A Dynamic Web Services Selection Algorithm Based on Trust Model for Grid Environment

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Abstract. In order to find the service nodes, which the users are satisfied with, in a high speed and efficiency in open network environment, a new grid-oriented multi-level service selection model is proposed, which is based on the concept of user-similarity group. On this condition, direct trust calculation based on time decay is given and fine-grained recommendation trust calculation is studied, which can distinguish the ability of honesty. In addition, based on activity level of nodes, dynamic weight-allocation method is proposed, which can make the prediction results be closer to the fact. After job-interaction, the update algorithm about honesty ability of recommendation nodes is researched, which will provide more reasonable and reliable reference for the next prediction. Simulation results show that the service selection model and trust calculation methods are reasonable and accurate.

Keywords: grid computing, service selection, trust model, dynamic update, ability of honesty.

1 Introduction

Currently, scholars pay attention to the dynamic trust in open network environment increasingly, many models and programs about trust forecast and update are proposed.Among them, literature[3] proposes a trust evaluation model including the entity risk, literature[7] establishes the feedback mechanism in the authorization system, and dynamically adjusts user roles based on user behaviors. In addition, service selection based on trust metrics has become a popular topic [9-11].In order to find the service nodes which meet user requirements,existing researches were contribution to the rapid development of the trust model, our project team also has done some research work early [12-14], but there are still a number of shortcomings need to be addressed.

1) Many service selection models are not detailed enough and clear in selection level dividing,and waste the limited resources of the system to a certain extent.

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2) Most service selection models treat the trust value of entity as an important selection evidence,in the calculation of the trust value, however, both the direct trust and recommendation are need to be improved. For example, a simple weighted method to calculate the integrated trust value, this method is not objective, not flexible, not scientific, the focus of this article is to research a dynamic weighted method.

3) The trust value of entity is changing all the time, most of papers pay more attention to the update of the trust value, but less to the real-time updates of the recommended capacity of the recommended node.

Referring to the mentioned problems above, the level of service selection has been meticulously divided to find the service node meeting users need quickly. In the calculation of the integrated trust value, direct trust value and recommended trust value of service nodes use dynamic weighted calculation which is more scientific and flexible. After each job interaction, the trust value of the service node and the recommended capacity of recommended nodes are updated.

The part 2 describes a multi-level services selection model based on the open network, and Part 3 discusses the direct trust value, recommendation trust value, and the trust calculation method based on the dynamic weighted method, part 4 discusses update algorithm of the service node, and the real-time update scheme of the node recommended capacity, part 5 show the experimental results, part 6 is the conclusion.

2 Deployment Scenarios of Service Selection

2.1 Multi-level Service Selection Model

In order to find services more efficient and accurate in a large-scale dynamic grid environment, a multi-level and fine-grained service selection model is presented, as shown in Figure 1.

Service Autonomous Region:Each grid is an autonomous region that contains many services, whose type and quality are different. In order to meet the demand of more services,different services are sorted, at the same time. A service selection machine is set in each type of services to manage the internal service options scheme of this type.

Service Classification Region:The second level is a virtual classified region where the service selection machines from different grids will be unique. Each node can save the number of jobs and each job time records in this region, and it can sort services based on the amount of jobs in each period time. A standard period of time and number of operations requirements are given by users, service selector can lessen the service candidates based on its own information and the recommended information from recommended nodes.

Service Region:The top-level is a user-oriented level, which can render a collection of various service types in the entire network environment.

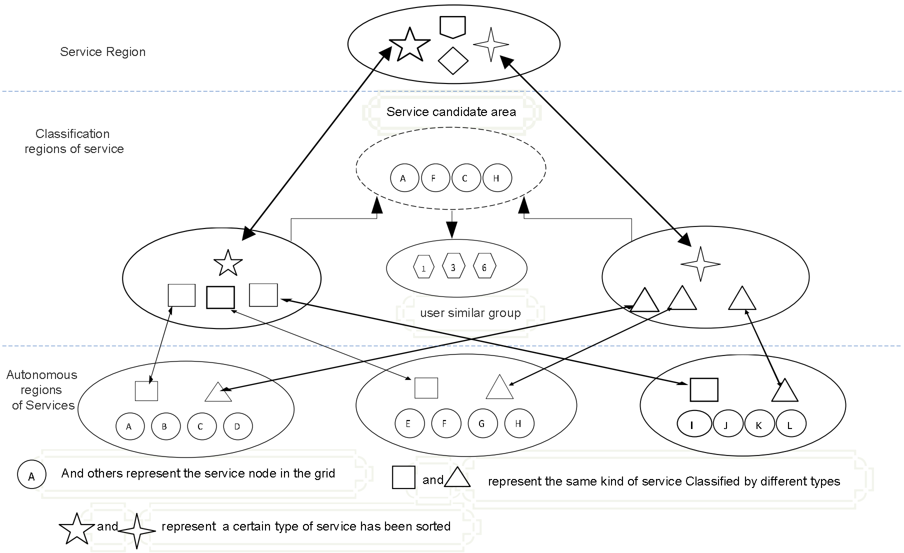

Fig. 1. Multi-level service selection model

2.2 Search Process of the Service Selection

In a huge open network environment, it is important to search effectively, if no efficient search methods, the search process will become very messy. The process of the service selection is as follows:

1) User nodes connect to the grid, query service region, propose the request of the types of services.

2) To access service classification area, where all network nodes that can provide the service were recorded, to get into the fine-grained hierarchical search.

3) The user nodes provide their standard time period parameters and the number of the system operations, service classification area takes the sorting operation according to the types of those services, search service nodes that meet the needs of user nodes.

4) The service candidate area take the sorting operation from high to low , according to the number of interactions of the service node in the recent time period, then the trust value of each node is given by the user evaluation in turn.

5) In order to evaluate the service node, it is necessary to consider both the direct trust value and recommended trust value. Recommendation trust,is need to consider some attributes for recommended, for example, whether they have the same service requests with the current user node in the recent period, or have similar requirements on quality of service. Then, examine the trust information of each node in the user similar group: a. last job interaction time; b.the trust value of the service node evaluation after the last interaction; c.the evaluation

of the Recommended honest ability of the current user from other user nodes; d.the evaluation of the user Recommended honest ability from the current user node.

6)To refer to the computing method on direct trust value recommended trust value and integrated trust value given in part 3, the overall trust value of the service node is gained.And to get the integrated trust value of each candidate service in the same method to refer to this information to choose an effective service node.

7) The user node interacts with the service node, and according to the job completion, the trust value of the service node and the recommendations ability are updated to provide the necessary reference for the next service selection.

3 Trust Value of Service Node

3.1 Calculation of Direct Trust Value

In order to make the direct trust value on a service node closer to the true value, take the nearest N interactions as the basis for calculating of direct trust value on this service node.

Assume a two-dimensional array $< \zeta_1, T_1 >, < \zeta_2, T_2 >, ..., < \zeta_i, T_i >$,every array records the last N interaction time T_i and trust evaluation value ζ_i.As trust value is dynamic, decaying with the time, the direct trust value$\vartheta_0$is as follows:

$$\vartheta_0 = \frac{\sum_{i=1}^{n} \eta_i * \zeta_i}{\sum_{i=1}^{n} \eta_i} \qquad i = 1, ..., n \tag{1}$$

Here, the time attenuation coefficientη_i:

$$\eta_i = \begin{cases} 1 & T_x - T_j \le T \\ \frac{1}{e^{T_x - T_i - T_r}} & T_x - T_j > T_r \end{cases} \tag{2}$$

If the interval of the current operating time T_x before a operating time is less than a value T_r,it is considered that this trust value is not to be attenuated, the attenuation coefficient is 1.

As can be seen from the above equation, which has taken a conservative approach to the calculation of the trust value, the trust value of the service node must not be raised blindly.

3.2 Calculation of Recommendation Trust Value

A service node will have a plurality of user nodes that had a job interactive with it, these user nodes formed a user similar group to a certain extent, they have the same type of service requirements, and the service demand for quality is similar, so recommended value of those users should be considered.

When it accesses a service node, current user node will query evaluation of the trust values from K nodes which interact with the service node in the recent time.The directly trust values gained by those K nodes on the service node to be

$x_1, x_2, ..., x_k$,which has attenuated by the time. At the same time this K nodes also have a different recommended honesty capability.

Let the comprehensive honesty ability of these recommendation nodes be $K'_1, K'_2, ..., K'_k$, which are provided from nodes of user-similarity group. the ones gained by user node are $K_1, K_2, ..., K_k$, here, K'_i and K_i are less than or equal to 1. Further,ρ_0 is the right weight of the of user-similarity group nodes on honesty ability of the recommendation nodes, ρ_1 is the weight of the current user node itself on these honesty abilities, the recommended trust value ϑ_1 on the service node is as follows:

$$\vartheta_1 = \frac{\sum_{i=1}^{k} (\rho_0 k'_i + \rho_1 k_i) * x_i}{\sum_{i=1}^{k} \rho_0 k'_i + \rho_0 k_i} \tag{3}$$

In this process, the current user node not only refers to its own evaluation about honesty ability of the recommendation node, but also refers to the evaluation of the other nodes in the user-similarity group, This recommendation results fit the exchanges of human society habits better.

3.3 Comprehensive Trust Value Calculation with Dynamical Weight-Allocation

Most of the literature use the expert opinion method or the average weight in computing the trust value method [8-12], resulting in the forecast results with a more subjective component,and being lack of dynamic adaptability.

This article will use a dynamic weight distribution scheme based on node activity to calculate the trust value of the service node.In fact,if an individual is more active in the human society, the quantity of people that communicate with him is more, at the same is his feedback.The recommendation trust value on this person evaluation will be more authentic, this idea also fit human cognitive habits well.

For a service node P_S, it is assumed that within a standard time period T, the quantity of user nodes that have interacted with service node is X, at the same time,number of operations is marked as M, $\beta(P_s)$ is the activity of service node P_S,then:

$$\beta(P_s) = \begin{cases} 1 & X > M \\ \frac{X}{M} & X < M \end{cases} \tag{4}$$

When there are more nodes interacting with the service node in the standard period of time,the value of $\beta(P_s)$ is larger,the trust value of service node will be relatively stable in the open network environment.

4 Trust Update Based on the Mean-Square Deviation

User nodes need to update direct trust value of service nodes after the job interaction completed, and the recommended honest ability of other recommendation nodes.

4.1 Update of Direct Trust Value

After each job interaction, user node holds the value of the trust evaluation of the service node.It is need to re-calculate the trust value of the service node at the next time, using the formula (1) and (2). Thus, user node will have a new cognitive on service node after each job interaction, the cognition is direct.

4.2 Update of Recommended Honesty Ability

For the user node, the recommendation nodes in the user-similarity group which has high credibility are more trustworthy.therefore it is need to distinguish the recommendation honesty ability. When the user nodeP_u and service node P_s completed the job interactions, it is need to update the honest ability of the recommended nodes, according to the actual implementation of the job.

After obtaining the recommendation information of the recommended node,we will do a mean calculation for all of the recommended trust value on the service node,then calculate a mean square deviation about each of the recommended nodes, so that the mean square deviation is larger, the recommended information is more unbelievable, It also shows the honesty ability of the recommended node should be updated in real time, in order to ensure the validity of the recommended information.

Set$M(\omega_r)$ be the collection of recommendation nodes within the user-similarity group which have interacted with the service nodeP_s,$TR(\omega_r, P_s)$ expresses the recommended trust value of the service nodeP_s,$|M| = K$,then:

$$E[TR(\omega_r, P_s)] = \sum_{i=1}^{k} \frac{TR(\omega_r, P_s)}{k} \tag{5}$$

The relative mean-square deviation of the recommended node ω_r is as follows:

$$\delta[TR(\omega_r, P_s)] = \sqrt{E[(TR(\omega_r, P_s) - TR(P_u, P_s)^2]) - \mu[TR(\omega_r, P_s)]^2} \tag{6}$$

$$\mu[TR(\omega_r, P_s)] = |E[TR(\omega_r, P_s)] - TR(\omega_r, P_s)| \tag{7}$$

The update formulas of the honest ability:

$$CH'(\omega_r, P_s) = \begin{cases} CH(\omega_r, P_s) + \tau(1-\varepsilon)CH(\omega_r, P_s) & \varepsilon < 1 \\ CH(\omega_r, P_s) - \gamma(1+1/\varepsilon)CH(\omega_r, P_s) & \varepsilon > 1 \end{cases} \tag{8}$$

Here:$0 < \tau < \gamma < 1$,$CH(\omega_r, P_u)$is the last evaluation of user nodeP_u on the honest ability of recommended node ω_r, $CH'(\omega_r, P_u)$ is the current evaluation on the honest ability after this job interaction ,$CH'(\omega_r, P_u) \in [0, 1]$.

$$\varepsilon = \frac{||E[TR(\omega_r, P_s)] - \vartheta(P_u, P_s)| - \mu[TR(\omega_r, P_s)]|}{\delta[TR(\omega_r, P_s)]} \tag{9}$$

5 Analysis of Simulation Experiment

5.1 Analysis of Multi-level Service Selection Model

Assume a network environment composed by S autonomous region, There are E service nodes in each autonomous regions and R service types across the grid, Each type of services has the same number of service nodes.During judging on a service node, each user node need determine its type of service firstly.if the service type is suitable, continue to predict the value of trust to obtain satisfactory service node. Set the time to judge the service type of a service node as 1 time unit, and then the time required for calculating a service node trust value as 3 time units.

The model of this article uses a hierarchical thought, and sorts the similar type of services. So when it searches for a satisfactory service node, the user does not need to broadcast-search, but searches rows in the front part of the service node (such as 0.3) to find the goal. And the user searches for a satisfactory service nodes needed for the longest time TS:

$$TS = R + E * \frac{S}{R} * 0.9 \tag{10}$$

Longest time required by the traditional model is longer because they do not adopt such a fine-grained hierarchical thought, so that a user searches for a satisfactory service node:

$$TS' = 4S * E \tag{11}$$

Set $S = 10$, $R = 5$ and$E$was set $3, 4, 5, 6, 7$, Figure 2 is the experimental comparison chart on search efficiency between a multi-level model of this article and reference model.

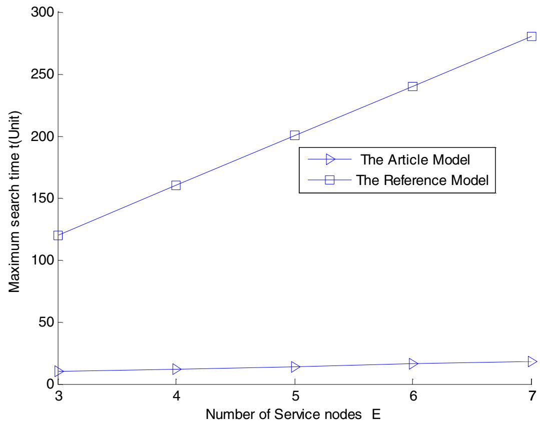

Fig. 2. Experimental comparison chart of the search efficiency

In Figure 2, The maximum time required in querying service nodes in the article model compared with the reference model is much less. That shows that the efficiency of the article model is higher.

5.2 Analysis on Update Honesty Ability

After the job interaction between user node and the service node, not only the direct trust value of service nodes should be updated, but also on the recommended node honest capability, that provide a more effective basis for the next credible projections.

It is considered to be not detailed enough on the update of recommended node honest ability in traditional model, most of them ignore the feedback evaluation of the current user on recommended node recommended capacity, Figure 3 shows the next credible prediction on the service node when the users get different recommended capacity feedback value.

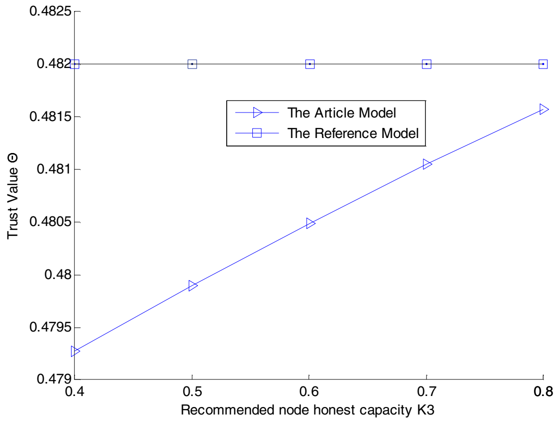

Fig. 3. experimental comparison chart of update of recommended honest ability

Figure 3 shows an update of the current user node on the recommended node honest ability and the recommended node honesty capability are obtained by assigning different weights to different recommended nodes the model of this article model, and thereby its recommended trust value is updated indirectly. Comprehensive update of the recommended node honest ability is not detailed enough in the reference model. Even if a recommended node honest ability has changed, the reference model predicts the overall trust value which is not sensitive enough on the service node. However this article model is more reasonable.

6 Conclusion

In open grid environment, a multi-level and fine-grained service selection model is researched,Thus user nodes can find the service node more efficiently and quickly.Dynamic weight-allocation method based on direct trust value and the recommendation trust value are stressed,And the method fit the habit of human society well,and makes the trust value more credible. The update of direct trust value on service node and honesty ability were researched, after the user node completes the job interaction with the service node,this can provide a more reasonable and reliable reference for the next service selection. Multiple experimental results show the new model is rational and scientific.

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