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具有動態資源管理之高效能叢集式資訊檢索系統設計(2/3)

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中文摘要

為了服務網路上每秒成千上萬個的使用者需求，資訊檢索系統需要索引結構來加速資料的搜尋。這個報告針對目前最熱門的索引結構─轉置檔案，提出一個查詢處理時間最佳化的方法。在轉置檔案中，每一個字彙都有一個相對應的文件編號串列(稱為轉置串列)來指示那一個文件包含這個字彙。壓縮轉置串列可以減少資訊檢索系統在查詢資料時所需的磁碟讀取時間並大幅改善資訊檢索系統的查詢速度。我們觀察到透過指派合適的編號給文件可以讓轉置串列在使用相同的壓縮方法下被壓縮的更好，並提升查詢處理的速度。在這個報告中，我們提出一個新的演算法，稱為 *Partition-based document identifier assignment* (*PBDIA*) algorithm，來為文件產生合適的編號。這個演算法可以有效率地指派連續的編號給那些包含有經常被查詢的字彙之文件，使得經查被查詢的字彙之轉置串列可以被壓縮得更好。實驗顯示我們所提的 *PBDIA* 演算法可以有效縮短查詢處理時間，而對於長查詢(long queries)與平行資訊檢索(parallel IR)更有明顯的好處。我們相信所提出的演算法可以應用於高效能與低成本的資訊檢索系統設計。

關鍵字: 轉置索引，轉置檔案壓縮，查詢處理，文件編號指派，*d*-gap 技術

英文摘要

Compressing an inverted file can greatly improve query performance of an *information retrieval system* (*IRS*) by reducing disk I/Os. We observe that a good *document identifier assignment* (*DIA*) can make the document identifiers in the posting lists more clustered, and result in better compression as well as shorter query processing time. In this paper, we tackle the NP-complete problem of finding an optimal *DIA* to minimize the average query processing time in an *IRS* when the probability distribution of query terms is given. We indicate that the *greedy nearest neighbor* (*Greedy-NN*) algorithm can provide excellent performance for this problem. However, the *Greedy-NN* algorithm is inappropriate if used in large-scale *IRS*es, due to its high complexity $O(N^2 \times n)$, where N denotes the number of documents and n denotes the number of distinct terms. In real-world *IRS*es, the distribution of query terms is skewed. Based on this fact, we propose a fast $O(N \times n)$ heuristic, called *partition-based document identifier assignment* (*PBDIA*) algorithm, which can efficiently assign consecutive document identifiers to those documents containing frequently used query terms, and improve compression efficiency of the posting lists for those terms. This can result in reduced query processing time. The experimental results show that the *PBDIA* algorithm can yield a competitive performance versus the *Greedy-NN* for the *DIA* problem, and that this optimization problem has significant advantages for both long queries and parallel *information retrieval* (*IR*).

Keywords: inverted index, inverted file compression, query evaluation, document identifier assignment, *d*-gap technique

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1. Introduction

Information retrieval systems (*IRSes*) that are wildly used in many applications, such as search engines, digital libraries, genomic sequence analyses, etc. (Kobayashi & Takeda 2000; Williams & Zobel 2002), are overwhelmed by the explosion of data. To efficiently search vast amounts of data, an inverted file is used to evaluate queries for modern large-scale *IRS*es due to its quick response time, high compression efficiency, scalability, and support for various search techniques (Witten et al. 1999; Zobel et al. 1998). An inverted file contains, for each distinct term in the collection, a list (called a posting list or synonymously an inverted list) of the identifiers of the documents containing that term. A query consists of keyword terms. To retrieve information, the query evaluation engine reads and decompresses the posting lists for the terms involved in the query, and then merges (intersection, union, or difference) corresponding posting lists to obtain a candidate set of relevant documents.

Compressing an inverted file can greatly increase query throughput (Zobel & Moffat 1995; Williams & Zobel 1999). This is because the total time of transferring a compressed posting list and subsequently decompressing it is potentially much less than that of transferring an uncompressed posting list. The document identifiers in a posting list are usually stored in ascending order. By using the popular *d*-gap compression approach (Witten et al. 1999; Moffat & Zobel 1992), efficient compression of an inverted file can be achieved. In addition, we observe that the *d*-gap compression approach can result in good compression if the document identifiers in the posting lists are clustered.

The query processing time in a large-scale *IRS* is dominated by the time needed to read and decompress the posting lists for the terms involved in the query (Moffat & Zobel 1996), and we observe that the query processing time grows with the total encoded size of the corresponding posting lists. This is because the disk transfer rate is near constant, and the decoding processes of most encoding methods used in the *d*-gap compression approach are on a bit-by-bit basis. If we can reduce the total encoded size of the corresponding posting lists without increasing decompression times, a shorter query processing time can be obtained.

A *document identifier assignment* (*DIA*) can make the document identifiers in the posting lists evenly distributed, or clustered. Clustered document identifiers generally can improve the compression efficiency of the *d*-gap compression approach without increasing the complexity of decoding process, hence reduce the query processing time. In this paper, we consider the problem of finding an optimal *DIA* to minimize the average query processing time in an *IRS* when the probability distribution of query terms is given. The *DIA* problem, that is known to be NP-complete via a reduction to the rectilinear *traveling salesman problem* (*TSP*), is a generalization of the problems solved by Olken & Rotem (1986), Shieh et al. (2003), and Gelbukh et al. (2003). Their research results showed that this kind of optimization problem can be effectively solved by the well-known *TSP* heuristic algorithms. The *greedy nearest neighbor* (*Greedy-NN*) algorithm performs the best on average, but its high complexity discourages its use in modern large-scale *IRS*es.

In this paper, we propose a fast heuristic, called *partition-based document identifier assignment* (*PBDIA*) algorithm, to find a good *DIA* that can make the document identifiers in the posting lists for frequently used query terms more clustered. This can greatly improve the compression efficiency of the posting lists for frequently used query terms. Where the probability distribution of query terms is skewed, as is the typical case in a real-world *IRS*, the experimental results show that the *PBDIA* algorithm can yield a competitive performance versus the *Greedy-NN* for the *DIA* problem. The experimental results also show that the *DIA* problem has significant advantages for both long queries and parallel *information retrieval* (*IR*).

The remainder of this paper is organized as follows. Section 2 describes the inverted index and explains why a *DIA* can affect the storage space required and change query performance. Section 3 derives a cost model for the *DIA* problem, and presents how to use the well-known *TSP* heuristic algorithms to solve this optimization problem. In Section 4, we propose a fast *PBDIA* algorithm. We show the experimental results in Section 5. Finally, Section 6 presents our conclusion.

2. General Framework

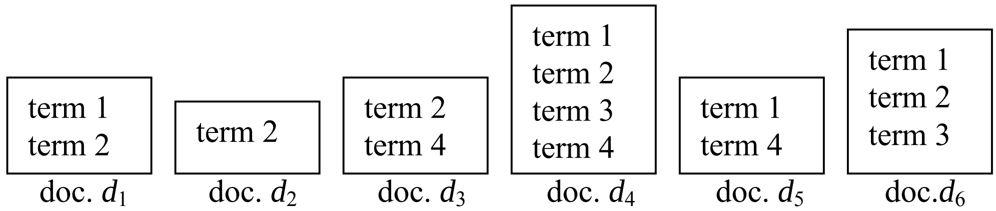
An inverted index consists of an index file and an inverted file. An index file is a set of records, each containing a keyword term t and a pointer to the posting list for term t. An inverted file contains, for each distinct term t in the collection, a posting list of the form

$$IL_t = \langle id_1, id_2, \ldots, id_{ft} \rangle,$$

where id_i is the identifier of the document that contains t, and frequency f_t is the number of documents in which t appears. The document identifiers are within the range 1...N, where N is the number of documents in the indexed collection. In a large document collection, posting lists are usually compressed, and decompression of posting lists is hence required during query processing.

Zipf (1949) observed that the set of frequently used terms is small. According to Zipf's law, 95% of words in all documents fall in a vocabulary with no more than 8000 distinct terms. This suggests that it is advisable to store the index records of frequently used terms in RAM to greatly reduce index search time. Hence, the significant portion of query processing time is to read and decompress the compressed posting list for each query term. This paper restricts attention to inverted file side only and investigates the *DIA* problem to improve the efficiency of an inverted file and the overall *IR* performance.

The d-gap compression approach (Witten et al. 1999; Moffat & Zobel 1992), the most popular approach for inverted file compression, consists of two steps. It first sorts the document identifiers of each posting list in increasing order, and then replaces each document identifier (except the first one) with the distance between itself and its predecessor. For example, the posting list <3, 8, 12, 15, 32> can be represented in d-gaps as <3, 5, 4, 3, 17>. And the second step is to encode (compress) these *d*-gaps using an appropriate coding method. Many coding methods, such as γ coding (Elias 1975), Golomb coding (Golomb 1966; Witten et al. 1999), skewed Golomb coding (Teuhola 1978), and batched LLRUN coding (Fraenkel & Klein 1985), have been proposed to compress posting lists through the estimates of *d*-gap probability distributions. The more accurately the estimate, the greater the compression can be achieved.



(a) Example documents

DIA I: { $d_1 \rightarrow 1$, $d_2 \rightarrow 2$, $d_3 \rightarrow 3$, $d_4 \rightarrow 4$, $d_5 \rightarrow 5$, $d_6 \rightarrow 6$}

Posting list of term 1: <1, 4, 5, 6>   *d*-gap list of term 1: <1, 3, 1, 1>

Posting list of term 2: <1, 2, 3, 4, 6>   *d*-gap list of term 2: <1, 1, 1, 1, 2>

Posting list of term 3: <4, 6>   *d*-gap list of term 3: <4, 2>

Posting list of term 4: <3, 4, 5>   *d*-gap list of term 4: <3, 1, 1>

Total bits required to encode *d*-gaps with γ code = 26 bits

(b) *DIA* I result

DIA II: { $d_1 \rightarrow 3$, $d_2 \rightarrow 5$, $d_3 \rightarrow 4$, $d_4 \rightarrow 1$, $d_5 \rightarrow 6$, $d_6 \rightarrow 2$}

Posting list of term 1: <1, 2, 3, 6>   *d*-gap list of term 1: <1, 1, 1, 3>

Posting list of term 2: <1, 2, 3, 4, 5>   *d*-gap list of term 2: <1, 1, 1, 1, 1>

Posting list of term 3: <1, 2>   *d*-gap list of term 3: <1, 1>

Posting list of term 4: <1, 4, 6>   *d*-gap list of term 4: <1, 3, 2>

Total bits required to encode *d*-gaps with γ code = 20 bits

(c) *DIA* II result

Figure 1. An example to show different *DIA*s result in different compression results

d-gap value x	γ code
1	0
2	10 0
3	10 1
4	110 00

Table1. Some example codes for γ coding

One common characteristic of coding methods used in the d-gap compression approach is that small d-gap values can be coded more economically than large ones. If we can shrink the d-gap values, the compression ratio and query performance can be improved. Consider a document collection of 6 documents shown in Figure 1(a). Each document contains one or more terms. For example, the document d_1 contains term 1 and term 2, document d_2 contains term 2, etc. In Figures1(b) and 1(c), the notation $d_i \rightarrow j$ in *DIA*s I and II denotes that the document identifier j is assigned to the document d_i. According to the documents in Figure 1(a) and the *DIA*s I and II, the obtained posting lists and d-gap lists are shown in Figures 1(b) and 1(c). For *DIA* I, the d-gap values have nine 1s, two 2s, two 3s and one 4; whereas for *DIA* II, the d-gap values have eleven 1s, one 2 and two 3s. With γ coding in Table1, the compressed inverted file requires 26 bits for *DIA* I, whereas it requires 20 bits for *DIA* II. If every term is queried with equal probability, the query processing costs for *DIA* II will be much lower than that of *DIA* I. This is because *DIA* II can result in better compression for the given coding method without increasing the complexity of decoding process, hence improve query throughput by reducing both the retrieval and decompression times of posting lists. This example shows that different *DIA*s can result in different compression results and different query throughputs for a given coding method. In next section, we will introduce a query cost function for the *DIA* problem, and then derive a method to find a good *DIA* to shorten average query processing time when the probability distribution of query terms is given.

3. Document identifier assignment problem and its algorithm

The *DIA* problem is the problem of assigning document identifiers to a set of documents in an inverted file-based *IRS* in order to minimize the average query processing time when the probability distribution of query terms is given. In this section, we first formalize the problem, and then show how to use the well-known *greedy nearest neighbor* (*Greedy-NN*) algorithm to solve this problem.

3.1 Problem mathematical formulation

Let $D=\{d_1, d_2, \ldots, d_N\}$ be a collection of N documents to be indexed, and $\pi : \{ d_1, d_2, \ldots, d_N \} \rightarrow \{1, 2, \ldots, N\}$ be a *DIA* that assigns a unique identifier within the range $1\ldots N$ to each document in D. Let f_t be the total number of documents in which term t appears and $d_{t(1)}, d_{t(2)}, \ldots, d_{t(f_t)}$ be documents containing term t, then the posting list of the term t can be represented as $IL_t = <\pi(d_{t(1)}), \pi(d_{t(2)}), \ldots, \pi(d_{t(f_t)})>$. Without loss of generality, we assume that $\pi(d_{t(1)}) < \pi(d_{t(2)}) < \ldots < \pi(d_{t(f_t)})$. Assume a coding method C which requires $C(x)$ bits to encode a d-gap x. The size of a posting list IL_t for term t can then be expressed as

$$\sum_{i=1}^{ft} C(\pi(d_{t(i)}) - \pi(d_{t(i-1)})) \tag{1}$$

where we let $d_{t(0)}=0$ and $\pi(d_{t(0)})=0$ to simplify the expression of Eq.(1). Assume that the probability of a term t appearing in a query is p_t. Let X_t be a random Boolean variable representing whether term t appears in a query: $X_t=1$ if term t appears in a query and $X_t=0$ otherwise. The query processing time $Time_{QP}$ of posting list processing includes (1) retrieval time $Time_R$ of posting list

IL_t for each query term t, (2) decompression time $Time_D$ of posting list IL_t for each query term t, and (3) document identifier comparison time $Time_{Comp}$. Since the document identifier comparison time is relatively small (about 10% of query processing time) and does not change with different *DIA*s, the query processing time in this paper is defined only as

$$Time_{QP} = \sum_t X_t \times (Time_R(IL_t) + Time_D(IL_t)) \tag{2}$$

The average query processing time $AvgTime_{QP}$ is the expected value of $Time_{QP}$. That is,

$$AvgTime_{QP} = \sum_t p_t \times (Time_R(IL_t) + Time_D(IL_t)) \tag{3}$$

Since the disk transfer rate is near constant and the decoding processes of most coding methods used in *d*-gap compression approach are on a bit-by-bit basis, the retrieval and decompression times of a posting list IL_t for the term t appearing in a query grows with the size of the posting list IL_t. So

$$Time_R(IL_t) + Time_D(IL_t) = \text{constant} \times \sum_{i=1}^{f_t} C(\pi(d_{t(i)}) - \pi(d_{t(i-1)})) \tag{4}$$

Substituting Eq.(4) into Eq.(3), we obtain

$$AvgTime_{QP} = \text{constant} \times \sum_t p_t \times \sum_{i=1}^{f_t} C(\pi(d_{t(i)}) - \pi(d_{t(i-1)})) \tag{5}$$

We thus define the objective function $Cost(\pi)$ to reflect the average query processing time $AvgTime_{QP}$:

$$Cost(\pi) = \sum_t p_t \times \sum_{i=1}^{f_t} C(\pi(d_{t(i)}) - \pi(d_{t(i-1)})) \tag{6}$$

The objective of this research is to find a *DIA* $\pi : D \rightarrow \{1,2,3\ldots,N\}$ such that $Cost(\boldsymbol{\pi})$ is minimal. This optimization problem is called the *DIA* problem, and it is reduced to the *simple DIA* (*SDIA*) problem if the value of p_t for each term t is set to 1. The *SDIA* problem is the problem of finding a *DIA* to minimize the size of inverted file, and it is known to be NP-complete via a reduction to the rectilinear traveling salesman problem (Olken & Rotem 1986). Since the *DIA* problem is a generalization of the *SDIA* problem, the *DIA* problem is also a NP-complete problem.

3.2 Solving *DIA* problem via the well-known *Greedy-NN* algorithm

Shieh et al. (2003) showed that the *SDIA* problem can be solved by using *TSP* heuristic algorithms. Given a collection of *N* documents, a *document similarity graph* (*DSG*) can be constructed. In a *DSG*, each vertex represents a document, and the weight on an edge between two vertices represents the similarity of these two corresponding documents. The similarity $Sim(d_i, d_j)$ between two documents d_i and d_j is defined as:

$$Sim(d_i, d_j) = \sum_{t \in (T(d_i) \cap T(d_j))} 1 \tag{7}$$

where $T(d_i)$ and $T(d_j)$ denote the set of terms appearing in d_i and d_j, respectively, and $\cap$ denotes the intersection operator. Hence, the similarity between two documents is the number of common terms appearing in both documents. The *DSG* for the example documents in Figure 1(a) is shown in Figure 2. A *TSP* heuristic algorithm can then be used to find a path of the *DSG* visiting each vertex exactly once with maximal sum of similarities. If we follow the visiting order of vertices on the path to assign document identifiers, the sum of *d*-gap values for an inverted file can be decreased, and the size of inverted file compressed via the *d*-gap compression approach can be reduced. Shieh et al. (2003) showed that the *Greedy-NN* algorithm (Figure 3) can provide excellent performance for the *SDIA* problem.

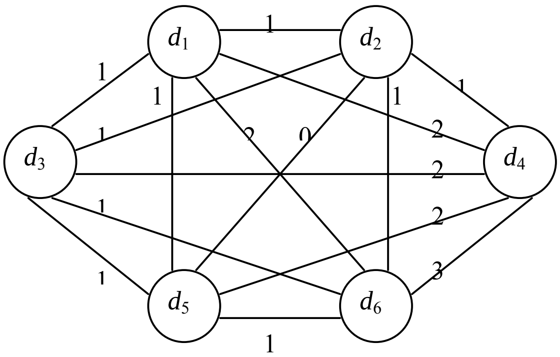


Figure 2. *DSG* for the example documents in Figure 1(a).

Algorithm Greedy_nearest_neighbor

Input:

$D=\{d_1, d_2, \ldots, d_N\}$: a collection of *N* documents to be indexed.

Output:

A *TSP* path: the visiting order of vertices is $\{v_1, v_2, \ldots, v_n\}$

Method:

1. Construct the *DSG*(*V*, *E*), where *V* is a set of vertices (in which each vertex represents a document) and *E* is a set of edges (in which each edge has a similarity value associated with it);
2. Pick a vertex $v \in V$ as v_1 such that the sum of similarity values associated with the adjacent edges of *v* is maximal;
3. $V' := V - \{v_1\}$; $i := 1$;
4. Find *v* in V' such that the similarity value of the edge (v, v_i) is maximal: if more than one such vertex exist, select one randomly;
5. $i := i+1$; $v_i := v$; $V' := V' - \{v_i\}$;
6. If $i<N$ then goto 3;
7. Output a *TSP* path with its visiting order of vertices being $\{v_1, v_2, \ldots, v_n\}$

Figure 3. The *Greedy-NN* algorithm for the *SDIA* problem

Using the same approach, The *DIA* problem can be solved using the *Greedy-NN* algorithm described in Figure 3, if the similarity $Sim(d_i, d_j)$ between two documents d_i and d_j in a *DSG* is redefined as:

$$Sim(d_i, d_j) = \sum_{t \in (T(d_i) \cap T(d_j))} p_t \tag{8}$$

where the probability of a term *t* appearing in a query is known to be p_t.

Although the *Greedy-NN* algorithm is very simple to implement, it is not very applicable to large-scale *IRS*es due to its high complexity. Given a collection of N documents and n distinct terms, the number of comparisons for calculating $Sim(d_i,d_j)$ given fixed i and j is $O(n)$, hence the total number of comparisons to construct a *DSG* for the *Greedy-NN* algorithm is $O(N^2 \times n)$. An algorithm with lower complexity yet still generates satisfactory results should be developed.

4. Partition-based document identifier assignment algorithm

Since the *DIA* problem is an NP-complete problem, the effort in search for an effective low-complexity method is needed. Although the *Greedy-NN* algorithm can be used to solve the *DIA* problem, its complexity is too high. In this section, we first present an optimal *DIA* algorithm for a single query term, and then propose an efficient *partition-based document identifier assignment* (*PBDIA*) algorithm for the *DIA* problem.

4.1 Generating an optimal *DIA* for a single query term

Consider a posting list IL_t for term t with f_t document identifiers in a collection of N documents. Using the d-gap technique, we can obtain f_t d-gap values: $d\text{-}gap_1$, $d\text{-}gap_2$,…, $d\text{-}gap_{ft}$. Assume a coding method C which requires $C(x)$ bits to encode a d-gap x. We want to know which d-gap probability distribution can minimize the size of posting list IL_t after compression using method C. That is, we want to know which d-gap probability distribution can minimize

$$\sum_{i=1}^{f_t} C(d\text{-}gap_i) \tag{9}$$

subject to

$$f_t \le \sum_{i=1}^{f_t} d\text{-}gap_i \le k \quad \text{and} \tag{10}$$

$$1 \le d\text{-}gap_i \le k \quad \text{for all } i,\ \ 1 \le i \le k \tag{11}$$

where k is the largest document identifier in the posting list IL_t. It is known that $C(x)$ is approximately proportional to $\log_2(x)$ for many popular coding methods, such as γ coding, skewed Golomb coding, and batched LLRUN coding. For these coding methods, we can use dynamic programming technique (Bellman and Dreyfus 1962) and find that minimizing Eq.(11) should meet two requirements: (1) maximize the number of d-gap values of 1; and (2) minimize the largest document identifier, i.e., k, in the posting list IL_t. If a *DIA* for term t can satisfy the above two requirements, the best compression and the fastest query speed for the posting list IL_t can be achieved.

According to the above observation, we propose the *simple partition-based document identifier assignment* (*SPBDIA*) algorithm to generate optimal *DIA*s for a given query term t. The *SPBDIA* algorithm consists of a partitioning procedure, an ordering procedure, and a document identifier assignment procedure. The partitioning procedure divides the given documents into two partitions in terms of query term t: one partition P(t) consists of documents containing query term t ; the other partition P(t') is made up of the documents without t. Then, the ordering procedure sets the order of partitions as P(t) followed by P(t'). Finally, the document identifier assignment procedure generates an appropriate *DIA* for the ordered partitions according to query term t: the documents in partition P(t) are assigned smaller consecutive document identifiers, while the documents in partition P(t') assigned larger consecutive document identifiers. The *SPBDIA* algorithm is illustrated in the following Example.

Example. There is a collection of 500 documents, among which 300 documents contain query term t. After partitioning, P(t) has 300 documents and P(t') has 200 documents. Then, the ordering procedure sets the order of partitions P(t) followed by P(t'). Finally, the document identifier assignment procedure assigns the document identifiers 1~300 to the 300 documents in partition P(t) and assigns the document identifiers 301~500 to the 200 documents in partition P(t'). ■

Documents in a partition can be arbitrarily assigned identifiers within the given range, hence the number of possible *DIA*s for the above Example is 300!×200!. Each of the 300!×200! *DIA*s satisfies the two requirements for minimizing Eq.(9), and hence gives both the best posting list compression and fastest query speed for query term t. The *SPBDIA* algorithm is simple, and its complexity is $O(N)$.

4.2 Efficient partition-based document identifier assignment algorithm for *DIA* problem

In a real-world *IRS*, a few frequently used query terms constitute a large portion of all term occurrences in queries (Jansen et al. 1998). Based on this fact, we assess that a *DIA* algorithm that allows those frequently used query terms to have better posting list compression can result in reduced average query processing time. Based on the *SPBDIA* algorithm, an efficient *partition-based document identifier assignment* (*PBDIA*) algorithm for the *DIA* problem can be developed.

Like the *SPBDIA* algorithm, the *PBDIA* algorithm also partitions the document set, orders these partitions, and then assigns document identifiers. The partitioning and ordering procedures of the *PBDIA* algorithm iterate n times given that there are n query terms. Then, the document identifier assignment procedure is performed as the last step of the *PBDIA* algorithm. Terms that are queried more frequently should take higher priority in document partitioning and partition ordering.

The *PBDIA* algorithm is given in Figure 4. A doubly linked list is used to store the partitions, and the two links of a partition maintain the ordering among these partitions. Given a collection of N documents and n distinct query terms, the number of comparisons for assigning documents to partitions in each iteration is $O(N)$. Since the *PBDIA* algorithm iterates for n times, the total number of comparisons for the *PBDIA* algorithm is $O(N\times n)$. Compared with the *Greedy-NN* algorithm, this complexity of *PBDIA* algorithm is distinctively low. This advantage brings the *PBDIA* algorithm a dark side, of course. Although the *PBDIA* algorithm targets on improving the compression efficiency for the frequently used query terms, it unavoidably decreases that for the other query terms. In reality, it is often the case that the popularities of the assorted query terms are very unbalanced. And this imbalance nature makes the *PBDIA* algorithm achieve very good query performance. In Section 5, we compare the search performance of the *Greedy-NN* and *PBDIA* algorithms for real-life document collections.

Algorithm Partition_based_document_identifier_assignment

Input:

$D=\{d_1, d_2, \ldots, d_N\}$: a collection of N documents to be indexed.

$T=\{t_1, t_2, \ldots, t_n\}$: a set of n distinct terms appearing in D.

$Prob=\{p_1, p_2, \ldots, p_n\}$: p_i denotes the probability of the term $t_i \in T$ appearing in a query.

Output:

A document identifier assignment $\pi : \{ d_1, d_2, \ldots, d_N \} \rightarrow \{1, 2, \ldots, N\}$ for the *DIA*.

Method:

1. Create an empty doubly linked list *PartList*; // to store partition
2. Create an empty doubly linked list *TempList*; //to store partition pairs
3. Assign all documents in D to a new partition P, and add P to the *PartList*;
4. Sort the terms in T in descending order according to their probabilities. Let t_{rank1}, $t_{rank2}, \ldots, t_{rankn}$ represent the sorted list.
5. **for** i:=1 to n **do**
   5.1 **while** *PartList* is not empty **do** **/*partitioning procedure*/**
      5.1.1 Get a partition P from the head of *PartList*, and then remove P from *PartList*;
      5.1.2 // At least one of the partitions $P(t_{ranki})$ and $P(t_{ranki}')$ should be nonempty
      Let $P(t_{ranki})$ be the partition containing the documents that are included in P and do contain the term t_{ranki} ; let $P(t_{ranki}')$ be the partition containing the documents that are included in P and do not contain the term t_{ranki} ;
      5.1.3 Add the partition pair $\{P(t_{ranki}),P(t_{ranki}')\}$ to the tail of *TempList*;
   5.2 **while** *TempList* is not empty **do** **/*ordering procedure*/**
      5.2.1 Get a partition pair $\{P(t_{ranki}),P(t_{ranki}')\}$ from the tail of *TempList*, and then remove $\{P(t_{ranki}),P(t_{ranki}')\}$ from *TempList*;
      5.2.2 **if** $P(t_{ranki})$ is empty **then** add $P(t_{ranki}')$ to the front of *PartList* and go to step 5.2;
      5.2.3 **if** $P(t_{ranki}')$ is empty **then** add $P(t_{ranki})$ to the front of *PartList* and go to step 5.2;
      5.2.4 **if** *PartList* is empty **then**
         Add $P(t_{ranki}')$ to the *PartList*; add $P(t_{ranki})$ to the front of *PartList*;
      else //*PartList* is not empty
         Get a partition P from the head of *PartList*, and get a document $d \in P$;
         if the document d contain the term t_{ranki} **then**
            Add $P(t_{ranki})$ to the front of *PartList*; add $P(t_{ranki}')$ to the front of *PartList*;
         else // the document d does not contain the term t_{ranki}
            Add $P(t_{ranki}')$ to the front of *PartList*; add $P(t_{ranki})$ to the front of *PartList*;
6. i:=1;
7. **while** *PartList* is not empty **do** **/*document identifier assignment procedure*/**
   7.1 Get a partition P from the head of *PartList*, and then remove P from *PartList*;
   7.2 **while** P is not empty **do**
      7.2.1 Get a document $d \in P$, and remove d from P;
      7.2.2 Assign document identifier i to the document d, and then i:=i+1;

Figure 4. The *PBDIA* algorithm for the *DIA* problem

5. Experiments

This section describes our experiments for evaluating the different *DIA* algorithms. Experiments were conducted on real-life document collections, and the average query processing time and the storage requirement for each *DIA* algorithm were measured. We also investigated the *DIA* problem in parallel *IR*.

5.1 Document collections and queries

Three document collections were used in the experiments. Their statistics are listed in Table 2. In this table, *N* denotes the number of documents; *n* is the number of distinct terms; *F* is the total number of terms in the collection; and *f* indicates the number of document identifiers that appear in an inverted file. The collections *FBIS* (Foreign Broadcast Information Service) and *LAT* (LA Times) are disk 5 of the TREC-6 collection that is used internationally as a test bed for research in *IR* techniques (Voorhees and Harman 1997). The collection *TREC* includes the *FBIS* and *LAT*.

Table 2. Statistics of document collections

		Collection		
		FBIS	*LAT*	*TREC*
# of documents	*N*	130,471	131,896	262,367
# of terms	*F*	72,922,893	72,087,460	145,010,353
# of distinct terms	*n*	214,310	168,251	317,393
# of document identifier count	*f*	28,628,698	32,483,656	61,112,354
Total size (Mbytes)		470	475	945

We followed the method (Moffat & Zobel 1996) to evaluate performance with random queries. For each document collection, 300 documents were randomly selected to generate a query set. A query was generated by selecting words from the word list of a specific document. To form the word list of a document, words in the document were folded to lower case, and stop words such as “the” and “this” were eliminated. The number of terms per query ranged from 1 to 65. For each query, there existed at least one document in the document collection that is relevant to the query. We also made the generated query set for each document collection have the following characteristics: (1) Query repetition frequencies followed a Zipf distribution; (2) The terms per query distribution followed the shifted negative binomial distribution. This made the distribution of generated queries closely resemble the distribution of real queries (Xie & O’Hallaron 2002; Wolfram 1992).

5.2 Experimental results

In Section 5.2.1, we first present the actual times taken by the *Greedy-NN* and the *PBDIA* algorithms. In Section 5.2.2, we then present the query performance of different *DIA* algorithms. In Section 5.2.3, we present the compression performance of different *DIA* algorithms. Finally, we study the *DIA* problem in parallel *IR* in Section 5.2.4.

The inverted files of the three test collections were constructed according to the *DIA*s generated by different *DIA* algorithms. We tested four different *DIA* algorithms: “*Random*”, “*Default*”, “*Greedy-NN*”, and “*PBDIA*”. The *Random* algorithm means that the document in a collection is randomly assigned document identifier. The *Default* algorithm means that the document in a collection is assigned document identifier in chronological order. The *Greedy-NN* and *PBDIA* algorithms were described in Section 3.2 and Section 4.2, respectively. For each *DIA* algorithm, we also tested five coding methods: γ coding (Elias 1975), Golomb coding (Golomb 1966; Witten et al. 1999), skewed Golomb coding (Teuhola 1978), batched LLRUN coding (Fraenkel & Klein 1985), and unique-order interpolative coding method (Cheng et al. 2004). For the following experiments, the parameter b for each posting list in Golomb coding was calculated using Witten’s approximation (Witten et al. 1999), and the parameter g for unique-order interpolative coding was set to 4 (Cheng et al. 2004).

All experiments were run on an Intel P4 2.4GHz PC with 512MB DDR memory running Linux operating system 2.4.12. The hard disk was 40GB, and the data transfer rate was 25MB/sec. Intervening processes and disk activities were minimized during experimentation.

5.2.1 Time taken by *Greedy-NN* and *PBDIA* algorithms

In Table 3, the performance in terms of completion time is shown. The times reported are the actual times taken by the algorithms to generate a *DIA* for the given document collection that has been inverted. Please note that the times presented in Table 3 consider neither the time spent in preliminary inversion of the document collection, nor the time needed to rebuild an inverted file with a new *DIA*.

Table 3 shows that the *PBDIA* algorithm is much faster than the *Greedy-NN* algorithm. This fact makes the *PBDIA* algorithm viable for use in large-scale *IRS*es. Such a fast *DIA* algorithm can be very useful for situations such as:

1. Dynamically changing probability distribution of query terms, and
2. Dynamically changing document collection.

Table 3. Time consumed by the *Greedy-NN* and the *PBDIA* algorithms

DIA algorithm	Collection		
	FBIS	*LAT*	*TREC*
Greedy-NN	23 hrs 59 mins	24 hrs 37 mins	198 hrs 2 mins
PBDIA	9 secs	10 secs	18 secs

5.2.2 Query performance of different *DIA* algorithms

In Table 4, the average query processing time ($AvgTime_{QP}$) and the speedup relative to the *Default* algorithm (*SP*) were measured according to Eq.(3). In Table 5, the average number of bits required to retrieve and decode an identifier during query processing ($AvgBPI_{QP}$) and the improvement over the *Default* algorithm (*Imp*) were measured according to Eq.(6). For each document collection, the generated query set was divided into three subsets: the short query set, the medium-length query set, and the long query set. The number of terms per query for the short, medium-length, and long query sets range from 1 to 8, 9 to 20, and 21 to 65, respectively.

All decoding mechanisms were optimized, including:

1. Replaced subroutines with macros.
2. Replaced calls to the log function with fast bit shifts.
3. Careful choice for compiler optimization flags.
4. Implementation used 32-bit integers, as that is the internal register size of the Intel P4 CPU.

Furthermore, the Huffman code of batched LLRUN coding was implemented with canonical prefix codes that can be decoded via a fast table look-up (Turpin 1998). With these optimizations, decoding of a document identifier only required tens of ns.

The experimental results are shown in Tables 4 and 5. Key findings are:

1. Table 4 shows that the query performance of the *Default* algorithm can be 10% faster than the *Random* algorithm. This indicates that the *Default* algorithm already captures some clustering nature, thus can serve as a rigid baseline in comparison with other fine-tuned algorithms.
2. Comparing Tables 4 and 5, one should observe that $AvgTime_{QP}$ is proportional to $AvgBPI_{QP}$. This verifies Eq. (4) in Section 3.1, and explains why a good *DIA* can result in better compression and reduced query processing time.
3. From Table 5, one should observe that both the *Greedy-NN* and *PBDIA* algorithms can result in better compression of posting lists for all tested coding methods except Golomb coding. This indicates that the *Greedy-NN* and *PBDIA* algorithms can improve the cache efficiency if a posting list cache is implemented.
4. Table 4 shows that both the *Greedy-NN* and *PBDIA* algorithms can reduce average query processing time for all tested coding methods except Golomb coding. And the query speedup differences between the *Greedy-NN* and *PBDIA* algorithms were only 3% on average. Considering the algorithm complexity, the *PBDIA* algorithm is a good choice for the *DIA* problem.
5. From Table 4, one should observe that Golomb coding cannot benefit much from the *Greedy-NN* and *PBDIA* algorithms in terms of query performance. This is because Golomb coding assumes that the *d*-gap values in a posting list following a Bernoulli model (Witten et al. 1999), hence both the compression result and the query processing time of Golomb coding are independent of *d*-gap distribution.
6. From Table 4, one should observe that the query speedup obtained by the *PBDIA* algorithm becomes higher as the query length increases. This is because that, as the number of query terms increases, more frequently used query terms are likely to be included, resulting in more advantage due to the *PBDIA* algorithm.
7. Table 4 shows that both γ coding and unique-order interpolative coding are recommended for real-world *IRS*es due to their fast query throughputs. In addition, compared with the other tested coding methods, these two coding methods benefit more from the *PBDIA* algorithm. We conclude that the *PBDIA* algorithm is viable for use in real-world *IRS*es.

Table 4. Query performance of different *DIA* algorithms ($AvgTime_{QP}$ is the average query processing time, and *SP* is the speedup relative to the *Default* algorithm)

(a) short queries

Collection	*DIA* algorithm	Coding Methods									
		γ coding		Golomb coding		Skewed Golomb coding		Batched LLRUN coding		Unique-order Interpolative coding	
		$AvgTime_{QP}$ (us)	*SP*	$AvgTime_{QP}$ (us)	*SP*	$AvgTime_{QP}$ (us)	*SP*	$AvgTime_{QP}$ (us)	*SP*	$AvgTime_{QP}$ (us)	*SP*
FBIS	*Random*	2989	0.93	2858	0.98	3894	0.96	3748	0.97	2746	0.95
	Default	2789	1.00	2802	1.00	3754	1.00	3636	1.00	2614	1.00
	Greedy-NN	2431	1.15	2790	1.00	3348	1.12	3275	1.11	2315	1.13
	PBDIA	2529	1.10	2808	1.00	3427	1.10	3320	1.10	2333	1.12
LAT	*Random*	2829	0.96	2704	0.99	3737	0.98	3654	0.97	2564	0.97
	Default	2724	1.00	2688	1.00	3645	1.00	3542	1.00	2476	1.00
	Greedy-NN	2268	1.20	2653	1.01	3137	1.16	3143	1.13	2085	1.19
	PBDIA	2379	1.15	2644	1.02	3234	1.13	3231	1.10	2150	1.15
TREC	*Random*	5822	0.90	5573	0.97	7556	0.93	7217	0.94	5448	0.91
	Default	5244	1.00	5380	1.00	7026	1.00	6781	1.00	4942	1.00
	Greedy-NN	4431	1.18	5353	1.01	6139	1.14	6032	1.12	4256	1.16
	PBDIA	4606	1.14	5292	1.02	6254	1.12	6171	1.10	4313	1.15

(b) medium-length queries

Collection	*DIA* algorithm	Coding Methods									
		γ coding		Golomb coding		Skewed Golomb coding		Batched LLRUN coding		Unique-order Interpolative coding	
		$AvgTime_{QP}$ (us)	*SP*	$AvgTime_{QP}$ (us)	*SP*	$AvgTime_{QP}$ (us)	*SP*	$AvgTime_{QP}$ (us)	*SP*	$AvgTime_{QP}$ (us)	*SP*
FBIS	*Random*	9388	0.93	8972	0.98	12222	0.97	11749	0.97	8613	0.95
	Default	8758	1.00	8795	1.00	11795	1.00	11402	1.00	8201	1.00
	Greedy-NN	7563	1.16	8746	1.01	10426	1.13	10225	1.12	7205	1.14
	PBDIA	7838	1.12	8798	1.00	10650	1.11	10387	1.10	7223	1.14
LAT	*Random*	8997	0.97	8605	1.00	11842	0.98	11562	0.97	8192	0.97
	Default	8684	1.00	8564	1.00	11580	1.00	11229	1.00	7932	1.00
	Greedy-NN	7126	1.22	8407	1.02	9851	1.18	9852	1.14	6607	1.20
	PBDIA	7434	1.17	8359	1.02	10098	1.15	9982	1.12	6755	1.17
TREC	*Random*	18475	0.92	17689	0.97	23936	0.94	22724	0.95	17273	0.93
	Default	16935	1.00	17153	1.00	22594	1.00	21666	1.00	16004	1.00
	Greedy-NN	14069	1.20	16942	1.01	19493	1.16	19058	1.14	13598	1.18
	PBDIA	14611	1.16	16713	1.03	19809	1.14	19280	1.12	13722	1.17

(c) long queries

Collection	*DIA* algorithm	Coding Methods									
		γ coding		Golomb coding		Skewed Golomb coding		Batched LLRUN coding		Unique-order Interpolative coding	
		$AvgTime_{QP}$ (us)	*SP*	$AvgTime_{QP}$ (us)	*SP*	$AvgTime_{QP}$ (us)	*SP*	$AvgTime_{QP}$ (us)	*SP*	$AvgTime_{QP}$ (us)	*SP*
FBIS	*Random*	20210	0.92	19399	0.98	26526	0.95	26049	0.96	18423	0.94
	Default	18594	1.00	18939	1.00	25316	1.00	24984	1.00	17269	1.00
	Greedy-NN	15882	1.17	18971	1.00	22131	1.14	21957	1.14	14979	1.15
	PBDIA	15871	1.17	18953	1.00	21972	1.15	22143	1.13	14377	1.20
LAT	*Random*	18029	0.96	17116	1.00	23591	0.98	22646	0.97	16477	0.97
	Default	17392	1.00	17035	1.00	23011	1.00	22033	1.00	15964	1.00
	Greedy-NN	13875	1.25	16624	1.02	19173	1.20	18984	1.16	13046	1.22
	PBDIA	13996	1.24	16298	1.05	19023	1.21	19212	1.15	12817	1.25
TREC	*Random*	37881	0.93	36023	0.98	49012	0.95	46584	0.96	35266	0.94
	Default	35096	1.00	35231	1.00	46547	1.00	44588	1.00	33008	1.00
	Greedy-NN	28372	1.24	34469	1.02	39489	1.18	38592	1.16	27523	1.20
	PBDIA	29152	1.20	33809	1.04	39766	1.17	39089	1.14	27401	1.20

Table 5. $AvgBPI_{QP}$ of different *DIA* algorithms ($AvgBPI_{QP}$ is the average number of bits required to retrieve and decode an identifier during query processing, and *Imp* is the improvement over the *Default* algorithm)

(a) short queries

Collection	*DIA* algorithm	Coding Methods									
		γ coding		Golomb coding		Skewed Golomb coding		Batched LLRUN coding		Unique-order Interpolative coding	
		$AvgBPI_{QP}$	*Imp* (%)	$AvgBPI_{QP}$	*Imp* (%)	$AvgBPI_{QP}$	*Imp* (%)	$AvgBPI_{QP}$	*Imp* (%)	$AvgBPI_{QP}$	*Imp* (%)
FBIS	*Random*	3.56	-10.6	3.21	0.3	3.31	-7.1	3.25	-5.5	3.15	-7.9
	Default	3.22	---	3.22	---	3.09	---	3.08	---	2.92	---
	Greedy-NN	2.78	13.7	3.24	-0.6	2.73	11.7	2.69	12.7	2.63	9.9
	PBDIA	2.95	8.4	3.23	-0.3	2.84	8.1	2.76	10.4	2.69	7.9
LAT	*Random*	3.32	-6.8	2.98	0.0	3.05	-4.8	3.00	-3.8	2.87	-4.7
	Default	3.11	---	2.98	---	2.91	---	2.89	---	2.74	---
	Greedy-NN	2.56	17.7	3.00	-0.7	2.48	14.8	2.47	14.5	2.35	14.2
	PBDIA	2.73	12.2	2.97	0.3	2.59	11.0	2.59	10.4	2.42	11.7
TREC	*Random*	3.75	-13.3	3.38	0.3	3.46	-9.5	3.40	-8.2	3.34	-10.6
	Default	3.31	---	3.39	---	3.16	---	3.14	---	3.02	---
	Greedy-NN	2.78	16.0	3.41	-0.6	2.72	13.9	2.69	14.3	2.65	12.3
	PBDIA	2.94	11.2	3.37	0.6	2.81	11.1	2.81	10.5	2.70	10.6

(b) medium-length queries

Collection	*DIA* algorithm	Coding Methods									
		γ coding		Golomb coding		Skewed Golomb coding		Batched LLRUN coding		Unique-order Interpolative coding	
		$AvgBPI_{QP}$	*Imp* (%)	$AvgBPI_{QP}$	*Imp* (%)	$AvgBPI_{QP}$	*Imp* (%)	$AvgBPI_{QP}$	*Imp* (%)	$AvgBPI_{QP}$	*Imp* (%)
FBIS	*Random*	3.57	-10.9	3.21	0.3	3.31	-6.8	3.25	-5.5	3.15	-7.9
	Default	3.22	---	3.22	---	3.10	---	3.08	---	2.92	---
	Greedy-NN	2.75	14.6	3.24	-0.6	2.70	12.9	2.66	13.6	2.61	10.6
	PBDIA	2.92	9.3	3.24	-0.6	2.81	9.4	2.75	10.7	2.66	8.9
LAT	*Random*	3.37	-6.3	3.03	0.3	3.11	-4.4	3.06	-3.7	2.94	-4.6
	Default	3.17	---	3.04	---	2.98	---	2.95	---	2.81	---
	Greedy-NN	2.58	18.6	3.06	-0.7	2.50	16.1	2.48	15.9	2.39	14.9
	PBDIA	2.73	13.9	3.02	0.7	2.59	13.1	2.60	11.9	2.44	13.1
TREC	*Random*	3.83	-12.0	3.42	0.3	3.53	-8.3	3.47	-7.1	3.40	-9.0
	Default	3.42	---	3.43	---	3.26	---	3.24	---	3.12	---
	Greedy-NN	2.82	17.5	3.45	-0.6	2.76	15.3	2.74	15.4	2.71	13.1
	PBDIA	2.99	12.6	3.41	0.6	2.85	12.6	2.86	11.7	2.75	11.9

(c) long queries

Collection	*DIA* algorithm	Coding Methods									
		γ coding		Golomb coding		Skewed Golomb coding		Batched LLRUN coding		Unique-order Interpolative coding	
		$AvgBPI_{QP}$	*Imp* (%)	$AvgBPI_{QP}$	*Imp* (%)	$AvgBPI_{QP}$	*Imp* (%)	$AvgBPI_{QP}$	*Imp* (%)	$AvgBPI_{QP}$	*Imp* (%)
FBIS	*Random*	3.31	-12.2	3.02	0.3	3.09	-8.4	3.03	-6.7	2.90	-9.0
	Default	2.95	---	3.03	---	2.85	---	2.84	---	2.66	---
	Greedy-NN	2.50	15.3	3.06	-1.0	2.47	13.3	2.43	14.4	2.37	10.9
	PBDIA	2.57	12.9	3.05	-0.7	2.47	13.3	2.48	12.7	2.34	12.0
LAT	*Random*	3.58	-6.2	3.21	0.3	3.28	-4.1	3.23	-3.5	3.13	-4.3
	Default	3.37	---	3.22	---	3.15	---	3.12	---	3.00	---
	Greedy-NN	2.66	21.1	3.24	-0.6	2.58	18.1	2.55	18.2	2.50	16.7
	PBDIA	2.73	19.0	3.19	0.9	2.58	18.1	2.63	15.7	2.48	17.3
TREC	*Random*	3.85	-10.6	3.43	0.3	3.54	-7.3	3.47	-6.1	3.41	-7.9
	Default	3.48	---	3.44	---	3.30	---	3.27	---	3.16	---
	Greedy-NN	2.78	20.1	3.46	-0.6	2.73	17.3	2.70	17.4	2.69	14.9
	PBDIA	2.92	16.1	3.41	0.9	2.79	15.5	2.81	14.1	2.71	14.2

5.2.3 Compression performance of different *DIA* algorithms

The compression results are shown in Table 6, and the metric used is the average number of *bits per identifier BPI*, defined as follows:

$$BPI = \frac{\text{The size of the compressed inverted file}}{\text{number of document identfiers } f}.$$

To reduce average query processing time, both the *Greedy-NN* and *PBDIA* algorithms target on improving the compression efficiency for the frequently used query terms. However, this is at the cost of sacrificing the compression efficiency for the less frequently used query terms. We need to know how much space overhead is needed to trade for this speed advantage. Results in Table 6 show that the *Greedy-NN* and *PBDIA* algorithms can speed up query processing with very little or no storage overhead.

Table 6. Compression performance of different *DIA* algorithms (*BPI* is the average bits per identifier of the inverted file for the test collection, and *Imp* is the improvement over the *Default* algorithm)

Collection	*DIA* algorithm	Coding Methods									
		γ coding		Golomb coding		Skewed Golomb coding		Batched LLRUN coding		Unique-order Interpolative coding	
		BPI	*Imp* (%)	*BPI*	*Imp* (%)	*BPI*	*Imp* (%)	*BPI*	*Imp* (%)	*BPI*	*Imp* (%)
FBIS	*Random*	7.06	-19.7	5.28	0.0	5.75	-10.6	5.38	-8.5	5.36	-10.3
	Default	5.90	---	5.28	---	5.20	---	4.96	---	4.86	---
	Greedy-NN	5.86	0.7	5.28	0.0	5.33	-2.5	4.88	1.6	4.85	0.2
	PBDIA	6.17	-4.6	5.28	0.0	5.42	-4.2	5.06	-2.0	4.95	-1.9
LAT	*Random*	7.12	-6.6	5.33	0.0	5.73	-3.2	5.43	-2.8	5.42	-3.8
	Default	6.68	---	5.33	---	5.55	---	5.28	---	5.22	---
	Greedy-NN	6.06	9.3	5.32	0.2	5.26	5.2	5.00	5.3	4.91	5.9
	PBDIA	6.35	4.9	5.32	0.2	5.33	4.0	5.12	3.0	5.01	4.0
TREC	*Random*	7.39	-16.7	5.50	-0.4	5.92	-9.2	5.59	-7.5	5.59	-9.6
	Default	6.33	---	5.48	---	5.42	---	5.20	---	5.10	---
	Greedy-NN	6.08	3.95	5.49	-0.2	5.39	0.6	5.03	3.3	4.99	2.2
	PBDIA	6.36	-0.5	5.49	-0.2	5.45	-0.6	5.18	0.4	5.08	0.4

5.2.4 *DIA* in parallel *IR*

This subsection investigates the *DIA* problem in an *IRS* that runs on a cluster of workstations. Assuming k workstations, the inverted file is generally partitioned into k disjoint sub-files, each for one workstation. When processing a query, all workstations have to consult only their own sub-files in parallel, and the query processing time is shortened. Ma et al. (2002)

indicated that near-ideal speedup on query processing can be obtained if an inverted file is partitioned using the interleaving partitioning scheme. For such a partitioning, *DIA* plays a crucial role in load balancing. The *PDBIA* algorithm can be applied to the inverted file to enhance the clustering property of posting lists for frequently used query terms, and can aid the interleaving partitioning scheme to yield better load balancing.

Table 7 shows the performance of parallel query processing using interleaving partitioning scheme with either the *Default* algorithm or the *PBDIA* algorithm. The metric is the speedup relative to sequential query processing with *Default* algorithm. Experiments were conducted on the *TREC* collection. The sub-file on each workstation was compressed using the unique-order interpolative coding method. The parallel query processing time was defined as max[$T_1,T_2,\ldots,T_k$], where T_i ($1 \le i \le k$) was the time needed to retrieve and decompress the (partial) posting lists for the query terms on the i^{th} workstation. Note that T_i did not include the document identifier comparison time (the reason being the same as described in Section 3.1). The experimental results show that the interleaving partitioning scheme can yield near-ideal speedups, as reported in Ma et al. (2002). In addition, using the *PBDIA* algorithm to enhance the clustering property of posting lists for frequently used query terms, the interleaving partitioning scheme yields super-linear speedups. Hence the *DIA* problem should deserve much attention in parallel *IR*.

Table 7. Speedup of parallel query processing

Method	The number of workstations					
	1*	2	4	6	8	10
Default algorithm + Interleaving partitioning	1.00	1.90	3.75	5.61	7.44	9.35
PBDIA algorithm + Interleaving partitioning	1.17	2.23	4.41	6.57	8.70	10.93

*: Without interleaving partitioning

6. Conclusion

In this paper, we study the *DIA*-based query optimization techniques for an *IRS* in which the inverted file is used to evaluate queries. We first define a cost model for query evaluation. Based on this model, we propose an efficient heuristic, called *partition-based document identifier assignment* (*PBDIA*) algorithm, for generating a good *DIA* to reduce average query processing time. The *PBDIA* algorithm can efficiently assign consecutive document identifiers to the documents containing frequently used query terms. This makes the *d*-gaps of posting lists for frequently used query terms very small, and results in better compression for popular coding methods without increasing the complexity of decoding processes. This can result in reduced query processing time. Experimental results show that the *PBDIA* algorithm can reduce the average query processing time by up to 20%. We also point out that the *DIA* problem has vital effects on the performance of long queries and parallel *IR*. Compared with the well-known *Greedy-NN* algorithm, the *PBDIA* algorithm is much faster and yields very competitive performance for the *DIA* problem. This fact should make the *PBDIA* algorithm viable for use in modern large-scale inverted file-based *IRS*es.

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計畫成果自評

本計畫規劃了一系列的研究，探討如何以最小的資源成本建置符合需求的叢集式資訊檢索系統，並透過動態的資源管理機制，讓系統在面對各種不同的外界環境時，能夠動態地調整系統的資源配置，將系統的資源發揮最大的效能，期以最小的資源成本提供使用者一個高效能和高服務品質的資訊檢索環境。在本年度的研究中，為了能夠有效增進系統效能與儲存空間利用率，我們發展了一個新的文件編號演算法。實驗顯示我們所提的演算法可以有效縮短查詢處理時間，而對於長查詢(long queries)與平行資訊檢索(parallel IR)更有明顯的好處。此一研究成果已經投稿到國際期刊 *Information Processing & Management* 並獲得接受。未來在此研究基礎上，本計畫將持續探討叢集式資訊檢索系統的負載、快取與資料管理方法，期能以最小的成本滿足給定的執行效能需求。並發展一資訊檢索雛型系統，實作並驗證所提各項技術之可行性。我們相信所提出的演算法可以應用於高效能與低成本的資訊檢索系統設計。