An Efficient Algorithm for the Nearest Smaller Problem on Distributed Shared Memory Systems with Applications *

T. Graf
Department ICG-4
Research Centre Jülich
52425 Jülich, Germany
t.graf@kfa-juelich.de

V. Kamakoti N. Balakrishnan
Laboratory for High Performance Computing
Supercomputer Education and Research Centre
Indian Institute of Science
Bangalore - 560 012, India
{ kama, balki }@serc.iisc.ernet.in

Abstract

We present a simple and efficient algorithm for the nearest smaller problem (NSP, [1]) on a distributed shared memory (DSM) system with applications to problems from diverse areas. We adopt the block distributed memory (BDM) model of computation as described in [2]. To the best of our knowledge this is the first known algorithm for the NSP on DSM systems. Since the NSP is fundamental in many problems, a solution for it on DSM systems implies DSM-based solutions for a variety of problems in diverse areas as discussed in this paper. Parallel algorithms known so far for the NSP are based on shared memory systems [1] and are therefore less scalable than our algorithm.

1. Introduction

1.1. Motivation

The nearest smaller problem (NSP) is a fundamental problem and finds extensive applications in merging sorted lists, triangulation, binary tree reconstruction, parenthesis matching etc., [1].

Based on their memory organization, parallel computing systems fall into two categories: *Shared memory systems* and *distributed memory systems*. Shared memory systems are relatively easy to program (due to a single address space) but less scalable than distributed memory systems. Configuring a distributed memory system to have a single address space results

in a system that is both scalable and easy to program. Such systems are called *scalable shared memory systems* or *distributed shared memory systems (DSM)*. In other words, a *DSM* system is a shared memory layer on top of any distributed memory system like IBM's SP2, CRAY's T3E, or a cluster of workstations. In [2] the *block distributed memory (BDM)* model of computation is presented which serves as a *bridge* between the shared memory programming model and the distributed memory message-passing architecture. In other words, the *BDM* model attempts to capture the performance of a *DSM* system. So far, all parallel algorithms for the NSP are based on shared memory systems; [1] presents a $\frac{n}{\log n}$ processor, $O(\log n)$ time *CREW-PRAM* parallel algorithm and a $\frac{n}{\log \log n}$ processor, $O(\log \log n)$ time *CRCW-PRAM* parallel algorithm for the NSP. This paper presents a simple and efficient algorithm for the NSP on *DSM* systems using the *BDM* model. To the best of our knowledge, this is the only reported algorithm for the NSP on *DSM* systems.

Definition 1 (Nearest Smaller [1]) *The input to this problem is an array $A = (a_1, a_2, \dots, a_n)$ of n elements from a totally ordered domain. For each a_i , $1 \leq i \leq n$, find the nearest element to its left and the nearest element to its right, that are less than a_i , if such elements exist. That is, for each $1 \leq i \leq n$, find the maximal $1 \leq j < i$, and the minimal $i < k \leq n$ such that $a_j < a_i$ and $a_k < a_i$. We say that a_j is the left match and a_k is the right match of a_i .*

In the rest of this paper we will concentrate on finding the *left match* for every element of a given input sequence. Finding the *right match* can be done in a similar fashion.

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The *BDM* model [2] is defined in terms of four parameters: *number p of processors*, *maximum initial latency time τ taken for a processor to receive the packet it requested from some other processor*, *time σ taken to inject a word into or receive a word from the network*, and *number m of consecutive words sent during each transfer*. The processors are connected to a common communication network. Data are communicated between processors via point-to-point messages in blocks of m consecutive words rather than a single word. This is done keeping in mind the *spatial locality* of programs in execution. Let PR_i , $0 \leq i \leq p-1$ denote the i^{th} processor in the *BDM* system. Any processor can communicate with any other processor, but the time for communication depends upon the latency and bandwidth of the network, as described in the following facts about the *BDM* given in [2]:

1. No processor can send or receive more than one *packet* (a block of m consecutive words) at a time.
2. The model allows the *initial placement* of input data in the local memories of the processors and the memory latency hiding technique of *pipelined prefetching*.
3. If π is any permutation on p elements, then, a remote memory request for b words issued by every processor PR_i and destined for processor $PR_{\pi(i)}$ can be completed in $\tau + m\sigma \lceil \frac{b}{m} \rceil$ time for *all* processors PR_i , $0 \leq i \leq p-1$, simultaneously. k remote access requests issued by k distinct processors and destined to the same processor will require $k(\tau + m\sigma)$ time to be completed, and the requests will be served in arbitrary order. k prefetch read operations issued by a processor can be completed in $\tau + km\sigma$ time, using *pipelined prefetching*. k prefetch read operations of k blocks of $\lceil \frac{n}{p} \rceil$ words each, can be completed in $\tau + \sigma km \lceil \frac{n}{pm} \rceil$ time.
4. There are two time-complexity measures for a parallel algorithm on the *BDM* model; the computation time T_{comp} , and the communication time T_{comm} . The measure T_{comp} refers to the maximum of the local computations performed on any processor as measured in the model of computation supported by it. The measure T_{comm} refers to the total amount of communication time spent by the overall algorithm in accessing remote data.

Definition 2 (IED Storage)

A sequence $F = (f(1), f(2), \dots, f(n))$ of n elements is said to be *Inorder Equally Distributed (IED)* stored on a two-dimensional array $B[1.. \frac{n}{t} : 0..t-1]$ in some $t \leq p$ processors $PR_{j_0}, PR_{j_1}, \dots, PR_{j_{t-1}}$ of a *BDM* machine if

and only if, $B[j, i] = f(i * (n/t) + j)$, for $0 \leq i \leq t-1$, $1 \leq j \leq n/t$ and $(B[1, i], B[2, i], \dots, B[\frac{n}{t}, i])$ are stored in processor PR_{j_i} in this order, $0 \leq i \leq t-1$.

2. Algorithm for the NSP

2.1. Preliminaries

Before presenting the algorithm we define some functions that are used by the algorithm.

1. **BDPRECOMP**: Performs prefix computation on a sequence *IED* stored on a p -processor *BDM* machine. For details refer Theorem A.1 in Appendix A.
2. **BLOCKMERGE**: Merges two sorted lists L_1 and L_2 each of length $t(n/p)$ elements, $t > 0$ an integer, such that L_1 is *IED* stored on an array BL_1 in the processors $PR_i, PR_{i+a}, \dots, PR_{i+(t-1)a}$ and L_2 is *IED* stored on an array BL_2 in the processors $PR_{i+ta}, PR_{i+(t+1)a}, \dots, PR_{i+(2t-1)a}$, for some integer $a > 0$, and outputs the merged sorted list L of length $2t(n/p)$, *IED* stored on an array BL in the processors $PR_i, PR_{i+a}, \dots, PR_{i+(2t-1)a}$. For details refer Theorem A.2 and the discussion preceding it in Appendix A.
3. **RANDOMROUTE**: A randomized function which routes the data stored in each of the processors to their respective destinations. The input to this function is a $\lceil \frac{n}{p} \rceil \times p$ array A of n elements initially stored one column per processor in a p -processor *BDM* machine. Each element of A consists of a pair $(i, data)$, where i is the index of the processor to which the *data* has to be relocated. For details refer Theorem A.3 in Appendix A.

2.2. The Algorithm

The Sequential Algorithm.

Definition 3 Let $A = (\Gamma, a_1, a_2, \dots, a_n)$ be an array of elements from a totally ordered domain, where Γ is a dummy element such that $\Gamma < a_i$, $1 \leq i \leq n$. Then,

1. $N_A := (a_{j_1}, a_{j_2}, \dots, a_{j_k})$ such that $j_1 = n$, $a_{j_{i+1}}$ is the left match of a_{j_i} , $1 \leq i < k$, and $a_{j_k} = \Gamma$.
2. $M_A := (c_1, c_2, \dots, c_r)$ is a subsequence of A comprising of the elements which do not have a left match, listed in the same order as they appear in A .
3. L_A is the list of elements having left matches along with their left matches.

We assume the standard stack operations $Push(e, S)$, which pushes the element e onto a stack S , $Top(S)$ which returns the topmost element of S , and $Pop(S)$ which returns and removes the topmost element of S .

Function SEQNSP(A) : (N_A, M_A, L_A)

Input: An array $A = (\Gamma, a_1, a_2, \dots, a_n)$ of elements from a totally ordered domain.

Output: N_A, M_A and L_A as defined in Definition 3.

begin

1. Let S be an empty stack; $N_A := M_A := L_A := \emptyset$;
 2. **Push**(Γ, S);
 3. **for** $i \leftarrow 1$ **to** n **do**
 4. **while** ($a_i < TOP(S)$) **Pop**(S); **endwhile**;
 5. **if** ($TOP(S) = \Gamma$) **then append** (a_i) **to** M_A ;
 6. **else append** ($\langle a_i, TOP(S) \rangle$) **to** L_A ;
 7. **Push**(a_i, S);
 8. **endfor**;
 9. $N_A :=$ contents of S from top to bottom;
 10. **return**(N_A, M_A, L_A)
- end.**

Theorem 1 Given an array A of n elements, the function SEQNSP(A) takes $O(n)$ time.

The Distributed Algorithm for DSM systems.

We assume that the input array A is of the form $(\Gamma, a_1, a_2, \dots, a_n)$. W.l.o.g. we assume that n is a power of 2. We first present a *divide-and-conquer* algorithm for the NSP which we then parallelize: Split A it into two halves $A_1 = (\Gamma, a_1, a_2, \dots, a_{n/2})$ and $A_2 = (\Gamma, a_{n/2+1}, a_2, \dots, a_n)$ and solve the NSP for A_1 and A_2 separately. Let the solutions for A_1 and A_2 be $(N_{A_1}, M_{A_1}, L_{A_1})$ and $(N_{A_2}, M_{A_2}, L_{A_2})$, respectively. We will now see how to compute (N_A, M_A, L_A) .

Lemma 1 If an element $e \in M_{A_2}$ has a left match l , then $l \in N_{A_1}$.

Proof: Obviously, $l \in A_1$. Let $N_{A_1} = (a_{j_1}, a_{j_2}, \dots, a_{j_k})$. Suppose $l \notin N_{A_1}$, then $l = a_r$ such that $j_i > r > j_{i+1}$ for some $1 \leq i < k$. We obtain easily that $a_r > a_{j_i}$ and $j_i > r$. This implies that a_{j_i} is closer to e than l and less than e , contradicting our assumption that l is the left match of e . $\square$

We easily see that M_{A_2} and $N_{A_1} = (a_{j_1}, a_{j_2}, \dots, a_{j_k})$ are sorted in decreasing order. Merge M_{A_2} with N_{A_1} to obtain $T_A := (a_{f_1}, a_{f_2}, \dots, a_{f_t})$ sorted in decreasing order. Form an auxiliary array $P[1..t]$ such that for every element $a_{f_i} \in T_A$, $P[i] := \langle f_i, a_{f_i} \rangle$ if $a_{f_i} \in N_{A_1}$ and $P[i] := \langle 0, \Gamma \rangle$ otherwise, $1 \leq i \leq t$. We then

compute the suffix maxima $PMAX$, on the first entries of the P -array elements. We easily obtain the following

Lemma 2 Let $T_A = (a_{f_1}, a_{f_2}, \dots, a_{f_t})$. For $a_{f_i} \in M_{A_2}$, $1 \leq i \leq t$, we have

1. if $PMAX[i] = \langle 0, \Gamma \rangle$ then, a_{f_i} does not have a left match in A .
2. if $PMAX[i] = \langle f_r, a_{f_r} \rangle$ then, a_{f_r} is the left match for a_{f_i} in A .

Now, our method to compute N_A, M_A and L_A from $N_{A_1}, M_{A_1}, L_{A_1}, N_{A_2}, M_{A_2}$, and L_{A_2} is as follows: The list M_A is the list M_{A_1} appended to its tail the list of elements of M_{A_2} that satisfy condition 1 of Lemma 2, in the same order as they appear in M_{A_2} . The elements of L_A are the elements of L_{A_1}, L_{A_2} and those elements of M_{A_2} that satisfy condition 2 of Lemma 2. The list N_A consists of N_{A_2} (without last element Γ) appended to its tail all elements in N_{A_1} that are less than every element in M_{A_2} : Let e be the last, i.e. smallest, element of M_{A_2} and $a_{j_i} < e \leq a_{j_{i+1}}$ for $N_{A_1} = (a_{j_1}, a_{j_2}, \dots, a_{j_k})$; since $a_{j_k} = \Gamma$ such an $i, 1 \leq i \leq k$ exists. Hence, N_A is the list N_{A_2} appended to its tail the list $(a_{j_{i+1}}, \dots, a_{j_k})$. Definition 3 and Lemmas 1 and 2 imply the correctness of this method. Example 1 gives an illustration:

Example 1 (Divide and Conquer NSP) Let $A = (\Gamma, 7, 3, 2, 4, 6, 8, 1, 5)$. Hence, $A_1 = (\Gamma, 7, 3, 2, 4)$ and $A_2 = (\Gamma, 6, 8, 1, 5)$. We obtain $M_{A_1} = (7, 3, 2)$, $N_{A_1} = (4, 2, \Gamma)$, $L_{A_1} = (\langle 4, 2 \rangle)$, $M_{A_2} = (6, 1)$, $N_{A_2} = (5, 1, \Gamma)$, $L_{A_2} = (\langle 8, 6 \rangle, \langle 5, 1 \rangle)$, $T_A = (6, 4, 2, 1, \Gamma)$, $P = (\langle 0, \Gamma \rangle, \langle 4, 4 \rangle, \langle 3, 2 \rangle, \langle 0, \Gamma \rangle, \langle 0, \Gamma \rangle)$, and $PMAX = (\langle 4, 4 \rangle, \langle 4, 4 \rangle, \langle 3, 2 \rangle, \langle 0, \Gamma \rangle, \langle 0, \Gamma \rangle)$. Our merging method then returns

$L_A = L_{A_1} + L_{A_2} + (\langle 6, 4 \rangle)$; $M_A = M_{A_1} + (1) = (7, 3, 2, 1)$; and, $N_A = (5, 1, \Gamma)$

Now, the *distributed* algorithm works recursively, basically boiling down to the assumption that the n elements of the input A are *IED* stored on the array DA on the processors $PR_0, PR_1, \dots, PR_{p-1}$ of the p processors BDM machine. The BDM model permits to assume such initial placements (fact 2 on page 2). W.l.o.g. we assume that p is a power of two. We further assume that also L_A, M_A, N_A are *IED* stored on arrays $DL_{DA}, DM_{DA}, DN_{DA}$, respectively, on the processors $PR_0, PR_1, \dots, PR_{p-1}$. Each processor PR_i , $0 \leq i \leq p-1$, solves the NSP for the elements stored within itself sequentially using the function SEQNSP presented before. The p individual solutions are merged using a method similar to the *divide-and-conquer* approach discussed above to get the final

solution. The function BLOCKNSP below gives the pseudocode for this recursive DSM algorithm. We assume that DL_{DA}, n, p are *global* array and *global* variables, respectively, since this allows outputting the left match of an element e at any level of recursion. At the end of every level of recursion DL_{DA} is updated using the RANDOMROUTE function for all elements which found left matches during that level. All elements in the DL_{DA} array are assumed to be initialized to Γ at the beginning.

Function

BLOCKNSP(DA, S, E) : (DN_{DA}, DM_{DA})

Input: The sequence A of $(E - S + 1)n/p$ elements as defined above, IED stored on the array DA in the processors $PR_S, PR_{S+1}, \dots, PR_E, E \geq S$.

Output: DN_{DA} and DM_{DA} for DA , such that every entry of DN_{DA} and DM_{DA} is a dummy or is of the form $\langle DA[j, i], j, i \rangle$. The elements of DN_{DA} and DM_{DA} are assumed to be initialized to be dummy elements at the beginning.

begin

1. **if** ($S = E$) **then** solve the NSP for the n/p elements stored in the sequence $DA[j, S]$, $1 \leq j \leq n/p$, sequentially using the function SEQNSP; from the result form the arrays $DN_{DA}[j, S], DM_{DA}[j, S], DL_{DA}[j, S]$, $1 \leq j \leq n/p$;
return(DN_{DA}, DM_{DA});
 /* Note that if we scan the lists $DN_{DA}[j, S]$ and $DM_{DA}[j, S]$ in order from $j = 1$ to $j = n/p$ leaving the dummies we get N_A and M_A , respectively, as in Example 1 in *increasing* order. We assume w.l.o.g. that $E - S + 1$ is a power of two. */
2. **do in parallel** /* Corresponds to computing $N_1, M_1, N_2, M_2, L_1, L_2$ in Example 1. */
 $(DN_{DA}^1, DM_{DA}^1) := \text{BLOCKNSP}(DA, S, \frac{E-S+1}{2});$
 $(DN_{DA}^2, DM_{DA}^2) := \text{BLOCKNSP}(DA, \frac{E-S+1}{2} + 1, E);$
3. $DT_{DA} := \text{BLOCKMERGE}(DM_{DA}^2, DN_{DA}^1, S, \frac{E-S+1}{2}, 1);$
 /* Corresponds to computing T_A in Example 1. From the definitions of DM_{DA} and DN_{DA} we see that every element of DT_{DA} will be of the form $\langle DA[j, i], j, i \rangle$. */
4. **for** each processor $PR_i, S \leq i \leq E$, **do in parallel**,

for $j \leftarrow 1$ **to** n/p **do sequentially** /* Let $DT_{DA}[j, i] = \langle e, f, g \rangle$ */

if ($g > \frac{E-S+1}{2}$) /* $e \in DM_{DA}^2$ */ **then** $DP[j, i] := \langle 0, \Gamma \rangle$

else /* $e \in DN_{DA}^1$ */ $DP[j, i] := \langle g * (n/p) + f, e \rangle$;

/* Corresponds to computing the list P in Example 1. */

5. $DPMAX := \text{BDPRECOMP}(DP, Max);$

/* Corresponds to computing the list P_{MAX} in Example 1. */

6. $DPMIN := \text{BDPRECOMP}(DP, Min);$

/* Will be useful in finding DN_{DA} . */

7. **for** each processor $PR_i, S \leq i \leq \frac{E-S+1}{2}$, **do in parallel**,

for $j \leftarrow 1$ **to** n/p **do sequentially** /* All elements of DM_{DA}^1 belong to DM_{DA} . */

$DM_{DA}[j, i] := DM_{DA}^1[j, i];$

8. **for** each processor $PR_i, \frac{E-S+1}{2} + 1 \leq i \leq E$, **do in parallel**,

for $j \leftarrow 1$ **to** n/p **do sequentially** /* All elements of DN_{DA}^2 belong to DN_{DA} . */

$DN_{DA}[j, i] := DN_{DA}^2[j, i];$

9. **for** each processor $PR_i, S \leq i \leq E$, **do in parallel**

for $j \leftarrow 1$ **to** n/p **do sequentially** /* Let $DT_{DA}[j, i] = \langle e, f, g \rangle$. */

if $g \leq \frac{E-S+1}{2}$ **then** /* $e \in DN_{DA}^1$; let $DPMIN[j, i] = \langle a, b \rangle$. */

if ($a \neq 0$) **then** from the definition of DP we can see that there does not exist any element of DM_{DA}^2 that is less than e in DT_{DA} . From Example 1 and the discussion preceding it we see that $e \in DN_{DA}$ and hence $DN_{DA}[f, g] = \langle e, f, g \rangle$. This has to be updated in processor g . Hence add $\langle g, \langle f, e \rangle \rangle$ to an array $TEMP_1[1..n/p, i]$;

else /* $e \in DM_{DA}^2$; let $DPMAX[j, i] = \langle a, b \rangle$. */

if ($b = \Gamma$) **then** from the definition of DP we can see that e has no left match. Hence $DM_{DA}[f, g] = \langle e, f, g \rangle$. This has to be updated in processor g . Hence add $\langle g, \langle f, e \rangle \rangle$ to an array $TEMP_2[1..n/p, i]$;

if ($b \neq \Gamma$) then from the definition of DP we can see that b is the left match of e . Hence $DL_{DA}[f, g] = e$. This has to be updated in processor g . Hence add $\langle g, \langle f, e \rangle \rangle$ to an array $TEMP_3[1..n/p, i]$;

/* The arrays $TEMP_1, TEMP_2$ and $TEMP_3$ contain data to be routed. */

10. $(TEMP_1', c_1) := \text{RANDOMROUTE}(TEMP_1);$
 $(TEMP_2', c_2) := \text{RANDOMROUTE}(TEMP_2);$
 $(TEMP_3', c_3) := \text{RANDOMROUTE}(TEMP_3);$

/* The function RANDOMROUTE and Theorem A.3 can be applied to $TEMP_1, TEMP_2$ and $TEMP_3$. RANDOMROUTE updates the arrays DN_{DA}, DM_{DA} and DL_{DA} in all processors. */

11. for each processor $PR_i, S \leq i \leq E$, do in parallel

Scan the arrays $TEMP_1'[1..c_1(\frac{n}{p}), i]$, $TEMP_2'[1..c_2(\frac{n}{p}), i]$, $TEMP_3'[1..c_3(\frac{n}{p}), i]$ and update the arrays $DN_{DA}[1..n/p, i]$, $DM_{DA}[1..n/p, i]$ and $DL_{DA}[1..n/p, i]$;

12. return(DN_{DA}, DM_{DA})

/* Note that, if we scan the arrays $DN_{DA}[j, i]$ and $DM_{DA}[j, i]$ in order from $j = 1$ to $j = n/p$ and $i = 0$ to $i = p - 1$ leaving the dummies we get N_A and M_A as in Example 1, respectively, in *increasing* order. */
end.

At the end of execution of the function BLOCKNSP , the following facts about $e := DA[j, i]$ are satisfied:

1. If there exists a left match l for e then, $DL_{DA}[j, i] = e$ and $DM_{DA}[j, i] = \text{dummy}$.
2. If there is no left match for e then, $DL_{DA}[j, i] = \Gamma$ and $DM_{DA}[j, i] = \langle e, j, i \rangle$.
3. If $e \in DN_{DA}$ then, $DN_{DA}[j, i] = \langle e, j, i \rangle$.

Time Complexity.

From Theorem 1 and the Function BLOCKNSP we see that steps 1, 4, 7, 8 and 9 take $O(n/p)$ time. Theorem A.2 implies that step 3 takes $O(\frac{n \log_2(\frac{E-S+1}{2})}{p})$ computation time and $O((\tau + \sigma m \lceil \frac{n}{pm} \rceil) \log_2(\frac{E-S+1}{2}))$ communication time. Theorem A.1 implies that steps 5 and 6 take $4\tau \lceil \frac{\log_2(E-S+1)}{\log_2(\frac{\tau}{\sigma m} + 1)} \rceil + \tau + \sigma m$ communication time and $O(\frac{n}{p} + \frac{\tau \log_2(E-S+1)}{\sigma m \log_2(\frac{\tau}{\sigma m} + 1)})$ computation time. For each execution of the RANDOMROUTE function in

step 10 at most n/p elements are destined per processor. Hence $\alpha \leq 1$ in Theorem A.3. Substituting for α in Theorem A.3 we see that step 10 takes $2(\tau + c \lceil \frac{n}{p} \rceil)$ communication time and $O(c \lceil \frac{n}{p} \rceil)$ computation time with high probability, where c is a constant. Theorem A.3 also implies that c_1, c_2 and c_3 in step 10 can be output in constant time. Hence, step 11 takes $O(n/p)$ time. Let $t := E - S + 1$ and $T_{comp}(t)$ be the computation time taken by $\text{BLOCKNSP}(DA, S, E)$. From Theorem 1 we see that $T_{comp}(1) = O(n/p)$. From function BLOCKNSP we see that,

$$T_{comp}(t) = T_{comp}(\frac{t}{2}) + O\left(\frac{n \log_2 t}{p} + \frac{\tau \log_2 t}{\sigma m \log_2(\frac{\tau}{\sigma m} + 1)}\right)$$

$$= O\left(\frac{n \log_2^2 t}{p} + \frac{\tau \log_2^2 t}{\sigma m \log_2(\frac{\tau}{\sigma m} + 1)}\right)$$

Let $T_{comm}(t)$ be the communication time taken by $\text{BLOCKNSP}(DA, S, E)$. From Theorem 1 we see that $T_{comm}(1) = 0$. From function BLOCKNSP we see that,

$$T_{comm}(t) = T_{comm}(\frac{t}{2}) + O\left((\tau + \sigma m \lceil \frac{n}{pm} \rceil) \log_2 t\right)$$

$$= O\left((\tau + \sigma m \lceil \frac{n}{pm} \rceil) \log_2^2 t\right)$$

Given the input array DA , the function is called as $\text{BLOCKNSP}(DA, 0, p-1)$. This and the above discussion imply the following theorem.

Theorem 2 *The NSP can be solved in $O\left((\tau + \sigma m \lceil \frac{n}{pm} \rceil) \log_2^2 p\right)$ communication time and $O\left(\frac{n \log_2^2 p}{p} + \frac{\tau \log_2^2 p}{\sigma m \log_2(\frac{\tau}{\sigma m} + 1)}\right)$ computation time on a DSM system using the BDM model of computation.*

3. Applications

Our BDM-based algorithm for the NSP gives BDM-based algorithms for the following problems, that are mapped onto the NSP in [1]:

1. **Triangulating monotone polygons** (a monotone polygon is one that can be split into two monotone polygonal chains such that the vertices of the chains are increasing (or decreasing) by the x -coordinate).
2. **Reconstruction of binary trees from their traversals** (from *inorder* and *preorder* traversals).

3. **Parentheses matching** (find the level of nesting for each parenthesis in a legal sequence of parenthesis, and also find for each parenthesis its left mate).

4. Conclusion

In this paper we presented a simple and efficient algorithm for the nearest smaller problem (*NSP*), which, to the best of our knowledge is the first of its kind for *DSM* systems. Since the *NSP* is fundamental in many problems, a solution for it on *DSM* systems implies *DSM*-based solutions for a variety of problems in diverse areas as discussed in this paper.

A. Appendix

Function BDPRECOMP(A, ∇) : (A').

Input: Given a sequence of ordered pairs $\langle a_1, data_1 \rangle, \langle a_2, data_2 \rangle, \dots, \langle a_r, data_r \rangle$, *IED* stored on the array A on a p -processor *BDM* machine, $data_i$ is the data (if any) associated with a_i , $1 \leq i \leq r$. ∇ is a binary associative operator $\in \{+, Min, Max, \dots\}$.

Output: A sequence of ordered pairs $\langle a'_1, data'_1 \rangle, \langle a'_2, data'_2 \rangle, \dots, \langle a'_r, data'_r \rangle$, *IED* stored on the array A' on the p -processor *BDM* machine, where, $a'_i = \nabla_{k=1}^i a_k$ and $data'_i$ is the data associated with a'_i (if any).

From Theorem 9 of [4] we infer the following theorem.

Theorem A.1 ([4]) *Given a sequence $(a_1, a_2, \dots, a_r)$ of numbers IED stored on a p -processor BDM, we can compute the prefix sums $ps_i = \sum_{j=1}^i a_j$, $1 \leq i \leq r$, in $4\tau \lceil \frac{\log_2 p}{\log_2(\frac{\sigma_m}{\sigma_m+1})} \rceil + \tau + \sigma m$ communication time and $O(\frac{n}{p} + \frac{\tau \log_2 p}{\sigma m \log_2(\frac{\sigma_m}{\sigma_m+1})})$ computation time. This complexity holds for prefix maxima, prefix minima and similar associative operators.*

Theorem A.2 ([3]) *Function*

BLOCKMERGE(BL_1, BL_2, i, t, a) *takes* $O(\frac{n \log_2 t}{p})$ *computation time and* $O((\tau + \sigma m \lceil \frac{n}{pm} \rceil) \log_2 t)$ *communication time.*

Function RANDOMROUTE(A) : (A', c)

Input: Input array $A[1 : \lceil \frac{n}{p} \rceil, 0 : p-1]$ *IED* stored on a p -processor *BDM* machine, such that each element of A consists of a packet ($i, data_i$) of constant size, where i is the index of the processor to which $data_i$ has to be

routed. α is a constant such that no processor is the destination of more than $\alpha \lceil \frac{n}{p} \rceil$ elements on the whole.

Output: Output array $A'[1 : c \lceil \frac{n}{p} \rceil, 0 : p-1]$ holding the routed data *IED* stored on a p -processor *BDM* machine, such that all the data with the processor PR_i , $0 \leq i \leq p-1$, as the destination will be available in one of the locations $A'[j, i]$, $1 \leq j \leq c \lceil \frac{n}{p} \rceil$, in the processor PR_i , where c is larger than $\max\{1 + \frac{1}{\sqrt{2}}, \alpha + \frac{\sqrt{\alpha}}{2}\}$. The function stores a copy of c in every processor PR_i , $0 \leq i \leq p-1$.

The function is implemented using the *randomized-routing* algorithm suggested in [2].

Theorem A.3 *The function RANDOMROUTE(A) completes within $2(\tau + c \lceil \frac{n}{p} \rceil)$ communication time and $O(c \lceil \frac{n}{p} \rceil)$ computation time with high probability, where c is larger than $\max\{1 + \frac{1}{\sqrt{2}}, \alpha + \frac{\sqrt{\alpha}}{2}\}$, $p^2 < \frac{n}{6 \ln n}$ and α is such that every processor is a destination for at most $\alpha \frac{n}{p}$ messages. $\square$*

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