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Parallel Geometric Algorithms.

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PARALLEL GEOMETRIC ALGORITHMS

A Dissertation

**Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy**

in

The Department of Computer Science

by

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August 1992

In memory of my beloved father

Teh-Ming Lee (Oct. 22, 1911 - Aug. 6, 1991)

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Table of Contents

Acknowledgements	iii
List of Tables	vi
List of Figures	vii
Abstract	viii
Chapter 1 Introduction	1
1.1 Basic Geometric Problems	2
1.2 Computation Models for Parallel Geometric Algorithms	5
1.3 Outline of the Dissertation	8
Chapter 2 The Maxima Problem	11
2.1 Introduction	11
2.2 Preliminaries	13
2.2.1 Data Structures	13
2.2.2 Hypercube Machine and Data Communications	14
2.3 Parallel Maxima Algorithm	19
2.3.1 The Main Algorithm	19
2.3.2 The Subalgorithm FILTER_S	22
2.3.3 The Subalgorithm FILTER_G	23
2.3.3.1 Case 1 of FILTER_G	26
2.3.3.2 Cases 2 to 6 of FILTER_G	30
2.3.3.3 Proof of Correctness of FILTER_G	33
2.4 Analysis of Time Complexity	34
2.5 Generalizations and Concluding Remarks	37
Chapter 3 The Voronoi Diagram	41
3.1 Introduction	41
3.2 Preliminaries	42
3.2.1 Definition of Planar Voronoi Diagram	42
3.2.2 Mesh of Trees and Data Communications	44
3.2.3 Constructing Voronoi Diagram by Geometric Inversion	46

3.3 Constructing Voronoi Diagram on a Mesh of Trees	48
3.3.1 Constructing Voronoi Diagram from Convex Hull	48
3.3.2 Constructing Three-Dimensional Convex Hull	51
3.3.3 Algorithm for Merging Two Convex Hulls	52
3.3.3.1 Determining Internal and External Faces	54
3.3.3.2 Identifying Critical External Faces	57
3.3.3.3 Generating New Faces	60
3.3.3.4 Load Balancing Operations	64
3.3.3.5 Analysis of Time Complexity	68
3.3.3.6 Generalizations of the Convex Hull Algorithm	69
3.4 Discussions	70
Chapter 4 The Congruent Patterns	71
4.1 Introduction	71
4.2 Finding Congruent Patterns on a Mesh of Trees	73
4.2.1 Preprocessing	75
4.2.2 Checking Edge-Length Equality of P and G	79
4.2.3 Finding Single Congruent Pattern	82
4.2.4 Finding Multiple Congruent Patterns	85
4.2.4.1 Checking the Existence of Starting Edges	86
4.2.4.2 Counting Edge Number of Each Pattern	91
4.2.4.3 The Main Procedure Multiple_Patterns	94
4.2.5 The Main Algorithm	95
4.3 Final Remarks	98
Chapter 5 Conclusion	99
5.1 Discussing of the Research Results	99
5.2 Future Work	103
Bibliography	107
Vita	112

List of Tables

Table	Page
5.1 Time Complexity for Maxima Algorithms	100
5.2 Time Complexity for Voronoi Diagram Algorithms	101
5.3 Time Complexity for Congruent Pattern Algorithms	102

List of Figures

Figure	Page
1.1 The convex hull of a two-dimensional point set	3
1.2 Triangulation of a point set	4
1.3 Shared-memory and interconnection network SIMD models	7
1.4 Some popular SIMD interconnection networks	7
 2.1 The set of maxima = $\{p_1, p_2, p_3, p_4\}$	 11
2.2 A 3-d hypercube and its two subcubes	15
2.3 Broadcast data from two subcubes to other six subcubes	16
2.4 Actions of subalgorithm FILTER_S	22
2.5 Tasks for Case 1 in subalgorithm FILTER_G	26
2.6 Tasks for Case 2 in subalgorithm FILTER_G	30
 3.1 The Voronoi diagram of a set of points	 43
3.2 A 4×4 mesh of trees	44
3.3 Inversion between a point in the plane and its image on the sphere	47
3.4 The distribution of faces after the MULTI_CAST operation	49
3.5 Merge convex hulls CH(A) and CH(B)	53
3.6 Polar coordinate systems of Σ_A and Σ_B	61
 4.1 A test pattern P and a PSLG with 3 patterns congruent to P	 72
4.2 Using $RR_{p,4}$ in P to compute $RR_{g,6}$, $RR_{g,11}$, and $RR_{g,18}$ in G	76
4.3 Information stored in the $n \times n$ MOT after P and G are initialized	79
 5.1 A simple polygon P and the visibility polygon of viewpoint z	 104
5.2 A set of segments and its visibility graph	105
5.3 Removing hidden-surfaces of rectangular objects	106

Abstract

Geometric algorithms have many important applications in science and technology. Some geometric problems require fast response time that could not be achieved by traditional sequential algorithms. However, the speed, power and versatility of parallel computers can be exploited to develop efficient geometric algorithms as shown in this dissertation. Our study focuses on designing efficient parallel geometric algorithms and analyzing their computational complexities.

In this research, first we developed a parallel algorithm to find the *maxima* of a set of N points in the d -dimensional space, $d > 3$, on a hypercube SIMD machine. Our algorithm is a parallel implementation from the sequential algorithm given by Kung, Luccio, and Preparata [KLP75]. Although the time complexity, $O(N^{0.77} \log^{d-1} N)$, of our algorithm is not optimal, it is the first *sublinear time* algorithm for solving the high dimensional maxima problem.

Next, we developed another parallel algorithm to construct the *Voronoi diagram* of a point set in the plane. Our algorithm is based on the sequential algorithm given by Brown [B79]. We use an $N \times N$ mesh of trees (MOT) SIMD computer and get the optimal time complexity $O(\log^2 N)$.

Finally, we developed another MOT algorithm to solve the *congruent pattern* problem. Given a simple polygon P with k edges and a planar graph G with N edges, $N > k$. The problem is to find all the patterns (cycles) in G which are congruent to P . Our algorithm is based on the CREW PRAM algorithm given by Jeong, Kim, and Baek [JKB92]. We also use an $N \times N$ MOT and get the optimal time complexity $O(k \log N)$.

Chapter 1

Introduction

Geometry is a major branch of mathematics with important theory and applications. The treatises of ancient mathematicians often form the basis of efficient algorithms on geometry. Although algorithmic studies have appeared in the past century in the scientific literature and with an increasing intensity in the past two decades, it was only recently that systematic studies of geometric algorithms have been undertaken.

The field of geometric algorithms is interesting to study not only because of rich historical context but also because many new fundamental algorithms are being developed for important large-scale applications. *Computational Geometry*, as pioneered by Michael Ian Shamos [S75], is a young and fertile discipline dedicated to the design and analysis of algorithms for inherently geometric problems. A large number of applications such as pattern recognition, image processing, computer graphics, computer-aided design, VLSI circuit design, robotics, database search, operations research, and statistics have benefited from this discipline.

Geometric problems are usually easy to figure out, but some are relatively hard to solve on a computer. Many problems that can be solved easily by a person require non-trivial computer algorithms. For example, even a child can identify at a glance whether or not a given point lies inside a given polygon on a piece of paper. However, we need a special solving strategy and appropriate data structures to solve this problem on a computer.

Most of inherently geometric problems for which efficient algorithms have to be developed use both sequential and parallel processing techniques. The study of parallel geometric algorithms has recently begun in earnest, although the first major work was done by Anita Chow in 1980 [C80]. There are at least three reasons why parallel algorithms for geometric problems have become our special interest.

- (1) Geometric algorithms are often needed in critical on-line systems which require short response time. Even if optimal sequential algorithms exist for such problems, they do not ensure acceptable (or tolerable) response time for the large amount of data, such as image data, to be processed.
- (2) Efficient sequential algorithms do not exist for a large class of important high dimensional geometric problems.
- (3) It is feasible to design and implement efficient parallel geometric algorithms on an increasing number of commercial parallel machines [DS88].

1.1 Basic Geometric Problems

According to the nature of the geometric objects involved, such as points, lines, and polygons, some basic geometric problems can be categorized as follows.

(1) *Convex Hull*

The convex hull of a point set S in d -dimensional Euclidean space is the boundary of the smallest convex domain which contains S [PS88] (see Figure 1.1). Convex hull problems consist of finding the convex hull of a two-dimensional point set, the convex polygon of a simple polygon, the convex polyhedron of a set of three-dimensional point set, and the maxima of a d -dimensional point set ,etc..

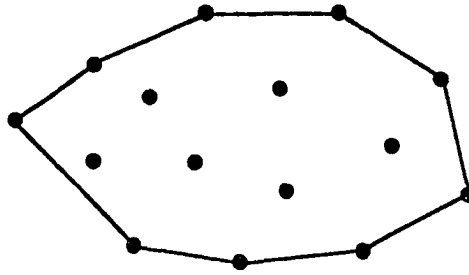


Fig. 1.1 The convex hull of a two-dimensional point set.

(2) *Intersections*

This problem is to detect the intersections of geometric objects, such as intersections of a set of line segments, intersections of a set of polygons, intersections of a set of polyhedra, and intersections of a set of iso-oriented rectangles.

(3) *Proximity*

- (a) **Closest pair** : Given a set of points in the plane, find two points whose mutual distance is smallest.
- (b) **All nearest neighbors** : Given a set of points in the plane, find a nearest neighbor for each point.
- (c) **Minimum distance** : Given two sets S_1 and S_2 of objects, such as arbitrary or convex point sets, find the minimum distance $d(s_i, s_j)$, where the pair $(s_i, s_j) \in S_1 \times S_2$.
- (d) **Voronoi diagram** : Given a set of points S in the plane, construct the Voronoi diagram of S . Constructing Voronoi diagram is an extension of proximity problems.

(4) *Visibility Problems*

- (a) **Visibility polygon from an edge :** Given a simple polygon P and an edge e of P , find the portion of the boundary of P that is visible from e . A point q in P is visible from the edge e if there exists a point r on e such that the line segment of q and r does not intersect the boundary of P .
- (b) **Visibility polygon from a point :** Given a set of disjoint polygons in the plane, find the portion of the boundary of these polygons which is visible from a given view-point.
- (c) **Visibility of a polygon :** For a polygon with or without holes, determine the portion of the polygon which is visible from a given view-point.
- (d) **Visibility of segments :** For a set of line segments in the plane or three-dimensional space, determine which segments are visible from a given point.

(5) *Decomposition Problems*

The problem is to decompose an object into more meaningful components. A common task is to decompose an object into convex parts. Decompositions are obtained by adding segments inside the object.

- (a) **Triangulation of a Point Set :** This problem is to find a triangulation of the input set in two or higher dimensions (see Figure 1.2).

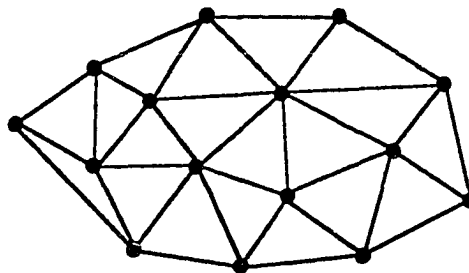


Fig. 1.2 Triangulation of a point set

- (b) **Triangulation of a Line Segment Set** : This problem is to find a triangulation of a set of input line segments in two or higher dimension.
- (c) **Trapezoidal Partitioning** : This problem is to find a partitioning of the input polygon into trapezoids.

1.2 Computation Models for Parallel Geometric Algorithms

SIMD computers are the major computing models for designing parallel geometric algorithms. In this class, all processors are supervised by the same control unit and receive the same instruction broadcast from the control unit, but they operate on different data sets from distinct data streams. According to the communication approaches, SIMD computers can be divided into the following two subclasses.

(1) *Shared-Memory (SM) SIMD Computers*

This subclass is also known as the Parallel Random Access Machine (PRAM). As the name implies, processors share a common memory. When two processors wish to communicate, they do so through the shared memory (see Figure 1.3). According to whether two or more processors can gain access to the same memory location simultaneously, the class of SM SIMD computers can be further divided into CREW (Concurrent-Read, Exclusive-Write), EREW, CRCW, and ERCW four models.

(2) *Interconnection-Network SIMD Computers*

The major disadvantage of SM PRAM is that it is not easily scalable. Limited system bus capacity and memory access collisions prohibit the use of a very high degree of parallelism. In the interconnection-network models each processor possesses a local memory and messages are passed over an interconnection network. They do

not suffer from the unscalability problem. The communication bandwidth and the number of communication links will increase when the number of processors increases. It is generally agreed upon that significant orders of speed improvement can only come from this subclass of SIMD computers [VDP89]. The following are popular networks for designing parallel geometric algorithms (refer Figure 1.4).

- (a) **Linear Array** : This is the simplest structure of interconnection networks. Each processor has its own memory. Processor P_i is linked to its two neighbors P_{i-1} and P_{i+1} through a two-way communication line. Each of the end processors, namely, P_1 and P_N , has only one neighbor.
- (b) **Mesh** : In a mesh network, the nodes are arranged into a two-dimensional lattice. Computation is allowed only between neighboring nodes; hence interior nodes communicate with four other processors. Some variants of the mesh model allow wrap-around connections between processors on the edge of the mesh. These connections may connect processors in the same row or column or they may be toroidal.
- (c) **Tree** : In this network, processors form a complete binary tree. Such a tree has d levels, numbered from 0 to $d-1$, and $N = 2^d - 1$ nodes each of which is a processor. The root is processor at level $d-1$ and all the leaves are at level 0.
- (d) **Mesh of Trees** : A mesh of trees of size m , where m is a power of 2, is defined as follows : Begin with m^2 nodes arranged in a square grid, but without any connecting edges. For each row of nodes, say v_1, \dots, v_m , in order from left, build a complete binary tree with these nodes as leaves, adding the interior nodes, which are not among the original m^2 nodes. Do the same for each column of the grid [U84].

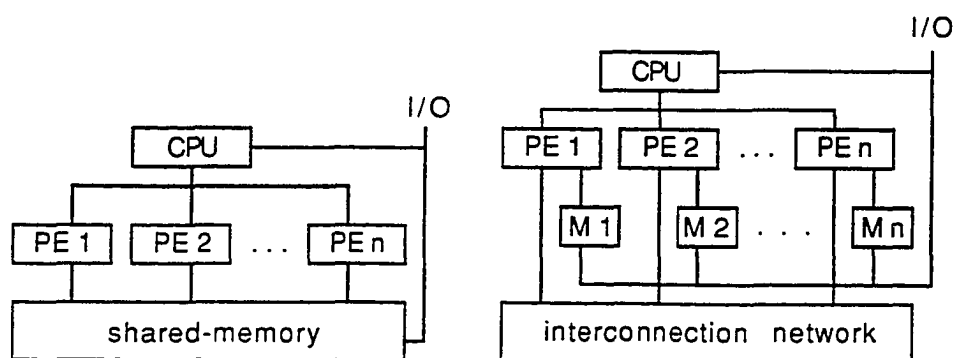
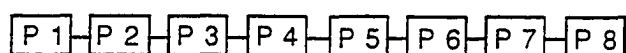
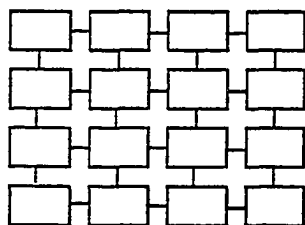


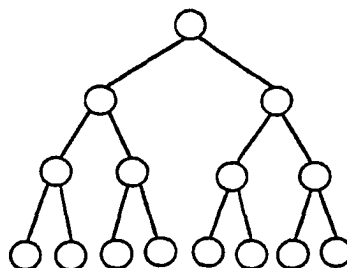
Fig. 1.3 Shared-memory and interconnection network SIMD models.



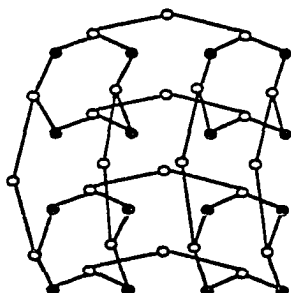
(a) linear array



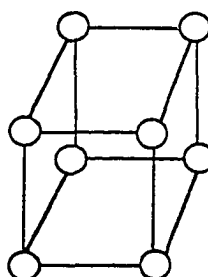
(b) mesh



(c) tree



(d) mesh of trees



(e) hypercube

Fig. 1.4 Some popular SIMD interconnection networks.

- (e) **Hypercube** : The hypercube structure is generally defined in a recursive manner. A hypercube of dimension 0 consists of one node. A hypercube of dimension d consists of two hypercubes of dimension $d-1$ whose corresponding nodes are connected. The nodes of a d -dimensional hypercube can be numbered by d -bit binary numbers in such a way that there is a physical connection between two nodes if and only if their binary representations differ by exactly one bit.

1.3 Outline of the Dissertation

In chapter 2, we present a parallel algorithm on a hypercube machine to solve the d -dimensional maxima problem, for $d > 3$. This is the first parallel algorithm for the d -dimensional maxima problem, and also the first *sublinear time* algorithm by using SIMD interconnection-network models.

In chapter 3, we develop an optimal parallel algorithm to construct the Voronoi diagram of a two-dimensional point set on a mesh of trees. This is the first algorithm developed on a mesh of trees and is the fastest algorithm for constructing Voronoi diagram by using SIMD interconnection-network models.

In chapter 4, we design a parallel algorithm on a mesh of trees to find all the patterns in a planar graph which are congruent to a given test pattern. This is the first and fastest algorithm for this problem by using SIMD interconnection-network models.

Finally, we conclude our research and discuss our future work in chapter 5. The three parallel geometric algorithms in chapter 2, 3, and 4 are summarized as follows.

(1) *The Maxima Problem*

Let S be a set of N points in d -dimensional space. For a point $p \in S$, we use $x_k(p)$ to denote the k th-dimensional coordinate value of p . For two distinct points p_i and p_j in S , we say that p_i dominates p_j if $x_k(p_i) \geq x_k(p_j)$, for $k = 1, 2, \dots, d$. A point p in S is called a *maximum* of S if there does not exist any other point q of S such that q dominates p . The maxima problem consists of finding all the maximums of S . This problem has many important applications in statistics, economics, operations research and computational geometry.

For this problem, we present a parallel algorithm on a hypercube machine. For a set of N points in d -dimensional space, our algorithm runs in $O(N^{0.77} \log^{d-1} N)$ time, assuming that there are N processors in the hypercube machine. If the size N of input point set is greater than $O(P)$, where P is the number of processors in the hypercube, our algorithm can be generalized to solve the maxima problem in $O((N/P^{0.23} \log^{d-2} P (\log(N/P) + \log P)))$ time.

(2) *The Voronoi Diagram*

The Voronoi diagram of a set S of N points in the plane is a polygonal subdivision of N regions in the plane, each containing one point of S , such that the region for each point p of S is the locus of points in the plane which are closer to p than to other points of S . The Voronoi diagram is an extremely useful data structure with many important applications in robotics, image processing, graph theory, and computational geometry [PS88, S78].

For this problem, we present an $O(\log^2 N)$ -time parallel algorithm on an $N \times N$ mesh of trees. Our algorithm transforms points of S into a set S' of points on a sphere in E^3 , then uses the divide-and-conquer approach to construct the three-dimensional

convex hull $CH(S')$ of S' , and finally transforms $CH(S')$ into the Voronoi diagram of S . Our convex hull algorithm can be used to construct the convex hull of any set of points in E^3 in $O(\log^2 N)$ time. Our algorithms are the fastest NC algorithms ever known for constructing planar Voronoi diagrams and three-dimensional convex hulls.

(3) *The Congruent Patterns*

Two planar patterns P_1 and P_2 are congruent if their corresponding boundary edges (e.g. edge e_i in P_1 and edge e_j in P_2) are of equal length and the corresponding interior angles (e.g. interior angle θ_i in P_1 and interior angle θ_j in P_2) between any pair of adjacent boundary edges are also equal. Finding congruent patterns arises frequently in computer-aided design (CAD), image analysis, pattern recognition, and computer vision. Given a test pattern P which is a simple polygon with k edges, and a planar straight-line graph (PSLG) G with n edges, where $k \leq n$, the *congruent pattern problem* is to locate all the cycles in G which are congruent to P .

For this problem, we present a parallel algorithm on an $N \times N$ mesh of trees. Our algorithm takes the optimal time complexity $O(k \log N)$, where $N = n$.

Chapter 2

The Maxima Problem

2.1 Introduction

Let S be a set of N points in d -dimensional space. For a point $p \in S$, we use $x_k(p)$ to denote the k -dimensional coordinate value of p . For two distinct points p_i and p_j in S , we say that p_i dominates p_j if $x_k(p_i) \geq x_k(p_j)$, $k = 1, 2, \dots, d$. A point p in S is called a *maximum* of S if there does not exist any other point q of S such that q dominates p . The maxima problem consists of finding each maximum of S . This problem has many important applications in statistics, economics, operations research and computational geometry. An example of 2-dimensional maxima is shown in Figure 2.1.

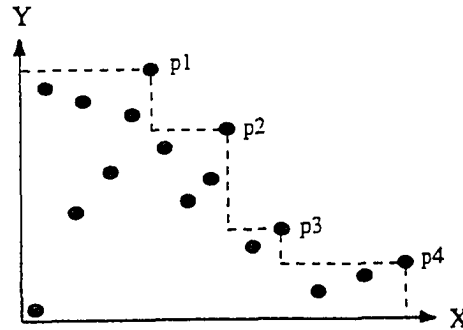


Fig. 2.1 The set of maxima = $\{p1, p2, p3, p4\}$.

In [KLP75], Kung, Luccio and Preparata showed that the sequential time complexity of the maxima problem is $O(N \log N)$ for $d \leq 3$. Their remarkable divide-and-conquer method solved the d -dimensional maxima problem sequentially in $O(N \log^{d-2} N + N \log N)$ time. It still remains an open problem whether or not this sequential time complexity can be improved.

In the past few years, several attempts were made for developing efficient parallel algorithms for the maxima problem ([ACG87] [AG86] [D86] [RS87] [S88b]). The algorithms given in [ACG87] and [AG86] solve the 2-dimensional maxima problem on CREW PRAM in $O(\log N)$ time using $O(N)$ processors. Furthermore, the algorithm in [ACG87], which is a clever implementation of the sequential algorithm given in [KLP75], solves the d -dimensional maxima problem on CREW PRAM in $O(\log^{d-2} N)$ time using $O(N)$ processors. Currently, this is the best parallel algorithm for the maxima problem on PRAM; any further improvement of this algorithm will imply the existence of better sequential algorithms. The PRAM models are based on abstract data communications. In reality, all multiprocessor systems are based on sparse interconnection networks such as trees, rings, meshes, shuffle-exchange networks, and hypercubes. Hence, it is important to investigate the parallel maxima algorithms for these realistic machine models.

In [D86], Dehne presented a parallel maxima algorithm for an $N^{1/2} \times N^{1/2}$ mesh-connected computer. He showed that, for $|S| = N$, this algorithm runs in $O(N^{1/2})$ time when $d \leq 3$, and $O(N^{0.5+\log(d-2)})$ time when $d > 3$. Clearly, this algorithm is optimal when $d \leq 3$, but it can be extremely bad when $d > 3$. For example, if $d = 4$, the time complexity of this algorithm is $O(N^{1.5})$, which is much worse than the best sequential algorithm. In [S88b], a parallel algorithm for solving 2-dimensional maxima problems on a hypercube machine is given. This algorithm runs in $O(\log^2 N)$ time using N processors for N points. To our knowledge, no sublinear-time parallel algorithm for the maxima problem of dimension greater than 3 has been developed for parallel systems with sparse interconnection networks.

In this chapter, we present a parallel hypercube implementation of the sequential algorithm given in [KLP75]. We show that for a set of N points in d -dimensional space, our algorithm runs in $O(N^{0.77} \log^{d-1} N)$ time, on a hypercube with $O(N)$ processors. If the size N of input point set exceeds $O(P)$, where P is the number of processors in the hypercube machine, our algorithm can be generalized to solve the maxima problem in $O((N/P^{0.23}) \log^{d-2} P (\log(N/P) + \log P))$ time.

2.2 Preliminaries

In this section, we introduce the data structures in each processor of hypercube, the architecture of hypercube machine, and the operations of data communications inside hypercube.

2.2.1 Data Structures

For the correctness and efficiency of our algorithm, we implement a stack STK_i in the private memory associated with processor PE_i . A stack entry consists of two fields, *point*, which is used to keep the d coordinate values $x_1(p_k), \dots, x_d(p_k)$ of some point p_k , and *flag*, which is used to indicate whether or not p_k has been detected as being dominated by some other point(s) in the input point set S of size $N = 2^n$, where n is the dimension of the hypercube, during the computing process. These two fields of the j -th entry of STK_i , where $j \geq 0$, are denoted as $STK_i[j].point$ and $STK_i[j].flag$. The 0-th entry of STK_i is called the bottom entry of the stack.

If $STK_i[j].point$ contains point p_k , then $STK_i[j].flag = 1$ indicates that point p_k is not a maximum of S . For each stack STK_i , we maintain a stack pointer SP_i , which points to the *current top entry* of STK_i . Two stack operations $push[p, f; STK_i]$ and

$pop[STK_i]$ are defined on STK_i . The *push* operation increments SP_i by 1, and store p and f into $STK_i[SP_i].point$ and $STK_i[SP_i].flag$, respectively. The *pop* operation returns pair (p, f) , which is $(STK_i[SP_i].point, STK_i[SP_i].flag)$, and then decrements SP_i by 1.

2.2.2 Hypercube Machine and Data Communications

An n -dimensional hypercube Q_n is a graph of $P = 2^n$ vertices, each labeled by a unique n -bit binary number, such that two vertices are connected by an edge if and only if their binary labels differ in one bit position. We define a k -dimensional subcube S_k of Q_n as a subgraph induced by vertices with $(n - k)$ -bit prefixes of their binary labels equal to a given $(n - k)$ -bit binary constant. Clearly, by ignoring the $n - k$ leftmost bits of the vertex labels, S_k is a k -dimensional hypercube. A k -dimensional subcube induced by vertex set $\{b, b+1, \dots, b+2^k-1\}$ is denoted as $S_k(b)$.

We say that two k -dimensional subcubes $S_k(b_1)$ and $S_k(b_2)$ of Q_n are adjacent if there are two adjacent vertices u and v (i.e. u and v are connected by an edge in Q_n) such that u is in $S_k(b_1)$ and v is in $S_k(b_2)$. By the definition of Q_n , if $S_k(b_1)$ and $S_k(b_2)$ are adjacent, then the vertices in $S_k(b_1)$ and $S_k(b_2)$ are pairwise adjacent in the following way : vertex u in $S_k(b_1)$ and vertex v in $S_k(b_2)$ are adjacent if the k -bit postfixes of their binary labels are identical. For two adjacent k -dimensional subcubes $S_k(b_1)$ and $S_k(b_2)$ of Q_n , we use $(S_k(b_1), S_k(b_2))$ to denote the subgraph of Q_n induced by vertices of $S_k(b_1)$ and $S_k(b_2)$. Since the $(n - k)$ -bit prefix of vertices of $S_k(b_1)$ and the $(n - k)$ -bit prefix of vertices of $S_k(b_2)$ are distinct in one bit position, $(S_k(b_1), S_k(b_2))$ can be treated as a $(k+1)$ -dimensional hypercube by replacing one of these two

prefixes with 0 and the other with 1. This simple fact will allow us to partition a hypercube into subcubes in a more general sense. A 3-dimensional hypercube and its 2 subcubes are shown in Figure 2.2.

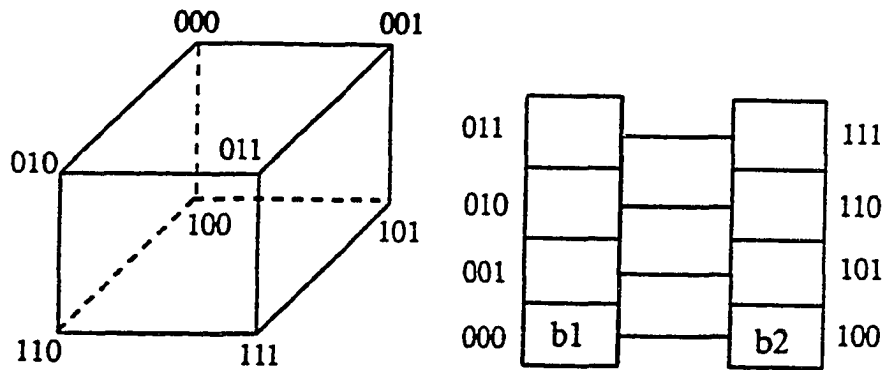


Fig. 2.2 A 3-d hypercube and its two subcubes with base addresses b_1 and b_2 .

A hypercube machine is a multiprocessor system in which processors and data links correspond to vertices and edges of a hypercube graph, respectively. For convenience, we also use Q_n to denote a hypercube machine with $P = 2^n$ processors. Each processor PE_i , where i is an n -bit binary label, is associated with a private (local) memory. Due to their regularity, small diameters, low connection degrees, and many additional attractive combinatorial and topological properties, hypercube machines have become one of the most important architectures for parallel computing.

Before we discuss our algorithm, we introduce two pairs of useful parallel operations *BROADCAST / CENSUS*, and *SORT / UNSORT*. The parameters for *BROADCAST* and *CENSUS* are b_1, m_1, b_2, m_2, b_3 and m_3 , where $b_1 \geq b_3$, and $b_2 \geq b_3$, $m_1 < m_3$, and $m_2 < m_3$. Here, each pair of b_i and m_i defines the subcube $S_{m_i}(b_i)$ of Q_n , and both $S_{m_1}(b_1)$ and $S_{m_2}(b_2)$ are subcubes of $S_{m_3}(b_3)$.

(1) $BROADCAST(b_1, m_1, b_2, m_2, b_3, m_3)$

This operation is a generalized parallel data broadcasting operation on a hypercube in the following sense: it broadcasts the pair (p, f) of the current top stack entry of PE_{b_1+j} , to the j -th processor in each of the m_1 -dimensional subcubes of $(S_{m_3}(b_3) - S_{m_2}(b_2)) - S_{m_1}(b_1)$, then each of the processors in $(S_{m_3}(b_3) - S_{m_2}(b_2)) - S_{m_1}(b_1)$ performs a *push* stack operation on the pair it received, see Figure 2.3. By treating each m_1 -dimensional subcube as a "super vertex", $BROADCAST$ can be carried out in $O(m_3 - m_1)$ time using conventional hypercube data broadcasting algorithm.

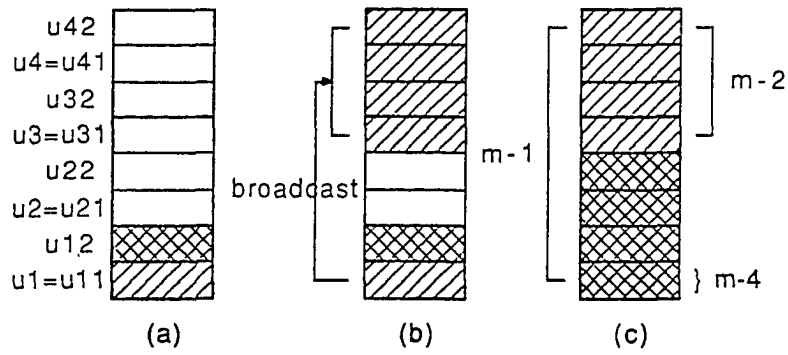


Fig. 2.3 Broadcast data in the 2 subcubes in (a) with base addresses u_{11} and u_{12} to other 6 subcubes.
 (b) After $BROADCAST(u_{11}, m-4, u_1, m-2, u_1, m-1)$.
 (c) After $BROADCAST(u_{12}, m-4, u_3, m-2, u_1, m-1)$.

(2) $CENSUS(b_1, m_1, b_2, m_2, b_3, m_3)$

The *flag* fields of the current top stack entries of the j -th processors of all m_1 -dimensional subcubes of $(S_{m_3}(b_3) - S_{m_2}(b_2)) - S_{m_1}(b_1)$ are logically *ORed*, and the obtained boolean value replaces the $STK_{b_1+j}[SP_{b_1+j}].flag$. Furthermore, each of the processors in $(S_{m_3}(b_3) - S_{m_2}(b_2)) - S_{m_1}(b_1)$ performs a *pop* stack operation to discard the *ORed* top entry. Considering the data communication pattern

involved, *CENSUS* is a reverse operation of *BROADCAST*, and it also takes $O(m_3 - m_1)$ time.

(3) *SORT*(b, m, k)

Each processor PE_i in $S_m(b)$ performs $(p^i, f^i) := pop(STK_i)$. Then, all the pairs of (p^i, f^i) , one in each processor, are sorted in parallel on their x_k coordinate values. Let (p^{j_i}, f^{j_i}) be the pair in PE_i after sorting, then $x_k(p^{j_i}) < x_k(p^{j_{i+1}})$. Once this is done, all processors PE_i in $S_m(b)$ perform $push[p^{j_i}, f^{j_i}; STK_i]$ in parallel. Using bitonic hypercube sorting algorithms, *SORT* takes $O(m^2)$ time.

(4) *UNSORT*(b, m, k)

This is the reverse operation of the latest *SORT* in the recursive process. Each processor PE_i in $S_m(b)$ performs $(p, f) := pop(STK_i)$. Clearly, $(p, f) = (p^{j_i}, f^{j_i})$, where (p^{j_i}, f^{j_i}) is the pair received by PE_i in the corresponding *SORT* operation. Then, each PE_i in $S_m(b)$ sends (p^{j_i}, f^{j_i}) back to PE_{j_i} , where the pair was stored before the corresponding *SORT* operation. Finally, all processors in $S_m(b)$ perform $push$ operation on the pair it received. This can be done in $O(m^2)$ time if data communication pattern of the corresponding *SORT* has been properly recorded.

The operations *BROADCAST* and *CENSUS*, and operations *SORT* and *UNSORT* are always performed in pairs on the current top stack entries. Proper pairing of *BROADCAST / CENSUS* and *SORT / UNSORT* operations is important for the correctness of algorithms *FILTER_S* and *FILTER_G*. They ensure the concerned points at different recursion levels to be put in the current top stack entries of all involved

processors, and their dominance status to be recorded in parallel. For this reason, we introduce a well-formed sequence of the four operations. We use "<" and ">" to represent *BROADCAST* and *CENSUS*, respectively. When *BROADCAST* or *CENSUS* is invoked, $m_3 = m_2 + 1$ must hold. We say that a processor PE_i is involved in a *BROADCAST* (*CENSUS*) operation if PE_i pushes (pops) an entry into (from) its stack during the operation. Clearly, the processors involved in a pair of *BROADCAST*($b_1, m_1, b_2, m_2, b_3, m_3$) / *CENSUS*($b_1, m_1, b_2, m_2, b_3, m_3$) are those in $(S_{m_3}(b_3) - S_{m_2}(b_2)) - S_{m_1}(b_1)$. Similarly, we use "(" and ")" to represent *SORT* and *UNSORT*, respectively. We say that a processor PE_i is involved in a pair of *SORT*(b, m, k) / *UNSORT*(b, m, k) operations if PE_i is in $S_m(b)$.

For any processor PE_i , if we list all *BROADCAST*, *CENSUS*, *SORT* and *UNSORT* operations PE_i involved from left to right as time passes during the computation, we get a sequence of mixed "<", ">", "(" and ")", which is called a *BCSU sequence*. We define *well-formed BCSU sequence* as follows : (a) an empty sequence is a *BCSU* sequence; (b) both $\langle T_1 \rangle$ and (T_1) are well-formed *BCSU* sequences, if T_1 is a well-formed *BCSU* sequence, and "<" and ">" ("(" and ")", respectively) correspond to a *BROADCAST* / *CENSUS* (*SORT* / *UNSORT*, respectively) pair with the same parameter values ; (c) $T_1 T_2$ is a well-formed *BCSU* sequence, if T_1 and T_2 are well-formed sequences; and (d) any sequence that can not be generated by (a), (b) and (c) is not a well-formed *BCSU* sequence. We will enforce the *BCSU* sequence for each processor to be well-formed. The symbolic notation of *BCSU* sequences for *BROADCAST* / *CENSUS* and *SORT* / *UNSORT* will provide us a very simple way of analyzing the correctness of our algorithm.

2.3 Parallel Maxima Algorithm

Our parallel algorithm for the maxima problem is based on an efficient and elegant sequential algorithm given in [KLP75]. A concise description of this algorithm appears in [PS88]. The divide-and-conquer algorithm employs double-recursion strategy, one on the problem size and the other on the dimension of points. The unique technique used in [KLP75] lead to a complexity that has not been surpassed for many years.

2.3.1 The Main Algorithm

The framework of our algorithm is as follows. Initially, points in S are distributed in N processors in the following way: (1) each PE_i has one point in its 0-th stack entry; (2) the input points are sorted on the x_d coordinate values such that for all PE_i in $S_{n-1}(b_1)$, the x_d coordinate value of $STK_i[0].point$ is less than the x_d coordinate value of any $STK_j[0].point$ in PE_j , where PE_j is in $S_{n-1}(b_2)$; (3) if $d \geq 3$, all points in $S_{n-1}(b_1)$ are sorted on their x_{d-1} coordinate values in such a way that $x_{d-1}(STK_i[0].point) < x_{d-1}(STK_j[0].point)$ if and only if $i < j$ for PE_i and PE_j in $S_{n-1}(b_1)$, and all points in $S_{n-1}(b_2)$ are sorted on their x_{d-1} coordinate values in the same way as in $S_{n-1}(b_1)$; and (4) $STK_i[0].flag$ is set to 0, a maximum, for all PE_i in Q_n . Using hypercube bitonic sorting algorithm for preprocessing, these initial conditions can be enforced in $O(\log^2 N)$ time. Since the preprocessing time is insignificant compared with the time required for the rest of the algorithm, we will ignore it in the time analysis.

Algorithm *MAXIMA*(b, m, d);

(* b : base address of subcube m (m -dimensional subcube) *)

(* d : d -dimensional point set *)

(* initial value : $b = 0$ and $m = n$ (hypercube dimension) *)

Input : a set S of n points in d -dimensional space;

Output : the set of all maximums in S ;

begin

if $m = 1$ (* S has only 2 points *)

then if $STK_b[SP_b].point$ is dominated by $STK_{b+1}[SP_{b+1}].point$

then $STK_b[SP_b].flag := 1$

else begin

parbegin

MAXIMA($b, m - 1, d$);

MAXIMA($b + 2^{m-1}, m - 1, d$);

parend

if $m \leq 3$

then *FILTER_S*($b, b + 2^{m-1}, m - 1, d - 1$)

else *FILTER_G*($b, b + 2^{m-1}, m - 1, d - 1$)

end;

end of *MAXIMA*;

Algorithm *MAXIMA* is initially invoked with $b = 0$ and $m = n$. Once it is terminated, each processor PE_i contains a point in the bottom entry of STK_i such that $STK_i[0].flag$ is 0 if and only if $STK_i[0].point$ is a maximum of S . To accomplish this, algorithm *MAXIMA* employs a divide-and-conquer strategy as follows: it divides

the m -dimensional subcube $S_m(b)$ into two subcubes $S_{m-1}(b)$ and $S_{m-1}(b + 2^{m-1})$, and find the maximum points of the two subsets of points associated with these two subcubes in parallel; then, by using either *FILTER_S* or *FILTER_G*, all points associated with $S_{m-1}(b)$ which are dominated by any point in $S_{m-1}(b + 2^{m-1})$ are detected and marked. The correctness and efficiency of *MAXIMA* depends on how *FILTER_S* and *FILTER_G* are designed.

The parameters b_1 , b_2 and m of subalgorithms *FILTER_S*(b_1, b_2, m, k) and *FILTER_G*(b_1, b_2, m, k) specify two adjacent $(m-1)$ -dimensional subcubes $S_{m-1}(b_1)$ and $S_{m-1}(b_2)$ of Q_n , and the combination $(S_{m-1}(b_1), S_{m-1}(b_2))$, as explained earlier, specifies an m -dimensional subcube S_m of Q_n in a general sense. During the computation, right before any *FILTER_S*(b_1, b_2, m, k) or *FILTER_G*(b_1, b_2, m, k) is invoked, the following *filter invariant condition* is enforced by the previous computation:

For all PE_i in $S_{m-1}(b_1)$, the x_l coordinate value of $STK_i[SP_i].point$ is less than the x_l coordinate value of any $STK_j[SP_j].point$, where PE_j is in $S_{m-1}(b_2)$ and $k < l \leq d$. If $k \geq 3$, the x_k coordinate value of $STK_i[SP_i].point$ of all PE_i in $S_{m-1}(b_1)$ ($S_{m-1}(b_2)$, respectively) are sorted in such a way that $x_k(STK_i[SP_i].point) < x_k(STK_j[SP_j].point)$ if and only if $i < j$ for two distinct PE_i and PE_j in $S_{m-1}(b_1)$ ($S_{m-1}(b_2)$, respectively).

Subalgorithms *FILTER_S*(b_1, b_2, m, k) and *FILTER_G*(b_1, b_2, m, k) are used to carry out the following operations :

For all PE_i in $S_{m-1}(b_1)$ if $STK_i[SP_i].point$ is dominated by any $STK_j[SP_j].point$ of PE_j in $S_{m-1}(b_2)$ in all coordinate values on x_1, \dots, x_k , then set $STK_i[SP_i].flag$ to 1.

2.3.2 The Subalgorithm *FILTER_S*

When $m \leq 3$, the subalgorithm *FILTER_S*(b_1, b_2, m, k) is invoked to perform the following operations (see Figure 2.4).

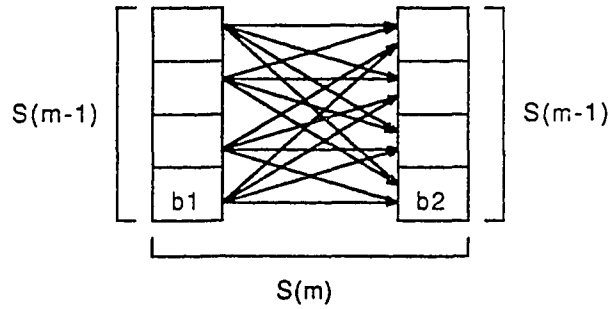


Fig. 2.4 Actions of subalgorithm *FILTER_S*.

procedure *FILTER_S*(b_1, b_2, m, k);

begin

- (1) Let A_1 and A_2 be the set of all entries of $S_{m-1}(b_1)$ and $S_{m-1}(b_2)$, respectively;
- (2) Send A_2 to each PE in $S_{m-1}(b_1)$;
- (3) For each point p associated to an entry in A_1 , determine whether or not p is dominated by any point q associated to an entry in A_2 on all x_j coordinate values, where $1 \leq j \leq k$, if p is dominated by q then logically *ORing* the *flag* field of the current top stack entry in its PE of $S_{m-1}(b_1)$ with an 1 else *ORing* with a 0.
- (4) Send each entry of A_2 in $S_{m-1}(b_1)$ back to its original PE in $S_{m-1}(b_2)$;

end of *FILTER_S*;

Since $m \leq 3$, ($S_{m-1}(b_1), S_{m-1}(b_2)$) is a generalized subcube of dimension m with no more than eight PEs. The time taken by *FILTER_S* is $O(2^{m+1}k) = C_1$, a constant.

2.3.3 The Subalgorithm **FILTER_G**

Subalgorithm *FILTER_G*(b_1, b_2, m, k) is somewhat more complicated. This subalgorithm is a parallel implementation of the sequential algorithm in [KLP75].

procedure *FILTER_G*(b_1, b_2, m, k);

(* b_1 and b_2 are the base addresses of the 2 subcubes of m *)

(* k is the # of dimension of point set *)

begin

(1) **if** $m \leq 3$ **then** *FILTER_S*(b_1, b_2, m, k); (* only 8 points or less left *)

(2) **else if** $k = 2$ **then** *FILTER_G2*(b_1, b_2, m); (* find 2-d maxima *)

else begin

(3) Decompose $(m - 1)$ -dimensional subcube $S_{m-1}(b_1)$ into four

$(m - 3)$ -dimensional subcubes $S_{m-3}(u_1), S_{m-3}(u_2), S_{m-3}(u_3)$ and $S_{m-3}(u_4)$,

where $u_1 = b_1, u_2 = b_1 + 2^{m-3}, u_3 = b_1 + 2 * 2^{m-3}$ and $u_4 = b_1 + 3 * 2^{m-3}$;

(4) Decompose each $S_{m-3}(u_i)$ into two $(m - 4)$ -dimensional

subcubes $S_{m-4}(u_{i1})$ and $S_{m-4}(u_{i2})$, where $u_{i1} = u_i$ and $u_{i2} = u_i + 2^{m-4}$;

(5) Decompose the $(m - 1)$ -dimensional subcube $S_{m-1}(b_2)$ into four

$(m - 3)$ -dimensional subcubes $S_{m-3}(v_1), S_{m-3}(v_2), S_{m-3}(v_3)$ and $S_{m-3}(v_4)$,

where $v_1 = b_2, v_2 = b_2 + 2^{m-3}, v_3 = b_2 + 2 * 2^{m-3}$ and $v_4 = b_2 + 3 * 2^{m-3}$;

(6) Decompose each $S_{m-3}(v_i)$ into two $(m - 4)$ -dimensional

subcubes $S_{m-4}(v_{i1})$ and $S_{m-4}(v_{i2})$, where $v_{i1} = v_i$ and $v_{i2} = v_i + 2^{m-4}$;

(* By the definition of hypercubes, $(S_{m-3}(u_i), S_{m-3}(v_i))$ is an

$(m - 2)$ -dimensional subcube, and $(S_{m-3}(u_{ij}), S_{m-3}(v_{ij}))$ is an

$(m - 3)$ -dimensional subcube, where $1 \leq i \leq 4$ and $1 \leq j \leq 2$; *)

(7) Let p^i denote the point $STK_{u_i}[SP_{u_i}]$. point, and let p^{\max} and q^{mid}

denote the points $STK_{b_1+2^{m-1}-1}[SP_{b_1+2^{m-1}-1}]$. point

and $STK_{b_2+2^{m-2}}[SP_{b_2+2^{m-2}}]$. point, respectively;

(8) Compare $x_k(q^{mid})$ with $x_k(p^{max})$, $x_k(p^4)$, $x_k(p^3)$, $x_k(p^2)$ and $x_k(p^1)$;

Case 1 : if $x_k(p^{max}) < x_k(q^{mid})$ then $FILTER1(b_1, b_2, m, k)$;

Case 2 : if $x_k(p^4) < x_k(q^{mid}) < x_k(p^{max})$ then $FILTER2(b_1, b_2, m, k)$;

Case 3 : if $x_k(p^3) < x_k(q^{mid}) < x_k(p^4)$ then $FILTER3(b_1, b_2, m, k)$;

Case 4 : if $x_k(p^2) < x_k(q^{mid}) < x_k(p^3)$ then $FILTER4(b_1, b_2, m, k)$;

Case 5 : if $x_k(p^1) < x_k(q^{mid}) < x_k(p^2)$ then $FILTER5(b_1, b_2, m, k)$;

Case 6 : if $x_k(q^{mid}) < x_k(p^1)$ then $FILTER6(b_1, b_2, m, k)$;

end;

end of $FILTER_G$;

Clearly, by the definition of hypercube, the 6 conditions in step (8) can be checked in $O(m) = C_3 m$ time, where C_3 is a constant.

The procedure $FILTER_G2$ in step (2), which is adapted from the 2-d maxima algorithm in [D86], uses divide-and-conquer method to solve the problem recursively and in parallel as follows.

procedure $FILTER_G2(b_1, b_2, m)$;

begin

(1) Sort the received point set s (a subset of S) by x_2 coordinate values in increasing order. Hence, the left half L of s , with lower x_2 values, will be moved to subcube $S_{m-1}(b_1)$ and the right half R of s , with higher x_2 values, will be moved to subcube $S_{m-1}(b_2)$.

(2) In order to combine the solutions in both subcubes, the processor containing a

point $p \in R$ with minimum x_2 value (x_{2_min}) with respect to R broadcasts $x_1(p)$ and x_{2_min} to all PEs in $S_{m-1}(b_1)$.

- (3) If any PE in $S_{m-1}(b_1)$ containing a point $t \in L$ that is a maximum with respect to L but $x_1(t) \leq x_1(p)$ then set their *flag* field of the current top stack entry to 1. This means that the point is dominated by a point in R .
- (4) Recursively solve the problem by steps (2) and (3).

end of *FILTER_G2*;

For the time complexity of *FILTER_G2*, we know that step (1) needs $O(\log^2 n)$ time by hypercube bitonic sorting, while steps (2) and (3) need only $O(\log n)$, respectively. Therefore, totally *FILTER_G2* needs $O(\log^2 n)$ time, where n is the size of s .

For executing *FILTER_G*(b_1, b_2, m, k), we enforce the following conditions to be held always.

- (A) The previous stated filter invariant condition hold for all *FILTER_G*(b_1, b_2, m, k) calls for $k \geq 3$. When $k = 2$, current top stack entry point of any PE_i in $S_{m-1}(b_1)$ is dominated by any current top stack entry point of any PE_j in $S_{m-1}(b_2)$ in coordinates x_3, \dots, x_d .
- (B) Subalgorithms *FILTER_S*(b_1, b_2, m, k) and *FILTER_G2*(b_1, b_2, m) correctly set the *flag* fields of current top stack entries during their computation.
- (C) If $STK_i[SP_i].point$ in PE_i of $S_{m-1}(b_1)$ is dominated by a $STK_j[SP_j].point$ in PE_j of $S_{m-1}(b_2)$ in the x_k coordinate value at the current recursion level, then *FILTER_G* continues to test whether or not it is dominated by $STK_j[SP_j].point$ in the x_{k-1} coordinate value at lower recursion levels.
- (D) If the x_k coordinate value of $STK_i[SP_i].point$ in PE_i of $S_{m-1}(b_1)$ has not been detected not dominated by the x_k coordinate values of some points

$STK_j[SP_j]$. point in PE_j of $S_{m-1}(b_2)$ in the current recursion level, then *FILTER_G* continues to test whether or not it is dominated by any of these points in the x_k coordinate value at lower recursion levels.

(E) For any processor PE_i , if we list all *BROADCAST*, *CENSUS*, *SORT* and *UNSORT* operations PE_i involved from left to right as time passes during the computation, then we will get a well-formed *BCSU* sequence.

In what follows, we describe the operations to be taken by *FILTER_G*(b_1, b_2, m, k), when $m > 3$ and $k > 2$, on a case-by-case basis. Let S^1 and S^2 be two sets of subgraphs of processors of Q_n . To simplify our presentation, we adopt the notion $filter_j[S^1|S^2]$ for the following operation: find all points in the current top stack entries of processors in S^1 that are dominated in x_l coordinate values, $1 \leq l \leq j$, by any point in the current top stack entries of processors in S^2 , and set their *flag* fields to 1.

2.3.3.1 Case 1 of *FILTER_G*

For *Case 1* : $x_k(q^{mid}) > x_k(p^{max})$, procedure *FILTER1* has two tasks, as in Figure

2.5.

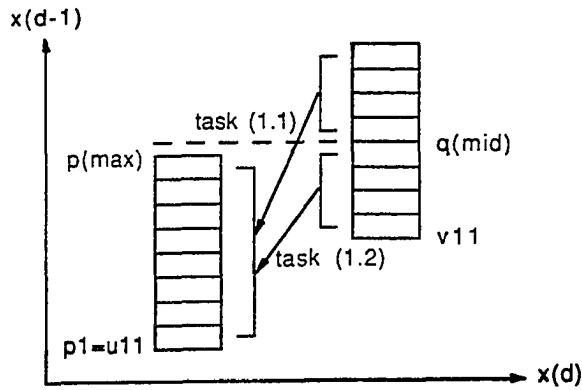


Fig. 2.5 Tasks for Case 1 in subalgorithm *FILTER_G*.

```

procedure FILTER1( $b_1, b_2, m, k$ );
  begin
    (1.1) call procedure FILTER_K1(1, 4,  $m - 2, v_3$ );
      (* do  $filter_{k-1}[S_{m-1}(u_1)|S_{m-2}(v_3)]$  *)
    (1.2) call procedure FILTER_K(1, 4,  $m - 2, v_1$ );
      (* do  $filter_k[S_{m-1}(u_1)|S_{m-2}(v_1)]$  *)
  end of FILTER1;

```

The procedures *FILTER_K1* and *FILTER_K* are as follows.

```

procedure FILTER_K1(first, last, mm, vv);
  begin
    BROADCAST(vv, mm, vv, mm, v1, m - 1);
    for  $r := first$  to  $last$  do
      begin
        BROADCAST( $u_{r1}, m-4, u_1, m - 2, u_1, m - 1$ );
        BROADCAST( $u_{r2}, m-4, u_3, m - 2, u_1, m - 1$ );
        for all  $S_{m-4}(u_{ij})$  and  $S_{m-4}(v_{ij}), 1 \leq i \leq 4$  and  $1 \leq j \leq 2$ ,
          parbegin
            SORT( $u_{ij}, m - 4, k - 1$ ); SORT( $v_{ij}, m - 4, k - 1$ );
          parend;
          for all  $S_{m-4}(u_{ij})$  and  $S_{m-4}(v_{ij}), 1 \leq i \leq 4$  and  $1 \leq j \leq 2$ ,
            parbegin
              FILTER_G( $u_{ij}, v_{ij}, m - 3, k - 1$ );
            parend;
          for all  $S_{m-4}(u_{ij})$  and  $S_{m-4}(v_{ij}), 1 \leq i \leq 4$  and  $1 \leq j \leq 2$ ,

```

```

parbegin
    UNSORT( $u_{ij}$ ,  $m - 4$ ,  $k - 1$ ); UNSORT( $v_{ij}$ ,  $m - 4$ ,  $k - 1$ );
parend;
    CENSUS( $u_{r2}$ ,  $m-4$ ,  $u_3$ ,  $m - 2$ ,  $u_1$ ,  $m - 1$ );
    CENSUS( $u_{r1}$ ,  $m-4$ ,  $u_1$ ,  $m - 2$ ,  $u_1$ ,  $m - 1$ );
end; (* end of outer for loop *)
    CENSUS( $vv$ ,  $mm$ ,  $vv$ ,  $mm$ ,  $v_1$ ,  $m - 1$ );
end;    (* end of procedure FILTER_K1 *)

```

```

procedure FILTER_K( $first$ ,  $last$ ,  $mm$ ,  $vv$ );
begin
    BROADCAST( $vv$ ,  $mm$ ,  $vv$ ,  $mm$ ,  $v_1$ ,  $m - 1$ );
    for  $r := first$  to  $last$  do
        begin
            BROADCAST( $u_{r1}$ ,  $m-4$ ,  $u_1$ ,  $m - 2$ ,  $u_1$ ,  $m - 1$ );
            BROADCAST( $u_{r2}$ ,  $m-4$ ,  $u_3$ ,  $m - 2$ ,  $u_1$ ,  $m - 1$ );
            for all  $S_{m-4}(u_{ij})$  and  $S_{m-4}(v_{ij})$ ,  $1 \leq i \leq 4$  and  $1 \leq j \leq 2$ ,
                parbegin
                    FILTER_G( $u_{ij}$ ,  $v_{ij}$ ,  $m - 3$ ,  $k - 1$ );
                parend;
                CENSUS( $u_{r2}$ ,  $m-4$ ,  $u_3$ ,  $m - 2$ ,  $u_1$ ,  $m - 1$ );
                CENSUS( $u_{r1}$ ,  $m-4$ ,  $u_1$ ,  $m - 2$ ,  $u_1$ ,  $m - 1$ );
            end; (* end of outer for loop *)
            CENSUS( $vv$ ,  $mm$ ,  $vv$ ,  $mm$ ,  $v_1$ ,  $m - 1$ );
        end;    (* end of procedure FILTER_K *)
    end;

```

Procedure *FILTER_K1* carries out task (1.1) and it has four iterations. Each iteration has eight concurrent calls of *FILTER_G*($u_{ij}, v_{ij}, m-3, k-1$), and engages 2^{m-3} *PE*s that form an $(m-3)$ -dimensional subcube in the general sense. By their preceding *SORT* operations, for each of the thirty-two calls, the condition (A) is enforced, assuming that (A) holds for x_k, \dots, x_d coordinate values of the points in the current top stack entries of all involving processors before call procedure *FILTER_K1*. The *BROADCAST* operations associated with these calls enforce conditions (C) and (D). Furthermore, it is easy to see that all *BROADCAST / CENSUS* and *SORT / UNSORT* pairs associated with any processor in $S_{m-1}(b_1)$ form a partial well-formed *BCSU* sequence ... <<(...)>> ..., where "..." between "(" and ")" is the *BCSU* sequence that will appear in the lower recursion levels of *FILTER_G*, and the two subsequences denoted as "..." not included between "(" and ")" correspond to the operations *BROADCAST*, *CENSUS*, *SORT*, and *UNSORT* performed in the higher recursive levels.

Clearly, if for each processor involved, *BROADCAST*, *CENSUS*, *SORT*, and *UNSORT* operations performed in the higher and lower recursion levels satisfy the requirement of well-formed *BCSU* sequence, then the entire *BCSU* sequence for the processor is well-formed, which is condition (E). Similar arguments can be used to show that conditions (A), (C), (D) and (E) hold for procedure *FILTER_K*, assuming that they hold for all other cases and in all recursion levels of concern (not including the bottom levels in which either *FILTER_S* or *FILTER_G2* is executed).

For task (1.1), which is carried out in procedure *FILTER_K1*, eight parallel calls of *FILTER_G*($u_{ij}, v_{ij}, m-3, k-1$) are created and executed concurrently for each of four iterations. Similarly, for task (1.2), eight parallel calls of *FILTER_G*($u_{ij}, v_{ij}, m-3, k$) are created and executed concurrently for each of the

four iterations in procedure *FILTER_K*. Let $F_k(2^m)$ denote the time taken by *FILTER_G*(b_1, b_2, m, k). Summarizing the previous discussions, we have

$$F_k(N) = 4F_k(N/8) + 4F_{k-1}(N/8) + 4S(N/8) + O(\log N),$$

where $S(N/8)$ is the time taken by a pair of *SORT* and *UNSORT*, and $O(\log N)$ is the time taken by all *BROADCAST* and *CENSUS* operations in the current recursion level.

2.3.3.2 Cases 2 to 6 of *FILTER_G*

For cases 2 to 6 in step (8) of *FILTER_G*, we develop a procedure for each case in the following.

- *Case 2* : $x_k(p^4) < x_k(q^{mid}) < x_k(p^{max})$. There are three tasks in procedure *FILTER2* (see Figure 2.6).

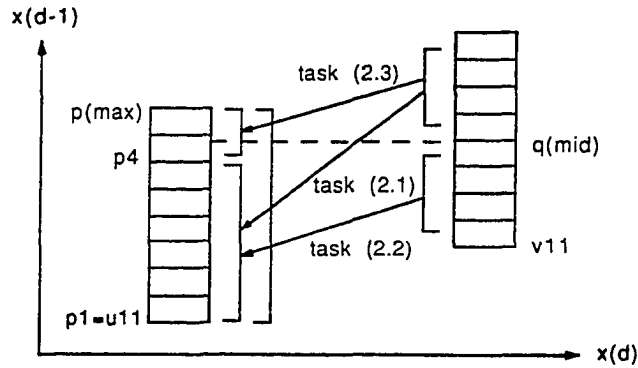


Fig. 2.6 Tasks for Case 2 in subalgorithm *FILTER_G*.

procedure *FILTER2*(b_1, b_2, m, k);

begin

(2.1) call procedure *FILTER_K1*(1, 3, $m - 2, v3$);

(* do $\tilde{filter}_{k-1}[\{S_{m-3}(u_1), S_{m-3}(u_2), S_{m-3}(u_3)\} \mid S_{m-2}(v_3)]$ *)

(2.2) call procedure *FILTER_K*(1, 4, $m - 2, v1$);

```

(* do filterk[Sm-1(u1)|Sm-2(v1)] *)
(2.3) call procedure FILTER_K(4, 4, m - 2, v3);
(* do filterk[Sm-3(u4)|Sm-2(v3)] *)
end of FILTER2;

```

Following the idea used in *Case 1*, we can carry out these tasks in three steps, steps 2.1, 2.2 and 2.3. In step 2.1, task (2.1) is divided into eight parallel $FILTER_G(u_{ij}, v_{ij}, m - 3, k)$ calls. In step 2.2, task (2.2) is carried out in three substeps, each substep performing eight parallel $FILTER_G(u_{ij}, v_{ij}, m - 3, k - 1)$ calls. In step 2.3, task (2.3) is carried out in four substeps, each step performing eight concurrent $FILTER_G(u_{ij}, v_{ij}, m - 3, k)$ calls. Therefore, the total time required is

$$F_k(N) = 5F_k(N/8) + 3F_{k-1}(N/8) + 3S(N/8) + O(\log N).$$

Furthermore, conditions (A), (C), (D) and (E) hold for this case, assuming that they hold for all other cases in all recursion levels of concern.

For the remaining four cases, we only list the tasks need to be carried out, and the time complexities. Using *Case 1* and *Case 2* as references, the details of the involved operations can be easily derived, and conditions (A), (C), (D) and (E) can be partially verified, for each of these remaining cases. For brevity, we omit these details.

- *Case 3* : $x_k(p^3) < x_k(q^{mid}) < x_k(p^4)$. There are three tasks in procedure $FILTER3$.

```

procedure FILTER3(b1, b2, m, k);
begin
(3.1) call procedure FILTER_K1(1, 2, m - 2, v3);
(* do filterk-1[Sm-2(u1)|Sm-2(v3)] *)

```

(3.2) call procedure *FILTER_K*(3, 4, $m - 2$, v_3);
 (* do *filter_k*[$S_{m-2}(u_3) | S_{m-2}(v_3)$] *)
 (3.3) call procedure *FILTER_K*(1, 3, $m - 2$, v_1);
 (* do *filter_k*[{ $S_{m-3}(u_1), S_{m-3}(u_2), S_{m-3}(u_3)$ } | $S_{m-2}(v_1)$] *)
end of *FILTER3*;

The time required for this case is :

$$F_k(N) = 5F_k(N/8) + 2F_{k-1}(N/8) + 2S(N/8) + O(\log N).$$

- *Case 4* : $x_k(p^2) < x_k(q^{mid}) < x_k(p^3)$. There are 3 tasks in procedure *FILTER4*.

procedure *FILTER4*(b_1, b_2, m, k);
begin
 (4.1) call procedure *FILTER_K1*(1, 1, $m - 2$, v_3);
 (* do *filter_{k-1}*[$S_{m-3}(u_1) | S_{m-2}(v_3)$] *)
 (4.2) call procedure *FILTER_K*(1, 3, $m - 2$, v_3);
 (* do *filter_k*[{ $S_{m-3}(u_1), S_{m-3}(u_2), S_{m-3}(u_3)$ } | $S_{m-2}(v_3)$] *)
 (4.3) call procedure *FILTER_K*(1, 2, $m - 2$, v_1);
 (* do *filter_k*[$S_{m-2}(u_1) | S_{m-2}(v_1)$] *)
end of *FILTER4*;

The time required for this case is :

$$F_k(N) = 5F_k(N/8) + F_{k-1}(N/8) + S(N/8) + O(\log N).$$

- *Case 5* : $x_k(p^1) < x_k(q^{mid}) < x_k(p^2)$. Two tasks are to be carried out in procedure *FILTER5*.

```

procedure FILTER5( $b_1, b_2, m, k$ );
  begin
    (5.1) call procedure FILTER_K(1, 4,  $m - 2, v_3$ );
      (* do  $filter_k[S_{m-1}(u_1)|S_{m-2}(v_3)]$  *)
    (5.2) call procedure FILTER_K(1, 1,  $m - 2, v_1$ );
      (* do  $filter_k[S_{m-3}(u_1)|S_{m-2}(v_1)]$  *)
  end of FILTER5;

```

The time required for this case is :

$$F_k(N) = 5F_k(N/8) + O(\log N)$$

- *Case 6* : $x_k(q^{mid}) < x_k(p^1)$. One task to be carried out in procedure *FILTER6*.

```

procedure FILTER6( $b_1, b_2, m, k$ );
  begin
    (6.1) call procedure FILTER_K(1, 4,  $m - 2, v_3$ );
      (* do  $filter_k[S_{m-1}(u_1)|S_{m-2}(v_3)]$  *)
  end of FILTER6;

```

The time required for this case is :

$$F_k(N) = 4F_k(N/8) + O(\log N).$$

2.3.3.3 Proof the Correctness of *FILTER_G*

Before we analyze the time complexity of algorithm *MAXIMA*, let us first show that subalgorithm *FILTER_G*(b_1, b_2, m, k) is correct. Let us consider conditions (A) through (E) in section 4.3 for the subalgorithm *FILTER_G*(b_1, b_2, m, k). For

procedure *FILTER_G2*, it is converted correctly from the 2-d maxima algorithm in [D86]. For *FILTER_S*, we know that condition (B) can be easily enforced. Since conditions (A), (C), (D) and (E) are enforced for all six cases (in a way as we demonstrated in *Case 1*), by a simple induction we know that conditions (A) through (E) hold for *FILTER_G*.

Then, we need to show that these conditions ensure that all points in the current top stack entries of all PE_i in $S_{m-1}(b_1)$ that are dominated by any current top stack entry point of $S_{m-1}(b_2)$ will be eventually marked. Condition (A) allows for comparing the x_l , $l = k, k-1, \dots, 1$, coordinate values of current top stack entry points of $S_{m-1}(b_1)$ with current top entry points of $S_{m-1}(b_2)$. Conditions (C) and (D) guarantee that all current top stack entry points of $S_{m-1}(b_1)$ dominated by any current top stack entry point of $S_{m-1}(b_2)$ will be eventually marked at the bottom level of recursion by either *FILTER_S* or *FILTER_G2*, using condition (B). Condition (E) is important, since it makes conditions (A), (C) and (E) valid during the entire computing process, and it allows for comparing the current top stack entry points of any PE_i in $S_{m-1}(b_1)$ with many current top entry points of $S_{m-1}(b_2)$ at lower recursion levels, and carrying all the comparison results back so that the final status of this point can be properly recorded and reported.

2.4 Analysis of Time Complexity

At first, let us consider the time complexity of *FILTER_G*. Summarizing all six cases, we have

$$F_k(N) = \begin{cases} 4F_k(N/8) + 4F_{k-1}(N/8) + 4S(N/8) + O(\log N), & \text{for Case 1;} \\ 5F_k(N/8) + 3F_{k-1}(N/8) + 3S(N/8) + O(\log N), & \text{for Case 2;} \\ 5F_k(N/8) + 2F_{k-1}(N/8) + 2S(N/8) + O(\log N), & \text{for Case 3;} \\ 5F_k(N/8) + F_{k-1}(N/8) + S(N/8) + O(\log N), & \text{for Case 4;} \\ 5F_k(N/8) + O(\log N), & \text{for Case 5;} \\ 4F_k(N/8) + O(\log N), & \text{for Case 6.} \end{cases}$$

Since sorting $N = 2^n$ numbers on a hypercube machine Q_n can be done in $O(\log^2 N)$ time, $S(N) = O(\log^2 N)$. Also, as we mentioned before, the time complexity $F_2(N)$, where $N = 2^n$, of *FILTER_G2*(b_1, b_2, n) is $O(\log^2 N)$ time. Since both $S(N)$ and $F_2(N)$ are $O(\log^2 N)$, we may select a constant C_2 such that $S(N) \leq C_2 \log_8^2 N$ and $F_2(N) \leq C_2 \log_8^2 N$. We can also select a constant C_3 such that $C_3 \log_8 N$ is greater than each of the $O(\log N)$ terms in the above relations. Remember that *FILTER_S* takes C_1 amount of time. Using these constants, the worst-case performance of *FILTER_G* can be determined by looking at the following relations.

- (i) $F_k(N) = 4F_k(N/8) + 4F_{k-1}(N/8) + 4C_2 \log_8^2 N + C_3 \log_8 N$;
- (ii) $F_k(N) = 5F_k(N/8) + 3F_{k-1}(N/8) + 3C_2 \log_8^2 N + C_3 \log_8 N$;
- (iii) $F_k(N) = C_1$, if $N \leq 8$; and
- (iv) $F_2(N) = C_2 \log_8^2 N$.

Let

$$F_k^1(N) = 4F_k(N/8) + 4F_{k-1}(N/8) + 4C_2 \log_8^2 N + 4C_3 \log_8 N \quad \text{and}$$

$$F_k^2(N) = 5F_k(N/8) + 5F_{k-1}(N/8) + 5C_2 \log_8^2 N + 5C_3 \log_8 N.$$

Clearly, $F_k(N) < \max \{F_k^1(N), F_k^2(N)\}$. For $F_3^1(N)$, we have

$$F_3^1(N) = 4^j F_3^1(N/8^j) + \sum_{i=1}^j 4^i \{F_2^1(N/8^i) + C_2 \log_8^2(N/8^{i-1}) + C_3 \log_8(N/8^{i-1})\}$$

$$\begin{aligned}
&< C_1 4^{\log_8 N-1} + (1 + C_2 + C_3) \sum_{i=1}^{\log_8 N-1} 4^i (\log_8 N - i)^2 \\
&< C_1 4^{\log_8 N-1} + (1 + C_2 + C_3) 4^{\log_8 N} \log_8^2 N \\
&< C 4^{\log_8 N} \log_8^2 N,
\end{aligned}$$

where $C = 1 + C_1 + C_2 + C_3$ is a constant. We prove that $F_k^1(N) < kC 4^{\log_8 N} \log^{k-1} N$, for $k > 3$, by induction. Suppose that this claim is true for $k-1$, and consider $F_k^1(N)$.

$$\begin{aligned}
F_k^1(N) &= 4^j F_k^1(N/8^j) + \sum_{i=1}^j 4^i F_{k-1}^1(N/8^i) + C_2 \sum_{i=1}^j 4^i \log_8^2(N/8^{i-1}) + C_3 \sum_{i=1}^j 4^i \log_8(N/8^{i-1}) \\
&< C_1 4^{\log_8 N} + (k-1)C \sum_{i=1}^{\log_8 N-1} 4^i 4^{\log_8(N/8^i)} \log_8^{k-2}(N/8^i) + (C_2 + C_3) \sum_{i=1}^{\log_8 N-1} 4^i (\log_8 N - i)^2 \\
&< C_1 4^{\log_8 N} + (k-1)C \sum_{i=1}^{\log_8 N-1} 4^{\log_8 N} \log_8^{k-2}(N/8^i) + (C_2 + C_3) 4^{\log_8 N} \log_8^2 N \\
&< ((k-1)C + C_1 + C_2 + C_3) 4^{\log_8 N} \log_8^{k-1} N \\
&< kC 4^{\log_8 N} \log_8^{k-1} N.
\end{aligned}$$

This completes the induction. By similar analysis, we have

$$F_k^2(N) < kC 5^{\log_8 N} \log_8^{k-1} N.$$

Therefore, $F_k(N) = \max \{ F_k^1(N), F_k^2(N) \} = O(5^{\log_8 N} \log^{k-1}(N))$.

Let $T(N)$ be the total running time of algorithm *MAXIMA*, then

$$\begin{aligned}
T(N) &= T(N/2) + F_{d-1}(N) = O(5^{\log_8 N} \log^{d-1} N) \\
&= O(N^{\log_8 5} \log^{d-1} N) = O(N^{0.77} \log^{d-1} N).
\end{aligned}$$

In summary, our hypercube algorithm *MAXIMA* solves the d -dimensional maxima problem of input size N in $O(N^{0.77} \log^{d-1} N)$ time, using $O(N)$ processors. The final results are in all bottom stack entries (the 0-th entries) of all stacks (note that when *MAXIMA* is completed, the 0-th stack entry is also the current top stack entry) such that $STK_j[0].point$ is a maximum point if and only if $STK_j[0].flag = 0$.

2.5 Generalizations and Concluding Remarks

A parallel algorithm for the maxima problem is adaptive if for a fixed P , which is the number of processors, it can be still usable and efficient when the input size increases. We can modify our algorithm *MAXIMA* to obtain an adaptive hypercube algorithm *MAXIMA_A*. Without loss of generality, assume that N is a multiple of P . Then, initially each processor contains N/P points.

To generalize our algorithm, we implement a stack in each processor such that each entry is an array of N/P elements, each having two fields *point* and *flag*. By slightly modifying *BROADCAST*, *CENSUS*, *SORT* and *UNSORT* we can obtain similar algorithms *BROADCAST_A*, *CENSUS_A*, *SORT_A* and *UNSORT_A* for *MAXIMA_A*. Let $S^A(N)$ denote the time for the *SORT_A* operation, which sorts N numbers in n -dimensional hypercube of P processors such that the sorted sequence are distributed in the memories associated to these processors, each with N/P numbers. By bitonic sorting algorithm, $S^A(N) = O((N/P)(\log(N/P) + \log^2 P))$. The *BROADCAST_A* can be done in no more than $O((N/P)\log P)$ time. The time complexity for *CENSUS_A* and *UNSORT_A* are the same as that for *BROADCAST_A* and *SORT_A*, respectively.

The generalized algorithm of $FILTER_S(b_1, b_2, m)$ can be converted into an algorithm $FILTER_S_A(b_1, b_2, m)$ that takes $O(N/P)$ time, since $m \leq 3$. By modifying the algorithm in [D86], we can obtain an algorithm $FILTER_G2_A(b_1, b_2, m)$, which is a generalized version of $FILTER_G2(b_1, b_2, m)$, that takes $O((N/P)(\log(N/P) + m^2))$ time. Then $FILTER_G_A(b_1, b_2, m, k)$, the generalized version of $FILTER_G(b_1, b_2, m, k)$, is almost the same as the one described in the previous section. The six cases of $FILTER_G_A(b_1, b_2, m, k)$ are now defined slightly differently. Point p_j , $1 \leq j \leq 4$, is the point with the smallest x_k coordinate value among all N/P points in the current top stack entry of $S_{m-1}(u_j)$. Point p^{\max} is the point with the largest x_k coordinate value among all N/P points in the current top stack entry of $S_{m-1}(u_4)$, and point q^{mid} is the point with the smallest x_k coordinate value among all N/P points in the current top stack entry of $S_{m-1}(v_3)$.

Determining which of the six cases is true takes $O(m)$ time. Using similar analysis for $F_k(N)$, we obtain $F_k^A(2^m) = O(P^{0.77}(N/P)(\log(N/P) \log^{k-2} P + m^{k-1})) = O(P^{0.77}(N/P) \log^{k-2} P (\log(N/P) + \log P))$, which is the running time of $FILTER_G_A(b_1, b_2, n, k)$. Since the total time for the generalized maxima algorithm is $T^A(P) = T^A(P/2) + F_{d-1}^A(P)$, we know that $T^A(P) = O((N/P^{0.23}) \log^{d-2} P (\log(N/P) + \log P))$. According to the currently best sequential algorithm, the best parallel algorithm should not take less than $O((N/P) \log^{d-2} N)$ time. However, this does not mean that a parallel algorithm running in less than $O((N/P) \log^{d-2} N)$ time is not possible, since it is not known whether or not $\Omega(N \log^{d-2} N)$ is the lower bound for the sequential time complexity of the maxima problem.

As we know, our algorithm *MAXIMA* is the first sublinear-time algorithm for the d -dimensional maxima problem on parallel machines with sparse interconnection networks when $d > 3$. The main factor in achieving the sublinear time complexity is sub-algorithm *FILTER_G*. This algorithm partitions a given problem or subproblem into several subproblems, which we call as tasks, and each is assigned to a set of subcubes so that the load of all processors are balanced and the data communication between processors through the links connecting them is minimized as much as possible. One may wonder that the overhead caused by operations *SORT* and *UNSORT* might be a reason why the complexity is not as low as the algorithms on the PRAM models. By the analysis of $F_k(N)$, we note that even if we can somehow eliminate all *SORT* and *UNSORT* operations in the recursive process, the time complexity remains the same. The main reason for the factor $N^{0.77}$ lies in the way the problem is partitioned. It is interesting to note that we have tried to partition the operation $filter_k[S^1|S^2]$ in several different ways, and our analysis shows that the complexity we obtained is the best among all the possibilities we have tried.

It remains as an open problem whether or not our results can be significantly improved. For example, is it possible to obtain a hypercube maxima algorithm that runs in $O(N^c)$ time such that c is a constant less than 1? More challengingly, can we design a hypercube maxima algorithm that runs in $O(\log^{f(d)})$ time, where $f(d)$ is a linear function of dimension d of the point space? We believe that due to the limitation of data communication in hypercube machines, finding these algorithms are not simple.

Theoretically, our algorithm *MAXIMA* runs in less than linear time. In practice, however, the situation may be different. Since a hypercube contains a Hamiltonian circuit (as given by Gray Code), a pipeline algorithm using the ring structure

embedded in the hypercube runs in $O(dN)$ time. Such an algorithm may be better than the performance of *MAXIMA* for small d . Considering the communication overheads, sequential algorithms can be better than their parallel counterparts. Combining the sequential algorithm and pipeline processing on the ring embedded in the hypercube, we can easily obtain a hypercube maxima algorithm of time complexity $O(N \log^{d-3}(N/P) + (N/P)(\log^{d-2}(N/P) + \log^2 P))$ for the case $N > O(P)$. In general, one may combine our algorithm with pipeline algorithm and sequential algorithm and determine when and how they should be employed to yield an efficient parallel hypercube maxima algorithm that is most suitable for given n , N , and d , which are the dimension of hypercube, input point set and the dimension of point space, respectively.

Chapter 3

The Voronoi Diagram

3.1 Introduction

The Voronoi diagram of a set S of N points in the plane is a polygonal subdivision of N regions in the plane, each containing a point of S , such that the region for each point p of S is the locus of points in the plane which are closer to p than to other points of S . The Voronoi diagram is a very useful data structure with many applications in computational geometry, robotics, image processing, and graph theory ([PH77], [S78]).

The sequential time complexity of the problem of constructing a Voronoi diagram is $O(N \log N)$, where $N = |S|$. The $O(N \log N)$ -time sequential algorithm described in [PH77] uses the divide-and-conquer strategy, but its merging step seems difficult to be parallelized. Previous parallel algorithms are based on the sequential algorithm proposed by Brown who reduced the construction of Voronoi diagram to the problem of finding the three-dimensional convex hull of a set of points on a sphere [B79]. In [C80], Chow gave a PRAM algorithm with time complexity $O(\log^3 N \log \log N)$, where N is the number of PEs in the PRAM. This has been improved to $O(\log^3 N)$ in [ACGOY85]. Chow also proposed an $O(\log^4 N)$ -time algorithm on Cube-Connected-Circles [C80]. In [L86], Lu presented an $O(\sqrt{N} \log N)$ -time algorithm for constructing the Voronoi diagram on the $\sqrt{N} \times \sqrt{N}$ mesh-connected computer. In [S88b], Stojmenovic presented an algorithm on the hypercube machine with N processors, and the time complexity of this algorithm is $O(\log^3 N)$ time.

In this chapter, we present an $O(\log^2 N)$ -time parallel algorithm for constructing the Voronoi diagram of a set S of N points in the plane on the $N \times N$ mesh of trees. Our algorithm is also based on the sequential algorithm presented in [B79]. More specifically, our algorithm transforms points of S into a set S' of points on a sphere, then uses the divide-and-conquer approach to construct the three-dimensional convex hull $CH(S')$ of S' , and finally transforms $CH(S')$ into the Voronoi diagram of S . Our convex hull algorithm can be used to construct the convex hull of any set of points in E^3 in $O(\log^2 N)$ time. Our algorithms are the fastest NC algorithms ever known for constructing planar Voronoi diagrams and three-dimensional convex hulls. This chapter is organized as follows. In section 3.2, we provide some fundamentals that are useful in the rest of the chapter. In section 3.3, we present our parallel Voronoi diagram algorithm. The subalgorithms used for constructing the three-dimensional convex hull of a set of points in E^3 will be presented in several subsections. We conclude this chapter in section 3.4.

3.2 Preliminaries

In this section, we describe the definition of planar Voronoi diagram, the structure and basic data routing operations of the mesh of trees, and the sequential algorithm for constructing Voronoi diagram as given in [B79].

3.2.1 Definition of Planar Voronoi Diagram

For any two points p and q in the plane, the set of points in the plane not farther to p than to q is the half-plane containing p that is defined by the perpendicular bisector of the line segment connecting p and q . We denote this half-plane by $H(p, q)$. For

a given set S of points in the plane, the set of points not farther to $p_i \in S$ than to any other point in S forms a convex polygonal region V_i containing p_i defined as

$$V_i = \bigcap_{\substack{p_j \in S \\ i \neq j}} H(p_i, p_j).$$

Each of these N polygonal regions is called a *Voronoi polygon*, and the partition of the plane by these polygons is referred to as the *Voronoi diagram* of S , denoted by $Vor(S)$. The vertices and the line segments of the diagram are *Voronoi vertices* and *Voronoi edges*, respectively. To avoid degeneracies, we assume that *no four points of S are co-circular*. If a Voronoi polygon is bounded, then it is constructed entirely by the edges whose two endpoints are Voronoi vertices; if it is unbounded, then it includes two semi-infinite lines as edges. The semi-infinite edges are also called *rays*. Every Voronoi vertex v is the common intersection of exactly three edges of the diagram, i.e. the degree of each vertex is 3; furthermore, v is equidistant from the three points of S which are closest to v , i.e. the circle determined by these three points is centered at v and contains no other points of S . The Voronoi diagram of a point set is shown in Figure 3.1.

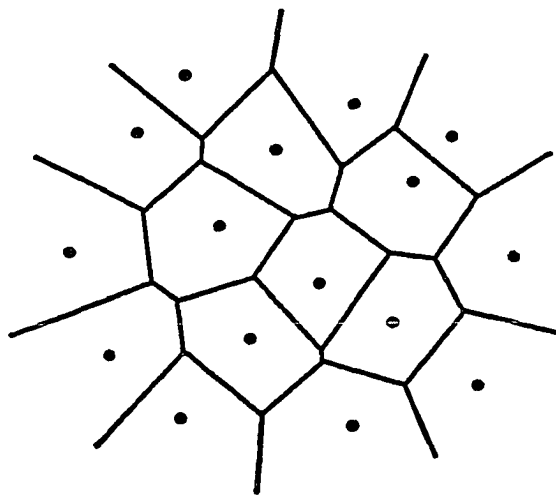


Fig. 3.1 The Voronoi diagram of a set of points.

3.2.2 Mesh of Trees and Data Communications

The $N \times N$ mesh of trees (*MOT*) is constructed from an $N \times N$ array of processors by adding processors and data links to form a complete binary tree in each row and column. The processors in the array are called *leaf processors*, denoted as $LP_{i,j}$, $0 \leq i, j \leq N - 1$. The processors corresponding to the roots of the trees are called *root processors*; and the root processor of processors in row i (resp. column j) is denoted as RP_i^r (resp. RP_j^c). All remaining processors are called *internal processors* (denoted as *IP*'s). The total number of processors is $3N^2 - 2N$. Most of the computing is done in the N^2 $LP_{i,j}$'s. The remaining processors are used for communication between *LP*s, and may also be used to carry out some simple operations such as summing and comparison. A 4×4 *MOT* is shown in Figure 3.2.

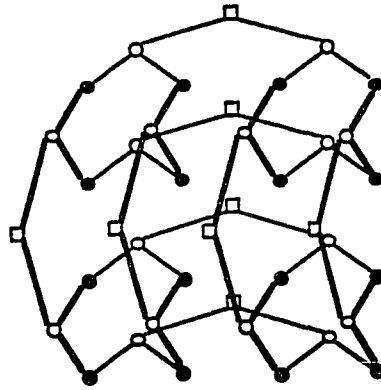


Fig. 3.2 A 4×4 mesh of trees (\bullet : LP, \circ : IP, \square : RP).

The mesh of trees is the fastest general parallel multiprocessor architecture known when considered only in terms of speed. Many problems can be solved on the mesh of trees in $O(\log^c N)$ time, where c is a small constant. The following operations on the mesh of trees are useful for constructing more powerful operations that can be used for designing efficient algorithms.

$RTL_R(i, j)$: root to leaf in a row. Send a data item from RP_i^r , the root of row i , to $LP_{i,j}$ in the same row tree.

$LTR_R(i, j)$: leaf to root in a row. Send a data item from the leaf processor $LP_{i,j}$ to RP_i^r , the root of row i .

$LTL_R(i, j, k)$: leaf to leaf in a row. Send a data item from $LP_{i,j}$ to $LP_{i,k}$.

$BROADCAST_R(i)$: broadcast in a row. Broadcast a data item from RP_i^r , the root of row i , to all LP 's in row i .

$AND_R(i)$: logic AND in a row. Perform the logic AND function of the specified data item in each LP in row i and return the final result up to the root processor RP_i^r .

$SUM_R(i)$: summation of a row. Find the summation of specified data stored in all LP 's in row i and store the result in RP_i^r , the root of row i .

$SORT_R(i)$: sort in a row. Sort N numbers, which are stored in LP 's in row i , in non-decreasing order so that the sorted numbers are put into the LP 's in the same row, one number per LP .

Similarly, we can define operations RTL_C , LTR_C , LTL_C , $BROADCAST_C$, AND_C , SUM_C , and $SORT_C$ to be performed among processors in a column tree. Note that LTL is constructed by a pair of LTR and RTL operations, and $SORT$ is constructed by using RTL , LTR , LTL , $BROADCAST$ and SUM operations [L92]. Additional census operations such as OR , MAX and MIN performed on a row or column tree can also be defined. Each of these operations takes $O(\log N)$ time.

Since the MOT can be recursively defined [L92], we define a sub- MOT as a sub-structure of the $N \times N$ MOT that satisfies the definition of MOT . We are particularly interested in the sub- MOT that contains leaf processors in the first row, row 0, of the

$N \times N$ MOT. We use $MOT(m, k)$ to denote the sub-MOT that contains $2^m \times 2^m$ leaf processors $LP_{i,j}$, $0 \leq i \leq 2^m - 1$ and $k2^m \leq j \leq (k+1)2^m - 1$, for $0 \leq k < N/2^m$, together with internal processors and the root processor to form a complete tree in each row and column of the $2^m \times 2^m$ array. Clearly, $MOT(m, k)$ is a $2^m \times 2^m$ MOT, and all parallel operations, including those mentioned above, for the $N \times N$ MOT can be executed on all sub-MOT's $MOT(m, k)$ concurrently.

3.2.3 Constructing Voronoi Diagram by Geometric Inversion

An algorithm for constructing the Voronoi diagram of a set S of N points in the plane using a geometric transformation called *inversion* is given in [B79]. The inversion I is a point-to-point transformation determined by two parameters, q , the *center* of inversion, and r , the *radius* of inversion. An inversion transforms a plane which does not contain its inversion center to a sphere with the inversion center on it, and vice versa. The interior and exterior of the sphere correspond to the two half-spaces separated by the plane. For a set S of points in the xy -plane, if q is not in the xy -plane, then by inversion we obtain a set S' of points on a sphere in E^3 , i.e. for a point p in the xy -plane, $I(q, r, p)$ is on the sphere. Another important property of inversion is involuntary, that is, $I(q, r, I(q, r, p)) = p$. Inversion transformation is described in detail in [D72].

The following sequential algorithm for constructing the Voronoi diagram of a set S of points in the plane is based on the sequential algorithm given in [B79] and the parallel algorithms given in [C80] and [L86]. The proof of correctness of this algorithm is given in [B79]. This algorithm can be implemented with sequential time complexity $O(N \log N)$, which is optimal.

Algorithm *VORONOI*(*S*)**begin**

- (1) Choose $q = (0, 0, 1)$ as the inversion center and choose radius $r = 1$. Perform the inversion for each point $p_i = (x_i, y_i) \in S$ to obtain $p'_i = (x'_i, y'_i, z'_i)$, where $x'_i = y'_i = x_i/(x_i^2 + y_i^2 + 1)$, and $z'_i = (x_i^2 + y_i^2)/(x_i^2 + y_i^2 + 1)$. Let the set of inversion images of points in S be S' (see Figure 3.3).
- (2) Construct the convex hull of S' . Denote this convex hull by $CH(S')$, which is the set of all triangular faces F_j on the hull. Each face is represented by the three end points of the edges bounding the triangle.
- (3) Each face F_j performs the "reinversion" to map its end points $p'_{j,1}$, $p'_{j,2}$ and $p'_{j,3}$ to the points $p_{j,1}$, $p_{j,2}$ and $p_{j,3}$ on the xy -plane, and find the center c_j of their circumcircle. Each c_j is a Voronoi vertex in $Vor(S)$. If q and $CH(S')$ are on the same side of the plane containing F_j then set $v_j = 1$ else set $v_j = 0$.
- (4) For each c_j with $v_j = 1$, find the point c_k such that F_k is an adjacent face of F_j in $CH(S')$. Note that there are three such c_k 's. If $v_k = 1$, then (c_j, c_k) is a Voronoi edge with end points c_j and c_k ; otherwise, the semi-infinite line originating from c_j is a ray in $Vor(S)$.

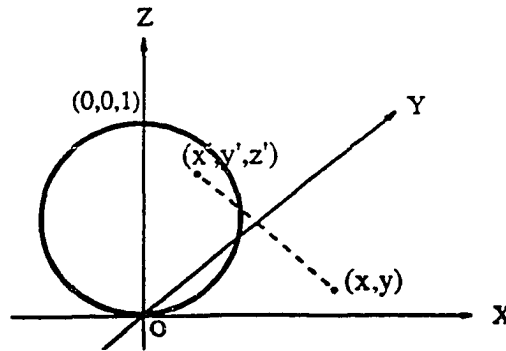
end *VORONOI*;

Fig. 3.3 Inversion between a point in the plane and its image on the sphere.

3.3 Constructing Voronoi Diagram on a Mesh of Trees

Our Voronoi diagram algorithm is derived directly from the algorithm *VORONOI* described in section 3.2.3. Assume there are exactly N points in S , and initially each is stored in an LP in the first row of the $N \times N$ mesh of trees. Then, step (1) of the parallel version of *VORONOI* can be done in $O(1)$ time. All faces of the three-dimensional convex hull $CH(S')$ are triangles, and there are no more than $2N-4$ faces in $CH(S')$. Suppose each processor $LP_{0,j}$ in the first row of the mesh of trees contains at most two faces of $CH(S')$, where each face is represented by the three points in S' it passes through, and three edges connecting the points. Then, step (3) of the parallel version of algorithm *VORONOI* finds all Voronoi vertices of $Vor(S)$ in $O(1)$ time.

3.3.1 Constructing Voronoi Diagram from Convex Hull

Consider the parallel implementation of step (4) of algorithm *VORONOI*. Let the two faces stored in $LP_{0,j}$ be named as $F_{0,j,1}$ and $F_{0,j,2}$, respectively. The following procedure *MULTI_CAST* can be used to distribute all faces stored in row 0 of the mesh of trees to all LP 's such that each $LP_{i,j}$, $i \neq j$, contains faces $F_{0,i,1}$, $F_{0,i,2}$, $F_{0,j,1}$, and $F_{0,j,2}$.

procedure *MULTI_CAST*

begin

for $0 \leq j \leq N - 1$ **do in parallel**

 Use *LTR_C* to send $F_{0,j,1}$ and $F_{0,j,2}$ in $LP_{0,j}$ to RP_j^c ;

 Use *BROADCAST_C* to broadcast $F_{0,j,1}$ and $F_{0,j,2}$ in RP_j^c to all LP 's in column j ;

Use *LTR_R* to send $F_{0,j,1}$ and $F_{0,j,2}$ in $LP_{j,j}$ to RP'_j ;

Use *BROADCAST_R* to broadcast $F_{0,j,1}$ and $F_{0,j,2}$ in RP'_j to all LP 's in row j ;

endfor

end *MULTI_CAST*

Consider the 4×4 *MOT*. The distribution of faces by *MULTI_CAST* is shown in Figure 3.4. In this figure, each 3-tuple $\langle 0, a, b \rangle$ represents the face $F_{0,a,b}$ originally stored in $LP_{0,a}$. Procedure *MULTI_CAST* is used in several subalgorithms. Let us see how the step (4) of the parallel version of algorithm *VORONOI* can be carried out efficiently by using this procedure.

LP(0,0) $\langle 0,0,1 \rangle$ $\langle 0,0,2 \rangle$	LP(0,1) $\langle 0,1,1 \rangle$ $\langle 0,1,2 \rangle$ $\langle 0,0,1 \rangle$ $\langle 0,0,2 \rangle$	LP(0,2) $\langle 0,2,1 \rangle$ $\langle 0,2,2 \rangle$ $\langle 0,0,1 \rangle$ $\langle 0,0,2 \rangle$	LP(0,3) $\langle 0,3,1 \rangle$ $\langle 0,3,2 \rangle$ $\langle 0,0,1 \rangle$ $\langle 0,0,2 \rangle$
LP(1,0) $\langle 0,1,1 \rangle$ $\langle 0,1,2 \rangle$ $\langle 0,0,1 \rangle$ $\langle 0,0,2 \rangle$	LP(1,1) $\langle 0,1,1 \rangle$ $\langle 0,1,2 \rangle$	LP(1,2) $\langle 0,2,1 \rangle$ $\langle 0,2,2 \rangle$ $\langle 0,1,1 \rangle$ $\langle 0,1,2 \rangle$	LP(1,3) $\langle 0,3,1 \rangle$ $\langle 0,3,2 \rangle$ $\langle 0,1,2 \rangle$ $\langle 0,1,2 \rangle$
LP(2,0) $\langle 0,2,1 \rangle$ $\langle 0,2,2 \rangle$ $\langle 0,0,1 \rangle$ $\langle 0,0,2 \rangle$	LP(2,1) $\langle 0,2,1 \rangle$ $\langle 0,2,2 \rangle$ $\langle 0,1,1 \rangle$ $\langle 0,1,2 \rangle$	LP(2,2) $\langle 0,2,1 \rangle$ $\langle 0,2,2 \rangle$	LP(2,3) $\langle 0,3,1 \rangle$ $\langle 0,3,2 \rangle$ $\langle 0,2,1 \rangle$ $\langle 0,2,2 \rangle$
LP(3,0) $\langle 0,3,1 \rangle$ $\langle 0,3,2 \rangle$ $\langle 0,0,1 \rangle$ $\langle 0,0,2 \rangle$	LP(3,1) $\langle 0,3,1 \rangle$ $\langle 0,3,2 \rangle$ $\langle 0,1,1 \rangle$ $\langle 0,1,2 \rangle$	LP(3,2) $\langle 0,3,1 \rangle$ $\langle 0,3,2 \rangle$ $\langle 0,2,1 \rangle$ $\langle 0,2,2 \rangle$	LP(3,3) $\langle 0,3,1 \rangle$ $\langle 0,3,2 \rangle$

Fig. 3.4 The distribution of faces after the *MULTI_CAST* operation.

procedure *CH_TO_VOR*

begin

Broadcast q to all LP 's of the mesh of trees.

Use procedure *MULTI_CAST* to distribute all faces stored in row 0 of the mesh of trees to all LP 's such that each $LP_{i,j}$, $i \neq j$, contains faces $F_{0,i,1}$, $F_{0,i,2}$, $F_{0,j,1}$, and $F_{0,j,2}$.

for all $LP_{i,j}$ **do in parallel**

if $i < j$ compare two pairs of faces, $F_{0,i,1}$ and $F_{0,j,1}$, and $F_{0,i,1}$ and $F_{0,j,2}$, to see whether they are adjacent or not. If yes, compute the Voronoi edges determined by them;

if $i > j$ compare two pairs of faces, $F_{0,i,2}$ and $F_{0,j,1}$, and $F_{0,i,2}$ and $F_{0,j,2}$, to see whether they are adjacent or not. If yes, compute the Voronoi edges determined by them;

endfor

end *CH_TO_VOR*

Procedure *CH_TO_VOR* converts the convex hull of S' to the Voronoi diagram of S . Its time complexity is obviously $O(\log N)$, since the procedure *MULTI_CAST* requires $O(\log N)$ time and the parallel for-statement takes $O(1)$ time. Let $T_{CH}(N)$ denote the time taken for constructing the convex hull of N points in E^3 . Since any convex hull algorithm on the $N \times N$ MOT requires $\Omega(\log N)$ time, we have the following fact:

Lemma 1 : The Voronoi diagram of a set S of N points in the plane can be constructed in $T_{CH}(N)$ time on an $N \times N$ mesh of trees.

3.3.2 Constructing Three-Dimensional Convex Hull

The crucial part of our Voronoi diagram algorithm is constructing the three-dimensional convex hull $CH(S')$ in parallel. Note that the points in S' obtained by inversion have coordinates x' , y' and z' . For convenience, we rename them as x , y and z , respectively. It is important to note that the x and y coordinates we are used in the rest of section 3.3 are not the same as the ones used for points in S . Without loss of generality, assume that no two points in S' have the same x -coordinate value. Our algorithm for constructing three-dimensional convex hull uses the divide-and-conquer technique to divide S' into subsets, by the sorted x -coordinate values, constructs the convex hulls of these small subsets in parallel using sub-*MOT*'s, then merges these small three-dimensional convex hulls into larger three-dimensional convex hulls in parallel. An important invariant is that the faces of the convex hull of a subset of points are always stored in *LP*'s in the first row of the sub-*MOT* assigned to the subset, each *LP* containing no more than two faces, before the merge process of the next level starts. This invariant is required not only to simplify the algorithm, but also to ensure the claimed time complexity of the algorithm. The mainframe of our convex hull algorithm is given below.

Algorithm *CONVEX_HULL*

Input : a set of N points on a sphere in E^3 , one point in each $LP_{0,j}$;

Output : the set of faces in $CH(S')$, at most two faces in each $LP_{0,j}$.

begin

Sort all points in $LP_{0,j}$'s such that $x(p_{0,j}) < x(p_{0,j+1})$, where $p_{0,j}$ is the point in $LP_{0,j}$ and $x(p_{0,j})$ is the x -coordinate of $p_{0,j}$;

for all $2^i \times 2^i$ *MOT*(2, k) such that $0 \leq k < N/4$ **do in parallel**

```

        Construct the convex hull of 4 points in  $4 \times 4$  sub-MOT MOT(2, k);
    endfor
    for i = 3 to log N do
        for all MOT(i, k) such that  $0 \leq k < N/2^i$  do in parallel
            Use procedure MERGE to merge the convex hulls of points in two
             $2^{i-1} \times 2^{i-1}$  sub-MOT's of MOT(i, k) to obtain the convex hull of
            all points in MOT(i, k);
        endfor
    endfor
end CONVEX_HULL

```

The sorting step takes $O(\log N)$ time. Finding the convex hulls of four points in all 4×4 sub-*MOT*s can be done in constant time. There are $O(\log N)$ iterations for recursively constructing the convex hulls of subsets of S' by procedure *MERGE*. Thus, the overall time complexity of *CONVEX_HULL* depends on the efficiency of procedure *MERGE*.

3.3.3 Algorithm for Merging Two Convex Hulls

Merging a pair of smaller three-dimensional convex hulls $CH(A)$ and $CH(B)$, whose faces are stored in two sub-*MOT*'s, of point sets A and B to obtain the convex hull $CH(A \cup B)$ consists of two basic tasks: (1) for each face F_{Ai} on $CH(A)$ (resp. F_{Bj} on $CH(B)$), determine it as an external or internal face of $CH(A \cup B)$. An *external face* is a face which will not be "covered" by $CH(A \cup B)$ after the merging, while an *internal face* means one that will be covered in $CH(A \cup B)$. (2) Remove all internal faces of $CH(A)$ and $CH(B)$, and find new faces that will appear on $CH(A \cup B)$. By the

assumption that no two points in $A \cup B$ have the same x -coordinate value, $CH(A)$ and $CH(B)$ are separated by an xy -plane. Recall that a face in the convex hull of any subset of S' , with more than two points, is a triangle defined by three points in S' and three edges connecting them. Thus, an external face in $CH(A)$ (resp. $CH(B)$) is adjacent to at most one internal face of $CH(A)$ (resp. $CH(B)$) along their shared edge. We refer to the external faces that are adjacent to internal faces as *critical external faces*.

It is a simple fact that all edges shared by external and internal faces of $CH(A)$ (resp. $CH(B)$) form a closed circuit. We denote this circuit by C_A (resp. C_B). Each new face of $CH(A \cup B)$ is defined either by two vertices on C_A (they must be the endpoints of an edge in C_A) and one vertex on C_B , or by two vertices on C_B (they must be the endpoints of an edge in C_B) and one vertex on C_A (see Figure 3.5). Once all critical external faces are identified, new faces can be created along C_A and C_B .

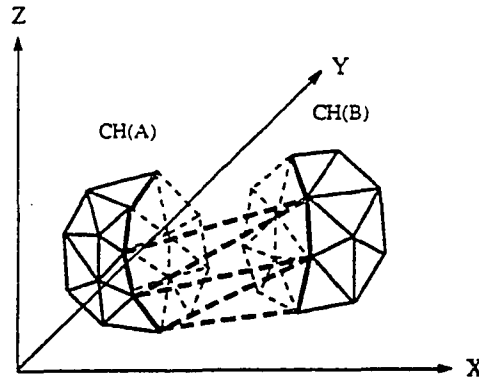


Fig. 3.5 Merge convex hulls $CH(A)$ and $CH(B)$. The thick solid line segments are the edges on circuits C_A and C_B , respectively.

The procedure *MERGE* below is presented for merging on the $N \times N$ mesh of trees, which is $MOT(\log_2 N, 0)$. The faces of $CH(A)$ and $CH(B)$ are stored in *LP*'s in the first rows of the sub-*MOT*'s $MOT(\log_2 N - 1, 0)$ and $MOT(\log_2 N - 1, 1)$, respectively. This procedure can be generalized to the ones for all sub- $MOT(i, k)$'s that are executed concurrently.

procedure *MERGE*

Input: Faces of $CH(A)$ and $CH(B)$ stored in the LP 's in row 0 of $MOT(\log_2 N - 1, 0)$ and $MOT(\log_2 N - 1, 1)$, respectively.

Output: Faces of $CH(A \cup B)$ stored in the LP 's in row 0 of $MOT(\log_2 N, 0)$.

begin

Use procedures *CHECKFACE_A* and *CHECKFACE_B* to determine all internal faces of $CH(A)$ and $CH(B)$;

Use procedures *CRITICAL_FACE_A* and *CRITICAL_FACE_B* to determine all critical external faces of $CH(A)$ and $CH(B)$;

Use procedures *NEW_FACE_A* and *NEW_FACE_B* to discover all new faces of $CH(A \cup B)$;

Use procedure *REBALANCE* to enforce the invariant that each LP in the first row, row 0, of the mesh of trees contains at most 2 faces of $CH(A \cup B)$.

end *MERGE*

3.3.3.1 Determining Internal and External Faces

The following description is for determining the external and internal faces in $CH(A)$. We use the same approach, but switch the roles of $CH(A)$ and $CH(B)$, to determine the external and internal faces in $CH(B)$. Let P_{Ai} be the plane containing the face F_{Ai} of $CH(A)$. P_{Ai} divides the entire 3-dimensional space into two half-spaces. Denote the half-space that contains $CH(A)$ as H_{Ai} . Face F_{Ai} belongs to $CH(A \cup B)$ if $CH(B)$ lies entirely in the half-space H_{Ai} . The equation for the plane containing the triangle face with three end points (x_1, y_1, z_1) , (x_2, y_2, z_2) , and (x_3, y_3, z_3) can be expressed as follows:

$$\begin{bmatrix} x & y & z & 1 \\ x_1 & y_1 & z_1 & 1 \\ x_2 & y_2 & z_2 & 1 \\ x_3 & y_3 & z_3 & 1 \end{bmatrix} = ax + by + cz + d = 0$$

All faces of $CH(A)$ are stored in $LP_{0,j}$, $0 \leq j \leq N/2-1$, and all faces of $CH(B)$ are stored in $LP_{0,j}$, $N/2 \leq j \leq N-1$. By our recursion invariant, each processor contains at most two faces. For convenience, we may enforce each of LP to contain exactly two faces by adding dummy faces if necessary. These dummy faces will be replaced by new faces when they are generated. The following procedure determines for each of the faces of $CH(A)$, which are stored in $LP_{0,j}$, $0 \leq j \leq N/2-1$, whether it is internal or external. A flag, *extn*, is assumed for each face. We assume that each leaf processor $LP_{i,j}$ has a local variable $EXT_{i,j}$, and each root processor RP_j^r and RP_j^c has a local variable EXT_j^r and EXT_j^c , respectively.

procedure CHECKFACE_A

Input: Faces of $CH(A)$ and $CH(B)$ stored in the LP 's in row 0 of $MOT(\log_2 N/2, 0)$ and $MOT(\log_2 N/2, 1)$, respectively.

Output : The faces remain where they were, but the *extn* field of a face of $CH(A)$ is set 1 if it is external, 0 otherwise.

begin

for all $LP_{i,j}$ **do in parallel**

$EXT_{i,j} := 1;$

endfor

Use procedure *MULTI_CAST* to distribute all faces stored in row 0 of the *MOT* to

all LP 's such that each $LP_{i,j}$, $i \neq j$, contains faces $F_{0,i,1}$, $F_{0,i,2}$, $F_{0,j,1}$, and $F_{0,j,2}$;

```

for all  $LP_{i,j}$  do in parallel
  if  $i < N/2$  and  $j > N/2$  and  $i \neq j$  then
    if  $CH(A)$ ,  $F_{0,j,1}$  and  $F_{0,j,2}$  are not all on the same side of plane  $P_{0,i,1}$  then
       $EXT_{i,j} := 0$ ;
    if  $j < N/2$  and  $i > N/2$  and  $i \neq j$  then
      if  $CH(A)$ ,  $F_{0,j,1}$  and  $F_{0,j,2}$  are not all on the same side of plane  $P_{0,i,2}$  then
         $EXT_{i,j} := 0$ ;
  endfor
for  $0 \leq j \leq N/2-1$  do in parallel
  Perform an AND operation on the  $EXT_{i,j}$ 's in row  $j$  using the row tree and store
  the result, which is denoted by  $EXT_j^r$ , in  $RP_j^r$ ;
  Route  $EXT_j^r$  to  $LP_{0,j}$  using a pair of RTL_R and LTL_C operations, set  $extn_{0,j,1}$ 
   $:= EXT_j^r$ ;
endfor
for  $0 \leq j \leq N/2-1$  do in parallel
  Perform an AND operation on the  $EXT_{i,j}$ 's in column  $j$  using the column tree
  and store the result, which is denoted by  $EXT_j^c$ , in  $RP_j^c$ ;
  Route  $EXT_j^c$  to  $LP_{0,j}$  using a RTL_C operation, set  $extn_{0,j,2} := EXT_j^c$ ;
endfor
end CHECKFACE_A

```

After the *MULT_CAST* operation, only those $LP_{i,j}$'s such that $i < N/2$ and $j > N/2$, or $i > N/2$ and $j < N/2$ contains faces of $CH(A)$ and $CH(B)$. Each of such LP 's contains exactly four faces (including dummy ones), two from each of $CH(A)$ and $CH(B)$. Furthermore, $LP_{i,j}$ and $LP_{j,i}$ receive the same set of faces (see Figure 3.4).

For the sake of load balancing, we let each of these LP 's compare one face from $CH(A)$ with two faces from $CH(B)$. The time complexity of this procedure is $O(\log N)$, because all of its parallel operations take no more than $O(\log N)$ time.

3.3.3.2 Identifying Critical External Faces

As mentioned in the beginning of section 3.3.3, each of the critical external faces of $CH(A)$ (resp. $CH(B)$) shares exactly one edge with an internal face of $CH(A)$ (resp. $CH(B)$), and these shared edges form a circuit C_A (resp. C_B). To generate new faces on $CH(A \cup B)$, we need to locate these critical external faces and the shared edges. The following procedure is used to find all critical external faces on $CH(A)$, and for each of them identify its edge shared by an internal face of $CH(A)$. The logical-and Boolean operator " \bullet " is used. The procedure *CRITICAL_FACE_B* for identifying critical external faces of $CH(B)$ is similar.

procedure *CRITICAL_FACE_A*

Input: Faces of $CH(A)$ stored in the LP 's in row 0 of $MOT(\log_2 N/2, 0)$. Faces of $CH(A)$ have been classified as internal or external.

Output: The faces remain where they were, but the edges shared by the critical external and internal faces of $CH(A)$ are marked.

begin

Use procedure *MULTI_CAST* to distribute all faces stored in row 0 of $MOT(\log_2 N/2, 0)$ to all LP 's such that each $LP_{i,j}$, $i \neq j$, contains faces $F_{0,i,1}$, $F_{0,i,2}$, $F_{0,j,1}$, and $F_{0,j,2}$.

for all $LP_{i,j}$ do in parallel

if $i < j$ and $F_{0,i,1}$ and $F_{0,j,1}$ share an edge e and $(extn_{0,i,1} \bullet extn_{0,j,1} = 0)$ then

```

    if  $extn_{0,i,1} = 0$  and  $extn_{0,j,1} = 1$  then mark the edge  $e$  of  $F_{0,j,1}$ 
    else if  $extn_{0,i,1} = 1$  and  $extn_{0,j,1} = 0$  then mark the edge  $e$  of  $F_{0,i,1}$ ;
  if  $i < j$  and  $F_{0,i,1}$  and  $F_{0,j,2}$  share an edge  $e$  and  $(extn_{0,i,1} \bullet extn_{0,j,2} = 0)$  then
    if  $extn_{0,i,1} = 0$  and  $extn_{0,j,2} = 1$  then mark the edge  $e$  of  $F_{0,j,2}$ 
    else if  $extn_{0,i,1} = 1$  and  $extn_{0,j,2} = 0$  then mark the edge  $e$  of  $F_{0,i,1}$ ;
  if  $i > j$  and  $F_{0,i,2}$  and  $F_{0,j,1}$  share an edge  $e$  and  $(extn_{0,i,2} \bullet extn_{0,j,1} = 0)$  then
    if  $extn_{0,i,2} = 0$  and  $extn_{0,j,1} = 1$  then mark the edge  $e$  of  $F_{0,j,1}$ 
    else if  $extn_{0,i,2} = 1$  and  $extn_{0,j,1} = 0$  then mark the edge  $e$  of  $F_{0,i,2}$ ;
  if  $i > j$  and  $F_{0,i,2}$  and  $F_{0,j,2}$  share an edge  $e$  and  $(extn_{0,i,2} \bullet extn_{0,j,2} = 0)$  then
    if  $extn_{0,i,2} = 0$  and  $extn_{0,j,2} = 1$  then mark the edge  $e$  of  $F_{0,j,2}$ 
    else if  $extn_{0,i,2} = 1$  and  $extn_{0,j,2} = 0$  then mark the edge  $e$  of  $F_{0,i,2}$ ;
  endfor
for all  $LP_{0,j}$ ,  $0 \leq j \leq N/2-1$ , do in parallel
  begin
    if  $F_{0,j,1}$  and  $F_{0,j,2}$  share an edge  $e$  and  $extn_{0,j,1} = 0$  and  $extn_{0,j,2} = 1$  then mark  $e$ 
      of  $F_{0,j,2}$ ;
    if  $F_{0,j,1}$  and  $F_{0,j,2}$  share an edge  $e$  and  $extn_{0,j,1} = 1$  and  $extn_{0,j,2} = 0$  then mark  $e$ 
      on  $F_{0,j,1}$ ;
  end
endfor
Use procedure MULTI_COLLECT to collect the status of external faces of  $CH(A)$ 
  in all  $LP$ 's and update the faces in  $LP$ 's the first row, row 0, of  $MOT(\log_2 N/2, 0)$ ;
end CRITICAL_FACE_A

```

In procedure *CRITICAL_FACE_A*, all faces of $CH(A)$ are distributed to all LP 's. Then, faces of $CH(A)$ are compared with each other, and all critical external faces are marked. Finally, all faces of $CH(A)$ are sent back to where they were before the procedure *MULTI_CAST* was executed. The marked faces replace their original copies in $LP_{0,j}$'s. Before we present procedure *MULTI_COLLECT*, we define a new operation on the mesh of trees.

COLLECT_R(i) : collect items in a row. Collect a set of data items stored in LP 's in row i , and put all collected items in RP'_i , the root of row i .

We similarly define an operation *COLLECT_C(i)*, to collect items in column i . Due to the bounded interconnection degree of binary tree structure, the performance of *COLLECT* depends on the number of data items to be collected and the size of each data item. If the number of data items is a small constant, and the size of each item is bounded by a small constant, then *COLLECT_R(i)* requires $O(\log N)$ time. In our case, since each critical external face of $CH(A)$ can share exactly one internal face of $CH(A)$, the number of data items to be collected in a row or column is at most two, and each item is a record for a face, with contains a fixed amount of information.

procedure *MULTI_COLLECT*

begin

for $0 \leq j \leq N - 1$ do in parallel

 Use *COLLECT_C* to collect faces with marked edges in all LP 's in column j and store the collected faces in RP_j^c ;

 Use *COLLECT_R* to collect faces with marked edges in all LP 's in row j and store the collected faces in RP_j^r ;

```

    Use RTL_R to send collected faces in  $RP_i^r$  to  $LP_{0,j}$ ;
    Use RTL_C to send collected faces in  $RP_i^c$  to  $LP_{0,j}$ ;
  endfor
  for  $LP_{0,j}$  do in parallel
    Replace the original  $F_{0,j,1}$  and/or  $F_{0,j,2}$  by ones with marked edges (if any);
  endfor
end MULTI_COLLECT

```

Since *MULTI_COLLECT* takes $O(\log N)$ time, the time complexity of procedure *CRITICAL_FACE_A* is $O(\log N)$.

3.3.3.3 Generating New Faces

The marked edges of critical external faces of $CH(A)$ (resp. $CH(B)$) form a circuit C_A (resp. C_B), as shown in Figure 3.5. The new faces of $CH(A \cup B)$ are generated along these two circuits. For a critical external face F of $CH(A)$ with marked edge $e = (p_a, p_b)$, where $p_a = (x_a, y_a, z_a)$, $p_b = (x_b, y_b, z_b) \in S'$, we define its *representative point* of F as follows: the representative point of F is p_a , if $\cos^{-1}(y_a/(y_a^2 + z_a^2)^{1/2}) > \cos^{-1}(y_b/(y_b^2 + z_b^2)^{1/2})$; p_b , otherwise. Note that $\cos^{-1}(y/(y^2 + z^2)^{1/2})$ is the angle between op' and the y -axis, where p' is the projection of $p = (x, y, z)$ in the yz -plane and o is the origin. Clearly, the set of representative points of all critical external faces of $CH(A)$ is exactly the vertex set of circuit C_A . The representative points of critical external faces of $CH(B)$ are defined similarly.

Let C'_A and C'_B be the circuits in the yz -plane obtained by projecting C_A and C_B to the yz -plane, respectively. Let o'_A and o'_B be two points in the yz -plane such that they are internal to C'_A and C'_B , respectively. Clearly, o'_A (resp. o'_B) can be found in

$O(\log N)$ time by finding a point in the triangle formed by any three non-collinear points of C'_A (resp. C'_B). We introduce two polar coordinate systems Σ_A and Σ_B : Σ_A has origin o'_A and polar axis in the direction of the y -coordinate, and Σ_B has origin o'_B and polar axis in the opposite direction of the y -coordinate. Let $\gamma_A(p)$ and $\gamma_B(p)$ be the polar angle of the image of point p in Σ_A and Σ_B , respectively. The vertices of C_A (resp. C_B) are uniquely ordered by the non-decreasing order of their images' polar angles γ_A in Σ_A (resp. Σ_B). These two coordinate systems and the orders of vertices in C'_A and C'_B are shown in Figure 3.6. These orders are important to determine the new faces of $CH(A \cup B)$.

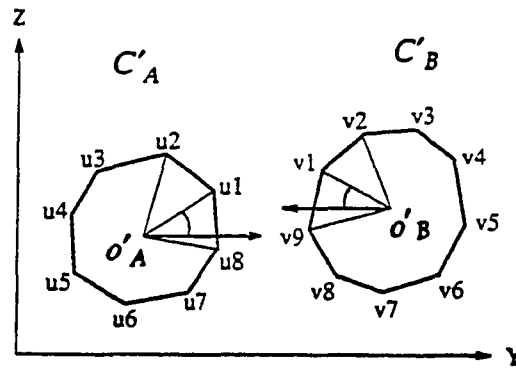


Fig. 3.6 Polar coordinate systems Σ_A and Σ_B . u_i 's and v_j 's are projections of vertices on C'_A and C'_B , respectively.

For each critical external face F_{Ai} of $CH(A)$ with a marked edge e_{Ai} in circuit C_A , a new triangle face $F(e_{Ai}, p_{Bj})$ of $CH(A \cup B)$ bounded by e_{Ai} and a vertex p_{Bj} of circuit C_B can be identified. Let $P(e_{Ai}, p)$ denote the plane that contains edge e_{Ai} of C_A and vertex p of C_B . Define angle $\theta(F_{Ai}, p)$ associated with critical external face F_{Ai} of $CH(A)$ and a vertex point p of C_B as the convex angle formed by the plane $P(e_{Ai}, p)$ and face F_{Ai} . This angle can be computed using the normal vectors of $P(e_{Ai}, p)$ and F_{Ai} .

Let $\xi(F_{Ai}) = \max \{ \theta(F_{Ai}, p_j) \mid p_j \text{ is a vertex of } C_B \}$, $V(F_{Ai}) = \{ p \mid p \text{ is a vertex of } C_B \text{ and } \theta(F_{Ai}, p) = \xi(F_{Ai}) \}$, and $p(F_{Ai})$ be the point p in $V(F_{Ai})$ with the smallest polar angle $\gamma_B(p)$. For each critical external face F_{Ai} , we can uniquely define a face $F(e_{Ai}, p(F_{Ai}))$. Let $F_A = \{ F(e_{Ai}, p(F_{Ai})) \mid F_{Ai} \text{ is a critical external face of } CH(A) \}$, be the set of new faces of $CH(A \cup B)$ that share edges of critical external faces of $CH(A)$. Similarly, we can define $P(e_{Bi}, p)$, $\theta(F_{Bi}, p)$, $V(F_{Bi})$ and $p(F_{Bi})$ for each critical external face F_{Bi} of $CH(B)$ by interchanging "A" and "B" in their corresponding definitions for critical external faces F_{Ai} of $CH(A)$. Then, we can obtain a set F_B of external faces of $CH(A \cup B)$. It is easy to verify that the faces in $F_A \cup F_B$ form a set of new faces of $CH(A \cup B)$. We are ready to present the procedure for generating the new faces of $CH(A \cup B)$. The following procedure generates new faces which share marked edges of critical external faces of $CH(A)$.

procedure NEW_FACE_A

Input : Faces of $CH(A)$ and $CH(B)$ stored in the LP 's of row 0 of $MOT(\log_2 N/2, 0)$ and $MOT(\log_2 N/2, 1)$, respectively, with edges of the critical external faces shared by the internal faces marked.

Output : Original faces of $CH(A)$ and $CH(B)$ remain where they were, and new faces of $CH(A \cup B)$ sharing edges with external faces of $CH(A)$ are generated and stored in $LP_{0,0}, \dots, LP_{0,N/2-1}$.

begin

Find o'_B for the marked edges stored in row 0 of $MOT(\log_2 N/2, 1)$.

for $j \geq N/2$ **do in parallel**

 Compute $\gamma_B(p)$ for the representative point p of each of the critical external face of $CH(B)$ stored in row 0 of $MOT(\log_2 N/2, 1)$, using coordinate system Σ_B ;

endfor

Use procedure *MULTI_CAST* to distribute all faces stored in row 0 of the mesh of trees to all *LP*'s such that each *LP_{i,j}*, $i \neq j$, contains faces $F_{0,i,1}$, $F_{0,i,2}$, $F_{0,j,1}$, and $F_{0,j,2}$;

for all *LP_{i,j}* do in parallel

if $i < N/2$ and $j \geq N/2$ then

begin

if $F_{0,i,1}$ and $F_{0,j,1}$ are both critical external faces then

Use the marked edge $e_{0,i,1}$ of $F_{0,i,1}$ and the representative point $p_{0,j,1}$ of $F_{0,j,1}$ to compute $\theta(e_{0,i,1}, p_{0,j,1})$ and create a triangular face $F'_{i,j}(1) = F(e_{0,i,1}, p_{0,j,1})$;

if $F_{0,i,1}$ and $F_{0,j,2}$ are both critical external faces then

Use the marked edge $e_{0,i,1}$ of $F_{0,i,1}$ and the representative point $p_{0,j,2}$ of $F_{0,j,2}$ to compute $\theta(e_{0,i,1}, p_{0,j,2})$ and create a triangular face $F'_{i,j}(2) = F(e_{0,i,1}, p_{0,j,2})$;

end

if $j < N/2$ and $i \geq N/2$ then

begin

if $F_{0,i,2}$ and $F_{0,j,1}$ are both critical external faces then

Use the marked edge $e_{0,i,2}$ of $F_{0,i,2}$ and the representative point $p_{0,j,1}$ of $F_{0,j,1}$ to compute $\theta(e_{0,i,2}, p_{0,j,1})$ and create a triangular face $F''_{i,j}(1) = F(e_{0,i,2}, p_{0,j,1})$;

if $F_{0,i,2}$ and $F_{0,j,2}$ are both critical external faces then

Use the marked edge $e_{0,i,2}$ of $F_{0,i,2}$ and the representative point $p_{0,j,2}$ of

$F_{0,j,2}$ to compute $\theta(e_{0,i,2}, p_{0,j,1})$ and create a triangular face $F''_{i,j}(2) = F(e_{0,i,2}, p_{0,j,2})$;

end

endfor

for $0 \leq j < N$ do in parallel

Use *MAX_R* operation on row j to find the face F' whose θ value is the maximum among all newly created faces F' (if exists), and if there is more than one such face, find the one with the largest γ_B value; put this face in RP_j^r ;

Use *RTL_R* and *LTL_C* to route this face to $LP_{0,j}$ and set its *extn* to 1;

Use *MAX_C* operation on column j to find the face whose θ value is the maximum among all newly created faces F'' (if exists), and if there is more than one such face, find the one with the largest γ_B value; put this face in RP_j^c ;

Use *RTL_C* and *LTL_R* to route this face to $LP_{0,j}$ and set its *extn* to 1;

endfor

end NEW_FACE_A

The time complexity of procedure *NEW_FACE_A* is obviously $O(\log N)$. Procedure *NEW_FACE_B* is similar to *NEW_FACE_A*.

3.3.3.4 Load Balancing Operations

After creating new faces, we have to remove internal faces in $CH(A)$ and $CH(B)$ by the procedure *NEW_FACE*. We know that each $LP_{0,j}$ in row 0 contains at most four faces: at most two original faces from either $CH(A)$ or $CH(B)$, and at most two

new faces of $CH(A \cup B)$. However, we know that there are at most $2 \times (|A| + |B|) - 4$ faces in $CH(A \cup B)$. The objective of the rebalancing operations is to enforce each processor $LP_{0,j}$ to contain at most two faces of $CH(A \cup B)$. This is the invariant required for the recursive algorithm *CONVEX_HULL* to operate correctly and efficiently. The technique used is the classical parallel packing method.

There are basically two types of packing problems, *down-packing* and *up-packing*. The down-packing problem is defined as follows. Consider a linear array such that each of its entry contains either one or no data item. The task of down-packing is to move data items from entries of high indices to entries of low indices in such a way that all data items are in consecutive entries, each of these low-indexed entries contains one item, and the relative order of the items is unchanged. The up-packing is similar to the down-packing; except for the direction of data movement. Consider how to perform down-packing on the LP 's in row 0 of the mesh of trees. Let each $LP_{0,j}$ have a flag $f_{0,j}$, which has value 1 if it has a data item to be packed, or 0, otherwise. The following procedure is used to compute the prefix sums of the $f_{0,j}$'s for all $LP_{0,j}$'s.

procedure PREFIX

begin

for $0 \leq j \leq N-1$ **do in parallel**

 Use *LTR* to send $f_{0,j}$ from $LP_{0,j}$ to the root RP_j^c of column j ;

 Use *BROADCAST_C* to broadcast $f_{0,j}$ to all LP 's in column j ;

 Perform *SUM_R* to compute the partial sum $prefix_{0,j} = \sum_{k=0}^j f_{0,k}$'s in row j , and

 store $prefix_{0,j}$ in RP_j^r , the root of row j ;

Use *RTL_R* and *LTL_C* operations to route $prefix_{0,j}$ from RP_j^r to $LP_{0,j}$;
endfor
end PREFIX

With procedure *PREFIX* at disposal, the down-packing algorithm is simple.

procedure DOWN_PACK
begin
 Use *PREFIX* to compute $prefix_{0,j}$ for all $LP_{0,j}$'s, the *LP*'s in row 0;
for all $LP_{0,j}$ **do in parallel**
 $dest_{0,j} := prefix_{0,j} - 1$;
endfor
for $0 \leq j \leq N-1$ **do in parallel**
 Use *LTR*, *RTL*, *LTR* and *RTL* operations to route $data_{0,j}$ from $LP_{0,j}$ to RP_j^c ,
 then to $LP_{j,dest_{0,j}}$, then to $RP_{dest_{0,j}}$, then to $LP_{0,dest_{0,j}}$;
endfor
end DOWN_PACK

Similarly, we can define procedures *POSTFIX* and *UP_PACK*. Clearly, procedures *DOWN_PACK* and *UP_PACK* require $O(\log N)$ time. The rebalancing algorithm, which has time complexity $O(\log N)$, is as follows.

procedure REBALANCE

Input : Faces of $CH(A)$, $CH(B)$ and new faces of $CH(A \cup B)$ stored in the *LP*'s in row 0 of the *MOT* and each of these *LP*'s contains at most four faces.
Output : Faces of $CH(A \cup B)$ are stored in the *LP*'s in row 0 of the *MOT* and each of these *LP*'s contains at most two faces.

begin

for all $LP_{0,j}$, $0 \leq j \leq N-1$ **do in parallel**

Remove all faces in $LP_{0,j}$ whose *extn* is equal to 0;

if there are k faces in $LP_{0,j}$ whose *extn*'s are equal to 1 **then**

Label them f_1, \dots, f_k , respectively (* $k \leq 4$ *);

endfor

Use *SUM_R* operations on *LP*'s in row 0 to compute the numbers N_l , $1 \leq l \leq 4$,

where N_l is the total number of faces labeled f_l in all *LP*'s of row 0 (* Note:

$N_1 \geq N_2 \geq N_3 \geq N_4$, and $\sum_{l=1}^4 N_l \leq 2N - 4$ *);

Use *DOWN_PACK* to pack all faces labeled f_1 in all $LP_{0,j}$'s;

Use *UP_PACK* to pack all faces labeled f_2 in all $LP_{0,j}$;

Use *DOWN_PACK* to pack all faces labeled f_3 in all $LP_{0,j}$'s;

Use *UP_PACK* to pack all faces labeled f_4 in all $LP_{0,j}$'s;

if $N_1 + N_2 > N$ **then**

begin

Use a modified *DOWN_PACK* procedure to pack all faces labeled f_4 in all $LP_{0,j}$'s to consecutive $LP_{0,j}$'s starting from LP_{0, N_3} ;

Use *UP_PACK* to pack all faces labeled f_2 in all $LP_{0,j}$'s that contains a face labeled f_1 and a face labeled f_2 ;

end

end REBALANCE

If $N_1 + N_2 > N$, then after four packing operations, some $LP_{0,j}$'s may still contain more than two faces. Using a procedure similar to *DOWN_PACK*, we can move all faces labeled f_4 "downward" so that each of the first N_3 $LP_{0,j}$'s contains exactly one face labeled f_3 , and the next N_4 $LP_{0,j}$'s contain exactly one face labeled f_4 . Then, by up-packing the faces labeled f_2 in those $LP_{0,j}$'s that contain a f_1 -labeled face and a f_2 -labeled face all the way "upward", each $LP_{0,j}$ is guaranteed to contain no more than two external faces of $CH(A \cup B)$.

3.3.3.5 Analysis of Time Complexity

Based on the fact that each of the procedures *CHECKFACE*, *CRITICAL_FACE*, *NEW_FACE* and *REBALANCE*, takes $O(\log N)$ time on the $N \times N$ mesh of trees, the complexity of *MERGE* is also $O(\log N)$. Since there are $\log N$ merging levels, we have the following results.

Theorem 1: For any set S of N points in E^3 , with no more than three points in the same plane, the convex hull $CH(S)$ can be computed on the $N \times N$ mesh of trees in $O(\log^2 N)$ time.

By lemma 1, we have

Theorem 2: For a set S of N points in E^2 , the Voronoi diagram of S can be computed on the $N \times N$ mesh of trees in $O(\log^2 N)$ time. More specifically, the algorithm *VORONOI* of section 3.2.3 can be implemented on the $N \times N$ mesh of trees in $O(\log^2 N)$ time.

3.3.3.6 Generalizations of the Convex Hull Algorithm

The assumption in Theorem 1 that there are no more than three points of S in the same plane is important. If there are more than three points of S in the same plane, triangularity of faces of $CH(S)$ may no longer hold. For any convex hull $CH(S)$ of any point set S in E^3 , one can always triangulate each face of $CH(S)$ into triangles to obtain a convex hull such that each of its face is a triangle. We call such a convex hull as a *triangulated convex hull* of S . By slightly modifying the second step of algorithm *CONVEX_HULL*, i.e. the step of computing convex hulls of four points in all 2×2 sub-*MOT*, a triangulated convex hull can be constructed. Then, without changing the rest of the algorithm *CONVEX_HULL*, a triangulated convex hull of any point set S can be computed. Hence, we have a collorary of theorem 1.

Corollary 1: For any set S of N points in E^3 , the triangulated convex hull of S can be computed on the $N \times N$ mesh of trees in $O(\log^2 N)$ time.

If in the process of procedure *MERGE*, associated with each triangle face $F_{0,j,k}$, $k = 1, 2$, we always keep its three adjacent faces, then after the triangulated convex hull is obtained, for all processor $L_{0,j}$ we perform a parallel step to mark the edges of $F_{0,j,k}$ shared by its adjacent face that are in the same plane containing $F_{0,j,k}$, and use a pair of *MULTI_CAST* and *MULTI_COLLECT* operations to eliminate all marked edges, then we obtain the set of all edges that bound the faces of $CH(S)$. Therefore, we have the following generalization of theorem 1.

Theorem 3: The convex hull of any set S of N points in E^3 can be computed on the $N \times N$ mesh of trees in $O(\log^2 N)$ time.

3.4 Discussions

We presented efficient algorithms for constructing the Voronoi diagram of a set of N points in E^2 and constructing the convex hull of a set of N points in E^3 . Both algorithms require $O(\log^2 N)$ time. Our algorithms are the fastest NC algorithms ever known for constructing planar Voronoi diagrams and three-dimensional convex hulls. Our Voronoi diagram algorithm can easily be converted into an $O(\log^2 N)$ -time algorithm for constructing the Delaunay triangulation of a set N planar points.

The Voronoi diagram considered in this chapter is commonly called planar nearest point Voronoi diagram. There are many variations of the Voronoi diagram. For example, the planar farthest point Voronoi diagram of a set S of points in the plane is the polygonal division of the plane, each region V_i is the locus of points that is farther from p_i than from other points in S . Based on the sequential algorithm given in [B79] and our convex hull algorithm, the planar farthest point Voronoi diagram of N points can also be constructed in $O(\log^2 N)$ time on the $N \times N$ mesh of trees.

Finding efficient parallel algorithms for constructing Voronoi diagrams of higher dimensions may be interesting. It remains open whether or not the general method, proposed in [B79], of reducing the problem of constructing the k -dimensional Voronoi diagram to the problem of constructing $(k + 1)$ -dimensional convex hull is suitable for efficient parallelization.

Chapter 4

The Congruent Patterns

4.1 Introduction

Two planar patterns P_1 and P_2 are congruent if their corresponding boundary edges (e.g. edge e_i in P_1 and edge e_j in P_2) are of equal length and the corresponding interior angles (e.g. interior angle θ_i in P_1 and interior angle θ_j in P_2) between any pair of adjacent boundary edges are also equal. Finding congruent patterns arises frequently in computer-aided design (CAD), image analysis, pattern recognition, and computer vision. Given a test pattern P which is a simple polygon with k edges, and a planar straight-line graph (PSLG) G with n edges, where $k \leq n$, the *congruent pattern problem* is to locate all the cycles in G which are congruent to P .

A *test pattern* P is a simple polygon which is used as a prototype for the congruence problem. Because P is a simple polygon, it has the same number of vertices and edges. We denote the test pattern as $P = \{V_p, E_p\}$, where the vertex set $V_p = \{v_{p,1}, v_{p,2}, v_{p,3}, \dots, v_{p,k}\}$ and the edge set $E_p = \{e_{p,1}, e_{p,2}, e_{p,3}, \dots, e_{p,k}\}$. Here, k is the number of vertices and edges of P , respectively. We assign the indices of V_p and E_p in clockwise order and denote $e_{p,i}$ as the edge between $v_{p,i}$ and $v_{p,i+1}$. If $i = k$ then set $i + 1 = 1$. We also denote the *interior angle* at vertex $v_{p,i}$ as $\theta_{p,i}$, and the set of interior angles as Θ_p .

A *planar straight-line graph* (PSLG) is a planar graph whose edges are all straight-line segments. We denote the PSLG as $G = \{V_g, E_g\}$, where the vertex set V_g

$= \{v_{g,1}, v_{g,2}, v_{g,3}, \dots, v_{g,m}\}$ and the edge set $E_g = \{e_{g,1}, e_{g,2}, \dots, e_{g,n}\}$. Here, m and n are the number of vertices and edges of G , respectively. According to the classical *Euler's formula*, we know that $m \leq n$. A test pattern and a PSLG are shown in Figure 4.1.

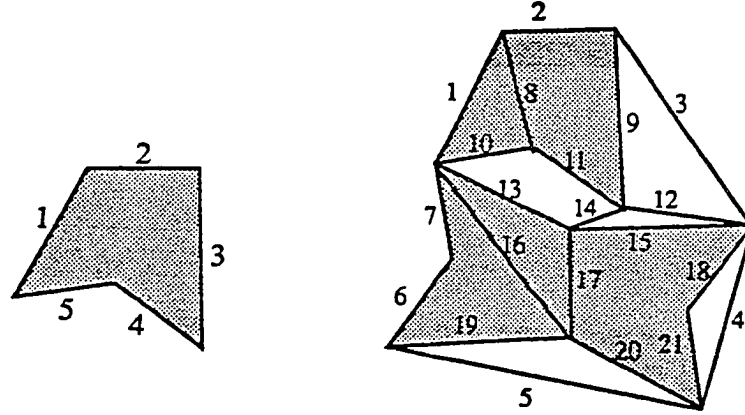


Fig. 4.1 A test pattern P and a PSLG with 3 patterns congruent to P .

There are some previous papers that discuss the congruence problem. In 1984, Sugihara described a sequential algorithm for determining whether two polyhedra are congruent or not. The asymptotic time complexity of this algorithm is bounded by $O(n \log n)$, where n is the number of edges of the polyhedra [S84]. In 1987, Atkinson developed a sequential algorithm for determining all the Euclidean congruences between two n -point sets in 3-dimensional space. The time complexity of this algorithm is $O(n \log n)$ which is optimal [A87]. In 1990, Shih, Lee and Yang developed an $O(n^2)$ parallel algorithm for finding the congruent patterns P in a PSLG on shared memory model with k PEs and $O(kn)$ memory, where n and k are the number of edges in G and P respectively [SLY90]. In 1992, Jeong, Kim and Baek presented another parallel algorithm to solve the same problem on SIMD machine. Their algorithm takes $O(\log n \log \log n)$ time if each edge in the test pattern has unique length; otherwise in $O(k \log n \log \log n)$ time, where k is the number of patterns [JKB92].

In this chapter, we present an $O(k \log n)$ -time parallel algorithm for reporting all the patterns in G which are congruent to P on an $n \times n$ mesh of trees. The structure of mesh of trees and all the operations of data communications in this chapter, such as $RTL_R(i, j)$, $LTR_R(i, j)$, $LTL_R(i, j, k)$, $AND_R(i)$, and $BROADCAST_R(i)$, have been defined in section 3.2.2. Our algorithm determines the congruent patterns by considering all cases of whether edges in G or P are distinct or not. On the other hand, if G and P are polyhydra and are projected on a two dimensional plane then our algorithm with slight modification, may also be able to report the congruent patterns in G and its time complexity is still $O(\log n)$. This chapter is organized as follows. In section 4.2, we present a mesh of trees algorithm to solve the congruent pattern problem. We also analyze the time complexity for each subalgorithm and the main algorithm. Finally, we present conclusion in section 4.3.

4.2 Finding Congruent Patterns on a Mesh of Trees

Since our test pattern P is a simple polygon, to find a pattern in G congruent to P is just to find a *cycle* which congruent to P . A *cycle* in a graph is a *path* in which the origin and destination vertices are the same. There are three key points we have to check for finding congruent cycle (denoted as C , i.e. a pattern) in G . (1) Each edge in C should be equal to its corresponding edge in P . (2) Each interior angle between any two adjacent edges in C should be equal to its corresponding interior angle in P . (3) The turning direction between any two adjacent edges in C should be equal to its corresponding turning direction in P . Besides, different edge length between P and G will generate different amount of congruent patterns. For this property, we need to consider the following four cases :

Case 1 : P has some equal-length edges, but G has distinct edges;

Case 2 : P and G have distinct edges, respectively;

Case 3 : G has some equal-length edges, but P has distinct edges;

Case 4 : P and G have some equal-length edges, respectively.

Lemma 4.1 : If the test pattern P has equal-length edges, but G has no equal-length edges, then there is no any pattern in G congruent to P.

Proof : Assume there is at least one pattern in G congruent to P, then the congruent pattern in G would have equal-length edges because there are equal-length edges in P.

A contradiction. □

Lemma 4.2 : If P and G have distinct edges respectively, then there is zero or only one pattern in G congruent to P.

Proof : Assume that more than one congruent patterns can be found in G, then each pair of corresponding edges in these patterns is equal. Therefore, G will have some edges with equal length. This is a contradiction. So we conclude that there is zero or only one congruent pattern can be found in G. □

Lemma 4.3 : If G has equal-length edges, but P has distinct edges, then there are zero, one, or more patterns in G congruent to P.

Proof : Assume there is no more than one congruent pattern in G, then according to Lemma 4.2, we know that there are no equal-length edges in G. A contradiction. Since it is possible to form more congruent patterns by using those equal-length edges as the common edges between any two adjacent or overlapping congruent patterns. □

Lemma 4.4 : If G has equal-length edges, and P also has equal-length edges, then there are zero, one, or more patterns in G congruent to P .

Proof : The proof is same as Lemma 4.3, because the congruent pattern number in G is independent of the edge-length equality in E_p of P . □

In this section, we first develop two procedures to perform the initial operations on P and G , respectively. Then, we develop two other procedures to check the length equality in E_p and E_g , respectively. In section 4.2.3, we discuss *Case 1* and *Case 2*, and develop a procedure to find single pattern. In section 4.2.4, we discuss *Case 3* and *Case 4*, and develop another procedure to find multiple patterns. Finally, by calling the procedures in sections 4.2.1 to 4.2.4, we develop the main algorithm to find all congruent patterns in section 4.2.5.

4.2.1 Preprocessing

In order to modularize our algorithm, we have to do some initial operations. For test pattern P , first, we broadcast $e_{p,1}$ (the two end-points $v_{p,1}$ and $v_{p,2}$ of the starting edge) to all LP 's of the $k \times n$ MOT, and compute its length. Next, we broadcast $e_{p,i}$ (its two end-points, $v_{p,i}$ and $v_{p,i+1}$) to all LP 's in row i , for $2 \leq i \leq k$. Finally, we compute the *relative route* of $e_{p,i}$, denoted as $RR_{p,i}$, in each LP from row 2 to row k .

The relative route of $e_{p,i}$ contains $e_{p,1}$ and its length, $e_{p,i}$ and its length, the *bridge* between $e_{p,1}$ and $e_{p,i}$, denoted as $b_{p,i}$, the interior angle between $e_{p,1}$ and bridge, denoted as $\alpha_{p,i}$, and the interior angle between bridge and $e_{p,i}$, denoted as $\beta_{p,i}$. That is,

$$RR_{p,i} = (e_{p,1}, \alpha_{p,i}, b_{p,i}, \beta_{p,i}, e_{p,i}).$$

Note :

1. Bridge $b_{p,i}$ connects $v_{p,2}$ and $v_{p,i}$.
2. The turning directions of first-edge and bridge, and bridge and second-edge are all clockwise.
3. In $RR_{p,2}$, there is no bridge and $\alpha_{p,2} = \beta_{p,2}$ because $e_{p,1}$ and $e_{p,2}$ are connective edges.
4. $e_{p,2}$ is the bridge of $RR_{p,3}$.

A relative path of $e_{p,i}$ is shown in Figure 4.2. For the initial operations of P we develop a procedure as follows.

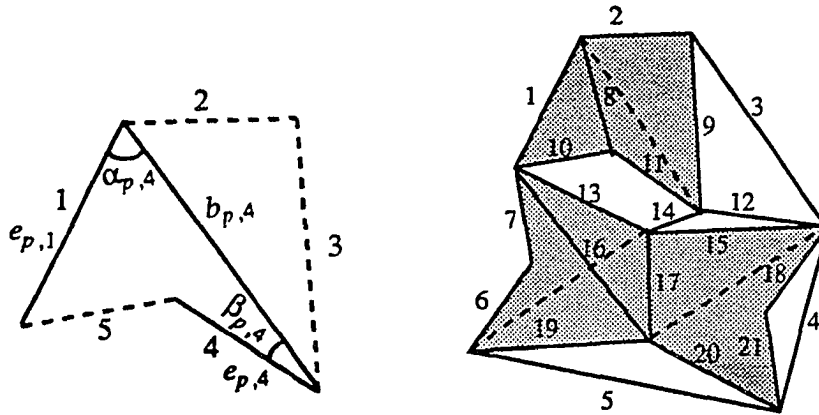


Fig. 4.2 Using $RR_{p,4}$ in P to compute $RR_{g,6}$, $RR_{g,11}$, and $RR_{g,18}$ in G.

Procedure INITIALIZE_P;

Input : The edge set E_p with k edges in P. Each edge is denoted by the coordinate values of its two end-points in the plane. These edges have been arranged in clockwise order previously.

Output : 1. Each $LP_{1,j}$ (in the first row) stores $e_{p,1}$ and its length.

2. From row 2 to row k , each $LP_{i,j}$ stores $RR_{p,i}$ (the relative route of $e_{p,i}$).

begin

(1) At first, assume the two end-vertices ($v_{p,1}$ and $v_{p,2}$) of $e_{p,1}$ are loaded to the root

processor RP_i^r in row i , for $1 \leq i \leq k$;

(2) **for** $1 \leq i \leq k$ **do in parallel**

Use $BROADCAST_R(i)$ to broadcast $v_{p,1}$ and $v_{p,2}$ in RP_i^r to all LP 's in row i ;

endfor;

(3) Then, assume the two end-vertices of $e_{p,i}$ ($v_{p,i}$ and $v_{p,i+1}$) are loaded to the root

processor RP_i^r in row i , for $2 \leq i \leq k$, if $i=k$ then set $i+1=1$;

(4) **for** $2 \leq i \leq k$ **do in parallel**

Use $BROADCAST_R(i)$ to broadcast $v_{p,i}$ and $v_{p,i+1}$ in RP_i^r to all LP 's in row i ;

endfor;

(5) **for** $1 \leq i \leq k$ and $1 \leq j \leq n$ **do in parallel**

Each $LP_{i,j}$ computes the length of $e_{p,1}$ by its two end-points $v_{p,1}$ and $v_{p,2}$;

endfor;

(6) **for** $2 \leq i \leq k$ and $1 \leq j \leq n$ **do in parallel**

Each $LP_{i,j}$ computes the record $RR_{p,i}$ by the two end-points $v_{p,1}$ and $v_{p,2}$ and

the two end-points $v_{p,i}$ and $v_{p,i+1}$;

endfor;

end of INITIALIZE_P;

Steps (2) and (4) need $O(\log n)$ time, while other steps take constant time. Therefore, the time complexity for procedure $INITIALIZE_P$ is $O(\log n)$. After executing procedure $INITIALIZE_P$, each LP in row i ($1 \leq i \leq k$) stores the length value of $e_{p,1}$, and each LP in row j stores the record $RR_{p,j}$, for $2 \leq j \leq k$.

For the initial operations of planar graph G , first, we broadcast $e_{g,j}$ to all LP 's in column j , for $1 \leq j \leq n$, and each column has k LP 's. Then compute the length of $e_{g,j}$ in each LP . The procedure is given below.

Procedure *INITIALIZE_G*;

Input : The edge set E_g with n edges in planar graph G . Each edge is denoted by the coordinate values of its two end-points in the plane.

Output : Each $LP_{i,j}$ (in the same column) stores the vertices $v_{g,j}$ and $v_{g,j+1}$ and the length of $e_{g,j}$ between them.

begin

(1) At first, assume each edge (say $e_{g,j}$) and its two end-points (e.g. $v_{g,h}$ and $v_{g,i}$) in G is randomly loaded to the root processor RP_j^c in column j , for $1 \leq j \leq n$;

(2) **for** $1 \leq i, j \leq n$ **do in parallel**

Use *BROADCAST_C(j)* to broadcast each vertex pair in RP_j^c to all $LP_{i,j}$'s in column j ;

endfor;

(3) **for** $1 \leq i, j \leq n$ **do in parallel**

Each $LP_{i,j}$ computes the length of edge $e_{g,j}$ with end-points $v_{g,h}$ and $v_{g,i}$;

endfor;

end of *INITIALIZE_G*;

In this procedure, step (2) takes $O(\log n)$ time, but other steps need only constant time. Hence, the time complexity for procedure *INITIALIZE_G* is $O(\log n)$. After P and G are initialized, the information stored in each LP are shown in Figure 4.3.

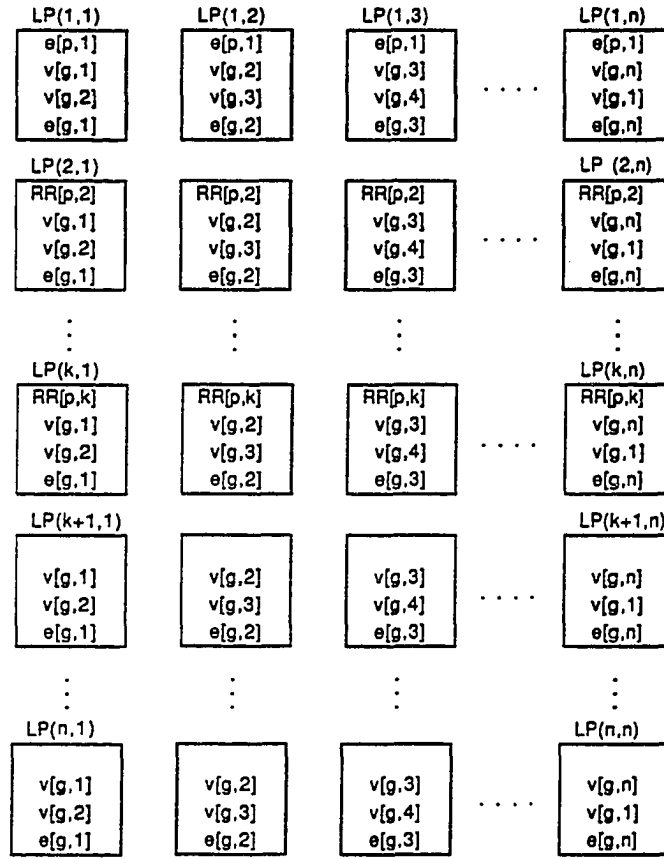


Fig. 4.3 Information stored in the $n \times n$ MOT after P and G are initialized.

4.2.2 Checking Edge-Length Equality of P and G

After invoking the initial operations on P and G, for the computing convenience of our main algorithm, we have to check the edge-length equality for the edge sets E_p and E_g , respectively, and return the result to the main algorithm. The length of an edge is the *distance* between its two end-points. To check the edge-length equality of P and G, we assume that the initial operations of P and G have been done by procedures *INITIALIZE_P* and *INITIALIZE_G*, respectively. Then, for test pattern P, we develop the procedure *CHECK_P_LENGTH* to check whether there are equal-length

edges in P or not, and return the result (a TRUE/FALSE flag) to the root processor of column 1. Similarly, for planar graph G , we develop the procedure *CHECK_G_LENGTH* to check whether there are equal-length edges in G or not, and return the result to the root processor of row 1. Procedure *CHECK_P_LENGTH* is shown below.

procedure *CHECK_P_LENGTH*;

Input : The edge lengths of $e_{p,i}$ in $RP_{i,i}$, for $1 \leq i \leq k$, which are computed in procedure *INITIALIZE_P*;

Output : The final logic value of edge-length flag EL_p in RP_1^c ;

begin

(1) **for** $1 \leq i \leq k$ **do in parallel**

 Use *BROADCAST_C*(i) to broadcast $e_{p,i}$ in $LP_{i,i}$ to all LP 's in column i ;

endfor;

(2) **for** $1 \leq i \leq k$ and $1 \leq j \leq n$ **do in parallel**

 (* Each $LP_{i,j}$, $i \neq j$, compares the length of $e_{p,i}$ and $e_{p,j}$. *)

if $|e_{p,i}| = |e_{p,j}|$ **then** set $EL_{i,j} = \text{TRUE}$ **else** set $EL_{i,j} = \text{FALSE}$;

endfor;

(3) **for** $1 \leq i \leq k$ **do in parallel**

 Use global *AND_R*(i) operation to do the logic AND function for each flag $EL_{i,j}$ in each LP of row i ;

endfor; (* The ANDed result in each row is censused up to RP_i^r in row i . *)

(4) **for** $1 \leq i \leq k$ **do in parallel**

 Use *RTL_R*(i) operation to route the ANDed value of $EL_{i,j}$ in RP_i^r to its left-most leaf processor $LP_{i,1}$;

endfor;

(* After this step, all ANDed $EL_{i,j}$ values are routed to all LP 's in column 1. *)

(5) Use global $AND_C(i)$ operation to do the logic AND function for each flag $EL_{i,j}$ in each LP of column 1 and store the final value as EL_p in RP_1^c ;

(* The final ANDed value of EL_p is censused up to RP_1^c in column 1. *)

end of CHECK_P_LENGTH;

Step (2) in this procedure needs only constant time, while each of the other steps needs $O(\log n)$ time. Thus, the time complexity for procedure $CHECK_P_LENGTH$ is $O(\log n)$. The procedure $CHECK_G_LENGTH$ is shown below.

procedure CHECK_G_LENGTH;

Input : The edge length of $e_{g,j}$ in each $LP_{i,j}$ of the $n \times n$ MOT after executing procedure $INITIALIZE_G$;

Output : The final logic value of edge-length flag EL_g in RP_1^c ;

begin

(1) **for** $1 \leq j \leq n$ **do in parallel**

Use $BROADCAST_R(j)$ to broadcast $e_{g,j}$ in $LP_{j,j}$ to all LP 's in row j ;

endfor;

(2) **for** $1 \leq i \leq n$ and $1 \leq j \leq n$ **do in parallel**

(* Each $LP_{i,j}$, $i \neq j$, compares the length of $e_{g,i}$ and $e_{g,j}$. *)

if $|e_{g,i}| = |e_{g,j}|$ **then** set $EL_{i,j} = \text{TRUE}$ **else** set $EL_{i,j} = \text{FALSE}$;

endfor;

(3) **for** $1 \leq j \leq n$ **do in parallel**

Use global $AND_C(j)$ operation to do the logic AND function for each flag $EL_{i,j}$ in each LP of column j ;

endfor;

(* Note : The ANDed result in each column is censused up to the root processor RP_j^c in column j . *)

(4) **for** $1 \leq j \leq n$ **do in parallel**

Use $RTL_C(j)$ operation to route the final ANDed value of $EL_{i,j}$ in RP_j^c to its uppermost leaf processor $LP_{1,j}$;

endfor;

(* After this step, all the ANDed $EL_{i,j}$ values are routed to all LP 's in row 1. *)

(5) Use global $AND_R(i)$ operation to do the logic AND function for each flag $EL_{i,j}$ in each LP of row 1 and store the final value as EL_g in RP_1^r ;

(* The final ANDed value of EL_g is censused up to the root processor RP_1^r in row 1. *)

end of $CHECK_G_LENGTH$;

Step (2) needs only constant time, but each of the other steps needs $O(\log n)$ time. So the time complexity of procedure $CHECK_G_LENGTH$ is $O(\log n)$.

4.2.3 Finding Single Congruent Pattern

To find congruent patterns efficiently, we have to analyze the properties of length equality of P and G (i.e. *Case 1* to *Case 4*). For *Case 1*, we know P has equal-length edges but all edges in G are distinct. Obviously, it is impossible to find any congruent patterns in G . Thus, we simply report the message "No congruent patterns found." In

Case 2, all edges in P and G are distinct, respectively. There can be at most one congruent pattern in G . For this case, we develop a procedure *SINGLE_PATTERN* to find the congruent pattern. We will discuss *Case 3* and *Case 4* in the next section.

procedure *SINGLE_PATTERN*;

Input : The outputs from procedures *INITIALIZE_P* and *INITIALIZE_G*;

Output : The congruent pattern in G for *Case 2*;

begin

(1) **for** $1 \leq i \leq k$ and $1 \leq j \leq n$ **do in parallel**

begin

(* Each $LP_{i,j}$ compares the length of $e_{p,i}$ and $e_{g,j}$ which are computed in *INITIALIZE_P* and *INITIALIZE_G* respectively. *)

if $|e_{p,i}| = |e_{g,j}|$ **then** $EQ = \text{TRUE}$ **else** $EQ = \text{FALSE}$;

if $|e_{p,1}| = |e_{g,j}|$ **then** set starting edge $e_{g,s} = e_{g,j}$ and set $ss = j$ in $LP_{1,j}$;

(* EQ is the flag for indicating whether the two edges are equal or not. *)

(* starting edge $e_{g,s}$ is the first edge of a congruent pattern in G . *)

(* ss is the index of the starting edge of the congruent pattern in G . *)

end;

endfor;

(2) **for** $2 \leq i \leq k$ and $1 \leq j \leq n$ **do in parallel**

if $LP_{i,j}$ with $EQ = \text{TRUE}$

then use the record $RR_{p,i}$ as the reference, to compute $RR_{g,j1}$ and $RR_{g,j2}$,

and find the starting edges $e_{g,s1}$ and $e_{g,s2}$;

endfor;

(* Refer Figure 4.2 on page 76 and the comments at the end of this procedure. *)

(3) for $1 \leq i \leq k$ and $1 \leq j \leq n$ do in parallel

Use $LTR_R(i, j)$ and $BROADCAST_R(i)$ operations to broadcast the starting edge $e_{g,s}$ and index ss in $LP_{1,ss}$ (with $EQ = TRUE$), to all $LP_{i,j}$'s;

endfor;

(4) for $1 \leq i \leq k$ and $1 \leq j \leq n$ do in parallel

if $LP_{i,j}$ with $EQ = TRUE$ and $e_{g,s1} \neq e_{g,s}$ and $e_{g,s2} \neq e_{g,s}$

then set $EQ = FALSE$;

endfor;

(5) for $1 \leq i \leq k$ and $1 \leq j \leq n$ do in parallel

if $LP_{i,j}$ with $EQ = TRUE$

then use LTL and LTR operations to send 1 and $e_{g,j}$ to RP_{ss}^c ;

endfor;

(6) RP_{ss}^c computes the sum S of all 1's received from step (5);

(7) if $S = k$ then RP_{ss}^c outputs all the edges, $e_{g,j}$, received from step (5);

(* These edges form a congruent pattern. *)

else print "No congruent pattern found.";

end of $SINGLE_PATTERN$;

(* Comments of step (2) :**

To compute $RR_{g,j}$, we have to consider the following two conditions. Assume $v_{g,j1}$ and $v_{g,j2}$ are the two end-points of $e_{g,j}$.

1. Use $v_{g,j1}$ as the common vertex of $e_{g,j}$ and $b_{g,j}$ to compute $RR_{g,j1}$ and find $e_{g,s1}$.
2. Use $v_{g,j2}$ as the common vertex of $e_{g,j}$ and $b_{g,j}$ to compute $RR_{g,j2}$ and find $e_{g,s2}$.

For computing the relative route $RR_{g,j}$, we also need to check the turning directions between $e_{g,s}$ and bridge $b_{g,j}$, and between $b_{g,j}$ and $e_{g,j}$, respectively. According to the property of $RR_{p,i}$, we know the above two turning directions should be all clockwise.

To check the turning direction between two connective edges, we have to compute the following determinant. If the value is negative then the turning direction is clockwise, otherwise the turning direction is counterclockwise.

For example, let (x_{i-1}, y_{i-1}) and (x_i, y_i) be the two end-points of $e_{g,s}$, and (x_i, y_i) and (x_{i+1}, y_{i+1}) are the two end-points of $b_{g,j}$, then

$$\Delta = \begin{bmatrix} x_{i-1} & y_{i-1} & 1 \\ x_i & y_i & 1 \\ x_{i+1} & y_{i+1} & 1 \end{bmatrix}$$

if $\Delta < 0$ then the turning direction between $e_{g,s}$ and $b_{g,j}$ is clockwise. ***)

For time complexity, steps (3) and (5) need $O(\log n)$ respectively, while other steps need constant time only. Therefore, the total time complexity of procedure *SINGLE_PATTERN* is $O(\log n)$.

4.2.4 Finding Multiple Congruent Patterns

For *Case 3*, G has equal-length edges but P has distinct edges. There can be 0, 1 or more congruent patterns in G and some pairs of them may be adjacent (i.e. have a common edge). For *Case 4*, both P and G have equal-length edges, respectively. We may also find 0, 1 or more congruent patterns in G , and some pairs of them may be adjacent or intersect each other. Hence, any edge in G may be a *common edge* of two adjacent or intersecting congruent patterns.

To find multiple patterns, first, we introduce some notations to distinguish different patterns in G . We use $ST1$ and $ST2$ to denote the starting edges of the first and second congruent pattern which $e_{g,j}$ belongs to, respectively. We also use flags $EQ1$ and $EQ2$ to denote that $e_{g,j}$ belongs to congruent pattern 1 and pattern 2, respectively.

Then, as in the procedure *SINGLE_PATTERN* in section 4.2.3, each LP also needs to parallel compare each edge pair $e_{p,i}$ and $e_{g,j}$, for $1 \leq i \leq k$ and $1 \leq j \leq n$, which are broadcasted by procedures *INITIALIZE_P* and *INITIALIZE_G*. If the pair of edges are of equal length, then set flags $EQ1$ and $EQ2$ to $TRUE$ and compute $ST1$ and $ST2$ by the $RR_{p,i}$ in this LP else set $EQ1$ and $EQ2$ to $FALSE$.

4.2.4.1. Checking the Existence of Starting Edges

Next, we have to check whether or not the two starting edges $ST1$ and $ST2$, in each LP , exist in G . For this step, we develop procedures *CHECK_EDGES_1* and *CHECK_EDGES_2* to parallel check all starting edges in *Case 3* and *Case 4*, respectively. If starting edge $ST1$ (or $ST2$) is in G , then store its index (order) in G (e.g. the j of $e_{g,j}$ in row 1) into this LP , else set $EQ1$ (or $EQ2$) to $FALSE$ (i.e. $ST1$ or $ST2$ is not an edge of G).

For *Case 3*, since all edges in P are distinct, after comparing the length of the edge pair $e_{p,i}$ and $e_{g,j}$ in each LP , we will find that only one pair of them is equal in the LP 's of each column. Therefore, for each column, procedure *CHECK_EDGES_1* needs to check starting edges only once. On the other hand, for *Case 4*, it is possible that one or more $(e_{p,i}, e_{g,j})$ pairs are equal in each column processors. In this case, for each column, procedure *CHECK_EDGES_2* needs to check starting edges k times. Procedures *CHECK_EDGES_1* and *CHECK_EDGES_2* are given below.

procedure *CHECK_EDGES_1*;

(* For *Case 3*, to check starting edges ST1 and ST2 in each *LP*, with EQ1 = TRUE and EQ2 = TRUE, are edges in *G* or not. *)

begin

(1) **for** $1 \leq i \leq n$ **do in parallel**

 Use *LTR_R*(*i*, *i*) and *BROADCAST_R*(*i*) operations to broadcast $e_{g,i}$ in $LP_{i,i}$
 to all the *LP*'s in row *i*;

endfor;

(2) **for** $1 \leq i \leq n$ and $1 \leq j \leq k$ **do in parallel**

if EQ1 = TRUE and EQ2 = TRUE in $LP_{i,j}$

then use *LTR_C*(*i*, *j*) and *BROADCAST_C*(*i*) operations to broadcast
 ST1, ST2, EQ1, EQ2, and their column index *y* (here, $y = j$) in
 $LP_{i,j}$ to all *LP*'s (from $LP_{1,r}$ to $LP_{n,r}$, for $1 \leq r \leq n$) in column *i*;

 (* Broadcast ST1, ST2, EQ1, EQ2, and *y* to all *n* *LP*s in same column. *)

 (* Note : in *Case 3*, in each column there is only one *LP* with EQ1 = TRUE and EQ2 = TRUE. Hence, this step only executes once. *)

endfor;

(3) **for** $1 \leq i \leq n$ and $1 \leq j \leq n$ **do in parallel**

if ST1 = $e_{g,i}$ in $LP_{i,j}$

then set EQ1 = TRUE and set $x1 = i$ **else** set EQ1 = FALSE;

if ST2 = $e_{g,i}$

then set EQ2 = TRUE and set $x2 = i$ **else** set EQ2 = FALSE;

endfor; (* $x1$ and $x2$ are row indices of the starting edges found. *)

(4) **for** $1 \leq i \leq n$ and $1 \leq j \leq n$ **do in parallel**

for each $LP_{i,j}$ **do the following steps in sequence**

 use $OR_C(j)$ operation to perform logic OR function for all EQ1 in
 each column j and send the final value to root processor RP_j^c ;

 then use $LTL_C(x1, y, j)$ operation to send EQ1 and $x1$ from $LP_{x1,j}$
 back to $LP_{y,j}$;

 use $OR_C(j)$ operation to perform logic OR function for all EQ2 in
 each column j and send the final value to root processor RP_j^c ;

 then use $LTL_C(x2, y, j)$ operation to send EQ2 and $x2$ from $LP_{x2,j}$
 back to $LP_{y,j}$;

endfor;

endfor;

end; (* of $CHECK_EDGES_1$ *)

(* All the operations of mesh of trees are defined in section 3.2.2. *)

(* After this step, the starting edge ST1 (and ST2) in each LP has been assigned an
index $x1$ (and $x2$) if its EQ1 (and EQ2) is updated to TRUE. *)

Steps (1), (2) and (4) take $O(\log n)$ time, while step (3) takes constant time, thus,
the total time complexity for $CHECK_EDGES_1$ is $O(\log n)$.

procedure $CHECK_EDGES_2$;

 (* For *Case 4*, to check starting edges ST1 and ST2 in each LP , with EQ1 = TRUE
 and EQ2 = TRUE, are edges in G or not. *)

begin

(1) **for** $1 \leq i \leq n$ **do in parallel**

Use $LTR_R(i, i)$ and $BROADCAST_R(i)$ operations to broadcast $e_{g,i}$ in $LP_{i,i}$ to all the LP 's in row i ;

endfor;

(2) **for** $1 \leq t \leq k$ **do** (* in sequence *)

(2.1) **for** $1 \leq i \leq n$ and $1 \leq j \leq n$ **do in parallel**

if $EQ1 = \text{TRUE}$ and $EQ2 = \text{TRUE}$ in $LP_{i,j}$

then use $LTR_C(i, j)$ and $BROADCAST_C(i)$ operations to broadcast $ST1$, $ST2$, $EQ1$, $EQ2$, and their column index y (here, $y = j$) in $LP_{i,j}$ to all LP 's in column i ;

endfor;

(* Broadcast $ST1$, $ST2$, $EQ1$, $EQ2$, and y to all n LP s in same column. *)

(* Note : in *Case 4*, in each column there are may be more than one LP with $EQ1 = \text{TRUE}$ and $EQ2 = \text{TRUE}$. Hence, this step has to be executed k times. *)

(2.2) **for** $1 \leq i \leq n$ and $1 \leq j \leq n$ **do in parallel**

if $ST1 = e_{g,i}$ in $LP_{i,j}$

then set $EQ1 = \text{TRUE}$ and set $x1 = i$ **else** set $EQ1 = \text{FALSE}$;

if $ST2 = e_{g,i}$

then set $EQ2 = \text{TRUE}$ and set $x2 = i$ **else** set $EQ2 = \text{FALSE}$;

endfor; (* $x1$ and $x2$ are row indices of the starting edges found. *)

(2.3) **for** $1 \leq i \leq n$ and $1 \leq j \leq n$ **do in parallel**

for each $LP_{i,j}$ **do** (* in sequence *)

use $OR_C(j)$ operation to perform logic OR function for all

```

        EQ1 in each column  $j$  and send the final value to root pro-
        cessor  $RP_j^c$ ;
        then use  $LTL\_C(x1, y, j)$  operation to send EQ1 and  $x1$ 
        from  $LP_{x1,j}$  back to  $LP_{y,j}$ ;
        use  $OR\_C(j)$  operation to perform logic OR function for all
        EQ2 in each column  $j$  and send the final value to root pro-
        cessor  $RP_j^c$ ;
        then use  $LTL\_C(x2, y, j)$  operation to send EQ2 and  $x2$ 
        from  $LP_{x2,j}$  back to  $LP_{y,j}$ ;

    endfor;

endfor;

endfor; (* end of step (2) *)

end; (* of CHECK_EDGES_2 *)

```

(* After this step, the starting edge ST1 (and ST2) in each LP has been assigned an index $x1$ (and $x2$) if its EQ1 (and EQ2) is updated to TRUE. *)

For time complexity, step (1) takes constant time, steps (2.1), (2.2) and (2.3) are same as steps (2), (3) and (4) in procedure *CHECK_EDGES_1*, respectively. In procedure *CHECK_EDGES_2*, step (2) executes k iterations. According the analysis of *CHECK_EDGES_1*, we know each iteration of step (2.1), (2.2) and (2.3) needs $O(\log n)$ time, hence, the total time complexity of *CHECK_EDGES_2* is $O(k \log n)$.

4.2.4.2 Counting Edge Number of Each Pattern

After check all starting edges, for each possible congruent pattern, we have to count the number (say S) of all edges (i.e. $e_{g,j}$) with same starting edge in G , respectively. If S equals k (the edge number of P), this means all these edges can form a congruent pattern, then output this congruent pattern, else ($S < k$) no pattern with this starting edge is found. For this step, we develop other two procedures *COUNT_EDGES_1* and *COUNT_EDGES_2* to count the edge number of each possible congruent pattern for *Case 3* and *Case 4*, respectively.

procedure *COUNT_EDGES_1*;

(* For *Case 3*, to send each group of edges in parallel, which may form a congruent pattern, to the *LP* in row 1 with the starting edge of this pattern. Since exactly only one congruent edge in each column, so one iteration to send edges is enough. *)

begin

for $1 \leq i \leq k$ and $1 \leq j \leq n$ **do in parallel**

begin (* in sequence *)

(1) The only $LP_{i,j}$ in each column with $EQ1 = \text{TRUE}$ sends 1 and its edge

$e_{g,j}$ from $LP_{i,j}$ to $LP_1, x1$ and stores in array $PA[ss, 1]$ by the fol-

lowing routing rule :

$(i, j) \Rightarrow (j, j) \Rightarrow (j, x1) \Rightarrow (1, x1)$

(* $x1$ is the column index of the starting edge of this pattern *)

(* The above routing rule will guarantee that all data in the same row routing in parallel without any conflict. *)

(* This rule is equivalent to the RAW (random access write) operation of PRAM machine described in [NS81] *)

The rule can be performed by the MOT operations as follows :

$LTL_C(i, j, j)$, $LTL_R(j, j, x1)$, and $LTL_C(j, 1, x1)$

(2) The only $LP_{i,j}$ in each column with $EQ2 = TRUE$ sends 1 and its edge $e_{g,j}$ from $LP_{i,j}$ to $LP_{1,x2}$ and stores in array $PA[ss, 2]$ by the following routing rule :

$(i, j) \Rightarrow (j, j) \Rightarrow (j, x2) \Rightarrow (1, x2)$

The rule can be performed by the MOT operations as follows :

$LTL_C(i, j, j)$, $LTL_R(j, j, x2)$, and $LTL_C(j, 1, x2)$

end;

endfor;

end of *COUNT_EDGES_1*;

In procedure *COUNT_EDGES_1*, since all *LP*'s do the data routing operations in parallel, so each of them spends $O(\log n)$ time in the operations of steps (1) and (2), respectively. Hence, the total time complexity is still $O(\log n)$.

procedure *COUNT_EDGES_2*;

(* For *Case 4*, to send each group of edges sequentially (one column at a time) , which may form a congruent pattern, to the *LP* in row 1 with the starting edge of this pattern. *)

begin

for $1 \leq i \leq k$ **do** (* in sequence *)

for $1 \leq j \leq n$ **do in parallel**

begin (* in sequence *)

(1) The only $LP_{i,j}$ in each column with $EQ1 = \text{TRUE}$ sends 1 and its edge

$e_{g,j}$ from $LP_{i,j}$ to $LP_{1,x1}$ and stores in array $PA[ss, 1]$ by the following routing rule :

$$(i, j) \Rightarrow (j, j) \Rightarrow (j, x1) \Rightarrow (1, x1)$$

(* $x1$ is the column index of the starting edge of this pattern *)

(* The above routing rule will guarantee that all data in the same row can be routed in parallel without any conflict. This rule is equivalent to the RAW operation of PRAM machine *)

The rule can be performed by the MOT operations as follows :

$$LTL_C(i, j, j), LTL_R(j, j, x1), \text{ and } LTL_C(j, 1, x1)$$

(2) The only $LP_{i,j}$ in each column with $EQ2 = \text{TRUE}$ sends 1 and its

edge $e_{g,j}$ from $LP_{i,j}$ to $LP_{1,x2}$ and stores in array $PA[ss, 2]$ by the following routing rule :

$$(i, j) \Rightarrow (j, j) \Rightarrow (j, x2) \Rightarrow (1, x2)$$

The rule can be performed by the MOT operations as follows :

$$LTL_C(i, j, j), LTL_R(j, j, x2), \text{ and } LTL_C(j, 1, x2)$$

end;

endfor;

endfor;

end of *COUNT_EDGES_2*;

For time complexity of procedure *COUNT_EDGES_2*, each *LP* has to do the operations in steps (1) and (2) for k iterations. Each iteration needs $O(\log n)$ time, as in procedure *COUNT_EDGES_1*, therefore, the total time is $O(k \log n)$.

4.2.4.3 The Main Procedure MULTIPLE_PATTERNS

We organize the above discussions and four procedures as the main procedure *MULTIPLE_PATTERNS* to find multiple congruent patterns in the following.

procedure *MULTIPLE_PATTERNS*(EL_p);

Input : The outputs from procedures *INITIALIZE_P* and *INITIALIZE_G*;

Output : The multiple congruent patterns in G for *Case 3* and *Case 4*;

begin

(1) **for** $1 \leq i \leq k$ and $1 \leq j \leq n$ **do in parallel**

begin

if $|e_{p,i}| = |e_{g,j}|$

then set $EQ1 = \text{TRUE}$ and $EQ2 = \text{TRUE}$;

(* Each $LP_{i,j}$ compares the length of edges $e_{p,i}$ and $e_{g,j}$ *)

if $|e_{p,1}| = |e_{g,j}|$

then set sum $S_{1,j} = 1$ and $ss = j$ in $LP_{1,j}$;

end;

endfor;

(2) **for** $2 \leq i \leq k$ and $1 \leq j \leq n$ **do in parallel**

if $LP_{i,j}$ sets its flag $EQ1 = \text{TRUE}$ or $EQ2 = \text{TRUE}$

then use the record $RR_{p,i}$ as the reference, to compute $RR_{g,j1}$ and $RR_{g,j2}$,

and find the starting edges $e_{g,s1}$, denoted as ST1, and $e_{g,s2}$, denoted as

ST2;

endfor;

```

(3) if  $EL_p = \text{FALSE}$  then call procedure CHECK_EDGES_1; (* for Case 3 *)
      else Call procedure CHECK_EDGES_2; (* for Case 4 *)
      (* To check whether edges ST1 and ST2 in each LP are starting edges or
         not. *)
(4) if  $EL_p = \text{FALSE}$  then call procedure COUNT_EDGES_1 (* for Case 3 *)
      else call procedure COUNT_EDGES_2; (* for Case 4 *)
      (* To count the edge number of any possible congruent pattern. *)
(5) for  $1 \leq ss \leq n$  do in parallel
      if  $S = k$  in  $LP_{1,ss}$ 
      then output the pattern arrays  $PA[ss, 1]$  and  $PA[ss, 2]$  in  $LP_{1,ss}$  to its root
           processor  $RP_{ss}^c$  in column  $ss$ .
           (* These edges form a congruent pattern and its starting edge is  $e_{g,ss}$  *)
      else print "There is no congruent pattern with  $e_{g,ss}$  as the starting edge.";
      endfor;
end of MULTIPLE_PATTERNS;

```

For the analysis of time complexity of procedure *MULTIPLE_PATTERNS*, steps (1), (2), and (5) need only constant time. For Case 3, Steps (3) and (4) need $O(\log n)$ time. For Case 4, steps (3) and (4) need $O(k \log n)$ time. Thus, the time complexity is $O(\log n)$ for Case 3, and $O(k \log n)$ for Case 4.

4.2.5 The Main Algorithm

In our main algorithm, we first call procedures *INITIALIZE_P* and *INITIALIZE_G* to do the initial operations on P and G respectively. Then, we call procedures

CHECK_P_LENGTH and *CHECK_G_LENGTH* to check whether there are equal-length edges in P and G, respectively. Finally, according to the property of length equality, we call procedures *SINGLE_PATTERN* and *MULTIPLE_PATTERNS* to solve *Case 1* to *Case 4*. The main algorithm *CONGRUENT_PATTERNS* is as follows.

Algorithm *CONGRUENT_PATTERNS*;

Input : A test pattern (simple polygon) P with k edges and a planar straight-line graph G with n edges, for $k \leq n$;

Output : The all patterns (cycles) in G which are congruent to P;

begin

- (1) Call procedure *INITIALIZE_P* to do initial operations on P;
- (2) Call procedure *INITIALIZE_G* to do initial operations on G;
- (3) Call procedure *CHECK_P_LENGTH* to check the edge equality for P, and receive the EL_p value from RP_1^c ;
- (4) Call procedure *CHECK_G_LENGTH* to check the edge equality for G; and receive the EL_g value from RP_1^r ;
- (5) **If** $EL_p = \text{TRUE}$ but $EL_g = \text{FALSE}$ **then** print "No congruent patterns in G.";

(* P has equal-length edges but all edges in G are distinct. This is *Case 1*. *)
- (6) **If** $EL_p = \text{FALSE}$ and $EL_g = \text{FALSE}$ **then** call procedure *SINGLE_PATTERN*;

(* All edges in P and G are distinct. Obviously, there is at most one congruent pattern in G. This is *Case 2*. *)
- (7) **If** $EL_p = \text{FALSE}$ but $EL_g = \text{TRUE}$ **then** call procedure *MULTIPLE_PATTERNS*(EL_p);

(* There are x congruent patterns in G, for $x \geq 0$. This is *Case 3* *)

(8) If $EL_p = \text{TRUE}$ and $EL_g = \text{TRUE}$ then call procedure
 $MULTIPLE_PATTERNS(EL_p)$;

(* There are y congruent patterns in G , for $y \geq 0$. This is *Case 4* *)

end of $CONGRUENT_PATTERNS$;

Theorem 4.1 : Given a test pattern P (a simple polygon) with k edges and a planar straight-line graph G with n edges, all the patterns (cycles) in G which are congruent to P can be found in $O(\log n)$ time on a mesh of trees, if each edge in P has unique length (for *Case 3*), otherwise (for *Case 4*) the time complexity is $O(k \log n)$.

Proof : From the algorithm $CONGRUENT_PATTERNS$, we know that step (5) runs in constant time, steps (1), (2), (3), (4) and (6) need $O(\log n)$ time, and steps (7) and (8) need $O(\log n)$ time for *Case 3* and $O(k \log n)$ time for *Case 4*. Hence, the total time complexity for algorithm $CONGRUENT_PATTERNS$ is $O(\log n)$ for P with distinct edges, otherwise (for general case, *Case 4*) is $O(k \log n)$. □

Corollary 4.1 : If all edges in P and G are distinct respectively, then the time complexity for finding congruent pattern on a mesh of trees is $O(\log n)$.

Proof : Obviously, this is *Case 2*. By Lemma 4.2, we know that there is zero or only one congruent pattern in G . Therefore, we have to execute steps (1), (2), (3), (4) and (6). So, from the proof in Theorem 4.1, the total time complexity for this case is $O(\log n)$. □

4.3 Final Remarks

We presented a MOT (mesh of trees) algorithm for reporting all patterns in a planar straight-line graph which are congruent to a given simple pattern. The MOT has $n \times n$ processors and the time complexity is $O(\log n)$ for the given has distinct edges, and $O(k \log n)$ for general case, they are all optimal.

It remains a problem whether or not MOT algorithms can give a same time complexity for finding similar patterns. A pattern in G is similar to a given pattern G if the *length rate* of each corresponding edge pair in P and G are equal, and they also have same interior angle and turning direction (as defined in Section 4.1). It also remains open that it is possible or not to develop an optimal parallel algorithm on a mesh of trees to solve the three-directional congruent pattern problems as described in [A87] and [S84]. If the polyhedra described in the two papers are projected on the plane, then maybe it is possible to develop similar MOT algorithms to solve these problems with better time complexity.

Chapter 5

Conclusion

We conclude the dissertation by discussing the contributions of our research, and the time complexities and open problems for our parallel geometric algorithms. Finally, we propose a plan for future work.

5.1 Discussing of The Research Results

(1) *The Maxima Problem*

In chapter 2, we developed a parallel algorithm to find the maxima of a point set on a hypercube machine with N processors. For a set of N points in d -dimensional space, our algorithm takes $O(N^{0.77} \log^{d-1} N)$ time. This is the first sublinear-time parallel algorithm for multiprocessor systems connected by sparse networks. If the size N of input point set is greater than P , the number of processors in a hypercube, then our algorithm can be generalized to solve the maxima problem in $O((N/P^{0.23}) \log^{d-2} P (\log(N/P) + \log P))$ time. Table 5.1 shows the time complexity of the various maxima algorithms.

It remains an open problem whether or not our results can be significantly improved. For example, is it possible to obtain a hypercube maxima algorithm which runs in $O(N^c)$ time such that c is a constant less than 1? Moreover, can we design a hypercube maxima algorithm which runs in $O(\log^{f(d)})$ time, where $f(d)$ is a linear function of the d -dimensional point set? Due to the limitation of data communication

in hypercube machine, we believe that it will not be easy to find such efficient algorithms.

The maxima problem has many important applications in statistics, economics, and operations research. With slight modifications, this algorithm can be extended to compute the contour which is spanned by the maximal elements and to compute the number of dominated points for every element of the input point set. This is the ECDF (empirical cumulative distribution function) searching problem [D86].

Table 5.1 Time Complexity for Maxima Algorithms

Algorithm	Model	Time Complexity	Dimension
[KLP75]	sequential	$O(N \log N)$	$d \leq 3$
[KLP75]	sequential	$O(N \log^{d-2} N + N \log N)$	$d > 3$
[ACG87]	CREW PRAM	$O(\log N)$	$d = 2$ and $N = P$
[ACG87]	CREW PRAM	$O(\log^{d-2} N)$	$d \geq 3$ and $N = P$
[D86]	mesh-connected	$O(N^{0.5})$	$d \leq 3$ and $N = P$
[D86]	mesh-connected	$O(N^{0.5+\log(d-2)})$	$d > 3$ and $N = P$
[S88]	hypercube	$O(\log^2 N)$	$d = 2$ and $N = P$
[ZL91]	hypercube	$O(N^{0.77} \log^{d-1} N)$	$d > 3$ and $N = P$
[ZL91]	hypercube	$O(N/P^{0.23} \log^{d-2} P(\log(N/P) + \log P))$	$d > 3$ and $N > P$

(2) The Voronoi Diagram

In chapter 3, we presented an optimal $O(\log^2 N)$ -time parallel algorithm to construct a three-dimensional convex hull of a point set in the space, where N is the size of the given point set. We then used the three-dimensional convex hull algorithm to construct the Voronoi diagram of a set of N points in the plane on an $N \times N$ mesh of

trees. The Voronoi diagram algorithm also runs in optimal time $O(\log^2 N)$. A comparison of time complexity for the various parallel algorithms for Voronoi diagram is given in Table 5.2.

Table 5.2 Time Complexity for Voronoi Diagram Algorithms

Algorithm	Model	Time Complexity
[B79]	sequential	$O(N \log N)$
[PS88]	sequential	$O(N \log N)$
[C80]	CREW PRAM	$O(\log^3 N \log \log N)$
[ACGOY85]	CREW PRAM	$O(\log^3 N)$
[C80]	cube-connected-cycles	$O(\log^4 N)$
[L86]	mesh-connected	$O(N^{0.5} \log N)$
[S88]	hypercube	$O(\log^3 N)$
[LZ92]	mesh-of-trees	$O(\log^2 N)$

It remains an open problem whether or not the geometric inversion approach introduced in [B79] can be used to develop a general and efficient parallel algorithm for constructing a $(k + 1)$ -dimensional convex hull. If so, we may use this convex hull to construct a k -dimensional Voronoi diagram.

The two-dimensional Voronoi diagram is one of the most useful data structures in computational geometry. It can be directly or indirectly used to solve *the nearest neighbor, all nearest-neighbors, convex hull, Delaunay triangulation, Euclidean minimum spanning tree*, and the *traveling salesman problem* easily and efficiently. Besides, it also has many important applications in robotics, image processing and graph theory ([PS88], [S78]).

(3) The Congruent Patterns

In chapter 4, we presented two parallel algorithms for reporting all the patterns (cycles) in a planar straight-line graph G which are congruent to a given test pattern P (a simple polygon), respectively. This algorithm runs on a mesh of trees parallel machine, with $n \times n$ processors. It takes the optimal time complexity $O(\log n)$ for the test pattern P with distinct edges, otherwise for general case, the optimal time complexity is $O(k \log n)$, where n is the edge number of G . A comparison of the time complexity of our algorithms with other parallel algorithms is given in Table 5.3.

Table 5.3 Time Complexity for Congruent Pattern Algorithms

Algorithm	Model	Time Complexity	Dimension
[S84]	sequential	$O(N \log N)$	$d = 3$ and $k = N$
[A87]	sequential	$O(N \log N)$	$d = 3$ and $k = N$
[SLY90]	CREW PRAM	$O(N^2)$	$d = 2$ and $k < N$
[JKB92]	CREW PRAM	$O(\log N \log \log N) *$	$d = 2$ and $k < N$
ours	mesh-of-trees	$O(\log N) *$	$d = 2$ and $k < N$
[JKB92]	CREW PRAM	$O(k \log N \log \log N) **$	$d = 2$ and $k < N$
ours	mesh-of-trees	$O(k \log N) **$	$d = 2$ and $k < N$

* : Each edge in the test pattern P has unique length.

** : Some edges in the test pattern P have not unique length (i.e. the general case).
 k and N are the edge number of P and G , respectively.

We wonder that it is possible to develop another efficient MOT algorithm to report all patterns in a given graph G which are similar to a given test polygon P . Besides, it remains an open problem whether or not our optimal algorithms can be generalized to find d -dimensional congruent polyhedra, for $d \geq 3$. Finding congruent

and similar patterns arises frequently in computer-aided design (CAD), image analysis, pattern recognition, and computer vision.

5.2 Future Work

In the near future, we plan to continue our research on the *visibility* problems, such as (1) computing the *visibility polygon* from a point inside or outside a given simple polygon, (2) computing the *visibility graph* of a segment set, or (3) Removing hidden surfaces from a three-dimensional image. All the above problems will be solved on a mesh of trees. The visibility problems have many applications in computer graphics, robotics, computer vision, and graph theory.

(1) *Computing Visibility Polygon*

Given a simple polygon P with n vertices and a viewpoint z in the plane, find all points on the boundary of P that are *visible* from z . All the visible boundary points form the *visibility polygon* (see Figure 5.1). For this problem, Gindy and Avis presented an $O(n)$ time sequential algorithm for finding the visibility polygon from a point inside P [GA81].

In [L83], Lee developed another sequential algorithm for finding the visibility polygon of a point inside or outside P . His algorithm also runs in $O(n)$ time, but it uses only one stack instead of three as required by [GA81]. In [AC91], Atallah and Chen presented a parallel algorithm for computing the visible portions of a simple polygonal chain with n vertices from a point in the plane. Their algorithm runs in $O(\log n)$ time using $O(n / \log n)$ processors in the EREW PRAM computational model, and hence is asymptotically optimal.

In [CG85], Chazelle and Guibas used *geometric duality* on the two-sided plane to solve various visibility and intersection problems about a simple polygon P with n vertices. Among their results are a simple $O(n \log n)$ algorithm for computing the illuminated subpolygon of P from a luminous side, an $O(\log n)$ algorithm for determining which side of P is first hit by a bullet fired from a point in a certain direction, and an $O(n \log n)$ algorithm for computing the first intersection of P with a light ray from the luminous edge. All of the above are sequential algorithms.

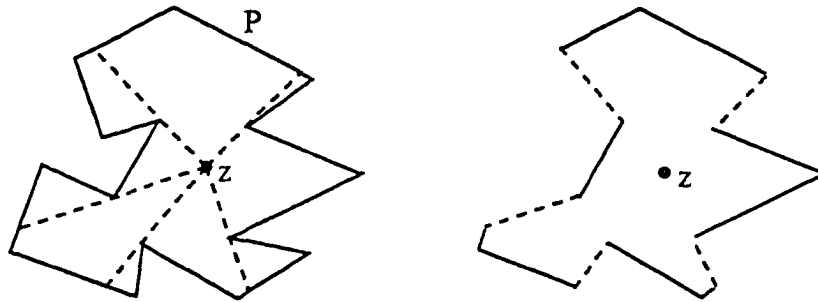


Fig. 5.1 A simple polygon P and the visibility polygon of viewpoint z .

For our research, we will try to use geometric duality approach to find the visibility polygon from a point inside or outside P . A reason is that geometric duality is a simpler way for solving this problem. The only problem is that it is generally not very easy to figure out the main idea of this approach.

(2) *Computing Visibility Graph*

Given a set S of n nonintersecting line segments in the plane, its visibility graph G_S is the undirected graph which has the endpoints of the line segments in S as nodes and in which two nodes (points) are adjacent whenever they *see* each other (the line segments in S are regarded as nontransparent obstacles, see Figure 5.2). For this

problem, Welzl [W85a] and Edelsbrunner [E87] have presented sequential algorithms to find G_S in $O(n^2)$ time, respectively.

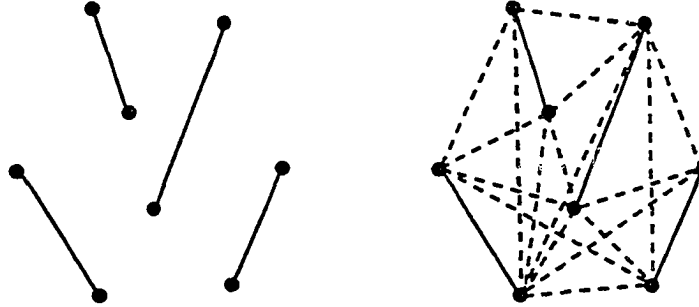


Fig. 5.2 A set of segments and its visibility graph.

In [H87], Hershberger described an $O(m + n \log \log n)$ sequential algorithm to solve this problem, where m is the number of edges of G_S . Because m can be as small as $O(n)$, the algorithm improved Welzl's algorithm. In [OW88], Overmars and Welzl presented an $O(m \log n)$ sequential algorithm for finding sparse G_S , where m is the edge number of G_S . For our research, we will try to develop a logarithmic time algorithm to find G_S on a mesh of trees.

(3) *Removing Hidden Surfaces*

For this problem, Reif and Sen presented a sequential algorithm for removing hidden surfaces in a three-dimensional terrain map [RS88]. This algorithm runs in $O((k + n) \log n \log \log n)$ time. In the same paper, they also presented a parallel algorithm which runs in time $O(\log^4(k + n))$ in a CREW PRAM model. In [B88], Bern presented a sequential algorithm for removing hidden surfaces of a set of n rectangles with sides parallel to the x and y axes, with viewpoint at $z = \infty$ (that is, an orthographic projection). Their algorithm runs in time $O(n \log n \log \log n + k \log n)$,

where k is the number of output line segments. In [MNU90], Mehlhorn, Naher, and Uhrig solved the same problem as in [B88]. Their algorithm runs in time $O(n \log n + k \log(n^2 / k))$ (see Figure 5.3).

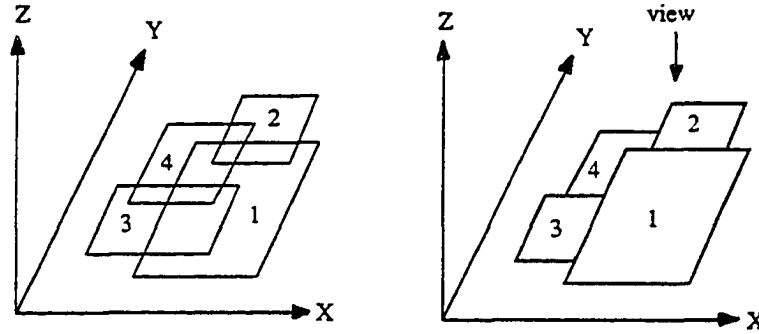


Fig. 5.3 Removing hidden-surfaces of rectangular objects.

In [BO90], Berg and Overmars presented a new and efficient sequential algorithm for computing the visibility map of a set of axis-parallel polyhedra (that is, polyhedra with their faces and edges parallel to the coordinate axes) as seen from a given view-point. For non-intersecting polyhedra with n edges in total, the algorithm runs in time $O((k + n) \log n)$, where k is the complexity of the visibility map. The algorithm can be extended to deal with intersecting polyhedra with only a slight increase in the time bound. For our research, we plan to develop an optimal parallel algorithm to solve a similar problem as in [B88] and [MNU90] on a mesh of trees.

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Vita

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DOCTORAL EXAMINATION AND DISSERTATION REPORT

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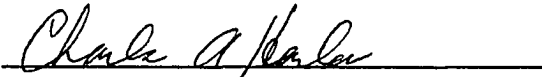
Title of Dissertation: Parallel Geometric Algorithms


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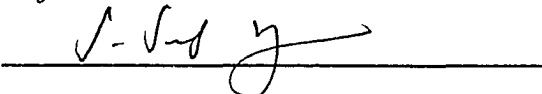

Major Professor and Chairman


Dean of the Graduate School

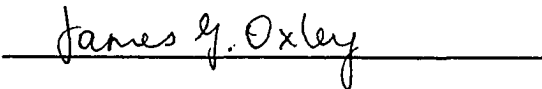
EXAMINING COMMITTEE:











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