Grid Resource Scheduling Based on Fuzzy Similarity Measures

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*Abstract***—Resource scheduling is one of the basic and key aspects in Grid Computing, which allocating the most suitable resources satisfying the requirement of users' applications. After reviewing some novel fuzzy similarity measures, this paper presents an unified one to determine the fuzzy similarity between two objects, especially two Grid resources. The approach is a family of fuzzy similarity measures, and any common measures can be obtained easily only by specifying a parameter h. The resource scheduling of Grid is just based on it. Then, a formal model of Grid resources with three layers is proposed for effectively and efficiently organizing and accessing all kinds of heterogeneous resources. This is helpful to reduce the cost of time and correspondence in allocating resources through describing resources, abstracting resources and providing unified system images. Over the organization of resources, the scheme of resource scheduling is also described. Finally, analyses show that this approach is feasible to the different application fields.**

*Keywords—***grid computing, fuzzy similarity measures, resource organization, resource scheduling, hyper topology space**

I. INTRODUCTION

Computational grids provide mechanisms for sharing and accessing large collections of remote resources such as computers, online instruments, storage space, data and applications, where the effective resource scheduling is challenging as resources are geographically distributed, heterogeneous in nature and might span numerous administrative domains. These resources are identified based on a set of desired attributes, which have various degrees of dynamism, from mostly static attributes, like operating system version, to highly dynamic ones, like network bandwidth or CPU load. How to find the optimal resources according to the requirement by users' applications has become one of the key issues of the Grid. As a core technology of Grid resource scheduling, the similarity measures of resources become one of the most important research problems in Grid Computing.

A similarity measure is an important tool for determining the degree of similarity between two objects, which is used in applications like Pattern Recognition, where the query pattern is just a very partial model of the user's desires and the user looks for patterns similar, according to some defined criterion, to it. Since Zadeh originated the idea of fuzzy sets, many different similarity measures between fuzzy sets have been proposed in the literature. Zwick et al. [1] reviewed and

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compared several similarity measures between fuzzy sets based on both geometric and set-theoretic. Pappis and Karacapilidis [2] proposed three similarity measures based on union and intersection operations, the maximum difference, and the difference and sum of membership grades. Liu [3] provided the axiom definition and properties of similarity measures between fuzzy sets. Ionescu et al. [4] investigated the application of Fuzzy Hamming distance as an implementation of a component-based procedure for evaluating the proximity measure between heterogeneous data. Buckley and Hayashi [5] used a similarity measure between fuzzy sets to determine whether a rule should be fired for rule matching in fuzzy control and neural networks. Although there are a large number of literatures introducing all kinds of strategies about fuzzy similarity measures, little work has been done to combine the fuzzy similarity measures with Grid resource scheduling.

In this paper, a family of fuzzy similarity measures is presented for feature spaces. Specifically, we will consider the determination of fuzzy similarity between Grid resources, but the measures that we present can also be applied in more general situations. For effectively and efficiently allocating resources based on the proposed fuzzy similarity measures, a Grid resource model, Hyper Topology Space based Resource Model (HTSRM), is proposed. The model could realize automatically unified organization and access of all kinds of heterogeneous resources by a new method of aggregating class reactions. This is helpful to reduce the cost of time and correspondence in allocating resources.

The remainder of this paper is organized as follows. Section 2 contains a description of the proposed fuzzy similarity measures. The scheme of resource organization and scheduling is presented in section 3, and analysis and conclusions are illustrated in section 4.

II. FUZZY SIMILARITY MEASURES

Fuzzy similarity measure is a significant conception in fuzzy set theory, which describes the similarity degree between two fuzzy subsets. In conventional similarity measures of heterogeneous objects, different methods are adopted for measuring similarity of the objects with different type of attributes. Undoubtedly, this increases the complexity and cost of computing. In addition, the similarity of objects relies not only on the distance between them, but also on the intrinsic

qualities of objects. At the same time, the values of many attributes are unclear or unspecific, which could be described with fuzzy sets. Of course, for the crisp values of attributes, we can do it as same as the above. So, an unified family of fuzzy similarity measures will be given in the following. Here, the Universal Logics operators are adopted to calculate the fuzzy similarity degrees of attributes between the two objects, then, all the calculating results will be put together. If it's different for the contribution of attributes to similarity, different weights will be attached to attributes of the objects.

A. Universal Logics operators

Literature [6] introduced the parameterized families of operators called Universal Logics operators which include zero-level universal AND operators (*ZUAND*) and zero-level universal OR operators (*ZUOR*).

(1) *ZUAND* operators

ZUAND operators are mapping: *T*: $[0,1] \times [0,1] \rightarrow [0,1]$,

$$
T(x_1, x_2, h) = (\max(0^m, x_1^m + x_2^m - 1))^\frac{1}{m}.
$$
 (1)

Three basic operators can be obtained by specifying the parameter *h*:

Min: $T(x_1, x_2, 1) = \min(x_1, x_2)$.

Probabilistic: $T(x_1, x_2, 0.75) = x_1 x_2$.

Lukasiewicz: $T(x_1, x_2, 0.5) = \max(0, x_1 + x_2 - 1)$.

(2) *ZUOR* operators

ZUOR operators are mapping: *S*: $[0,1] \times [0,1] \rightarrow [0,1]$,

$$
S(x_1, x_2, h) = 1 - (\max(0^m, (1 - x_1)^m + (1 - x_2)^m - 1))^{\frac{1}{m}}.
$$
 (2)

Three basic operators can be obtained by specifying the parameter *h*:

Max: $S(x_1, x_2, 1) = max(x_1, x_2)$. Probabilistic: $S(x_1, x_2, 0.75) = x_1 + x_2 - x_1 x_2$.

Lukasiewicz: $S(x_1, x_2, 0.5) = \min(1, x_1 + x_2)$.

In the above, real number *m* has relation with generalized correlation coefficient *h* as $m = (3 - 4h)/4h (1 - h)$, $h \in [0, 1]$, *m*∈*R*.

B. Family of fuzzy similarity measures Firstly, some notations are introduced:

P is the set of all objects,

p is an object, $p \in P$,

- *x* is an attribute of object *p*,
- *X* is the set of all attributes, $X=(x_1, x_2, \ldots, x_n)$,
- *Y* is the universe of discourse for *x*,
- *F*(*Y*) is the set of all fuzzy sets on *Y*,
- $\tilde{A}(v)$ $\widetilde{A}(y)$ is the membership function of \widetilde{A} , $\widetilde{A} \in F(Y)$,

 $y \in Y$, $\widetilde{A}(y) \in [0,1]$,

 \widetilde{A}^c $ilde{A}^c$ is the supplementary set of \tilde{A} , namely,

 \widetilde{A}^c (*y*) =1 - \widetilde{A} (*y*),

w(*i*) is the weight of the i -th attribute x_i , which is

decided by real situations, and $\sum_{i=1}^{n} w^{(i)}$ $\sum_{i=1}^{n} w^{(i)} = 1$,

 $\sigma(p,k)$ is the fuzzy similarity degree of object *p* and *k*.

Then, the general definition of fuzzy similarity measure is as follows:

Definition 1 A real function

$$
\sigma: F(Y) \times F(Y) \rightarrow [0, 1]
$$

is called a fuzzy similarity measure on $F(Y)$ if σ satisfies the following properties:

(i)
$$
\forall \tilde{A}, \tilde{B} \in F(Y), \sigma(\tilde{A}, \tilde{B}) = \sigma(\tilde{B}, \tilde{A});
$$

\n(ii) If $\tilde{A}(y) \in \{0, 1\}$, then $\sigma(\tilde{A}, \tilde{A}^c) = 0;$
\n(iii) $\forall \tilde{A} \in F(Y), \sigma(\tilde{A}, \tilde{A}) = 1;$
\n(iv) $\forall \tilde{A} \tilde{B} \tilde{C} \in F(Y)$ if $\tilde{A} \subset \tilde{B} \subset \tilde{C}$ the

 $(iv) \forall \tilde{A}, \tilde{B}, \tilde{C} \in \mathbf{F}(Y), \text{ if } \tilde{A} \subseteq \tilde{B} \subseteq \tilde{C}, \text{ then } \sigma(\tilde{A}, \tilde{C}) \leq$ $\min{\{\sigma(\widetilde{A}, \widetilde{B}), \sigma(\widetilde{B}, \widetilde{C})\}}$.

Accordingly, the fuzzy similarity degree of object *p* and *k* is defined by a unified equation as follows:

$$
\sigma(p,k) = \sum_{i=1}^{n} w^{(i)} \sigma^{(i)}(p,k,h_i) , \qquad (3)
$$

where $\sigma^{(i)}(p, k, h_i)$ denotes the fuzzy similarity degree of object *p* and *k* on attribute x_i . About how to compute it, the discussion is given respectively according to the different type of attributes.

(1) The finite attribute domains

Suppose that the *Y_i* of attribute x_i is finite, that is, $Y_i = \{y_1,$ y_2, \ldots, y_n . Then, the fuzzy similarity degree of object *p* and *k* on attribute x_i can be defined as follows:

$$
\sigma^{(i)}(p,k,h_i) = \frac{\sum_{y_i \in Y_i} T(\tilde{A}(y_i), \tilde{B}(y_i), h_i)}{\sum_{y_i \in Y_i} S(\tilde{A}(y_i), \tilde{B}(y_i), h_i)}
$$

=
$$
\frac{\sum_{y_i \in Y_i} (\max(0^m, \tilde{A}(y_i)^m + \tilde{B}(y_i)^m - 1))^{\frac{1}{m}}}{\sum_{y_i \in Y_i} (1 - (\max(0^m, (1 - \tilde{A}(y_i))^m + (1 - \tilde{B}(y_i))^m - 1))^{\frac{1}{m}}},
$$
 (4)

where $\sigma^{(i)}(p, k, h_i) \in [0,1]$, $\tilde{A}(y_i)$ is the membership function of \tilde{A} defined on the universe of discourse Y_i for x_i of object p , and $\widetilde{B}(y_i)$ is the one of \widetilde{B} defined on Y_i for object k .

It's obvious that Equation (4) denotes a family of fuzzy similarity measures for using the parameter h_i . Especially, three common fuzzy similarity measures can be obtained by specifying *hi*:

(i) The Max-Min measure

$$
\sigma^{(i)}(p,k,1) = \frac{\sum_{y_i \in Y_i} T(\widetilde{A}(y_i), \widetilde{B}(y_i), 1)}{\sum_{y_i \in Y_i} S(\widetilde{A}(y_i), \widetilde{B}(y_i), 1)}
$$

$$
= \frac{\sum_{y_i \in Y_i} \min(\widetilde{A}(y_i), \widetilde{B}(y_i))}{\sum_{y_i \in Y_i} \max(\widetilde{A}(y_i), \widetilde{B}(y_i))}.
$$
(5)

(ii) The Probabilistic measure

$$
\sigma^{(i)}(p,k,0.75) = \frac{\sum_{y_i \in Y_i} T(\widetilde{A}(y_i), \widetilde{B}(y_i), 0.75)}{\sum_{y_i \in Y_i} S(\widetilde{A}(y_i), \widetilde{B}(y_i), 0.75)}
$$

$$
= \frac{\sum_{y_i \in Y_i} \widetilde{A}(y_i) \widetilde{B}(y_i)}{\sum_{y_i \in Y_i} (\widetilde{A}(y_i) + \widetilde{B}(y_i) - \widetilde{A}(y_i) \widetilde{B}(y_i))}.
$$
(6)

(iii) The Lukasiewicz measure

$$
\sigma^{(i)}(p,k,0.5) = \frac{\sum_{y_i \in Y_i} T(\tilde{A}(y_i), \tilde{B}(y_i), 0.5)}{\sum_{y_i \in Y_i} S(\tilde{A}(y_i), \tilde{B}(y_i), 0.5)}
$$

$$
= \frac{\sum_{y_i \in Y_i} \max(0, \tilde{A}(y_i) + \tilde{B}(y_i) - 1)}{\sum_{y_i \in Y_i} \min(1, \tilde{A}(y_i) + \tilde{B}(y_i))}.
$$
(7)

(2) The infinite attribute domains

If $Y_i = [a,b]$, similar to $Y_i = \{y_1, y_2, \dots, y_n\}$, we can define the similarity degree of object p and k on attribute x_i as follows:

$$
\sigma^{(i)}(p,k,h_i) = \frac{\int_a^b T(\widetilde{A}(y_i), \widetilde{B}(y_i), h_i) dy_i}{\int_a^b S(\widetilde{A}(y_i), \widetilde{B}(y_i), h_i) dy_i}
$$

$$
= \frac{\int_a^b (\max(0^m, \widetilde{A}(y_i)^m + \widetilde{B}(y_i)^m - 1))^{\frac{1}{m}} dy_i}{\int_a^b (1 - (\max(0^m, (1 - \widetilde{A}(y_i))^m + (1 - \widetilde{B}(y_i))^m - 1))^{\frac{1}{m}}) dy_i}.
$$
 (8)

In the same way, the three common fuzzy similarity measures, the max-min measure, the Probabilistic measure and the Lukasiewicz measure, can also be obtained by specifying the parameter *hi*.

III. RESOURCE ORGANIZATION AND SCHEDULING

Before allocating appropriate Grid resources required by users' applications, it's necessary to organize resources well. Now a new Grid resource model, HTSRM, will be presented to describe resources, abstract resources and provide unified system images.

A. Resource organization

The HTSRM is a hyper topology space in the whole and will be divided to three layers which are Primitive Resource Layer, Aggregating Resource Layer and Service Resource Layer. Each layer has different forms and topology structures, and can be divided into several sub-layers again. The detailed description of each layer is given as follows.

(1) Primitive Resource Layer (PRL)

In Computing Grid, resources are identified based on a set of attributes such as the speed of CPU, memory size, disk size and so on. The PRL contains all information of Grid resources which is denoted by hyper nodes, and one node only denotes the corresponding information of one resource used independently. So, the PRL is really a Grid resource space.

Definition 2 *Resource* is an object denoted by a multidimensions attribute vector of (x_1, x_2, \ldots, x_n) , where x_i represents a given attribute of the resource object. So, $p(x_1, x_2)$ x_2, \ldots, x_n is used to describe a resource *p*.

Definition 3 *Grid resource space* is represented as *P*, which is a real linear space of *n* dimensions and contains the whole grid computing resources. For a resource described by *n* orthogonal attributes, $p(x_1, x_2, \ldots, x_n) \in P$.

Definition 4 In the Grid Resource Space *P*, each resource *p* is called a *hyper node*.

From those analyses, it's obvious that the Grid resource space is disorder and not easy to use without unified images. So, a particular ordering space formation, hyper topology space, will be proposed to change the random space structure.

(2) Aggregating Resource Layer (ARL)

This layer aims at how to change the first layer of PRL, the random space structure, to a particular ordering one. It will explore the concept of hyper topology space.

Definition 5 Let *P* be a Grid Resource Space, and let the space family of all subspaces on *P* be *T*, then *T* is called a *hyper topology structure* for *P*, and *P* is a *foundation space* for *T*. *P* together with its topology *T* is called a *hyper topology space* for *P*, represented by (*P*, *T*).

The hyper topology space is the advanced organizational form after the qualitative changes took place in the inherent structure of Grid Resource Space. It breaks away from original Grid Resource Space where each element or sub space exist independently, makes the elements of whole Grid Resource Space compose a unified organic whole, and makes the whole produce new important qualities on the advanced level.

Definition 6 Let *R* be a binary relation on *P*, if *R* meets following three conditions:

(i) *R* is self reversible: to any element $x \in P$, there exits *xRx*;

(ii) *R* is symmetrical: to any elements *x*, $y \in P$, there exits *xRy* and *yRx* at same time;

(iii) *R* is transferable: to any elements *x*, *y*, $z \in P$, if there exits *xRy* and *yRz*, it is certain to implicate *xRz*.

Then *R* is called a *equivalence relation* on *P*, and represented by $R_{\rm E}$.

Definition 7 Let R_E be a equivalence relation on P , $x \in P$, set { $y \mid y \in P$, *x* $R_E y$ } is called *the equivalence class* about R_E and generated by *x*, and represented by $c = [x]$.

Definition 8 Let *P* be a Grid resource space, *T* be the hyper topology structure about P , (P, T) be their hyper topology space. If two subspace **A**, **B** on *P* there exist relation *R*, and $R \in \mathcal{T}$, then *R* is called a topology correlation relation between **A** and **B**, and represented by R_T or *t*.

Definition 9 In Grid resource space *P*, if a certain topology correlation equivalence relation in the hyper topology structure is represented by $R_{\rm E}$, then, in the P , a set composed of all the elements or regions of containing this relation is called the equivalence class generated under the mapping of $R_{\rm E}$, and the set of all equivalence classes is called *the quotient set*, represented by P'/R_E generally.

Definition 10 For a Grid resource space *P*, if a certain topology correlation equivalence relation in the hyper topology structure *T* is represented by t ($t \in T$), then, in the *P*, the subspace family composed of all the regions or subspaces that satisfy the relation defined by t , is called the quotient space generated under the mapping of *t*, represented by $Q = P / t$.

Using the topology correlation equivalence relation to partition the information space, then regrouping and arranging, a kind of new orderly topology structure form, one of quotient space arranged according to the equivalence class, is just be generated, and represented by *A*. This rearrangement ordering process is called *the aggregating class reaction* or *the clustering reaction* of Grid resource space.

Axiom 1 For the aggregating class space *A* and the quotient space *Q*, there exists a mapping:

$$
f: A \rightarrow Q
$$
, $c = f(a)$.

Where $a \in A$ denotes any one aggregating node in ARL, *c*∈*Q* represents the equivalence class in PRL mapping into *a*.

(3) Service Resource Layer (SRL)

This layer is a user interface to all kinds of applications, like Grid services. All needs of applications will be found in the layer. And the uniform services are provided and the heterogeneous characteristics among resources are shielded perfectly. So it's not necessary for users to think about how to select resources when applications will run.

Generally, the end services in SRL can be aggregated to the three kinds: *Human*, *information*, and *artificial object*, which achieve the uniform viewpoint and unify the top-level resource partition. All applications would start from above services. However, it should be seen that the end services are the three kinds by no means and concerned with the concrete application domains.

Axiom 2 For the end service space *S* and the quotient space *A*, there exists a mapping:

$$
g: \mathbf{S} \rightarrow 2^A, \quad a' = g(s).
$$

Where $s \in S$ denotes any one end service node in SRL, *a'* ⊂ *A* represents the subspace in ARL mapping into *s*.

Figure 1. Hierarchy of HTSRM

Through the above analysis, the hierarchy of HTSRM can be showed in Fig. 1. In PRL, the hyper nodes, p_1 to p_w , are listed to represent any primitive Grid resources, such as CPUs, disks, printers, etc. By aggregating class reactions automatically, upper nodes, a_1 to a_v , are formed in ARL and represent the common characteristics of equivalent resources. These nodes may be computing, storing, data ones, and so on. After processing again and again in ARL, the layer of SRL is formed finally. Here, it only contains three main nodes, s_1 , s_2 and *s*3, which represents human, information, and artificial object respectively. Those are just end services for user to run their applications, represented by u_1 to u_d . For example, the application u_1 may only use s_3 , but u_2 use s_1 and s_3 , and all that.

In the whole, this is a process of bottom-up aggregating and top-down scheduling of Grid resources. Thereinafter, the scheme of resource scheduling will be described.

B. Resource scheduling

In order to run Grid applications, we have to look for suitable resources satisfying a given set of constraints. Users need to locate and acquire resources in order to execute jobs. To allocate the most suitable resource for a given job, an effective scheme over the organization of HTSRM is described in the following.

Suppose that QR (q_1, q_2, \ldots, q_r) represents the resource request of a job, *qi* the *i*-th query constrain.

Step 1: According to *QR* (q_1, q_2, \ldots, q_r) , the end service s_i can be decided firstly, $s_i \in S$.

Step 2: Expand s_i to the finer granularity by using the mapping *g*, that is

$$
a_i' = g(s_i).
$$

Then, for any $a_{ij} \in a_i'$, compute $\sigma(a_{ij}, QR)$, and find out a_i which satisfies

$$
\sigma(a_i, QR) = \max_i \sigma(a_{ij}, QR).
$$

In computing $\sigma(a_{ij}, QR)$, it needs to be stated that the fuzzy similarity degree and weight of a_{ij} and QR on one certain attribute are both equal to 1 only if the attribute isn't determined no matter in any objects.

Step 3: Further expand a_i to the finer granularity by using the mapping *f*, that is

Then, for any $p_{ij} \in c_i$, compute $\sigma(p_{ij}, QR)$, and find out p_i which satisfies

$$
\sigma(p_i,QR) = \max_i \sigma(p_{ij},QR).
$$

Therefore, p_i is just the most suitable resource which satisfies the conditions of resource request. This resource will be allocated to execute the job.

IV. ANALYSIS AND CONCLUSIONS

The unified fuzzy similarity measures proposed in this paper are helpful to realize effective and efficient resource scheduling. It's embodied by the following several aspects.

 (1) The approach proposed in this paper is a family of fuzzy similarity measures, and any common measures, like the max-min one, the Probabilistic one and the Lukasiewicz one, can be obtained by specifying the parameter *h*. So, the different measures can be determined according to the real application fields, which provide extremely great flexibility and adaptability.

(2) No matter the values of attributes are fuzzy or not, the similarity degrees of two object on the attributes can be calculated easily.

(3) The fuzzy similarity should be self reversible and symmetrical. From Equation (3), it's obvious that $\sigma(p, p) = 1$ and $\sigma(p,k) = \sigma(k, p)$.

(4) It's efficient for resource scheduling, because the most suitable resource can be found and allocated shortly in a limited range of Grid resource space.

(5) The unified fuzzy similarity measures proposed in this paper make users' programming easier because the unified equation is adopted for different type of attributes.

To sum up, the family of fuzzy similarity measures proposed in this paper promotes the effective and efficient Grid resource scheduling. And, it is a general approach and can be used not only for Grid Computing, but also for Pattern Recognition, Data Mining, and so forth. In future, our emphasis of work is mainly on research of learning of the parameter *h*.

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REFERENCES

- [1] R. Zwick, E. Carlstein, and D. V Budescu, "Measures of similarity among fuzzy concepts: a comparative analysis", International Journal of Approximate Reasoning, vol. 1, pp. 221–242, 1987.
- [2] C. P. Pappis and N. I. Karacapilidis, "A comparative assessment of measures of similarity of fuzzy values", Fuzzy Sets and Systems, vol. 56, pp. 171–174, 1993.
- [3] X. C. Liu, "Entropy, distance measure and similarity measure of fuzzy sets and their relations", Fuzzy Sets and Systems, vol. 52, pp. 305–318, 1992.
- [4] M. Ionescu, A. Ralescu and S. Visa, "Fuzzy similarity measure between heterogeneous data", The Annual Meeting of the North American Fuzzy Information Processing Society, pp. 463–466, 2007.
- [5] J. J. Buckley and Y. Hayashi, "Fuzzy input-output controllers are universal approximates", Fuzzy Sets and Systems, vol. 58, pp. 273–278, 1993.
- [6] H. C. He, Principle of Universal Logics, Beijing: Science Press, 2006.