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A Direct Trust Aggregation Algorithm Based on the Minimum Variance Time Sequence Weight

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Abstract: Direct trust relationship is the foundation of research on the indirect recommendation trust between agents and the global trust degree. In view of the lack of analysis and attention on the direct trust in the current research of dynamic trust relationship, this paper proposed a minimum variance time sequence weight based on direct trust aggregation algorithm which is constrained by the fuzzy integration operator orness measurement level. The algorithm introduces the concept of agent reputation, elaborates the evolution process and the law of the trust in the process of direct interaction, and further characterizes the complexity and stability of direct trust relationship. The simulation experimental results show that the model has a good dynamic adaptability and scalability compared with the conventional model.

Keywords: Direct trust, Minimum variance, Orness measurement, Time sequence weight, Trust degree, Dynamics modeling.

1. INTRODUCTION

1.1. Research Background

The theory and technology of dynamic trust management are a basic research task of trusted computing technology [1-3]. Many scholars put forward a variety of dynamic trust relationship prediction models in the open environment based on the mathematical methods and tools used to describe the uncertainty phenomenon [3-17]. These models reflect the dynamics, complexity and uncertainty of trust relationship from different aspects, making people understand the nature of the dynamic trust relationship, and promoting the research and the development of related theory of trust relationship effectively.

Social psychology study indicates that trust is a complex human psychological activity. It is necessary to get the final result through combined work of a variety of factors. Trust refers to future in the past. The past is certain and invariable, but it is not well-founded to use the trust to infer the unknown future in the past. It is filled with certain uncontrollability and risk. Usually, trust can be obtained mainly by two methods; the direct and the indirect [18]. Most of the existing models accept the importance of the direct trust. Only when the direct trust evidence is insufficient, it could use the indirect recommended information to judge, but the direct trust relationship is the foundation of indirect trust relationship. It is impossible to speak of the indirect recommend trust without the direct trust relationship. However, researches by various scholars' are obviously insufficient for the direct trust relationships between the agents.

(1) When there is no direct interaction experience or recommendation trust, initialization trust is the key problem which directly affects the subsequent trust judgment. The existing models do not carry deep analysis and discussion about the trust initialization problem.

(2) It is likely to lead to wrong judgment if we are directed to make simple aggregation or assume the distribution probability of some typical because of the evaluation of trust satisfaction degree, which, produced by the previous experience, is left in the complex distributed dynamic environment; the inter behavior and the number of interactions of both sides of the trust relationship agent are difficult to determine, the distribution of trust evaluation data is difficult to predict, and the variance size is uncertain.

(3) The existing models carry no further discussion about the essential characteristics of the direct trust after the aggregation of historical trust evaluation data, and have no clear conclusion of the relationship between the dynamics and the stability of the agent trust relationship.

This paper solved the above mentioned problems by researching the connotation of the direct trust relationship between the subject and the object. First, it discussed the initialization problem of trust, put forward an aggregation algorithm of direct trust based on the weight of minimum variance of time sequence under the constraint of a fuzzy integration operator orness measurement level, and then it discussed this algorithm in detail, proposing some basic ideas and validating them.

1.2. Related Research Work

Since Blaze and others put forward the concept of trust management in 1996, trust theory research has gradually become an important research direction in the field of security. Nowadays, in the existing trust relationship models, few scholars focus on the research of direct trust relationship in the study of these models.

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(1) Direct trust issues were seldom mentioned in models, but the first interaction trust relationship of entities was established by the direct recommendation trust. For example, the PTM model based on the evidence theory proposed by Almenarez *et al.* [5, 6]; the trust model based on the vector mechanism put forward by Hassan *et al.* [7]; the trust model based on the theory of the half ring proposed by George *et al.* [8]; the trust model based on the entropy theory proposed by Sun *et al.* [9, 10] and the trust model based on the cloud mode proposed by He *et al.* [11]. Dimitri proposed the model based on the Bayesian network model and used the Kalman information filter mechanism [12]. Claudiu proposed the dynamic trust model based on the reinforcement learning method of machine learning [13]. Also, the dynamical recommend trust model based on the normal distribution of the Bayesian formula was proposed by Shao *et al.* [14].

(2) Some models have portrayed the direct trust relationship simply, but lack of discussion on the dynamic adaptability has affected the practicability of the model. For example, a trust model based on fuzzy logic proposed by Song *et al.* [15]; a trust model based on fuzzy set theory proposed by Tang *et al.* [16]; and a trust model based on the theory of fuzzy relationship proposed by Yu *et al.* [17].

2. DYNAMIC MODELING OF DIRECT TRUST RELATIONSHIP

The dynamic of trust relationship mainly reflects that trust has an evolving relationship with time [18]. This uncertainty should be presented by the modeling of trust relationship. For some agent, an agent is credible, but for other agent, it is likely to be completely unreliable. The relationship evaluation of direct trust produced by the interaction of two agents is characterized by its complexity and its variances are difficult to predict. These are determined by the complexity and uncertainty of the trust relationship in the dynamic distributed environment. So using statistical method model for the trust relationship directly could lead to systematic judgment error.

For the trust evaluation data, using the non-statistical analysis method to model is consistent with the essential characteristics of the trust relationship. Non-statistical method is different from the classical statistical methods. Its theoretical basis is no longer the law of large numbers and central limit theorem. Generally speaking, the reliable determination of the classic statistic is a large sample data and it obeys the typical probability distribution. But non-statistical method does not have special requirements of the distribution of data and the size of the sample, and the processing result is consistent with the classical statistical method in the case of large sample and typical probability distribution.

2.1. The Initialization of the Direct Trust Relationship

The trust relationship initialization of two agents is finished by the direct way or the indirect way [4]. But if any agent lacks understanding of the object, main body cannot get any information about the object. So according to the maximum uncertainty principle, the trust degree of the subject should be 0.5 to indicate that the trust of subject to object is uncertain.

However, the social psychology experience of the trust relationship tells us that if an object comes from a trusted environment, the credible degree of main body will be improved greatly, and vice versa. So, assigning a trust degree greater than 0.5 or less than 0.5 will be more in line with the behavior habits of the people. This appears simple but promotes rapid convergence of the system.

In another case, when the object of trust has never interacted with the other subject directly, but has interacted through other agent, the trust degree of the subject to the object is assigned a value as close as possible to the object of reputation. The trust degree of object is estimated as the trust degree of subject to object, completing the initialization of the trust relationship. The reputation of object is an inner attribution..

2.2. The Dynamics Modeling of Direct Trust Relationship

First, the definition of direct trust relationship and direct trust aggregation algorithm is given. Then, the dynamic of trust relationship is further analyzed.

Definition 1: (Direct trust relationship) Direct trust indicates that in a given context, the trust of an agent is based on the historical record of the interaction with another agent. In this paper, DT (e_i, e_j) shows the direct trust of agent e_i to agent e_j and is denoted as DT_{ij}. The value of the trust space is defined as $DT_{ij} \in [0,1]$. e_i is called the subject of trust and e_j is called the object of trust.

Definition 2: (Direct trust aggregation algorithm) Trust evaluation collection DT={$DT_{ij}(1)$, DT_{ij} (2), DT_{ij} (3), …, DT_{ij} (h-1), DT_{ij} (h)} is the product of the recent h times interaction processes of the subject of trust e_i and the object of trust e_j. Where DT_{ij} (k) means the trust degree of the k-th interaction, DT_{ij} (k) $\in [0,1]$, k=1, 2,…, h. The data of trust evaluation is estimated by the chronological order of interaction; DT_{ij} (1) indicates an interaction relatively longer from now, DT_{ij} (h) represents the most recent one from now. The trust degree of e_i to e_j is:

$$DT(e_i,e_j)=DT_{ij}=\begin{cases}\sum_{k=1}^{h} w(k)DT_{ij}^{(k)}, & h\neq 0, h\leq H\\ 0.5\, or\, CW_j, & h=0\end{cases} \tag{1}$$

Where, w(k) is the weight of trust evaluation DT_{ij} (k) which is produced at the k-th interaction, and meets w(k) ≥ 0 (k=1, 2, …, h), $\sum_{k=1}^{h} w(k)=1$. CW_j is the reputation of the object of trust e_j.

In the algorithm, we use w (k) (k = 1, 2, ..., h) to make reasonable weight about the direct trust, which is produced in the interaction of two agents in different periods. The weight sequence {w(k)} (k=1, 2, …, h) is a function of time and changes over time. It also reflects the dynamic of trust relationship. {w(k)} (k=1, 2, …, h) is an increasing time sequence and meets the social psychology characteristics of the trust relationship which also means that people always give greater weight when new interaction occurs. This reflects the property that the trust relationship changes over time and dynamic attenuation at the same time (that is, the longer the interval, the lesser the contribution of the previous trust value can judge the trust relationship).

Obviously, the key of the algorithm is to determine the trust DT_{ij} (k) which is produced by the k-th interaction of the subject of trust e_i and the object of trust e_j. In order to make the weight sequence {w(k)} (k=1, 2, …, h) more effective, the minimum variance model is used to determine the weight vector time sequence [19] to determine the weight vector of time sequence {w(k)} (k=1, 2, …, h) and gain the weight of minimum variance of time sequence [20].

First, calculating the variance of time sequence weight {w(k)} (k=1, 2, …, h):

$$D^2(\{w(k)\}) = \sum_{k=1}^{h}\frac{1}{h}(w(h) - E(w(k)))^2$$

$$= \frac{1}{h}\sum_{k=1}^{h}(w(k))^2 - (\frac{1}{h}\sum_{k=1}^{h}w(k))^2$$

$$= \frac{1}{h}\sum_{k=1}^{h}(w(k))^2 - \frac{1}{h^2}$$

Where, $E(w(k)) = \frac{1}{h}\sum_{k=1}^{h}w(k)$ is the expectation of weight w(k) (k=1, 2, …, h).

Then, the operator of fuzzy set orness measurements is used as the constraint condition [21] and the minimum variance time sequence weight is obtained, establishing the mathematical programming model that has constraint [19]:

$$\min D^2(\{w(k)\}) = \frac{1}{h}\sum_{k=1}^{h}(w(k))^2 - \frac{1}{h^2}$$

$$s.t.\ orness(\{w(k)\}) = \frac{1}{h-1}\sum_{k=1}^{h}(h-k)w(k) = \alpha, \quad 0 \le \alpha \le 1$$

$$w(k) \ge 0 (k = 1,2,\cdots,h), \sum_{k=1}^{h} w(k) = 1$$

Structuring Lagrange function and solving this model:

$$L(w,\lambda_1,\lambda_2) = \frac{1}{h}\sum_{k=1}^{h}(w(k))^2 - \frac{1}{h^2} - 2\lambda_1(\frac{1}{h-1}\sum_{k=1}^{h}(h-k)w(k) - \alpha)$$

$$-2\lambda_2(\sum_{k=1}^{h}w(k) - 1)$$

Where, λ_1 and λ_2 are the parameters of Lagrange function.

The partial derivative of $L(w,\lambda_1,\lambda_2)$ on w(k) (k=1, 2, …, h) and the parameters λ_1 and λ_2 of Lagrange are:

$$\frac{\partial L}{\partial w(k)} = 0 \ \ (k = 1,2,\cdots,h), \qquad \frac{\partial L}{\partial \lambda_i} = 0 \ (i = 1,2)$$

where:

$$\frac{\partial L}{\partial w(k)} = \frac{2w(k)}{h} - 2\lambda_1\frac{h-k}{h-1} - 2\lambda_2 = 0 \quad (k = 1,2,\cdots,h)$$

$$\frac{\partial L}{\partial \lambda_1} = -2(\frac{1}{h-1}\sum_{k=1}^{h}(h-k)w(k) - \alpha) = 0$$

$$\frac{\partial L}{\partial \lambda_2} = -2(\sum_{k=1}^{h}w(k) - 1) = 0$$

Therefore:

$$w(k) = \frac{(6h - 12k + 6)\alpha - 2h + 6k - 2}{h(h+1)}, \qquad k = 1,2,\cdots,h \tag{2}$$

For any k, $w(k) \ge 0$, simplify this, that is:

$$(6h - 12k + 6)\alpha \ge 2h - 6k + 2, \ \ k = 1,2,\cdots,h \tag{3}$$

For formula (3), assuming $(6h-12k+6) = 0, (6h-12k+6) > 0$ and $(6h-12k+6) < 0$, and comprehending this, we could know that when:

$$\frac{h-2}{3h-3} \le \alpha \le \frac{2h-1}{3h-3} \tag{4}$$

formula (3) is established.

In other words, we could get the weight of the time sequence w(k) (k=1, 2, …, h) under the constraint condition that is formula (4), and satisfying $w(k) \ge 0 \ (k = 1,2,\cdots,h), \sum_{k=1}^{h} w(k) = 1$.

Then we make further discussion about formula (2). For formula (2), the derivative with respect to k:

$$\frac{dw(k)}{dk} = \frac{-12\alpha + 6}{h(h+1)}$$

When $\frac{dw(k)}{dk} > 0$, w(k) is strictly monotone increasing function of k and combines formula (4):

$$\frac{h-2}{3h-3} \le \alpha < \frac{1}{2} \tag{5}$$

So w(k+1) > w(k), k=1,2,…,h-1, the sequence {w(k)} is monotone increasing sequence, and the bigger the k, the greater the value of w (k).

Thus, under the constraint condition of formula (5), we could get the weight of monotone increasing sequence for formula (2) {w(k)} (k=1, 2, …, h), and we could obtain the interaction of the direct trust if we take {w(k)} into formula (1).

3. THE VALIDITY ANALYSIS OF THE MODEL

3.1. Stability

From the perspective of social psychology and behavioral science, the evolution of the trust relationship is caused by the trust insufficient cognition of the subject to the object, especially in the initial interactive stage, the single trust subject has great randomness on the cognition of the object, and the present trust relationship has uncontrolled ambiguity and randomness. However, most subjects have regular cognition on the object. Along with the increase in the interaction times, the trust of the agent to the object ultimately tends to a stable value and this value is creditworthiness.

Definition 3: (Creditworthiness) Creditworthiness is an inherent property of the agent and the trust degree of this agent is the external performance of most agents. CW_j is the creditworthiness of agent j and $CW_j \in [0,1]$.

Although creditworthiness is the inherent attribute of an agent and is objective existence, but to get creditworthiness of an agent is almost impossible. The trust degree of the subject of trust for the object of trust is the external performance of the inner creditworthiness of the object of trust. In other words, the creditworthiness of the object is manifested through a long-term interaction with a large number of subjects.

Deviation is defined to describe the stability of trust degree.

Definition 4: (Deviation) The trust evaluation data set DT is produced by the h times interaction process of the subject of trust to the object of trust and its definition is same as definition 2. Now sorting the data in DT from small to large and forming new sequence:

$$DT_{ij}^{(n)} \le DT_{ij}^{(n+1)}$$

In above formula, n=1,2,…,h-1. Data deviation of trust evaluation is defined as follows:

$$\delta_n = DT_{ij}^{(n+1)} - DT_{ij}^{(n)}$$

Obviously, when δ_n is smaller, the data distribution is close, and when δ_n is greater, the data distribution is loose. If we use $\max_n \delta_n (n = 1, 2, \cdots, h-1)$ to show the distribution of the deviation of the set DT, the trust degree of subject to object tends to be stable gradually with the increasing number of interaction and the participation of more agents according to the above analysis, so:

$$\lim_{n\to\infty} \max_n \delta_n = 0 \qquad (6)$$

Meanwhile,

$$\lim_{m\to\infty} DT_{ij} = CW_j \qquad (7)$$

In formula, m means the number of interactions, and m=1,2,3,…. Formula (6) and formula (7) indicate that with the increasing number of interactions, DT_{ij} becomes stable and the trust degree eventually converges to creditworthiness within a certain duration and scope. So according to the above analysis, the following statement is true.

Proposition 1. The trust degree is stable and eventually converges to creditworthiness.

3.2. Availability

The complexity of trust relationship is decided by incomplete cognition among the agents, and it is showed that the trust relationship is always in a dynamic evolution process. The key of modeling is that it can reflect the dynamic evolution and re-evaluate the dynamic evolution with the change in time and context.

In order to better improve the efficiency of decision in the field of natural language decision, Yager [22] introduced the Ordered Weighted Averaging (OWA). Two fuzzy measurements, the orness measurement and andness measurement are proposed based on the OWA. Where, the orness measurement regards the positive attitude of the decider [23, 24]. It is the subjective decision factor for OWA. Under this measurement level, the trust relationship can be modeled better.

(1) Under the constraint condition of orness measurement level α, the time weight sequence {w(k)} (k=1, 2, …, h) by the minimum variance model (formula (2)) obtained is monotone increasing if the condition of formula (5) is satisfied. The new interactive behavior can obtain bigger weight when the direct trust relationship judged is ensured. Simultaneously, the attribute of the trust relationship decay with time-varying is reflected.

(2) In the constraint condition of formula (5), the different distribution of weight sequence {w(k)} (k=1, 2, …, h) can be computed by the different orness measurement level α values. It is convenient for the flexible selection in dynamic environment. Fig. (**1**) describes the distribution of time weight sequence w(k) (k=1, 2, …, 10), when h is 10, the values of minimum variance model are obtained when the

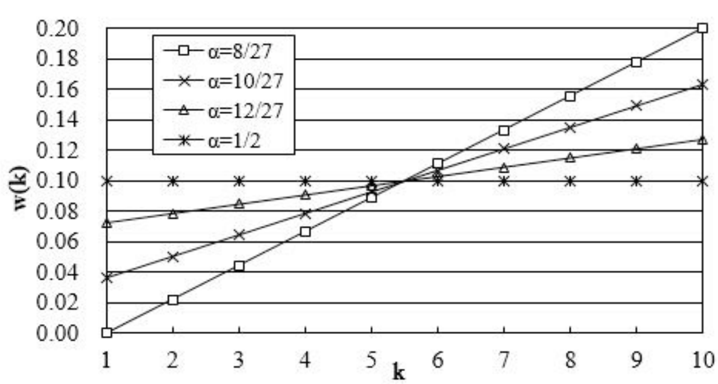

Fig. (1). The distribution of time weight sequence is computed by minimum variance model.

constraint condition of orness measurement level α satisfies the condition of formula (5).

(3) The relationship of weight sequence {w(k)} (k=1, 2, …, h) is:

$$w(k+1)-w(k)=\frac{6-12\alpha}{h(h+1)}>0,\quad k=1,2,\cdots,h-1$$

So, the sequence {w(k)} (k=1, 2, …, h) is an increment arithmetic sequence. For certain α and h, the adjacent weight coefficients are equal and have nothing to do with k. The iteration process is not complex and easy to calculate. It has good linear characteristic.

From the above analysis, the appropriate weight sequence {w(k)} (k=1, 2, …, h) can be computed by selecting the appropriate α. It can effectively control the emphasis for historical evidence. It can better reflect the dynamically adaptive capacity and scalability of themodel. It completely accords with the grasp of the nature of trust relationship. Consequently, the following proposition is true.

Proposition 2. The direct trust aggregation algorithm which is decided by formula (1), formula (2) and formula (5) is effective for the evaluation of trust.

4. SIMULATION EXPERIMENT AND RESULTS

4.1. The Process of Simulation Experiment and the Result

This paper proposed a direct trust aggregation algorithm which is simple and effective. From the simulation experiment, it can be shown that the algorithm is a good way to model the trust relationship of direct interaction between the agents and has good mathematical property.

In the modeling experiment, the NetLogo [25] platform was accepted to realize direct interaction between the agents. NetLogo is a programmable modeling environment for simulating natural and social phenomena. NetLogo is particularly well suited for modeling complex systems developing over time. In order to verify the validity and the stability of the model, the experiment is simplified. Two agents are set. One agent is a subject of trust, denoted by E_i. Another agent is an object of trust, denoted by E_j. E_j (request) to E_i (service), interactive requests (create links) are induced. E_i judges the trust of E_j. If the trust is available (the threshold of this paper is 0.7,), the creation of links can be allowed and completed (the interaction is set up), otherwise if refused (the subject of trust does not trust the object of trust, hence the request of service is refused).

Table 1. Simulation experimental parameters and notations.

Parameters	Notations	Possible Values
The historical data of interaction	h	10
Orness measurement level	α	8/27 or 10/27 or 12/27
Aggregation times (the times of interaction request)	m	20
Trust threshold	λ	0.7000

In the combination of different data (five set of trust historical evaluation data and three values of α), 15 rounds in all are completed, and every round loops 20 times to simulate the direct trust calculation results and interaction behavior under different historical data records. The three experiment results include the succeeded interaction and the failed interaction which show the related conclusions. Before the experiment, the data of this experiment needed is provided.

The major parameters are listed in Table **1**.

In Table **2**, there are 3 data sets, with each set including 10 trust historical evaluation simulation data obtained by random-float. Let random-seed be 1 and round to four decimal places. For the data set (one), there are ten sorts of random data ranging between 0.7000 and 0.9999. The ten sorts of data which are greater than 0.7000 are selected to simulate the subject of trust to evaluate the object of trust for last 10 times and to show the completion of interaction. For the

Table 2. The initial trust historical evaluation data of simulation experiment.

m	Trust Historical Evaluation Simulation Data (One)	Trust Historical Evaluation Simulation Data (Two)	Trust Historical Evaluation Simulation Data (Three)
1	0.7564	0.5897	0.4528
2	0.8059	0.8403	0.6519
3	0.8123	0.7431	0.9276
4	0.7653	0.6380	0.5297
5	0.9234	0.7602	0.7204
6	0.8965	0.6928	0.2419
7	0.9122	0.5795	0.8533
8	0.9273	0.5603	0.3107
9	0.7796	0.7714	0.8723
10	0.8637	0.6428	0.7265

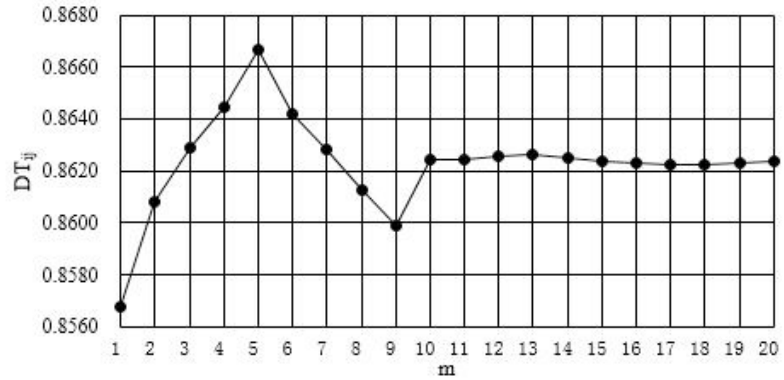

Fig. (2). The distribution trend of the simulation experiment (one) result of 20 times aggregation.

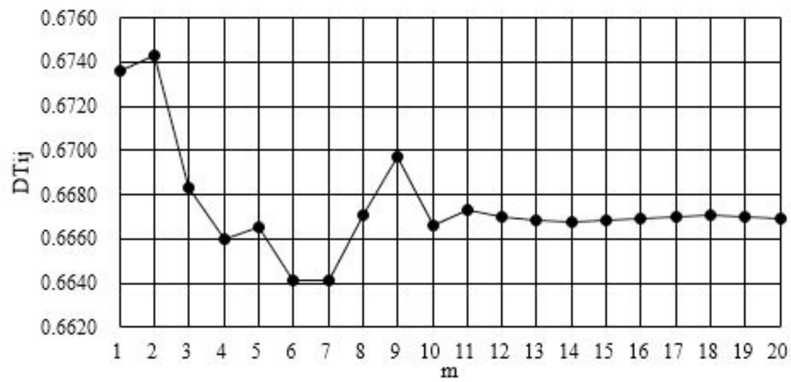

Fig. (3). The distribution trend of the simulation experiment (two) result of 20 times aggregation.

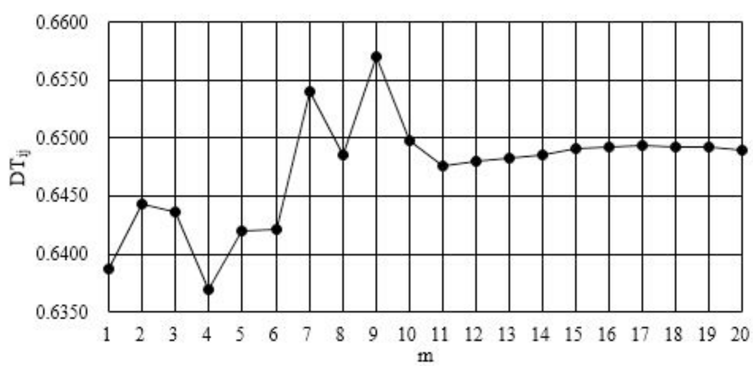

Fig. (4). The distribution trend of the simulation experiment (three) result of 20 times aggregation.

data set (two), there are ten sorts of random data ranging between 0.5500 and 0.8500. The ten sorts of data are selected to simulate the phenomenon which includes that the variance of data is smaller and the interaction is failing. The time of completion of interaction is 4 and the time of failing interaction is 6. For the data set (three), there are ten sorts of random data which range between 0.2500 and 0.9500. The ten sorts of random data are selected to simulate the phenomenon which includes that the variance of data is greater and the interaction is failing. The time of completion of interaction is 5 and the time of failing interaction is 5.

Three sets of data were selected in Table **2** to conduct the experiment. Orness measurement level α was assumed as 10/27, Loop computations were 20 times; the earliest data were substituted for the new data which were computed by each loop. Figs. (**2-4**) show the distribution trend of 20 times aggregation in three experiments. It can be visually seen that the direct trust degree after the aggregation gradually converges to the stability of a smaller range with the increasing number of interactions. From the experiment (one), it is easy to know that all the directed links between E_i and E_j can be built successfully. In experiment (two) and experiment (three), all the directed links between E_i and E_j are not built successfully because the trust degree of subject to object is lower.

Comparing Figs. (**2-4**), it can be seen that the data distributions after aggregation are all complex no matter how small or large the variance of the historical data is. It is impossible to predict the historical record distribution of the trust degree. No matter how the distribution of the historical data is, the trust degree always converges to the stability in a small range in the case of interactions which increase gradually.

Table 3. The direct trust degrees computed by the simulation experiment (one) in the 20 times interaction.

m	DT_{ij}	m	DT_{ij}	m	DT_{ij}	m	DT_{ij}
1	0.8568	6	0.8642	11	0.8624	16	0.8623
2	0.8608	7	0.8628	12	0.8626	17	0.8623
3	0.8629	8	0.8613	13	0.8626	18	0.8623
4	0.8645	9	0.8599	14	0.8625	19	0.8623
5	0.8666	10	0.8624	15	0.8624	20	0.8624

4.2. The Analysis of Experimental Results

The two propositions which are proposed above are validated clearly by the above simulation experiments. Actually, in every simulation experiment, when the loop time is (h+1)th, the new computed trust is a substitute for the previous data. The trust converges to the reputation of the agent with each aggregation. Until the interaction time is greater than h+2, the direct trust of the agent tends to be stable and converges to reputation.

The direct trust degrees which are computed by the simulation experiment (one) in the 20 times interaction are listed in Table **3**.

From Fig. (**2**) and Table **3**, it is known that the direct trust undergoes several aggregates ($m \geq h+1$) before it converges to a constant gradually. The constant can be a reputation estimation of agent. Consequently, the following inference can be derived.

Inference: in the process of multiple interactions, the trust degree which is the subject of trust e_i for the object of trust e_j converges to the reputation of the object gradually. The formula of reputation is:

$$CW_j = \frac{\sum_{m=1}^{h+1}\sum_{k=1}^{h} w(k)DT_{ij}^{(k)}}{h+1} \quad h \neq 0, \quad h \leq H \tag{8}$$

In this case, the orness measurement level α=10/27 and the trust historical evaluation simulation data (one) are selected. The reputation CW_j = 0.8622 of the object of trust $E_j^{(1)}$ can be computed by the formula (8). Furthermore, the reputation CW_j = 0.8616 of the object of trust $E_j^{(1)}$ can be computed based on the orness measurement level α=10/27 and the trust historical evaluation simulation data (one) . Through several experiments, it can be found that the impact of α on the reputation CW_j is small when the historical evaluation data are the same, with the inherent reputation of the object of trust E_j essentially unchanged.

On the contrary, the reputation CW_j = 0.6680 of the object of trust E_j can be computed based on the orness measurement level α=10/27 and the trust historical evaluation simulation data (two). Furthermore, the reputation CW_j = 0.6459 of the object of trust E_j can be computed based on the orness measurement level α=10/27 and the trust historical evaluation simulation data (three). It can be found that the inner trust degree of different objects is presented after the aggregation of different historical trust records.

Above all, from the simulation experiment (shown in Figs. (**2-4**)), it can be clearly found that the trust degree of the subject of agent for the object of agent becomes stable gradually by the increase in interactions, proving formula (6) and formula (7) to be correct.

CONCLUSION

The direct trust relationship is the basis of the trust relationship between the agents. The direct trust of each agent is the basis of obtaining the indirect trust of the subject of agent for the object of agent. Consequently, the recommended result will be error if there is no direct trust. Based on the direct interaction process and direct trust relationship between the agents, this paper studied some characteristics of the trust relationship between the agents. The direct trust aggregation algorithm which is constrained by the fuzzy integration operator orness measurement level α based on the minimum variance time sequence weight was proposed. The impact of time sequence weight on the algorithm and the result has been discussed in detail. It can be found that the algorithm is simple and effective and has well convergence and expansibility from the experiment.

Certainly, the problem of this paper studied was the direct trust relationship between the agents, which cannot show the indirect recommendation trust and global trust degree. Consequently, the next works would be based on further understanding of the problems which include the relevant property of the dynamic trust relationship, the essential attributes of the trust and reasonable measurement, on the basis of which, the adapting problem of the global trust relationship between the agents and trust management can be further studied in a complex environment.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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Declared none.

REFERENCES

[1] M. Ji, and M. A. Orgun, "Trust management and trust theory revision," *IEEE Transactions on Systems, Man and Cybernetics,* vol. 36, no. 3, pp. 451-460, 2006.

[2] H. Z. Li, and M. Singhal, "Trust management in distributed systems," *IEEE Computer,* vol. 40, no. 2, pp. 45-53, 2007.

[3] M. Blaze, J. Feigenbaum, and J. Lacy, "Decentralized trust man-

agement," In: *Proceedings of the 1996 IEEE Symposium on Security and Privacy,* Washington: IEEE Computer Society Press, 1996, pp. 164-173.

[4] F. Almenarez, A. Marin, D. Diaz, and J. Sanchez, "Developing a model for trust management in pervasive devices," In: *Proceedings of the 3rd IEEE Int'l Workshop on Pervasive Computing and Communication Security (PerSec 2006),* Washington: IEEE Computer Society Press, 2006, pp. 267-272.

[5] F. Almenarez, A. Marin, C. Campo, and R. C. Garcia, "PTM: A pervasive trust management model for dynamic open environments," In: *Proceedings of the 1st Workshop on Pervasive Security, Privacy and Trust*, Boston, 2004.

[6] H. Jameel, L. X. Hung, U. Kalim, A. Asjjad, S. Y. Lee, and Y. K. Lee, "A trust model for ubiquitous systems based on vectors of trust values," In: *Proceedings of the 7th IEEE Int'l Symp. on Multimedia,* Washington: IEEE Computer Society Press, 2005, pp. 674-679.

[7] G. Theodorakopoulos, and J. S. Baras, "On trust models and trust evaluation metrics for ad-hoc networks," *IEEE Journal on Selected Areas in Communications,* vol. 24, no. 2, pp. 318-328, 2006.

[8] Y. Sun, W. Yu, Z. Han, and K. J. R. Liu, "Information theoretic framework of trust modeling and evaluation for an-hoc networks," *IEEE Journal on Selected Areas in Communications,* vol. 249, no. 2, pp. 305-319, 2006.

[9] Y. Sun, W. Yu, Z. Han, and K. J. R. Liu, "Trust modeling and evaluation in ad-hoc networks," In: *Proceedings of the Global Telecommunications Conf., Globecom, 2005,* Washington: IEEE Computer Society Press, 2005, pp. 1-10.

[10] R. He, J. W. Niu, and G. W. Zhang, "CBTM: A trust model with uncertainty quantification and reasoning for pervasive computing," *LNCS,* vol. 3758, pp. 541-552, 2005.

[11] D. Melaye, and Y. Demazeau, "Bayesian dynamic trust model," *LNCS,* vol. 3690, pp. 480-489, 2005.

[12] C. Duma, and N. Shahmehri, "Dynamic trust metrics for peer-to-peer system," In: *Proceedings of the 16th Int'l Workshop on Database and Expert Systems Applications (DEXA 2005)*, Washington: IEEE Computer Society Press, 2005, pp. 776-781.

[13] K. Shao, F. Luo, N. X. Mei, and Z. T. Liu, "Normal distribution based dynamical recommendation trust model," *Journal of Software,* vol. 23, no. 12, pp. 3130-3148, 2012. (in Chinese with English abstract).

[14] S. S. Song, K. Hwang, and M. Macwan, "Fuzzy trust integration for security enforcement in grid computing," In: *Proceedings of the Int'l Symposium On Network and Parallel Computing (NPC 2004), LNCS,* vol. 3222, pp. 9-21, 2005.

[15] W. Tang, and Z. Chen, "Research of subjective trust management model based on the fuzzy set theory," *Journal of Software,* vol. 14, no. 8, pp. 1401-1408, 2003. (in Chinese with English abstract).

[16] F. J. Yu, H. G. Zhang, and F. Yan, "A Fuzzy Relation Trust Model in P2P System," In: *Proceeding of the 2006 International Conference on Computational Intelligence and Security (CIS'2006) Part 2, IEEE Press,* 2006, pp. 1497-1502.

[17] X. Y. Li, and X. L. Gui, "Cognitive model of dynamic trust forecasting," *Journal of Software,* vol. 21, no. 1, pp. 163-176, 2010. (in Chinese with English abstract).

[18] X. Y. Li, and X. L. Gui, "Research on dynamic trust model for large scale distributed environment," *Journal of Software,* vol. 18, no. 6, pp. 1510-1521, 2007. (in Chinese with English abstract).

[19] R. Fullér, and P. Majlender, "On obtaining minimal variability OWA operator weights," *Fuzzy Sets and Systems,* vol. 136, pp. 203-215, 2003.

[20] Z. S. Xu, "*Multiple-period MAGDM under linguistic assessments*," Technical Report, 2007.

[21] R. R. Yager, "On ordered weighted averaging aggregation operators in multi-criteria decision making," *IEEE Transactions on Systems, Man, and Cybernetic,* vol. 18, pp. 183-190, 1988.

[22] R. R. Yager, "On ordered weighted averaging aggregation operators in multicriteria decision making," *Transactions on Systems, Man and Cybernetics,* vol. 18, no. 1, pp. 183-188, 1988.

[23] K. J. Engemann, D. Filev, and R. R. Yager, "Modeling decision making using immediate probabilities," *International Journal of General Systems,* vol. 24, no. 3, pp. 181-194, 1996.

[24] D. Filev, and R. R. Yager, "Analytic properties of maximum entropy OWA operators," *Information Sciences,* vol. 85, no. 1, pp. 11 - 27, 1995.

[25] U. Wilensky, "*Center for Connected Learning and Computer-Based Modeling*", Northwestern University, Evanston, IL. (1999). NetLogo. http://ccl.northwestern.edu/netlogo/

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