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데이터 편재 하에서 히스토그램 변환 기법에 기초한 효율적인 병렬 결합 알고리즘

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An Efficient Parallel Join Algorithm Based on Histogram Equalization in Present of Data Skew

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ABSTRACT

본 논문에서는 데이터 분포가 편재된 상황하에서 부하의 불균형과 버켓 오버플로우 문제를 해결하기 위해 히스토그램 변환 기법을 이용한 데이터 분산 방법과 이를 기초로 한 병렬 결합 알고리즘을 제안한다. 제안된 알고리즘의 성능은 시뮬레이션과 하이퍼큐브형 병렬 컴퓨터 상에서 실험적인 방법에 의하여 분석되었다. 그 결과 제안된 알고리즘이 기본의 해쉬 결합 방법보다 우수함을 보인다.

1. Introduction

In relational database systems, join operations are the most complex and time consuming ones which limit performance of such systems. Many parallel join algorithms have been proposed for parallel relational database systems[4,6,8]. Among them, the parallel hash-based join algorithm(PHJA) has been found to be superior to other join algorithms for the uniform distribution of data[4,8].

In real databases, it is often found that certain values for a given attribute occur more frequently than other values. This phenomenon is referred to as data skew. It is known that data distribution for many textual databases follows a variant of Zipf's law, representing skewed data distribution[5]. With such data distribution, the PHJA shows two major problems in performance: load imbalance and bucket overflow[2,10]. This is because data skew can give rise to non-uniform distribution after hashing. Thus, the effectiveness of the PHJA depends on the degree of uniformity in data distribution. As pointed out in [4,9], most algorithms proposed for the PHJA limit exploiting parallelism as the skewness of data distribution becomes large.

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Several algorithms have been proposed to overcome such limitations of the PHJA in data skew[2,3,10]. Algorithms proposed in [2] and [3] are based on bucket size tuning. The algorithms are proved to be effective with slightly skewed data. However, they can not remedy the problems of load imbalance and bucket overflow in highly skewed data. In [10], the proposed algorithm added an extra scheduling phase to the usual partitioning and joining phase to solve the two problems above. However, performance study in [9] indicated that, unless the data is highly skewed, the algorithm proposed in [10] becomes markedly worse than that of PHJA. This is because heuristics in the scheduling phase require many steps for efficient join operations. Moreover, assumptions and approximations employed in the heuristic algorithm are not valid in slightly skewed or uniform data distributions.

This paper proposes an efficient algorithm, called *skew resolution join algorithm*(SRJA), for parallel join operations with skewed data. We propose a methodology for partitioning relations evenly across all processors in a parallel database system. Using the histogram equalization technique, the framework transforms the histogram of skewed data to uniform distribution that corresponds to the relative computing power of node processors in the system. We performed simulation and experiment on a real parallel computer with the Zipf-like distribution of hashed values for join attributes. Both simulation and experiment results indicate that the proposed algorithm exhibits better performance than the conventional PHJA in the presence of data skew, with negligible overhead in the absence of data skew.

2. Data distribution framework

The following assumptions are made in the remainder of this paper. The parallel database system has P autonomous processors numbered by $1, 2, \ldots, P$, each having its own memory and disk, which are linked through an interconnection network. There exist two joining relations labeled as R and S in the database, with R being the smaller one. Initially, both relations are horizontally partitioned into disjoint subsets of the tuples and evenly distributed across all the processors.

2.1 Histogram equalization

Suppose that $\overline{x}$ is a discrete random variable and $g(x)$ is a monotonic transformation function of the discrete real variable x. Then the histogram equalization process can be considered as a transformation $\overline{y} = g(\overline{x})$. In the transformation, the input random variable $\overline{x}$, ranged over $x_1, x_2, \ldots, x_J$, $(x_1 \leq x_2 \leq \cdots \leq x_J)$ is mapped into an output random variable $\overline{y}$, ranged over $y_1, y_2, \ldots, y_K (y_1 \leq y_2 \leq \cdots \leq y_K)$, such that the output probability density follows a uniform density.

Since a histogram of discrete random variables can be approximated by

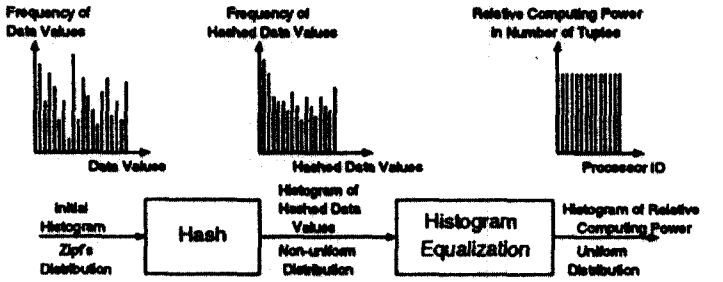


Figure 1. Data distribution framework for parallel joins.

continuous random variables, we first obtain the transfer function in the continuous case. Because the transformation is monotonic, the fundamental theorem of random variable[7] follows that $f_{\bar{y}}(y)=\frac{f_{\bar{x}}(x)}{g'(x)}$ where, $f_{\bar{x}}(x)$ and $f_{\bar{y}}(y)$ are the probability densities of $\bar{x}$ and $\bar{y}$, respectively and $g'(x)$ is the derivative of $g(x)$. Hence $\int_{y_1}^{y} f_{\bar{y}}(y)dy=\int_{x_1}^{x} f_{\bar{x}}(x)dx$. The integral on the right is the cumulative distribution function $F_{\bar{x}}(x)=P(\bar{x}\le x)$ of the input variable $\bar{x}$. Thus $\int_{y_1}^{y} f_{\bar{y}}(y)dy=F_{\bar{x}}(x)$. In the special case for which the output density is forced to be a uniform density, $f_{\bar{y}}(y)=\frac{1}{y_K-y_1}$ for $y_1\le y\le y_K$, the histogram equalization transfer function becomes

$$y=g(x)=(y_K-y_1)F_{\bar{x}}(x)+y_1. \quad (1)$$

Let us now return to the discrete case. Suppose that $H_{\bar{x}}(x)$ for $x=x_1, x_2, \ldots, x_J$ represents the fractional number of occurrence frequencies of input values. Then the cumulative probability distribution of the input variable, $F_{\bar{x}}(x)$, is approximated by its normalized cumulative histogram as follows: $F_{\bar{x}}(x)\approx\sum_{m=x_1}^{x} H_{\bar{x}}(m)$. Hence equation (1) can be modified by

$$y=g(x)=(y_K-y_1+1)\times\sum_{m=x_1}^{x} H_{\bar{x}}(m)+y_1. \quad (2)$$

Our data distribution framework for parallel joins with the aim is shown in figure 1. Initially, we have a histogram of data values of the join attribute for a relation. Then, we hash the data values. Finally, the histogram of the hashed values is transformed into a uniformly distributed histogram using equation (2). Thus, given an arbitrary data histogram, we can obtain even distribution of data among processors. In our histogram equalization, an input random variable $\bar{x}$ indicates the h distinct hashed values of the join attribute and an output random variable $\bar{y}$ corresponds to the processor

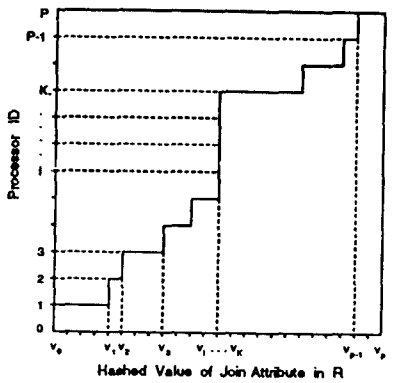


Figure 2. Transfer function for histogram equalization.

id, numbered by $1,2,\ldots,P$. Then the histogram equalization transfer function is obtained from equation (2) as

$$y = g(x) = \lceil P \sum_{m=0}^{x} H_x(m) \rceil \qquad (3)$$

where $\lceil\ \rceil$ is ceiling function.

2.2 Finding upper boundary values

Since the transfer function in equation (3) is monotonically increasing function, an upper boundary value, x, for each partition is obtained by inverse transformation of equation (3). That is, the upper boundary value of the ith processor can be obtained by $g^{-1}(i)$. Let the P boundary values be $v_1, v_2, \ldots, v_P$ and the smallest hashed value of the join attribute of R be v_0. Then, a hashed value of the join attribute, a, falls into the range $v_{i-1} < a \leq v_i$ for $1 < i \leq P$. Figure 1 shows an example for determining the boundary values from a transfer function.

One complication arises in determining boundary values for partitioning in the presence of data skew. If $g^{-1}(i) = g^{-1}(j)$ for $i \neq j$, the processor $i(<j)$ would have much more tuples than other processors and processor j would have no tuples at all. In the worst case, where all the hashed values of the join attribute have a single value, all tuples in the relation R are mapped into a single processor.

Figure 2 illustrates a transfer function for histogram equalization. Note the case where one hashed value maps into different processor ids. In the case, it is still possible to equalize the histogram of the output random variable, by uniformly distributing the tuples to the processors into which that value is mapped. For correct join operations, however, all the tuples of S with the same boundary value should be distributed to the processors in which associated tuples of R are assigned. Figure 3 shows histograms for hashed values before and after equalization.

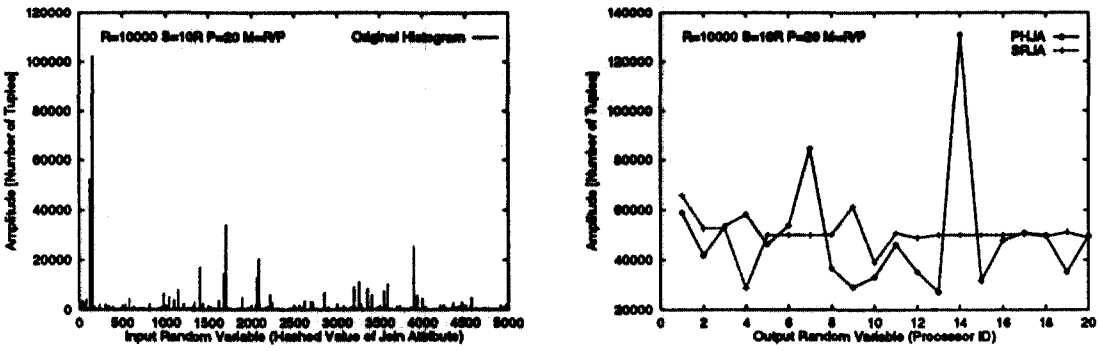
3. Parallel join algorithm

The basic procedure for our join algorithm consists of three major phases as follows.

Phase 1. Histogram evaluation phase

1.1 Each processor reads its portion of R, hashes the join attribute of each tuple and obtains a local cumulative histogram of the hashed values in parallel.

1.2 Each processor broadcasts its own local cumulative histogram, evaluates the global cumulative histogram using received local histograms for R in parallel.



(a) Histogram before equalization. **(b) Histogram after equalization.**

Figure 3. Histograms in a heavy skewed case.

1.3 Each processor determines the boundary values in parallel.

Phase 2. Partitioning phase

Each processor partitions and distributes its portion of both relations using the histogram equalization transfer function and the boundary values. As a result of this phase, the corresponding partitions of the two relations that have the same ranged boundary values reside on the same processor.

Phase 3. Joining phase

Each processor finally performs the joining step by using the conventional hash-based join algorithm on the partition pairs in parallel.

The I/O accesses from secondary storage and communication cost through an interconnection network become major limiting factors on the performance of parallel join operations. Therefore, the join algorithm should be carefully designed in order to minimize the I/O and communication costs. A useful general observation is that an imbalance in the number of tuples of the smaller relation R per processor is much worse than an imbalance in the number of tuples of the larger relation S per processor. This is because an imbalance in the number of building tuples per processor requires extra buckets in the local joins, thus driving up the number of I/Os significantly[8]. The partitioning scheme in our algorithm only attempts to balance tuples of the smaller relation R per processor to minimize the I/O cost. Thus, in contrast to the PHJA, our partitioning scheme has only one extra scan of each processor's portion of the smaller relation R. Moreover, our scheme requires additional communication cost for broadcasting the local histograms to each processor.

Note that during the local joining, the size of each bucket should be smaller than the memory capacity. However, nonuniform distribution of the join attribute values may generate bucket overflow. The performance in the presence of overflowed buckets diminishes because it requires extra I/O to spool to disk and then re-read to perform the join[2,8]. We can also use

the histogram equalization technique to resolve the bucket overflow. That is, we can adopt the histogram equalization technique for locally partitioning the portion of the relations distributed at each processor into several buckets suitable in memory.

4. Simulation

Simulation experiments are conducted for performance comparisons of the PHJA and our SRJA. The performance of both algorithms is evaluated in the presence of data skew. It is known that data distribution for many practical situations follows a variant of Zipf's Law[5]. In the Zipf's distribution, the probability of a duplication for the ith join attribute value over N possible values in a relation is given by

$$p_i = \frac{c}{i^{(1-\theta)}}, 1 \le i \le N,$$

$$\text{where } c = \frac{1}{H_N^{(1-\theta)}},$$

$$H_N^{(1-\theta)} = \sum_{i=1}^{N} \frac{1}{i^{(1-\theta)}}. \quad (4)$$

In the distribution, $\theta = 1$ corresponds to the uniform distribution, while $\theta = 0$ corresponds to a highly skewed case.

4.1 Simulation model

In our model, the PHJA and SRJA are simulated to obtain their total execution time. The total execution time comprises the CPU time, the I/O time, and the communication time. The execution time during the ith phase is sum of the three components : $T^i = T^{i}_{cpu} + T^{i}_{disk} + T^{i}_{comm}$. Thus the total execution time for the join operations can be expressed as $T = \sum_i T^i$.

The following assumptions are made in simulation experiments: the cost for writing the joined results into disks is not taken into account because this cost has the same effect on each join algorithm; the network has an ability of broadcasting and point-to-point communication with the same transmission cost.

Table 1. Parameter values for simulation.

t_{cm}	Time to compare with two attributes 3 uS
t_{hs}	Time to compute a hash function of a key 9 uS
t_{mv}	Time to move a tuple in memory 20 uS
t_{bj}	Time to build a join result tuple 10 uS
t_{ad}	Time to update a variable in memory 4uS
t_{sd}	Time for CPU to send a page over network 1 mS
t_{rv}	Time for CPU to receive a page over network 1 mS
t_{io}	Time to transfer a page between disk and memory 20mS
t_{tn}	Time to transfer a page in network 3mS
n	Number of tuples in a page 100
h	Number of elements in histogram table 5000
H	Size in pages of histogram table h/1000

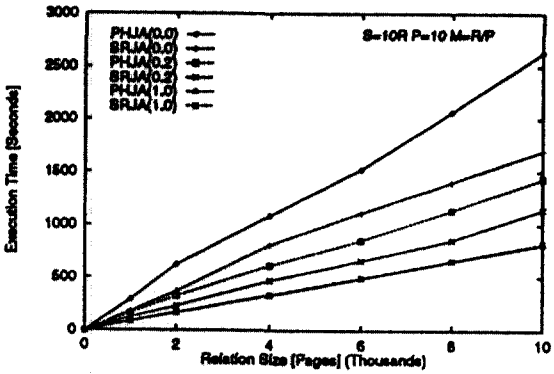
The simulation experiments are performed on the three cases of samples data distributions: $\theta = 1$(uniform distribution case), $\theta = 0.2$(mild skew case) and $\theta = 0$(heavy skew case). Each data in synthetic sample database for simulation experiments is obtained by random number generation by use of the equation (4). To evaluate communication cost for the partitioning phase, T_{comm}, for the three cases, let R_i and T_i be the number of pages received from, and transmitted to the processor i, respectively. Then, communication cost for PHJA and SRJA is given by

$T_{comm} = t_{tm} * \max\{(R_1+T_1),(R_2+T_2), \cdots,(R_P+T_P)\}$, where t_{tm} is time to transfer a page. For the purpose of a variance reduction on mean difference between the simulated costs of two algorithms, the same synthetic database is used to simulate both the PHJA and our SRJA[1].

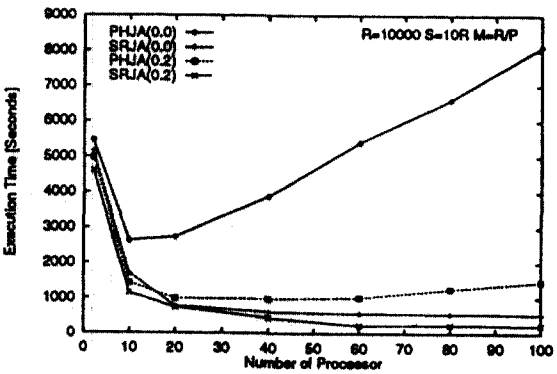
The parameter values of simulation experiments are as follows. The size of the relation S is ten times the size of the smaller relation R. The memory size on each processor is $M = R/P$. The domain size for the join attribute of each relation is 10000. The rest of parameters are set to the values shown in table 1[9].

Simulation experiments are execution driven. That is, performance is measured while actually executing the join algorithms of PHJA and SRJA. The PHJA is experimented by the following steps. The execution time for the partitioning phase is calculated in terms of the number of the basic operations by performing actual hash-based partitioning of the synthetic sample database. The execution time for the joining phase is evaluated by calculating the CPU and I/O time costs based on the number of I/O operations on the skewed partition. The total execution time for the PHJA is evaluated by adding the costs of the two phases.

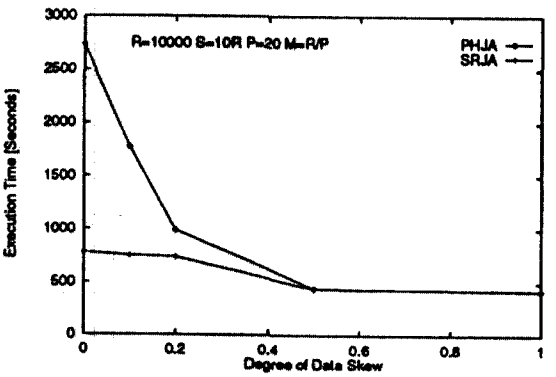
The SRJA is experimented similarly. The execution time for phase 1 and phase 2 of the SRJA is calculated in terms of the number of the basic operations by performing actual partitioning based on the histogram equalization methodology of the syntheticsample database.



(a) Execution time versus relation size.



(b) Execution time versus number of processors.



(c) Execution time versus degree of data skew.

Figure 4. Simulation result.

The execution time for the joining phase is obtained by the same method as used in the PHJA. The total execution time for the SRJA is evaluated by adding the costs of the three phases for each.

4.2 Simulation results

Several simulation experiments are performed by considering the three points of view: the effects of relation sizes, the effects of the system configurations, and the effects of the degree of data skew. Every simulation experiment are performed 10 times with the same parameter values. We take a mean value of the results of ten trials. Figure 4 shows simulation results.

Figure 4(a) shows the effects of the join algorithms on relation size in the three sample databases : uniform distribution case ($\theta=1$), mild skew case ($\theta=0.2$) and heavy skew case($\theta=0$). The simulation results show that 1) the total time costs of the PHJA and SRJA are linearly incremented by relation size, 2) the difference in the total time costs between the PHJA and SRJA in the heavy skew case is higher than that of the mild skew case and 3) the difference of the total time costs between the two algorithms in the uniform distribution case is little.

In figure 4(b), we show the effects of the join algorithms on the number of processors in two skewed sample databases. As the number of processors becomes large, the performance of the PHJA is rapidly degraded in the heavy skew case because of *bucket overflow* during the local joining phase. In this case, we show that SRJA outperforms the PHJA.

Finally, we show the effects of the degree of data skew in figure 4(c). As the degree of data skew becomes larger, performance of the PHJA is degraded rapidly. In the worst case, the PHJA may generate one large bucket leading to *load imbalance* and b*ucket overflow* which cause the performance degradation of parallel join operations.

5. Experimentation

To investigate the performance of our skew resolution join algorithm in real database system and provide more faith of simulation experiments, we implemented our algorithm in COREDB[11], which is is a 3-dimensional hypercube machine developed by KAIST's Computer Research Engineering Laboratory. Currently, each node consists of a 68030 CPU, 8Mbytes DRAM and Disk Controllers. The operating system is UNIX SystemV release 3.

To compare the SRJA with the PHJA implemented on COREDB, the sort-merge join operations are locally performed. It is because UNIX uses the virtual memory scheme as memory management method. In the virtual memory environment, the hash-based algorithm for local join do not perform well due to more disk I/O operations for swap-in and swap-out operations when main memory becomes full.

5.1 Experiments

For our experiments, we used

benchmark relations with the join attribute generated from Zipf's distribution. Table 2 shows the benchmark relation schema[12]. As in simulation experiments, experiments are conducted on the three cases of sample data distributions: $\theta = 1$(uniform distribution case), $\theta = 0.2$(mild skew case), and $\theta = 0$(heavy skew case). Each synthetic sample database for the experiments is obtained by a random number generation by use of the equation (4). We generate both relations with the same tuple distribution.

The parameter values for the experiments are as follows. The size of the smaller relation R is 2000 tuples. The size of the larger relation S is five times the size of the smaller relation R. The size of each tuple in both relations is 108 bytes. Thus total size of the relation R is about 200 KBytes and that of the relation S is about 1 MBytes. The domain size for the join attribute is 200 and the number of distinct hashed values in the histogram table for the SRJA is 50.

Table 2. Benchmark relation schema.

Attribute	Type	Range of Value	Order	Comment
Partition	Integer	0-9999	Sequential	Unique
Join	Integer	0-199	Random	Duplicate, Zipf Distribution
String	Char. Array		Fixed	100 Bytes Size

5.2 Experimental Results

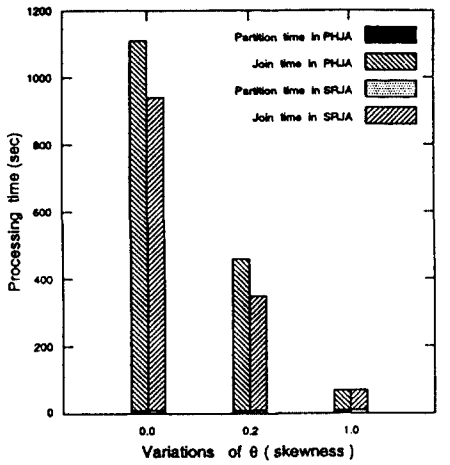
We perform the experiments for the three cases on the 4-node and 8-node configurations. Figure 5 shows our experimental results. In the figure, partitioning time for the SRJA is obtained by adding costs for the histogram evaluation phase and the partitioning phase in the SRJA. From the results, we observe the followings. Time cost for the histogram evaluation phase in the SRJA is negligibly small. Time cost for the local join operations is a dominating factor on performance of the parallel join algorithms in the skewed cases. As the dimension of hypercube(the number of nodes) increases, time costs for the partitioning phase of both algorithms are linearly increased. This is because of the characteristic of the hypercube communication method. In the uniform distribution case, performance of the SRJA do not become worse than that of the PHJA. This is because the PHJA gives a little but non-negligible skewed partitions in the uniform distribution case. However, in contrast to the PHJA, the SRJA gives even partitions among the processors.

To show the relative efficiencies of the two join algorithms, we measure the performance gain of the SRJA over the PHJA as follows:

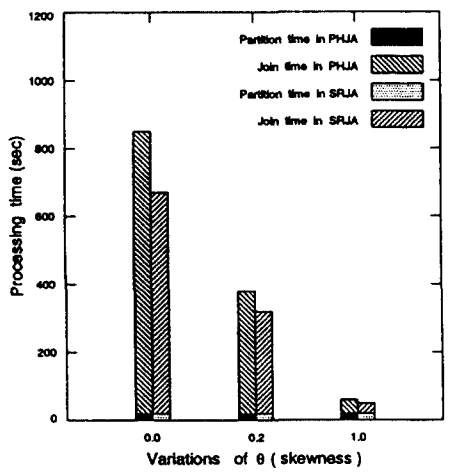
$$Performance\ gain = \frac{T_{PHJA} - T_{SRJA}}{T_{PHJA}} \times 100$$

Table 3 shows the performance gain measured from the experimental results. In the table, we observe that in the heavy skew case($\theta = 0.0$), as the dimension of hypercube increases, the performance gain is increased. This is because the PHJA gives a highly skewed partition in the heavy skew case and the size of such partition is not linearly

decreased as the number of node processors in the system increases. However, the size of the maximum skewed partition in the SRJA is linearly decreased as the number of node processors increases.



(a) 4-node hypercube computer.



(b) 8-node hypercube computer.

Figure 5. Experimental results

In the mild skew case($\theta = 0.2$), as the dimension of hypercube increases, the performance gain is reduced. This is because the size of the maximum skewed partition in both the PHJA and the SRJA is linearly decreased as the number of node processors increases.

Table 3. Performance gain.

	$\theta = 0.0$	$\theta = 0.2$	$\theta = 1.0$
4-node	16.39	24.58	-0.02
8-node	23.58	13.81	0.05

6. Conclusions

In this paper, we first have proposed a data distribution framework for parallel join. Our data distribution framework employs the histogram equalization technique, which evenly distributes data across processors. We then have proposed an efficient parallel join algorithm based on the data distribution framework which takes data skew into account. Our proposed join algorithm is carefully considered to minimize the I/O and communication costs and is designed to reduce bucket overflow and load imbalance for real world situations.

The performance of the proposed algorithm has been evaluated and compared with the parallel hash-based join algorithm by simulation and experiment on the real hypercube parallel computer with several synthetic databases. Comparison results from both the simulation and experiment have shown that the proposed algorithms have better performance than the parallel hash-based join algorithm in the presence of data skew, with negligible overhead in the absence of data skew.

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