ISSN 2047-3338

An Improvement on Fragmentation in Distribution Database Design Based on Clustering Techniques

Van Nghia Luong[1], Ha Huy Cuong Nguyen[2] and Van Son Le[3]

[1]Department of Information Technology, Pham Van Dong University, Quang Ngai, Viet Nam
[2]Department of Information Technology, Quang Nam University, Quang Nam, Viet Nam
[3]Department of Information Technology, Da Nang University of Education, Da Nang, Viet Nam

Abstract— **Distributed database design plays an important role in the design of distributed applications in general. The problem of optimizing distributed database includes the following problems: data fragmentation and data allocation. There are many different approaches to solve these problems. It also means that the design of distributed databases is difficult to carry out. This paper presents two algorithms (vertical and horizontal fragmentation) in distributed databases based on clustering techniques. The similar measures used in the two algorithms are developed from classical metrics. The experimental results show that segmentation results by two algorithms proposed are equivalent to the results of the classical algorithms.**

Index Terms—**Distributed Database, Fragmentation, Allocation, Similar Measure and Clustering**

I. INTRODUCTION

IN distributed computing environments, each unit of data (item) which is accessed at the station, (site) is not usually a relationship but part of the relationship. Therefore, to optimize the performance of the query, the relations of global schema are fragmented into items.

There are several types of data fragmentation that are use vertical fragmentation, horizontal fragmentation, mixed fragmentation and derived fragments. Two classical algorithms associated with horizontal fragmentation and vertical fragmentation are PHORIZONTAL and BEA respectively [11]. Many authors have proposed solutions improved the above two algorithms, as Navathe, et al., (1984) [13], Chakravarthy, et al., (1994) [3]..., However, the complexity of this algorithm is quite large, with vertical fragmentation problem is $O(n^2)$, where n is the number of attributes and horizontal fragmentation is $O(2^m)$, where m is the number of records [9], [11].

In recent years, several authors have incorporated to solve the problem of fragmentation and positioning, using the optimal algorithm [5]-[6], [10] or using the heuristic method [4], [7]. The execution time of algorithms significantly reduced compared with the classical algorithm.

The used technical association rules in data mining to vertical fragmentation has been mentioned in [8]. However, the data mining techniques do not attract many authors.

In this paper, we use knowledge-oriented clustering techniques for vertical and horizontal fragmentation problem. The measure of similarity was developed based on from the available measure of the classical algorithms in data mining.

In the clustering algorithm based on knowledge-oriented, we propose an algorithm that builds the initial equivalence relation based on the distance threshold. This approach differs from the previous works proposed by Hirano et al., [10] and Bean et al.,[2], in that the proposed algorithm automatically determines the number of clusters based on the data set of survey.

The paper is organized as follows: section 2 presents a brief overview of the basic concepts and the related work. We detail with the proposed vertical and horizontal fragmentation algorithms, in section 3 and section 4, respectively. We then discuss the main contributions of proposed approach in section 5.

II. BASIC CONCEPTS AND APPLICATION

A. Vertical Fragmentation

Vertical fragmentation is the collective decay properties of the relational schema R into the sub schema R_1, R_2, ..,R_m, such that each attribute in these sub schemas is often accessed together.

To show how often the same queries together, Hoffer and Severance introduced the concept attribute affinity [11].

If Q={q_1, q_2, .., q_m} is a set of applications, R(A_1, A_2, .., A_n) is a relational schemas. The relationship between q_i and attributes A_j is determined by using the values:

$$use(q_i, A_j) = \begin{cases} 1, & \mathrm{A_j} \text{ is engaged in } \mathrm{q_i} \\ 0, & \mathrm{A_j} \text{ is not engaged in } \mathrm{q_i} \end{cases} \quad (1)$$

Put (A_i, A_j) = {q∈Q | use(q, A_i). use(q, A_j) = 1}. Attribute affinity between A_i and A_j is:

$$Aff(A_i, A_j) = \sum_{q \in Q(A_i, A_j)} (\sum_{\forall S_l} ref_l(q) * acc_l(q)) \quad (2)$$

In particular, $ref_l(q)$: the number of pairs of attributes (A_i, A_j) is referenced in the application q at station S_l; $acc_l(q)$: frequency of access to applications q in station S_l.

BEA algorithm consists of two main phases:

(1) Permutations row, column affinity matrix of attribute to obtain the cluster affinity matrix (CA) which has global affinity measure AM (global affinity measure) [11] is the largest.

(2) Find the partition of the set of attributes from the matrix CA by exhaustive method, so that:

Z= CTQ *CBQ – COQ2 is the maxima, with:

$$CTQ = \sum_{q \in TQ} \sum_{\forall Sj} ref_j(q_j) acc_j(q_i)$$

$$CBQ = \sum_{q \in BQ} \sum_{\forall Sj} ref_j(q_j) acc_j(q_i)$$

$$COQ = \sum_{q \in OQ} \sum_{\forall Sj} ref_j(q_j) acc_j(q_i)$$

TABLE I. CLUSTER AFFINITY MATRIX CA

	A₁	***A₂***	**..**	***Aᵢ***	***A ᵢ₊₁***	**..**	***Aₙ***
A₁							
..			***TA***				
Aᵢ							
Aᵢ₊₁							
						BA	
Aₙ							

In which,

$AQ(q_i)= \{A_j | use(q_i, A_j)=1\}$;

$TQ=\{q_i | AQ(q_i) \subseteq TA\}$;

$BQ= \{q_i | AQ(q_i) \subseteq BA\}$;

$OQ=Q \setminus \{TQ \cup BQ\}$

The complexity of the algorithm is proportional to n^2.

Vertical fragmentation problem is converted to the clustering problem, based on the following concepts:

1) Attribute and the reference feature vector

Definition 1: The reference measure of transaction qi on attribute A_j, denoted by $M(q_i, A_j)$:

$$M_{ij} = M(q_i, A_j) = use(q_i, A_j) * f_i$$

In which M_{ij} is the frequency with which transactions qi reference to attribute A_j. With f_i is the frequency of transactions q_i and $use(q_i, A_j)$ is defined by formula (1).

Definition 2: VA_j reference feature vector of attribute A_j with reference transactions (q_1, q_2, ..,q_m) is defined as follows:

	q_1	q_2	…	q_m
$VA_j =$	M_{1j}	M_{2j}	…	M_{mj}

2) The similarity measure of two properties

Definition 3: The similarity measure of two attributes A_k, A_1 has two feature vectors corresponding to the reference transactions (q_1, q_2, ..,q_m):

$VA_k = (M_{1k}, M_{2k}, .., M_{mk})$

$VA_1 = (M_{1l}, M_{2l}, .., M_{ml})$

Is determined by the cosine measure:

$$s(A_k, A_l) \frac{VA_k * VA_l}{\|VA_k\| * \|VA_l\|} = \frac{\sum_{i=1}^{m} M_{ik} * M_{il}}{\sqrt{\sum_{i=1}^{m} M_{ik}^2} * \sqrt{\sum_{i=1}^{m} M_{il}^2}} \quad (3)$$

B. Horizontal Fragmentation

Horizontal fragmentation divided set records into a smaller set of records. Horizontal fragmentation is based on the query conditions, which are expressed through simple predicates of the form: $A_j\theta$<value>.

Set P_r = {Pr_1, Pr_2, ..,P_k} is a set of simple predicates extracted from a set of applications. A conjunction of the predicates, which is built from P_r will have the form:

$$p_1^* \wedge p_2^* \wedge .. \wedge p_n^*$$

Where p_i^* is a predicate, which received one of p_i or $\neg p_i$ values.

PHORIZONTAL algorithm uses the conjunction of the predicates $p_1^* \wedge p_2^* \wedge .. \wedge p_n^*$ to find the conditions for horizontal fragmentation of data [9]. The relation r(R) will be fragmented into {$r_1(R)$, $r_2(R)$,..,$r_k(R)$}, with $r_i(R) = \sigma_{F_i}(r(R))$, $1 \le i \le k$; F_i is a predicate, which forms the conjunction of the primary predicates [9].

C. Technical data clustering

Data clustering is similar gathering data together into clusters. Some classic clustering algorithms commonly used as K-Means (Mac Queen-1976), K-Medoids (Kaufman and Rousseeuw 1987), clustering stack area (agglomerative Hierachical Clustering) .. [3]. Depending on the type of data clustering that have the appropriate level of similarity measure.

The similarity measure to the objects represented by the binary data type variable:

Consider two vectors x_i and x_j, being represented by binary variables. Assuming binary variables have the same weight. We have event tables as Table II. Where q is the number of binary variables equal to 1 for the two vectors x_i and x_j, s is the number of binary variables equal to 0 for x_i but equal to 1 for x_j, r is the number of binary variables equal to 1 for x_i but is 0 for x_j, t is the number of binary variables equal to 0 for all vectors x_i and x_j.

TABLE II. EVENT TABLE FOR BINARY VARIABLES

	Object j			
		1	***0***	*Sum*
Object i	***1***	q	r	q+r
	0	s	t	s+t
	Sum	q+s	r+t	p

- The difference of two vectors xi and xj based on the symmetric binary dissimilarity are:

$$d(x_i, x_j) = \frac{r+s}{q+r+s+t} \qquad (4)$$

- The similarity measure between two vectors xi and xj is defined by the Jaccard coefficient:

$$sim(x_i, x_j) = 1 - d(x_i, x_j) \qquad (5)$$

III. VERTICAL FRAGMENTATION ALGORITHM IMPROVEMENTS (VFC)

A. *Proposition*

At the relational schema R(A_1, A_2, .., A_n), mapping s:RxR→ [0,1] defined by the formula:

$$s(A_i, A_j) = \begin{cases} 1, & when \;\; \mathrm{i} = j \\ 0, & \text{when } \mathrm{Aff}(\mathrm{A_i}, A_j) = 0 \\ \dfrac{Aff\,(A_i, A_j)}{L}, & when \;\mathrm{Aff}(\mathrm{A_i}, A_j) \neq 0, i \neq j \end{cases} \qquad (6)$$

Is a similar measure on R.

B. *Vertical fragmentation algorithm improvements (VFC)*

Input: Relational schema R(A_1, A_2, .., A_n)
An affinity matrix properties $(\mathrm{Aff}(A_i, A_j))_{nxn}$

Output: The vertical fragmentation of the relation R

Method: Applied techniques clustering of similarity measure (6) combinations R.

Example 1: Considering the relational schema R(A_1, A_2, A_3, A_4), with Table III. Matrix an affinity following attributes:

TABLE III. MATRIX AN AFFINITY

	A_1	A_2	A_3	A_4
A_1	45	0	45	0
A_2	0	80	5	75
A_3	45	5	53	3
A_4	0	75	3	78

Results clustering stack area as follows:

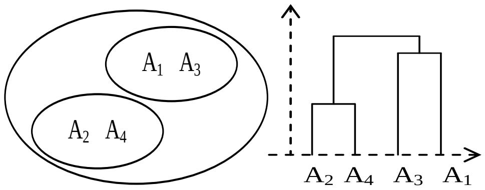


Figure 1. Results Segmentation Based On The Technical Vertical Clustering Stack Area

IV. HORIZONTAL FRAGMENTATION ALGORITHM IMPROVEMENTS (HFC)

A. *Vectorization binary of records*

Considering relations r(R)={T_1, T_2, ..,T_l}, set of simple predicates extracted from applications on r(R) là Pr={Pr_1, Pr_2, ..,Pr_m}. Vectorized binary of records under the rule:

TABLE IV. *VECTORIZATION BINARY*

	Pr_1	Pr_2	..	Pr_j	..	Pr_m
T_1	a_{11}	a_{12}	..	a_{1j}	..	a_{1m}
..		..				..
Ti	a_{i1}	a_{i2}	..	a_{ij}	..	a_{im}
..		..				..
T_1	a_{11}	a_{12}	..	a_{1j}	..	a_{1m}

$$\forall a_{ij} = \begin{cases} 1, \; when \; \mathrm{Ti}\; [\mathrm{Pr_j}] = true \\ 0, \; when \qquad \mathrm{Ti}\; [\mathrm{Pr_j}] = \; false \end{cases}$$

B. *Horizontal fragmentation algorithm improvements (HFC)*

Input: Relations r(R)={T_1, T_2, .., T_l) ;
Pr={Pr_1, Pr_2, ..,Pr_m}: A set of simple predicates

Output: The Horizontal fragmentation of the relation r(R) corresponding to Pr.

Method: Applied techniques clustering of similarity measure (5) combinations R

Example 2: Assuming there is a relation

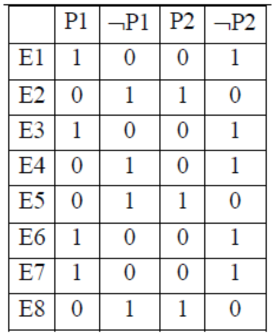
TABLE V. RELATIONS EMP

ENO	ENAME	TITLE
E1	JJoe	Elect-Eng
E2	M.Smith	Syst-Analyst
E3	A.Lee	Mech-Eng
E4	J.Smith	Programmer
E5	B.Casey	Syst-Analyst
E6	L.Chu	Elect-Eng
E7	R.David	Mech-Eng
E8	J.Jone	Syst-Analyst

Considering two predicate logic association:
P1=(TITLE>"Programmer");
P2=(TITLE<" Programmer").

From association relationships and predicate logic given, the input data set vectorization:

TABLE VI. VECTORIZATION RECORDS



	P1	¬P1	P2	¬P2
E1	1	0	0	1
E2	0	1	1	0
E3	1	0	0	1
E4	0	1	0	1
E5	0	1	1	0
E6	1	0	0	1
E7	1	0	0	1
E8	0	1	1	0

Implementing clustering algorithm on K-Medoid the vectorization with similarity measure (5): $sim(x_i, x_j) = 1 - d(x_i, x_j)$, which $d(x_i, x_j)$ calculated using the formula (4), the results:

TABLE VII. *RESULTS-BASED SEGMENTATION CLUSTERING TECHNIQUES HORIZONTAL*

K=2	K=3	K=4
Cluster 1: E1, E3, E6, E7 Cluster 2: E2, E4, E5, E8	Cluster 1: E1, E3, E6, E7 Cluster 2: E2, E5, E8 Cluster 3: E4	Cluster 1: E1, E3 Cluster 2: E2, E5, E8 Cluster 3: E4 Cluster 4: E6, E7

V. CONCLUSION

Apart from the results of tests on, try ghiem with data in [1], [2], the algorithm HFC, VFC have matches with the existing algorithm. It is noted that the horizontal segmentation algorithm based on predicate logic assembly, the cluster segment is due to the algorithm automatically determined; HFC algorithms, VFC using classical clustering techniques, the number of clustering is dependent on the user. So should be combined with expert knowledge to choose the appropriate number of clusters.

The complexity of algorithms HFC, VFC is the complexity of the integrated clustering algorithms, this complexity is less than the complexity of the classical algorithm segments in distributed databases.

In future, the two algorithms HFC, VFC will be improved by redefining the relationship between the measured attributes, records; Integrated high-performance algorithms.

REFERENCES

[1] Huima (2007), Distribution Design for Complex Value Databases, PhD Thesis, Massey University.

[2] I. Lungu, T. Vatuiu, A. G. Fodor (2006), Fragmentation solutions used in the projection of Distributed Database System, Proceedings of the 6th International Conference "ELEKTRO 2006", pp. 44-48, Edis-Zilina University Publishers.

[3] Jiawei Han, Micheline Kambel (2012), Data Mining: Concepts and Techniques, 3rd ed, Morgan Kaufmann Publishers.

[4] Shahidul Islam Khan, A. S. M. Latiful Hoque (2010), A New Technique for Database Fragmentation in Distributed Systems, International Journal of Computer Applications (0975 – 8887), pp. 20-24, Volume 5– No.9.

[5] Mehdi Goli·Seyed Mohammad Taghi Rouhani Rankoohi (2011), A new vertical fragmentation algorithm based on ant collective behavior in distributed database systems, © Springer-Verlag London Limited 2011.

[6] Adrian Runceanu (2007), Towards Vertical Fragmention in Distributed Databases, International Joint Conferences on Computer, Information and Systems Sciences and Engineering (CISSE 2007).

[7] C.L Bean, C.Kambhampati (2008), Automonous Clustering Using Rough Set Theory, Inter-national Journal of Automation and Computing, Vol.5 (No.1). pp. 90-102. ISSN 1476-8186.

[8] Jiawei Han, Micheline Kambel (2012), Data Mining: Concepts and Techniques, 3rd ed, Mor-gan Kaufmann Publishers.

[9] Marwa F. F. Areed, Ali I.El-Dosouky, Hesham A. Ali (2008), A Heuristic Approach for Horizontal Fragmentation and Allocation in DOODB. infos2008.fci.cu.edu.eg/infos/DB_02_P009-016.pdf.

[10] Shoji Hirano and Shusaku Tsumoto (2001), A Knowledge-Oriented Clustering Technique Based on Rough Sets, Computer Software and Applications Conference, COMPSAC'01.

[11] Narasimhaiah Gorla, Pang Wing Yan Betty (2010), Vertical Fragmentation in Databases Using Data-Mining Technique, IGI Global, distributing in print or electronic forms without written permission of IGI Global is prohibited.

[12] Yin-Fu Huang, Jyh-her Chen (2001), Fragment Allocation in Distributed Database Design, Journal of Information Science and Engineering, 491-506.

[13] Navathe S, Ceri S, Wiederhold G, Dou J (1984), Vertical partitioning algorithms for database design, ACM Trans Database Syst 9(4).

[14] Hoffer, J.A., And Severance, D.G (1975), The use of cluster analysis in physical database design. In Proceedings 1st International Conference on Very Large Databases (Framingham, Mass).