Pattern Recognition, Vol. 25, No. 7, pp. 741–747, 1992
Printed in Great Britain

0031-3203/92 $5.00 + .00
Pergamon Press Ltd
Pattern Recognition Society

HYPERCUBE ALGORITHMS FOR OPERATIONS ON QUADTREES

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(*Received* 26 *February* 1991; *in revised form* 29 *October* 1991; *received for publication* 20 *November* 1991)

Abstract—This paper describes parallel algorithms for the following operations on quadtrees—boolean operations (union, intersection, complement), collapsing a quadtree, and neighbor finding in an image represented by a quadtree. The architecture assumed in this paper is a hypercube with one processing element (PE) per hypercube node. It is assumed that the architecture is SIMD, i.e. all PEs work under the control of a single control unit.

Quadtrees Hypercube algorithms Image processing

1. INTRODUCTION

A quadtree[1] is a tree representation of a sparse image (in general, any two-dimensional (2D) array). The root of the quadtree represents the entire image. If the portion of the image represented by any node does not have the same gray value, the node is asigned four children. Each child represents one of the four quadrants of the image portion represented by its parent. This continues recursively until all the leaf nodes represent portions of the image with the same gray value.

Throughout this work we assume that the input image is binary. The algorithms can be extended to deal with gray-level/color images.

1.1. *Definitions*

The *level* of a quadtree node is its distance (in terms of number of links) from the root. The *height* of a quadtree is the greatest of the distances between the nodes of the quadtree and the root. The term node actually indicates a collection of pixels. A node at level l in a quadtree of height h represents a collection of $4^{(h-l)}$ pixels.

Every non-leaf node in the quadtree has exactly four children. Every leaf node is either filled (i.e. has a value of 1) or empty (i.e. has a value of 0).

Nodes representing single pixels have the same index as the shuffled row-major index of the pixel they represent. The index of nodes representing a collection of pixels is the smallest of the indices of the pixels represented. Shuffled row-major indexing for an 8×8 image is shown in Fig. 1(a).

A node X in tree T_1 is said to *cover* a node Y in tree T_2 if (i) there exists a node Z in T_2 such that Z is an ancestor of Y and index(Z) and level(Z) are equal to index(X) and level(X), respectively, or (ii) X is identical to Y. Node X in tree T_1 covers node Y in tree T_2 iff the portion of the image represented by X occludes the portion of the image represented by Y.

1.2. *Representation of the quadtree*

There are many ways in which a quadtree can be stored. The most expensive method is to store the actual tree including the values and the pointers at each node. A better way would be to store only the leaves of the quadtree along with the corresponding indices and values. Even this contains redundant information since information about empty leaves can be obtained given the information about filled leaves alone. We represent the quadtree using only its filled leaves. The advantage of our representation is that the number of processing elements (PEs) required to store the quadtree nodes is kept to a minimum. This makes load balancing easy, resulting in efficient processor utilization. Given a quadtree

0	1	4	5	16	17	20	21
2	3	6	7	18	19	22	23
8	9	12	13	24	25	28	29
10	11	14	15	26	27	30	31
32	33	36	37	48	49	52	53
34	35	38	39	50	51	54	55
40	41	44	45	56	57	60	61
42	43	46	47	58	59	62	63

Fig. 1(a). Shuffled row-major indexing for an 8 × 8 image.

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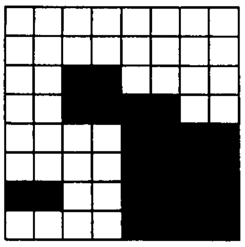


Index:	12	26	27	40	41	48
Level:	2	3	3	3	3	1

Fig. 1(b). A binary image and its 1D representation.

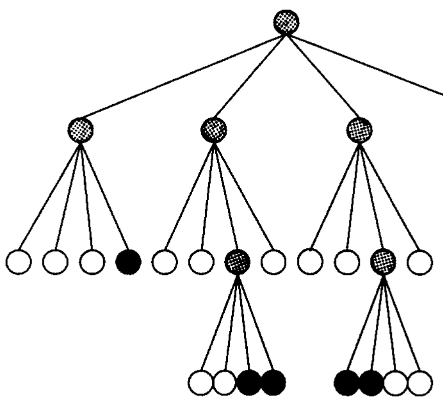


Fig. 1(c). A quadtree for Fig. 1(b).

with N filled nodes, either $\lfloor N/P \rfloor$ or $\lceil N/P \rceil$ nodes are stored in each PE (P = number of PEs). The index, and level of each filled leaf are stored in the *index* and *level* registers. An additional *value* register is needed for gray level/color images.

Figures 1(b) and (c) show a binary image, a quadtree for the same image, and the one-dimensional (1D) representation of the quadtree. The 1D representation of quadtrees is referred to as "linear quadtrees" in the literature.

The quadtree representation in a 1D array of PEs is said to be in standard form when (i) only filled leaf nodes are represented, (ii) the filled leaf nodes are arranged with their indices in increasing order, and (iii) every PE to the left of a PE having a filled leaf node has a filled leaf node of its own. All algorithms in this paper assume that the input is in standard form. The output of all algorithms is also in standard form.

1.3. *Earlier work*

Sequential algorithms for processing pointer-less quadtrees are described in references (2, 3). Parallel quadtree algorithms for various architectures can be found in the literature. Mei and Liu[4] consider quadtree algorithms for a 2D shuffle exchange network. The paper also assumes a static allocation of all image pixels (empty and filled) to processors, which in the case of sparse images would result in a lot of idle processors. Martin *et al.*[5] describe algorithms for a horizontally reconfigurable architecture. Hung and Rosenfeld[6] consider a mesh connected computer. It appears that their intersection/union algorithm assumes the availability of both empty as well as filled leaves, which represents redundant input. Our collapse algorithm is based on one of their quadtree building algorithms, while our neighbor finding algorithm is a modified version of their algorithm for the hypercube. Nandy *et al.*[7] describe linear quadtree algorithms for neighbor finding and boundary following on an MIMD hypercube. Their work does not give complexity analysis for the complete embedding of the quadtree.

2. HYPERCUBE PRIMITIVES

2.1. *Concentrate*

In the Concentrate algorithm we start with a subset of the processing elements, each containing data in register D, and the PE's rank (that is, the number of selected PEs with lower index than self) in register R. The objective is to move the data in register D such that $D(i)$ goes to the PE with index $R(i)$. This primitive is used to bring the 1D representation of a quadtree into standard form.

The Concentrate algorithm is described in reference (8). Figure 2(a) illustrates the concentrate operation. The time complexity of the algorithm is $O((N/P) \log P)$ where N is the size of the given input and P is the number of PEs.

2.2. *Merge*

Merging of two sorted arrays can be done on the hypercube using the bitonic merge algorithm. The

D	-	d_1	-	-	d_4	d_5	d_6	-
R	α	0	α	α	1	2	3	α
D(after Concentrate)	d_1	d_4	d_5	d_6	-	-	-	-

(a) Concentrate

D	d_0	d_1	d_2	d_3	-	-	-	-
R	2	3	6	7	α	α	α	α
D(after Generalize)	d_0	d_0	d_0	d_1	d_2	d_2	d_2	d_3

(b) Generalize

D	7	9	4	6	8	2	1	5
D(after +-scan)	7	16	20	26	34	36	37	42
S	1	0	0	1	0	0	1	0
D(after segmented +-scan)	7	16	20	6	14	16	1	6

(c) Non-segmented / Segmented Prefix Scan

Fig. 2. Hypercube primitives.

hypercube algorithm is described in reference (9). The merge algorithm takes time $O((N/P)\log P)$. The merge primitive is used in the quadtree intersection/union algorithm.

2.3. *Generalize*

In the Generalize algorithm we start with data in register D in the first k PEs. A detination PE index is available in register R and is such that $R(i-1) < R(i)$ for $0 \leq i \leq k$. For convenience, assume $R(-1) = 0$. The objective is to move the data in register D such that $D(i)$ goes to all the PEs with index k satisfying $<R(i)$ and $\geq R(i-1)$. This primitive is used to obtain the complement of a quadtree.

The Generalize algorithm is described in reference (8). Figure 2(b) illustrates the generalize primitive. The time complexity of the algorithm is $O((N/P)\log P)$.

2.4. *Segmented scans*

In the segmented prefix scan algorithm a 1-bit register S is used to indicate the start of a new segment when set to 1. Data is available in register D. A binary associative operator $\oplus$ is specified. The objective is to obtain in PE i the quantity $D(j) \oplus D(j+1) \oplus \cdots D(i)$ where j satisfies the following properties: (i) $j \leq i$, (ii) $S(j) = 1$, and (iii) for all k satisfying $j < k \leq i$ and $S(k) = 0$. Segmented scans are used in the quadtree union/intersection, collapse and in the neighbor finding algorithms.

The segmented scan algorithm is a modified form of the prefix scan algorithm presented in reference (8). Figure 2(c) illustrates the scan primitive. The time complexity of the algorithm is $O((N/P) + \log P)$.

2.5. *Sort*

Bitonic sort can be used to sort an array on the hypercube. The sorting algorithm is described in reference (9). The bitonic sort algorithm takes time $O(\log^2 N)$ when $P = N$. A faster deterministic sorting algorithm that runs in nearly logarithmic time is presented in reference (10). The complexity of this sorting algorithm is $O(\log N(\log\log N)^2)$ when $P = N$. Sort (N, P) is used throughout this paper to indicate the time taken to sort N elements on a hypercube with P PEs. The Sort primitive is used in the neighbor finding algorithm.

3. BOOLEAN OPERATIONS

3.1. *Intersection/union*

The intersection/union of two quadtrees T_1 and T_2 is a quadtree T such that the image represented by T is the intersection/union of the images represented by T_1 and T_2.

The intersection/union algorithm is outlined in Fig. 3.

Figure 4 illustrates the intersection/union algorithm through an example. The *Index*, *Level*, and *Tree-no* registers are set by merging the given quadtrees as mentioned in step 1 of the algorithm. Initially the *Cover* register is set as described in step 2—a "1" indicates a covering node, and "0" a node that has not been labeled yet. The contents of the *Cover* register are modified after determination of "leaders". The label "2" indicates a node covered by a filled leaf, and "3" a node covered by an empty leaf. The lines marked *Cover1* and *Cover2* in Fig. 4 show the contents of the cover register after step 2 and step 5 of the algorithm, respectively. The resulting tree after the intersection and union operations are obtained as described in step 5. These are available in registers *Inter* and *Union*.

1. Merge trees T_1 and T_2 such that the merged tree is sorted by ⟨index,level,tree-no⟩.
2. Let each node P examine its immediate successor X. The following cases may arise:

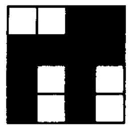
   a index(P) = index(X), level(P) = level(X), tree-no(P) < tree-no(X)
   b index(P) = index(X), level(P) < level(X)
   c index(P) < index(X).

   Case a P covers X and X covers P. Mark one of the nodes (say P, since P was the node that detected the covering) as "covering" and mark the other for deletion.

   Case b tree-no(P) must be different from tree-no(X) since no two filled leaves from the same tree will have identical indices. P covers X. Mark P as "covering" and X as "covered".

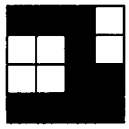
   Case c If index(X) < index(P) + size(P), then P covers X. Mark P as "covering" and X as "covered".
3. Split the nodes into segments with the covering nodes determined so far marking the start of new segments.
4. The index and level of the covering nodes (we will call these "leaders") are copied onto each node in the segment.
5. Each node in the segment checks whether it is covered by its leader. If yes, leave as such for intersection and invalidate the leader. For union remove these. If not, it is covered by an empty node. Remove these for intersection. Leave as such for union.
6. *Concentrate* to remove all nodes that were invalidated or marked for deletion. A *Collapse* algorithm will be required after union, to replace subtrees with all leaves filled, by a single node.

Fig. 3. Algorithm for the intersection/union of two quadtrees.



Index:	2	3	4	8	10	12	14
Level:	2	2	1	2	2	2	2

(a) Tree T_1

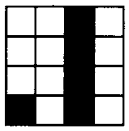


Index	0	1	4	6	10	11	12
Level	2	2	2	2	2	2	1

(b) Tree T_2

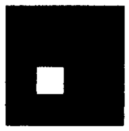
Index:	0	1	2	3	4	4	6	8	10	10	11	12	12	14
Level:	2	2	2	2	1	2	2	2	2	2	2	1	2	2
Tree-no:	1	1	0	0	0	1	1	0	0	1	1	1	0	0
Cover1:	0	0	0	0	1	0	0	0	1	0	0	1	0	0
Cover2:	3	3	3	3	1	2	2	3	1	2	3	1	2	2
Inter:	0	0	0	0	0	1	1	0	0	1	0	0	1	1
Union:	1	1	1	1	1	0	0	1	0	1	1	1	0	0

(c) Steps in the Union/Intersection Algorithm.



Index:	4	6	10	12	14
Level:	2	2	2	2	2

(d) Tree $T_1 \cap T_2$



Index:	0	4	8	10	11	12
Level:	1	1	2	2	2	1

(e) Tree $T_1 \cup T_2$

Fig. 4. Union/intersection.

For the intersection/union algorithm to work correctly we only need to correctly mark all the filled leaves in the given trees as "covering", "covered by a filled leaf" or "covered by an empty node". This is because we can retain all nodes covered by an empty leaf and remove those covered by a filled leaf for quadtree union. For intersection, we can retain all nodes covered by a filled leaf while removing the filled cover of those nodes and also remove nodes covered by an empty leaf.

The correctness of the union/intersection algorithm can be proved as follows. In step 2, cases a–c mark the covering nodes in the input quadtree correctly. Steps 3–5 mark the quadtree nodes that are covered by a filled leaf. We claim that the nodes in the given quadtrees that have not been marked so far are all covered by an empty leaf. This is true since all nodes covered by any leaf X appear as a continuous run of nodes after X in the sorted ordering described in step 1. This is because empty covering nodes are not available in our representation. Further, all nodes covered by P were not marked as "covered" in cases b and c.

A node X is covered by its leader Y iff index(Y) = index(X) − index(X) mod $4^{height-level(Y)}$. In step 5, invalidation of the leader can be done by the leader itself.

The merge in step 1 and the concentrate in step 6 take time $O((N/P)\log P)$. The prefix scan in steps 4 and 5 take $O((N/P) + \log P)$ time. Steps 2 and 3 also take $O((N/P) + \log P)$ time. Thus the intersection/union algorithm has an $O((N/P)\log P)$ time complexity.

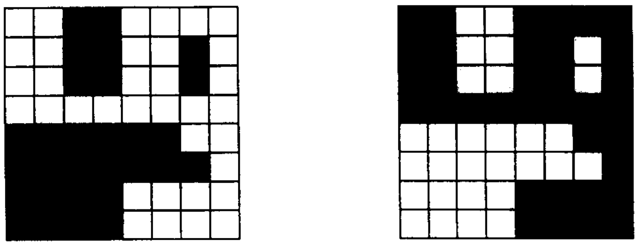
3.2. *Complement*

The complement algorithm is outlined in Fig. 5.

Let N_1 be the number of filled leaves in the given quadtree. Step 1 takes $O((N_1/P) + \log P)$ time and

1. Each node looks at its immediate successor and finds out the number of empty pixels between them.
2. The *generalize* algorithm is used to spread the empty nodes across the available processing elements.
3. A *collapse* algorithm is run to group empty nodes together and to bring the result to standard form.

Fig. 5. The Complementing algorithm.



(a) Tree T_3 (b) Complement of T_3

Index:	4	12	13	22	28	32	48	54
Level:	2	3	3	3	3	1	2	3

(c) 1D Repesentation of T_3

Index:		4	12	13	22	28	32	48	54							
Level:		3	3	3	3	3	1	2	3							
I1:		4	12	13	22	28	32	48	54	(64)						
I2:	(-1)	7	12	13	22	28	47	51	54							
NumEmpty:	4	4	0	8	5	3	0	2	9							
IndOfEmpty:	0	1	2	3	8	9	10	11	14	15	16	17	18	20	21	23
	24	25	26	27	29	30	31	52	55	56	57	58	60	61	62	63

(d) Steps in the Complement Algorithm

Index	0	8	14	15	16	20	21	23	24	29	30	31	52	53	55	56	60
Level	2	3	3	3	2	3	3	3	2	3	3	3	3	3	3	2	2

(e) 1D Representation of complement of T_3

Fig. 6. Complement algorithm.

steps 2 and 3 take $O((N/P) \log P)$ time, where N is the sum of sizes (in pixels) of the empty leaves in the given quadtree. The entire complement algorithm has an $O((N/P) \log P)$ time complexity. The algorithm, however, has a high worst-case space complexity.

The number of empty nodes is determined as follows: let A and B be the two leaf nodes between which we wish to find the number of empty nodes. Find the index i_1 of the rightmost node at the lowest level of the subtree rooted at A and the index i_2 of the leftmost node at the lowest level of the subtree rooted at B. $(i_2 - i_1 - 1)$ gives the number of empty nodes between A and B. (Minor modifications can be made for the first and the last leaf nodes.)

To reduce the amount of space required the fol-

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1. Each node determines the maximum number of pixels (filled or empty) it can represent. This is stored in register *NumPix*.
NumPix(i) = $4^{NTZP(i)}$ where *NTZP*(i) is the number of trailing zero-pairs in node index i.
2. The filled leaves of the quadtree are split into segments. A 1-bit register *segment* in each node is used to indicate whether that node is the beginning of a segment. Register *segment* is set to true if the index of the node being considered minus the index of the last pixel of the immediately preceding node is greater than 1. The index of the last pixel in any node = index of node + size of node − 1 where size of a node = $4^{(height - level)}$.
3. Each node obtains the number of pixels preceding it in the same segment and stores it in register *position*. This is just a segmented sum scan of the size of each node. 1 + the position of the last node in a segment gives the segment's length. A segmented backward copy scan makes this value available to each node in the segment in register *length*.
4. Each node stores in register *follow* the number of pixels following it (including self) in the same segment. This is just *length* − *position*. *Follow1* is set to the largest power of 4 ≤ the contents of the *follow* register in the same node.
5. The minimum of *NumPix* and *follow1* in each node gives the size of the largest block of filled leaves represented by that node. This is available in the register *MaxBlkFL*. The register *level1* is set based on the contents of *MaxBlkFL*.
6. Nodes that are redundant need to be deleted. A node is redundant when it represents only a subset of the pixels represented by another node. Using the index and level information each node first finds the number of its sibling nodes that have higher indices than self and the number of siblings with lower indices. By comparing this with the contents of the *position* and *follow* registers the node can determine whether it is redundant or not. If it is redundant it is marked for deletion.
7. *Concentrate* to remove nodes that were marked for deletion.

Fig. 7. Quadtree Collapse algorithm.

Index:	0	1	2	3	4	8	10	11	12
Level:	1	2	2	2	1	2	2	2	1
Size:	1	1	1	1	4	1	1	1	4
Seg:	1	0	0	0	0	0	1	0	0
Position:	0	1	2	3	4	8	0	1	2
Follow:	9	8	7	6	5	1	6	5	4
MaxBkSz:	4	1	1	1	4	1	1	1	4
Follow1:	4	4	4	4	4	1	4	4	4
NumPix:	16	1	1	1	4	4	1	1	4
Level1:	1	2	2	2	1	2	2	2	1
LSib:	0	1	2	3	4	8	2	3	12
Self+RSib:	64	3	2	1	12	8	2	1	4
Redun:	0	1	1	1	0	0	0	0	0

(a) Steps in Collapsing tree $T_1 \cup T_2$ from figure 4.

Index:	0	4	8	10	11	12
Level	1	1	2	2	2	1

(b) 1D Representation of Collapsed Tree T_{new}

Fig. 8. Collapsing a tree.

lowing modification can be used. Let l_1 and l_2 be the levels of nodes A and B. If $l_2 > l_1$ find the index of the ancestor of B in level l_1 (call this ancestor C). A notes down the level number l_1 along with the number of nodes between A and C, and level l_2 along with the number of nodes to the left of B having C as an ancestor. If $l_1 \geq l_2$ let D be the ancestor of A at level l_2. Now B notes down level l_2 along with the number of nodes between D and B and level l_1 along with number of nodes to the right of A having D as an ancestor. A *generalize* and a *compact* can now be done as in the earlier case. The time complexity is still $O((N/P) \log P)$ although the space required has been reduced.

The first method is illustrated in Fig. 6.

3.3. *Difference*

The difference operation between two trees can be carried out by complementing the second tree, followed by an intersection between the resulting tree and the first tree. The time taken by difference is $O((N/P) \log P)$.

4. COLLAPSING THE TREE

A quadtree needs to be collapsed when all the four children of a non-leaf node have identical values. Such nodes are redundant and can be removed after the contents of their *value* register is passed on to their parent node.

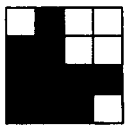
Figure 7 gives the steps in the collapse algorithm.

Steps 1 and 4–6 of the collapse algorithm take $O(N/P)$ time. Steps 2 and 3 take time $O((N/P) + \log P)$ and step 7 takes $O((N/P) \log P)$ time. Thus, the collapse algorithm has a worst case time complexity of $O((N/P) \log P)$.

Figure 8 illustrates the collapse algorithm.

5. NEIGHBOR FINDING

Our standard form for the representation of the quadtree stores the blocks in the image in Shuffled Row Major (SRM) order. We begin with this representation and compute the North, South, East, and West neighbors of each block. Note that any node looks only for nodes smaller than itself. The steps in the East neighbor finding algorithm are outlined in Fig. 9. Modifications for North, South, and West neighbor finding should be easy. The algorithm can also be extended for 8-neighbor finding.



Index:	1	2	3	4	8	12	13	14
Level:	2	2	2	2	1	2	2	2
Data:	1	2	3	4	5	6	7	8
CMAdd:	4	1	5	8	2	10	14	11
CMAdd1:	1	2	4	5	8	10	11	14
Data1:	2	1	5	3	4	6	8	7
RMSucc	2	5	6	3	10	11	16	15
Begin:	8	5	9	12	10	14	16	15
End:	8	5	9	12	11	14	16	15
Neighb:	4	3	0	0	14	7	0	0

Fig. 10. Steps in the neighbor finding algorithm.

1. Each node computes its Column Major/Row major address from its index by bit shuffling. These are available in registers *CMAdd* and *RMAdd*.
2. The nodes are then rearranged in increasing CM address order (Register *CMAdd1*). Note that all the East neighbors of any node will now appear as a continuous run. Each node just needs the Column Major addresses of its topmost and bottommost East neighbors. These addresses can be used to select the segment of nodes representing its East neighbors.
3. The row major address of the topmost neighbor of any node X is the address of the immediate successor of X in Row Major order. (This successor could be a filled or an empty node.) This is available in register *RMSucc*.

$$RMSucc(i) = RMAdd(i) + \sqrt{(size(X))}.$$

4. The row major addresses in *RMSucc* are converted into column major addresses and stored in *Begin*.
5. The highest possible column major address an East neighbor could have is computed and stored in *End*.
6. The computed column major addresses from steps 4 and 5 are sorted, tagged, and merged with the sorted sequence from step 2. Segmented scans can now be used to collect information from the *data* registers of the East neighbors.

Fig. 9. Neighbor finding algorithm.

Time complexity of steps 1 and 3–5 of the neighbor finding algorithm is $O(N/P)$. Steps 2 and 6 involve sorting and hence the neighbor finding algorithm takes $O((N/P) + Sort(N, P))$ time.

The neighbor finding algorithm is illustrated in Fig. 10.

6. CONCLUSIONS

In this paper we developed parallel algorithms for the following operations on quadtrees—boolean operations (union, intersection, complement), collapsing a quadtree, and neighbor finding in an image represented by a quadtree. We presented optimal or near optimal algorithms for an SIMD hypercube architecture for the above problems.

Acknowledgement—The authors would like to thank Ravi Ponnusamy for his help with this work and for his comments on earlier versions of this paper.

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