors. The main idea is to use a full binary full tree, called To-do tree which is inherited from their last paper, to guide the processes to insert the tasks at random empty memory locations and to pick newly inserted tasks to perform at random.

1.3 Statement of Results

In this thesis, we will introduce a randomized adaptive To-do tree algorithm which is similar to that presented by Dan Alistarh and Michael, etc. in their paper [1]. The performance of our algorithm depends on the input sequence of tasks but not a fixed value. It has no constraint on the number of tasks presented in the to-do tree. Additionally, our algorithm implemented by the compare-and-swap registers directly which makes the complexity of our algorithm to be quadratic.

In chapter 2, we will formally define the dynamic task allocation problem again and describe our adaptive To-do tree algorithm.

In chapter 3, we will give a framework for the performance analysis of our algorithm.

In chapter 4, we summarize our results, relate them to past work and discuss the open questions that arise from our work.

Chapter 2

The Model and Problem Statement

In this chapter, we will formally describe the system model we are working in and introduce the adaptive To-do tree algorithm, a randomized algorithm that could help us solve the dynamic asynchronous task allocation problem better.

2.1 Standard Model

The computation model we work in is the standard asynchronous shared memory mode with p processes $1, 2, \dots, p$, where up to $p-1$ processes may fail by crashing. The processes communicate with each other via the shared registers, which they could perform read, write and compare-and-swap (CAS) operations. Each process has a unique identifier i which is from an unbounded namespace and has a local random number generator to perform coin flip operations.

The mode we discuss is under the control of a strong adaptive adversary. At any point of time, it can see the entire history (all coin flip operations and the returned values). Depending on such history, it decides which processes take the next step. i.e. At any point of time, the adversary knows exactly which step each process will be executing next.

2.2 Problem Statement

() Dynamic asynchronous task allocation is the problem in which the p processes cooperatively execute tasks and the task are inserted into the data structure dynamically during the executing.

[What is task] For simplicity, the tasks are still abstracted and associated with shared registers. If a process changes the value of certain register from 0 to 1 successfully, it

means the task associated with this register is performed; if a process changes the value of certain register from 1 to 0, it means the task is inserted successfully and associated with that register. Additionally, we assume each task has a unique identifier $l_i \neq 0$. One simple implementation of such task identifier uniqueness is to assign each task with an identifier in the form $(id, count)$, where id is the id of the process to which the task is assigned and $count$ is the value of a local per-process counter, which is incremented on each newly inserted task.

[Complexity Metric] The complexity measure we use is the total number of operations (i.e. read, write, and CAS) that processes take during an execution.

Define an InsertTask operation is successful if it has inserted a task into the task array. Similarly, a DoTask operation is successful if it has performed a task at a leaf. A complete InsertTask or DoTask operation must be a successful operation, but not vice versa.

2.3 The Dynamic Adaptive To-Do Tree

[some concepts and definition, e.g. tree, counts, surplus, space] [Double Compare and Swap]

[Intro and detailed explanation of DoTask and InsertTask]

Method 1 DoTask()

```
1: while (true) do
2:    $v \leftarrow root$ 
3:   if ( $v.surplus() \leq 0$ ) then
4:     return  $\perp$ 
5:   end if

   /* Descent */
6:   while  $v$  is not a leaf do
7:      $(x_L, y_L) \leftarrow v.left.read()$ 
8:      $(x_R, y_R) \leftarrow v.right.read()$ 
9:      $s_L \leftarrow \min(x_L - y_L, 2^{height(v)})$ 
10:     $s_R \leftarrow \min(x_R - y_R, 2^{height(v)})$ 
11:     $r \leftarrow random(0, 1)$ 
12:    if  $((s_L + s_R) = 0)$  then
13:      Mark-up( $v$ )
14:    else if  $(r < s_L / (s_L + s_R))$  then
15:       $v \leftarrow v.left$ 
16:    else
17:       $v \leftarrow v.right$ 
18:    end if
19:  end while

   /*  $v$  is a leaf */
20:   $(x, y) \leftarrow v.read()$ 
21:   $(flag, l) \leftarrow v.TryTask(task[y + 1])$ 
22:   $v.CAS((x, y), (x, y + 1))$  // Update Insertion Count
23:   $v \leftarrow v.parent$ 
24:  Mark-up( $v$ )
25:  if  $flag = success$  then
26:    return  $l$ 
27:  end if
28: end while
```

Method 2 Insert(task l)

```
1: while (true) do
2:    $v \leftarrow root$ 

   /* Descent */
3:   while ( $v$  is not a leaf) do
4:      $(x_L, y_L) \leftarrow v.left.read()$ 
5:      $(x_R, y_R) \leftarrow v.right.read()$ 
6:      $s_L \leftarrow \min(x_L - y_L, 2^{height(v)})$ 
7:      $s_R \leftarrow \min(x_R - y_R, 2^{height(v)})$ 
8:      $r \leftarrow random(0, 1)$ 
9:     if  $((s_L + s_R) = 0)$  then
10:      Mark-up( $v$ )
11:     else if  $(r < s_L / (s_L + s_R))$  then
12:        $v \leftarrow v.left$ 
13:     else
14:        $v \leftarrow v.right$ 
15:     end if
16:   end while

   /*  $v$  is a leaf */
17:    $(x, y) \leftarrow v.read()$ 
18:    $flag \leftarrow v.PutTask(task[x + 1], l)$ 
19:    $v.CAS((x, y), (x + 1, y))$  // Update Insertion Count
20:    $v \leftarrow v.parent$ 
21:   Mark-up( $v$ )
22:   if ( $flag = success$ ) then
23:     return success
24:   end if
25: end while
```

Method 3 Mark-up(v)

```
1: if ( $v$  is not Null) then
2:   for ( $i = 0; i < 2; i++$ ) do
3:      $(x, y) \leftarrow v.read()$ 
4:      $(x_L, y_L) \leftarrow v.left.read()$ 
5:      $(x_R, y_R) \leftarrow v.right.read()$ 
6:      $v.CAS((x, y), (max(x, x_L + x_R), max(y, y_L + y_R)))$ 
7:   end for
8: end if
```

Chapter 3

Analysis

3.1 Correctness

The standard correctness condition for shared memory algorithm is linearizability which was introduced by M. Herlihy and J. M. Wing in 1990. The intuition of linearizability is the real-time behavior of method calls must be preserved, i.e. If one method call precedes another, then the earlier call must have taken effect before the later one. By contrast, if two method calls overlap, then we are free to order them in any convenient way since the order is ambiguous. Informally, a concurrent object is linearizable if each method call appears to take effect instantaneously at some moment between that its invocation and response. In the next section, we will first build the formal definition and terminology for linearizability, then prove our concurrent dynamic task allocation object is linearizable.

3.1.1 Definitions and Terminology

Definition 1. *History.* *A history (or execution) H , obtained by processes executing shared memory operations on concurrent objects, is a finite sequence of method invocation and response events.*

A history H may be related to several concurrent objects. When we consider the concurrency behavior of a specific object, we should focus on the subhistory of that object which is defined as follows:

Definition 2. *Subhistory.* *The subhistory $H|obj$ of history H is the subsequence of all invocation and response events in H whose object names are all obj .*

If a history H we consider is related to only one object obj , then the subhistory H_{obj}

is right the history H . Thus, in the following discussion, when we discuss the concurrency behavior of a specific object obj , the history H and the subhistory H_{obj} have no difference.

We use $inv_H(op)$ to denote the position of the invocation of operation op in history H . Similarly we use $rep_H(op)$ to denote the position of the corresponding response of op in H . Actually, for each operation op , it is not necessary to have a matching response. In this case, we call the operation op is pending and denote it as $rsp_H(op) = \infty$. Otherwise, we call the operation is complete in H .

Definition 3. Complete/Incomplete History. *A history is complete if all its operations are complete. A completion of an incomplete history H is an extension H' of H , such that H' contains exactly the same operations as H but the responses are added for the pending operations in H .*

Let H be a complete history. With each operation op in H we could associate a time interval $I_H(op) = [inv(op), rsp(op)]$. Similarly, for an uncomplete history, we denote the interval with respect to the pending operation op by $I_H(op) = [inv(op), \infty]$.

Definition 4. Sequential History. *A history is sequential if the first event in the history is an invocation, and each invocation, except possibly the last one, is immediately followed by a corresponding response.*

It is obvious that a sequential history is a total order over all operations. In order to distinguish with the history H we defined in definition 1, we use S to denote a sequential history.

Definition 5. Sequential Specification. *The sequential specification S_{obj} for a concurrent object obj is the set of all possible sequential histories for obj .*

We say a sequential history S satisfies the sequential specification of object obj means S is contained in the above sequential history set S_{obj} , i.e., $S \in S_{obj}$.

Definition 6. Valid Sequential History. *A sequential history S of object obj is valid (sometimes also called legal) if it satisfies the sequential specification of obj .*

With the above definitions, we could now define linearization as follows:

Definition 7. Linearization. *A history H linearizes to a sequential history S , if and only if S satisfies the following conditions: (1) S and H have the same operations, (2) sequential history S is valid, and (3) there is a mapping from each time interval $I_H(op)$ to a time point $t_H(op)$, $t_H(op) \in I_H(op)$, such that the sequential history S could be obtained by sorting the operations in H by their $t_H(op)$.*

In another word, a history H is linearizable if and only if we could find a such a sequential history S which satisfies the above three conditions.

Definition 8. Linearization Point. *For each operation op in history H , we call the time point $t_H(op)$ described in the above definition the linearization point of op .*

Definition 9. Linearizable Object. *A concurrent object is linearizable if every history H of that object is linearizable.*

In the following subsection, we will prove our concurrent dynamic task allocation object shown in Figure 1 is linearizable.

3.1.2 Analysis and Proofs

Through the definitions in subsection 3.1.1, one way to show a concurrent object obj is linearizable is to prove its arbitrary history H is linearizable. Specifically, to obtain the linearizability of obj , we need to identify for each DoTask or InsertTask operation op (i.e., interval $I_H(op)$) in H a linearization point, and prove that the sequential history S obtained by sorting these operations according to their linearization points satisfies the sequential specification of obj .

We notice that each complete DoTask or InsertTask operation can be associated with a unique task array slot with respect to the task it removed or inserted. Additionally, the removal count and insertion count are both monotonically increasing. Thus, we could associate the node counts with operations which have been propagated to that node. Next, we are going to define “an operation is counted at a node” recursively to formalize the operation propagation.

A DoTask operation is counted at a leaf when the removal count at the leaf is updated with the index of the task array slot where the successfully performed task is located. The definition for InsertTask operation is symmetric.

Now we define a DoTask operation is counted at an arbitrary inner node v and counting a InsertTask is symmetric as well.

Recall that the removal count of v is always updated though CAS operation (line 6, method 3). Notice that there could be more than one operations updating the count with the same value. We could therefore linearize all these operations that update the removal count of v with the same value y . For all these operations, only the first one in the linearization order counts the corresponding DoTask operation. In another word, a DoTask operation is counted at an inner node v as soon as the updating operation that counts the DoTask is linearized. Based this definition, no operation will be counted twice at a node.

Please note that, the update counting the DoTask at node v is not necessary performed by the DoTask operation itself, i.e, suppose process p is executes a DoTask operation and has successfully performed task l at certain leaf. Then the operation that counts this DoTask at node v could be a different process q if q updates the removal count first in the linearization order.

Given the above concepts and properties, we could prove the following result:

Lemma 1. *Let v be a tree node,*

(1) If (x, y) is the result by calling $v.read()$, then there exists a set of x successful InsertTask

operations and a set of y successful DoTask operation that have been counted at node v by the end of the execution of $v.read()$.

(2) If there are x DoTask operations that have been counted at v before the execution of $v.read()$, then the removal count value returned by $v.read()$ is not less than x .

Proof. □

Lemma 2. Consider a history H and an arbitrary operation op in H , let $t_H(op)$ be the point when the operation op is counted at the root, then $t_H(op)$ is between $inv_H(op)$ and $rsp_H(op)$.

Proof. The fact $t_H(op) > inv_H(op)$ is needless to prove. Without loss of generality, suppose process p executes op and op is a DoTask operation which has performed some task successfully at the leaf. When it walks back to root and executes Mark-up(root), there will be two cases:

Case 1: It increments the removal count successfully via CAS (line 6, method 3) at point τ . If it is the first one in the linearization order of all operations updating the removal count with the same value, then $t_H(op) = \tau$, therefore $t_H(op) < rsp_H(op)$. Otherwise, we could let $t_H(op) = \tau'$, where τ' is the first one in the linearization order updated the removal count of root. Obviously, $\tau' < \tau$, therefore $t_H(op) < rsp_H(op)$.

Case 2: It fails to increment the removal count. The compare and swap operation of p fails if and only if the value of the insertion and/or removal counts are/is updated at a point before τ , suppose it is τ' . Here are two subcases.

Subcase 2.1: If the removal count is incremented at τ' , it means the DoTask operation has already been counted by another process. Thus, $t_H(op) \leq \tau' < rsp_H(op)$.

Subcase 2.2: If it is not the removal count but the insertion count that is updated at τ' . We notice that the CAS operation (line 6, method 3) will be repeated by p , during the second iteration, if the CAS of p succeed at τ'' , then we could deduce that $t_H(op) \leq \tau''$, therefore $t_H(op) < rsp_H(op)$. If it fails again at point τ'' , then there must be another process updated the counts of root again. This time, the counts of the children will be noticed and

the DoTask operation will propagate to the root. We could deduce $t_H(op) < \tau''$. Thus, $t_H(op) < rsp_H(op)$ as well. \square

Under the above definitions and properties, we claim the point $t_H(op)$ when op is counted at the root is the linearization point of operation op .

Lemma 3. *The dynamic task allocation object in the above figure is linearizable.*

Proof. Consider an arbitrary history H containing DoTask and InsertTask operations. We should prove for any execution of our algorithm, the total order given by the linearization point is verifies the uniqueness and validity. If H is not complete, then we let all processes that have not finished their operations continue to take steps in an arbitrary order until all operations are completed. Every operation will finally be done is ensured by our computation model and the randomness of our algorithm. This way we obtain a completion H' of H and it suffices to prove H' is linearizable. Thus, to prove this lemma, we should prove the total order obtained by sorting the operations by their $t_H(op)$ values is valid.

The uniqueness is obvious. When multiple processes are calling TryTask(l) at the memory location, only one of them will receive success and the index l of the task, all the other competitor processes will get failure. Task l is performed successfully as long as the value of corresponding memory location is turned to 1. The following process will never repeatedly turn it be to 0 and turn 0 to 1 which is guaranteed by the our semantics of task insertion and removing.

Now we prove the validity, i.e. each task that is performed successfully must have been inserted before. We should prove the insertion operation of a task is always counted at the root before the removal operation. To prove this result holds for the root, we now prove it by induction from the leaf.

At the leaf, this holds because if and only if the insertion count of newly inserted task l has been incremented (line 19, method 2) then the following removal operation could read that (line 20, method 1) to know the available task l at the leaf and then try to perform it.

In another word, suppose the task l is inserted but the insertion count is not incremented (i.e. insertion has not been counted yet), then the following removal operation has no way to know the available task l , perform it and increment the removal count. Thus, the removal will not be counted.

For an arbitrary inner node v , we suppose, by the induction step and lemma 1, the result holds for children $v.left$ and $v.right$. We could notice that any process updates the insertion count and removal count as an atomic operation (line 6, method 3). If some remove operation has been counted at node v , then the corresponding insert operation for that task must have been counted at v simultaneously by the double compare-and-swap operation. Apply this to the root, then validity condition holds. \square

3.2 Performance

3.2.1 DoTask Analysis

3.2.2 InsertTask Analysis

3.3 Competitive Analysis

Chapter 4

Conclusions

4.1 Contributions

4.2 Future Work

Appendix A

First Appendix