Committee-based Member Verification for Dynamic Virtual Organizations

Zhen Wang and Junwei Cao*
Research Institute of Information Technology
Tsinghua National Laboratory for Information Science and Technology
Tsinghua University, Beijing 100084, P. R. China
**Corresponding email: jcao@tsinghua.edu.cn*

Abstract

A grid organizes geographically distributed CPU, storage and network resources across multiple organizations as one virtual administrative domain, which can be considered as a special type of virtual organizations (VO). To improve scalability and flexibility, a cyberinfrastructure (CI) environment is proposed to support formation and management of multiple such VOs to meet various computing demands for researchers and scientists in different areas. Due to dynamism and the wide range of resources in CI, verification of a new applicant and assignment of proper privileges become a major challenge for VO management. In this paper, a committee-based applicant verification method (CAVM) is proposed for a VO to evaluate and verify a new applicant automatically and comprehensively, inspired by real-world verification mechanisms. CAVM includes two layers: the representative layer using fuzzy k-nn (FKNN) method to make individual judgments on applicants and the committee layer using fuzzy decision making scheme to aggregate individual judgments to make a comprehensive decision. In particular, our work is compared with the eBay reputation system (ERS), the most widely used reputation system for e-commerce. Simulation results show higher performance of our approach in terms of distinguishing deceitful members from trustworthy members.

1. Introduction

As more and more domain-specific grid [1] infrastructures become available, a cyberinfrastructure (CI) [2] environment is required for formation and management of multiple such grid enabled virtual organizations (VO) [3, 4] for a larger scale cross-domain resource sharing. For example, the open science grid (OSG) [5] provides a general platform to aggregate resources from different grids and reorganizes them for many different scientific applications. Users and resource providers (RPs) who agree on the same usage policies and purposes are aggregated in one virtual administrative domain.

VO assigns different memberships to every member according to its requirements and reputation, and authorizes proper privileges based on Role-Based Access Control (RBAC) [6, 7] mechanisms. Since a VO is proposed for a specific scientific collaboration, it is frequently (re-)created, expanded to aggregate more resources, and finally dissolved to release these resources. Verification of new applicants and guarantee member security among VOs becomes a challenging issue. Many methods are proposed to address this issue including decentralized [8] and centralized security models [9]. For example, OSG developed a centralized mechanism, VOMS (Virtual Organization Membership Service) with EDG (European DataGrid) to verify new applicants artificially. In VOMS, a VO administrator selects one of its members as a representative who is familiar with the VO policy and the scientific project the VO is supporting. The representative checks the new applicant artificially from different aspects including usage plans, relationships with OSG, past memberships and so on. Such a centralized verification procedure is hard to adapt to more complex, dynamic and larger scale applications. The centralized architecture can't ensure objectiveness and comprehensiveness of verification. Meanwhile, it takes too long for both applicants and representatives to complete a verification procedure.

In this paper, we propose a decentralized and automatic verification method, a committee-based applicant verification method (CAVM), to help members in a VO to verify new applicants comprehensively, automatically and objectively. The most trustworthy and informed members in the VO are selected as representatives to found a VO committee to verify new applicants. Each representative contributes their judgments to the committee and a fuzzy decision-making scheme is proposed to make a compromising decision after comprehensive consideration of all these judgments. CAVM is particularly compared with the eBay reputation system (ERS) [10], the most widely used reputation system for e-commerce. Simulation and analysis results show CAVM is more accurate, stable and scalable than ERS.

The rest of this paper is organized as follows. Some relevant technologies including committee based recognition method and ERS are introduced in Section 2. CAVM is presented in details in Section 3 and performance of CAVM compared with ERS via simulation is included in Section 4. The paper concludes in Section 5.

2. Related Work

Member verification on Internet is a fundamental issue for all types of virtual communities, including P2P, e-commerce, grids and CI. As e-commerce is the most established driven force for virtual communities, many reputation systems are proposed to help buyers evaluate and verify unacquainted sellers online.

As a trade platform for buyers and sellers, an e-commerce system usually provides a reputation system for buyers to evaluate unknown sellers online, conduct successful trade and inhibit malicious and deceitful behaviors [11]. When a trade is completed, the buyer will provide a feedback to the seller, which is finally accumulated and calculated as the seller's reputation value. Reputation models in e-commerce can be roughly classified into two types: the accumulated reputation model and average reputation model. In the accumulate reputation model, feedbacks from buyers on a seller are accumulated as current reputation value of the seller. eBay [12, 13], Yahoo! and TaoBao [14] all adopt the accumulated trust model. The average trust model also accumulates all feedbacks to a seller, though divided by the number of feedbacks. Amazon and AuctionSoup adopt the average reputation model. Among existing reputation systems for e-commerce, ERS is most successful and referred by many other companies. In this paper, we compare CAVM with ERS for performance evaluation of our approach. The ERS is calculated following three simple policies:

- A buyer can give three different feedbacks, positive feedback 1, neutral feedback 0 or negative feedback -1, to a seller after a deal.
- The feedback to a seller is added to its current reputation value. The higher reputation is, the more trustworthy the seller is.
- A buyer is not allowed to provide more than 1 or less than -1 feedback to one seller in one month, which can avoid collusive deceitful behaviors.

While reputation systems for e-commerce provide an effective and feasible solution to seller evaluation, they cannot be directly applied in a CI environment for two reasons.

- Since a VO may have various requirements for new applicants, single reputation value can't provide sufficient information to evaluate and verify whether or not an applicant is totally consistent with complex VO policies.
- Reputation systems can be cheated by collusive deceitful behaviors when a coconspirator provides fictitious positive feedbacks to a certain member.

The committee has been widely used in real world scenarios to evaluate and verify an applicant to an organization. Inspired by this strategy, we design an automatic committee based decision making method to evaluate and verify new applicants, which can make a more comprehensive, reliable and robust decision whether or not an applicant is consistent with VO policies. In the next section, a detailed introduction to CAVM is given below.

3. Committee-based Applicant Verification

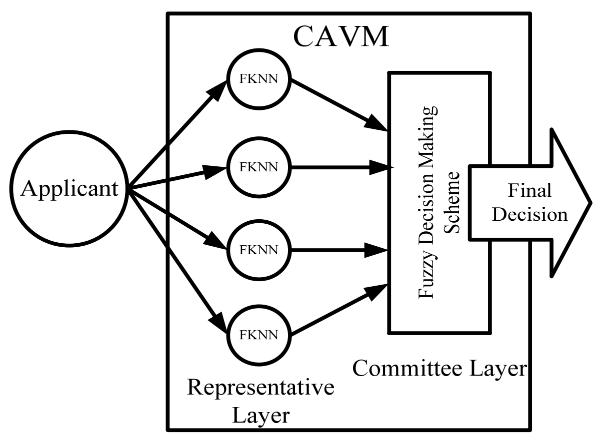

Figure 1. The architecture of CAVM

CAVM is a decentralized method consisting of two layers as shown in Figure 1: the representative layer making judgment individually and contributing them to the committee and the committee layer collecting judgments from representatives and making a comprehensive and compromising decision. The main purpose of CAVM is to evaluate the applicant into two classes: the one who is trustworthy and consistent with

VO policies and the one who is distrustful or has conflicting usage plan against VO policies. CAVM tries to consider opinions from all members and make a comprehensive decision.

In this paper, we generally use nodes to present both resource providers and users in the CI, and members to represent that a node belongs to a certain VO. The applicant is the node who wants to join the VO.

The VO administrator is responsible for selecting the most trustworthy, informed or important VO members as representatives of the VO committee. Since in virtual communities, member activity distribution obeys the Power-law [15, 16], it is reasonable to use the selected representatives to present opinions of all other members. The VO administrator can monitor all members and directly select the most trustworthy and informed members, who have relatively higher reputation values, as representatives.

3.1 The Representative Layer using FKNN

There are many types of pattern recognition methods for classification issues, including neural networks, fuzzy k-nearest neighbor (FKNN) classifier, Bayesian classifier, support vector machine (SVM) and so on. The Bayesian classifier requires to know the possibility distribution, SVM can't provide reliability theoretical analysis and neural networks may be unstable without mathematical theory supports. Compared with other methods, FKNN is a reliable and stable method with little overhead and strict mathematical support in theory and is good at classifying unknown samples with sparsity learning samples. In CAVM, we adopt FKNN as the method to classify applicants at the representative layer.

We divide a new applicant into three types: the one which is trustworthy, the one which needs to be further determined and the one which should be rejected. We denote the three types as p_1, p_2, and p_3, respectively. Each representative has a learning table recording the nodes which have been already classified based on this representative' past individual interaction history, as shown in Figure 2.

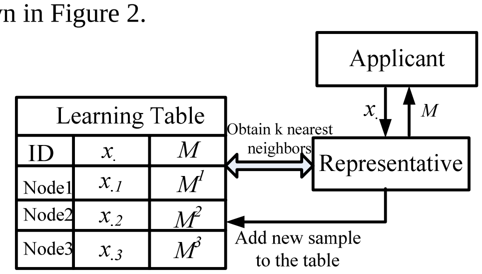

Figure 2. The learning table of a representative

The node in the table is described with the target vector x and classified with membership vector M=(μ_1,μ_2,μ_3), respectively representing the membership degree of belonging to the set p_1, p_2, or p_3. To evaluate a new applicant f, the representative firstly selects k nearest neighbors based on the distance to the target vector. The distance between x_1 and x_2 is calculated as:

$$\|x_1 - x_2\| = x_1 \bullet x_2 .$$

Assuming the new applicant is f with the target vector x_f and k nearest neighbors of f is x_h, $h=1,2…k$, and the h^{th} node has the target vector $x_{.h}$ and membership M^h=(μ^h_1, μ^h_2, μ^h_3), the judgment about an applicant f the representative makes is described by the membership vector M^f= (μ^f_1, μ^f_2, μ^f_3), which elements respectively indicate the degree of membership to the set p_1, p_2, and p_3. M^f can be calculated by FKNN as following:

$$\mu_i^f = \frac{\sum_{h=1}^{k} \mu_i^j (1/\|x_f - x_h\|^{2/(b-1)})}{\sum_{h=1}^{k} (1/\|x_f - x_h\|^{2/(b-1)})} \qquad i = 1,2,3,$$

where b is the weight that defines how the distance will affect the membership.

3.2 The Committee Layer using FDMM

The fuzzy decision making mechanism (FDMM) has two advantages, capability to handle uncertainty, fuzziness, and incomplete information adaptively and capability to make comprehensive decisions by integrating multiple factors. Considering weightiness discrepancy among different representatives and robustness of decisions, we use FDMM to comprehensively evaluate and aggregate various judgments from representatives [17, 18, 19]. In general, FDMM consists of four elements:

- The factor set, the list of representatives in our application;
- The weight vector, indicating the power that preventative affects on the final decision;
- The factor membership matrix, consisting of judgments about an applicant that representatives in the committee make;
- The evaluation set, the final decision that committee makes based on judgments from representatives and the weight vector.

Assuming there are n representatives in the committee, the i^{th} representative submits a judgment vector M_i of the applicant h to the committee and these judgments are aggregated and considered with the weight vector A=(a_1,a_2,…….a_n), respectively, representing the importance of corresponding representatives. 0 means totally unimportant and 1 means very important.

The factor membership matrix R is:

$$R = \begin{bmatrix} M_1 \\ M_2 \\ \vdots \\ M_n \end{bmatrix} = \begin{bmatrix} \mu^h{}_{11} & \mu^h{}_{12} & \mu^h{}_{13} \\ \mu^h{}_{21} & \mu^h{}_{22} & \mu^h{}_{23} \\ \vdots & \vdots & \vdots \\ \mu^h{}_{n1} & \mu^h{}_{n2} & \mu^h{}_{n3} \end{bmatrix}$$

The element $\mu^h{}_{ij}$ represents the membership degree of the applicant h to class p_j, judged by i^{th} representative. The $M(\wedge \vee)$ model is used to calculate and normalize the evaluation set B.

$$B = A \circ R = \{b_j \mid j = 1,2,3\}$$

$$b'_j = \max_i(\min(a_i, \mu_{ij})) \qquad i = 1,2,......,n,\ j = 1,2,3$$

$$b_j = \frac{b'_j}{\sum_{j=1}^{3} b'_j},\ j = 1,2,3,$$

where b_j represents the percentage degree the committee think the applicant should belongs to the class p_j. The committee can configure a threshold for b_j. If there is a b_j higher than the threshold, the committee will classify the applicant as p_j, since this decision can represent the majority view of the committee or VO members. If there is no b_j higher than the threshold, the committee can choose the highest one as the final decision or check up the applicant further.

4. Performance Evaluation

Currently no automatic verification system has been developed and deployed in any grid or CI environment, in which evaluation and verification procedures are accomplished artificially by an appointed and trustworthy expert. However, reputation systems have been widely used to assist buyers to evaluate unacquainted sellers in e-commerce environments. In this section, we compare our CAVM with ERS, which is regarded as the most successful and widely used system, and test CAVM performance by simulation experiments.

4.1 Simulation Configurations

In order to evaluate the CAVM performance, a simulated e-commerce environment is implemented with a reputation system totally consistent with that developed by eBay.

In the simulation environment, we assume there are a number of buyers and sellers and interactions occur between buyers and sellers at random. When an interaction is finished, a feedback is produced from the buyer to the seller. Also, continuous feedbacks from a buyer to a seller in a short time is not allowed according to ERS, which may be collusive deceitful or malicious behaviors. The behavior pattern of a seller is described using the vector PT=(pt_1, pt_2, pt_3), respectively representing possibilities of receiving positive feedbacks, neutral feedbacks and negative feedbacks. A seller who sells commodity with good quality has higher possibility of receiving positive feedbacks (can't guarantee all feedbacks are positive) while the seller who sells the counterfeit has higher possibility of receiving negative feedbacks (can also receive positive feedbacks). Detailed simulation configurations are included in Table 1 and described below.

Table 1. Parameters in the simulation

Number of sellers	100
Number of buyers	500
Number of representatives	5
Interaction frequency:	100/period
k (For FKNN classifier)	3
Classification threshold	0.5
Trustworthy seller: pt_1	0.95-1
Trustworthy seller: pt_2	0-0.01
Trustworthy seller: pt_3	0-0.04
Deceitful seller: pt_1	0.75-0.8
Deceitful seller: pt_2	0.04-0.11
Deceitful seller: pt_3	0.12-0.16
Number of deceitful sellers	10
Deceitful interaction frequency	2-5/period

4.1.1. Configurations for ERS. In the simulation, the reputation of a seller is accumulated by feedbacks from buyers according to ERS regulations: one positive feedback adds 1, one neutral feedback adds 0 and one negative feedback adds -1 to the reputation value. Continuous feedbacks within a month are forbidden to avoid collusive deceitful behaviors. According to the record in eBay, generally speaking, the number of interactions that occur in a month distributes mainly from 10 to 500. Since trade activities obey the Power-law [15, 16], it is reasonable to estimate that about 100 interactions occur every month on average. We assume there are about 100 interactions in a simulation period, representing interactions in a month in the actual systems, in which one buyer can provide feedbacks to one buyer only once.

4.1.2. Configurations for CAVM. In our simulation, CAVM obtains the three values, positive feedback value x_1, neutral feedback value x_2 and negative feedback value x_3 as target vector x=(x_1, x_2, x_3). Sellers are also divided into three classes: the trustworthy, the one need further artificial verification and the deceitful, respectively denoted as p_1, p_2, and p_3. When a failed interaction occurs between a representative and a seller, e.g. the seller sells a counterfeit to a representative, the representative will record this seller on his learning table as a classified sample for FKNN. The representative also learns when a successful interaction occurs. We just select the most informed buyers as representatives to found the committee. At the committee layer, the classification threshold

4.1.3. Deceitful behaviors. Deceitful behaviors always result in more accumulated positive feedbacks and would not have impact on the number of negative feedbacks. We simulate all types of deceitful behaviors by adding 2-5 positive feedbacks to a deceitful seller in each period, as the deceitful interaction frequency is set to 2-5 per period. Totally there are 10 deceitful sellers configured in the environment.

In order to obtain a statistical result, we repeat every experiment for ten times, the data shown in the figures below are mean values from 10 repeated experiments.

4.2 Performance Metrics

The main purpose of both ERS and CAVM is to distinguish deceitful members from trustworthy ones. Deceitful members may also have high reputation values due to collusive or any other deceitful behaviors. So main metrics should be defined to evaluate the performance of member classification. Errors of classifying trustworthy members as deceitful ones are negative errors (*NE*) and errors of classifying deceitful members as trustworthy ones are positive errors (*PE*).

ERS doesn't directly classify the sellers but just provide buyers with a referred rank, which is sorted by sellers' reputation values. We define positive errors and negative errors for ERS as follows:

PE = (Number of deceitful sellers with higher reputation than a trustworthy seller) / (Number of deceitful sellers);

NE = (Number of trustworthy sellers with lower reputation than a deceitful seller) / (Number of trustworthy sellers).

For CAVM, *NE* and *PE* are calculated exactly as defined:

PE = (Number of deceitful members classified as trustworthy ones) / (Number of deceitful members);

NE = (Number of trustworthy members classified as deceitful ones) / (Number of trustworthy members).

Obviously, the smaller *PE* and *NE* are, the higher performance of a reputation system. However, *PE* and *NE* changes as external environments or parameters change. An ideal classifier should be robust over different environments and parameters. We compare the performance of CAVM with that of ERS over different external environments in Section 4.3, which indicate that errors of CAVM is only a quarter of that of ERS. To evaluate robustness of our approach, we further check up PE and NE of CAVM with different parameters in Section 4.4 and find some optimal values as parameters evolve.

4.3 Performance Comparison over External Environments

There are two external factors having potential impact on the performance of CAVM and ERS, simulation time represented using the number of periods and the percentage of deceitful members in the environment. We investigate the performance of CAVM and ERS against these two configurations.

Figures 3 and 4 indicate how the performance of CAVM and ERS evolves as simulation time increases. The mean value of *PE* of CAVM is 1.98% and that of ERS is 7.75%, which is four times of that of CAVM. The mean value of *NE* of CAVM is 0.34% and that of ERS is 1.94%, which is five times of that of CAVM. It is obvious that CAVM has much higher performance than ERS as the system evolves over time.

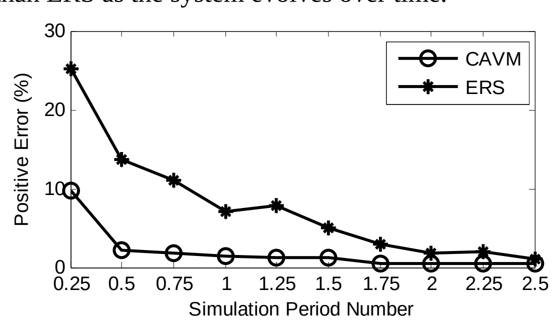

Figure 3. PE comparison of CAVM and ERS over time

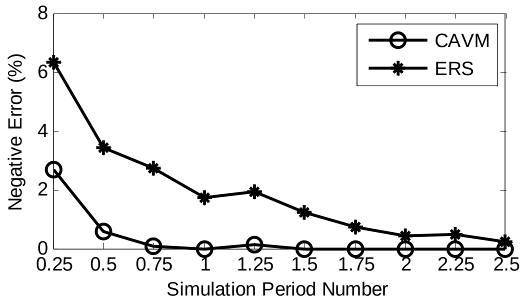

Figure 4. NE comparison of CAVM and ERS over Time

Besides that, we can find that *NE* and *PE* for both ERS and CAVM decrease as the number of interactions increases. That is because the longer a seller is observed, the more accurate the conclusion would be. The principle that one buyer can only give a feedback to a particular seller during one period limits the scale of deceitful behaviors. The effect of deceitful behaviors, which add limited falsehood positive feedbacks to a seller in every period, decreases as the number of period increases, since the final reputation mainly consists of feedbacks produced by real interactions. As shown in Figures 3 and 4, after about two periods with 200 interactions, CAVM and ERS have nearly the same performances and can classify sellers with very low *NE* and *PE*.

However, in an actual environment most of sellers have low reputation values and small number of historical interactions. In fact, the number of sellers distribute over reputation values based on an exponential distribution [15, 16]. So it is a significant problem to verify sellers with short historical data and low reputation values. As shown in Figures 3 and 4, ERS can't classify sellers with short histories accurately due to deceitful behaviors. That is why buyers prefer to choose sellers that have joined the eBay community for a long time, since only in this case, the reputation value of a seller is trustworthy and reliable.

CAVM can still identify most of deceitful members with very low *NE* and *PE* even if these members have short interaction histories. The first reason is that we comprehensively consider all three types of feedbacks to evaluate a member, not just positive feedbacks. The second is representatives in the committee contribute their own judgments to make a more general decision, which corresponds to expand the learning sample with different weights in FKNN. Compared with directly integrating learning samples from the representative to train one FKNN classifier, in CAVM, the most deceitful member has the highest frequency appearing in different representatives, which means they have more influence on the classifier and so are trustworthy members. In this way CAVM provides better performance than a single FKNN.

Figures 5 and 6 show the robustness of CAVM over different numbers of deceitful members. In this experiment, the simulation time equals to 0.25 period.

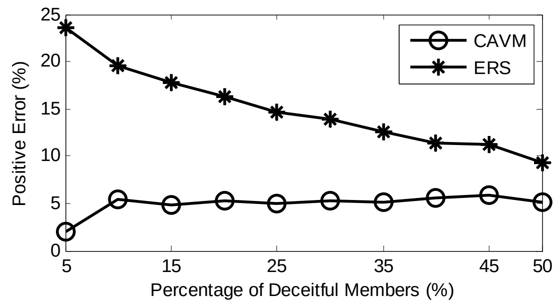

Figure 5. PE comparison of CAVM and ERS against the number of deceitful members

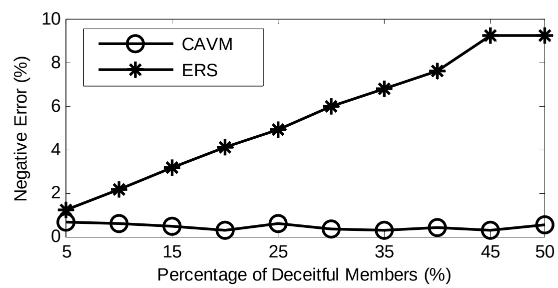

Figure 6. NE comparison of CAVM and ERS against the number of deceitful members

For ERS, *PE* decreases along but *NE* increases along with the percentage of deceitful members. But the absolute number of members classified into the wrong class increases. Both *NE* and *PE* for ERS are higher than those of CAVM.

For CAVM, the *NE* and *PE* keep stable over different percentages of deceitful members. This is because the accuracy and sensitiveness of CAVM is only influenced by learning samples of representatives, the configuration of FKNN and the number of representatives in the committee.

4.4 CAVM Parameter Analysis

There are two parameters that have impact on the final performance of CAVM, the number of representatives in the committee and the value of k for FKNN at the representative layer. We analyze the stableness of CAVM over these two parameters in Figures 7 and 8.

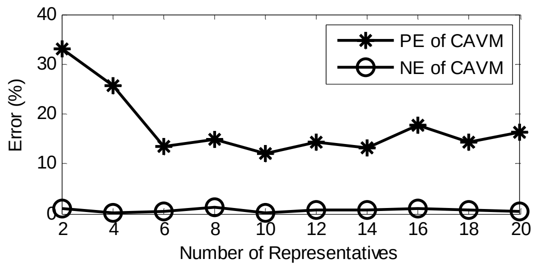

Figure 7. Performance of CAVM with different numbers of representatives

Figure 7 shows how the committee size influences the performance of CAVM. Generally speaking, more representatives lead to higher performance, namely lower *PE* and *NE*, because a larger committee contains more learning samples and covers large scale of situations. However, as illustrated in Figure 7, we can conclude that *NE* varies little no matter how many representatives involved in the committee. *PE* dramatically decreases if the number of representatives in the committee increases from 2 to 6 and keeps stable after that. That means the effect of the representative reduces to nearly zero if the committee already includes 6 representatives. Since the overhead of CAVM increases with the number of representatives, it is most efficient to include six representatives in the committee in our simulation experiments.

From Figure 7, we can conclude that there is a turning point for the number of representatives in CAVM. Before the turning point, the more representatives in the committee, the better performance of CAVM. After the turning point, the effect of adding new representatives in the committee decreases to almost zero. This turning point defines the optimal number of representatives in the committee for a certain application. This number is influenced by the number of deceitful members and the number of learning samples recorded by the representatives.

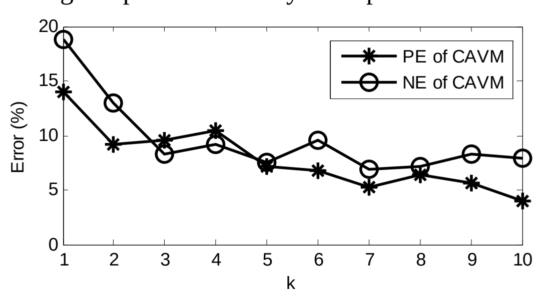

Figure 8. Performance of CAVM with different *k* values for FKNN

Figure 8 shows the performance of CAVM using different *k* values in FKNN. The overall trend is that *PE* and *NE* decrease as *k* increases. This is because more available learning samples in FKNN lead to a more accurate and comprehensive judgment. But this also brings more overhead for CAVM. We can find there is an inconspicuous turning point at *k*=3. If *k* is smaller than 3, the number of nearest neighbors has greater effect than that after *k*=3, on both *PE* and *NE* of CAVM. But after that point, the effect of *k* decreases though still reduces *NE* and *PE*.

Figure 8 proves that there also exists a turning point of *k* for the performance of CAVM. The effect of the number of available samples for a representative changes at the turning point: before that turning point, *k* has greater influence on CAVM performance but this effect greatly decreases after that point. This turning point indicates an optimal *k* value for an application. This number is influenced by the behavior pattern definition and the percentage of deceitful members.

Figures 7 and 8 show that performance of CAVM keep stable over different parameters. Also there exist optimal values for the number of representatives and *k*. We can get highest performance/cost ratio of CAVM using these parameter values at turning points.

5. Conclusion and Future Work

In this paper, we propose a committee-based applicant verification method for a CI environment to provide trust and reputation supports on building grid-type dynamic virtual organizations. The proposed implementation consists of the FKNN classifier on the representative layer and the fuzzy decision making scheme on the committee layer.

CAVM is a decentralized verification method used in a CI environment, which can provide stable, reliable and scalable services to help VO evaluate new applicants comprehensively and automatically. Because there is no other well-developed evaluation and verification method for CI currently, we evaluate the performance of CAVM by comparing it with the reputation system of eBay, which is widely used and referred. A simulation environment is developed to compare the performance of CAVM and ERS with different configurations and parameters. Experimental results show that CAVM can provide more accurate and stable evaluation services than ERS. Its decentralized architecture also ensures CAVM has high scalability and adaptability for CI applications.

Future work include implementation and deployment of CAVM in real world CI testbeds (e.g. OSG) and integration of CAVM trust and reputation management with VOMS.

Acknowledgement

This work is supported by National Science Foundation of China (grant No. 60803017), Ministry of Science and Technology of China under the national 863 high-tech R&D program (grants No. 2006AA10Z237, No. 2007AA01Z179 and No. 2008AA01Z118), Ministry of Education of China under the program for New Century Excellent Talents in University and the Scientific Research Foundation for the Returned Overseas Chinese Scholars, and Tsinghua University by the Future Information Technology foundation.

References

[1] I. Foster and C. Kesselman, *The Grid: Blueprint for a New Computing Infrastructure*, Morgan-Kaufmann, 1998.

[2] D. E. Atkins, K. K. Droegemeier, S. I. Feldman, H. GarciaMolina, M. L. Klein, D. G. Messerschmitt, P. Messina, et. al., Revolutionizing Science and Engineering through Cyberinfrastructure, *National Science Foundation Blue - Ribbon Advisory Panel on Cyberinfrastructure*, 2003.

[3] S. Y. Pu, M. K. O. Lee, and L. S. Yi, Virtual Organizations: the Key Dimensions, in *Proceedings of Academia/Industry Working Conference on Research Challenges*, pp. 27-29 April 2000.

[4] C. P. Holland, Business Trust and the Formation of Virtual Organizations, in *Proceedings of the 31st Hawaii International Conference on System Sciences*, pp.602-610, Jan. 1998.

[5] R. Pordes for the Open Science Grid Consortium, The Open Science Grid, in *Proceedings of Computing in High Energy and Nuclear Physics Conference*, Interlaken, Switzerland, 2004.

[6] A. Schaad, J. Moffett, and J. Jacob, The Role-based Access Control System of a European Bank : a Case Study and Discussion, in *Proceedings of the 6th ACM Symposium on Access Control Models and Technologies*, May 2001.

[7] N. Li, J. Byun, and E. Bertino, A Critique of the ANSI Standard on Role-Based Access Control, *IEEE Security and Privacy*, Vol. 5, No. 6, 2007.

[8] R. O. Sinnott, J. Watt, D.W. Chadwick, J. Koetsier, O. Otenko, and T. A. Nguyen, Supporting Decentralized, Security focused Dynamic Virtual Organizations across the Grid, in *Proceedings of the 2nd IEEE International Conference on e-Science and Grid Computing (e-Science'06)*, Amsterdam, Dec 2006.

[9] R. O. Sinnott, D. W. Chadwick, T. Doherty, D. Martin, A. Stell, G. Stewart, L. Su, and J. Watt, Advanced Security for Virtual Organizations: The Pros and Cons of Centralized vs Decentralized Security Models, in *Proceedings of the 8th IEEE International Symposium on Cluster Computing and the Grid (CCGrid'08)*, pp.19-22, May 2008.

[10] eBay, http://www.ebay.com.

[11] G. Zacharia, A. Moukas, and P. Maes, Collaborative Reputation Mechanisms in Electronic Marketplaces, in *Proceedings of the 32nd Annual Hawaii International Conference on System Sciences*, pp. 7, 1999.

[12] C. Dellarocas, Analyzing the Economic Efficiency of eBay-like Online Reputation Reporting Mechanisms, in *Proceedings of the 3rd ACM Conf. on E-Commerce*, 2001.

[13] P. Resnick and R. Zeckhauser, Trust among Strangers in Internet Transactions: Empirical Analysis of eBay's Reputation System, *The Economics of the Internet and E-Commerce*, 2002.

[14] Q. Li and Z. Liu, Research on Chinese C2C E-Business Institutional Trust Mechanism: Case Study on Taobao and Ebay(cn), in *Proceedings of International Conference on Wireless Communications, Networking and Mobile Computing*, pp. 3787-3790, 2007.

[15] M. Faloutsos, P. Faloutsos, and C. Faloutsos, On Power-Law Relationship of the Internet Technology, in *Proceedings of ACM SIGCOMM' 99*, pp. 251-262, Aug. 1999.

[16] R. Zhou and K. Hwang, PowerTrust: A Robust and Scalable Reputation System for Trusted Peer-to-Peer Computing, *IEEE Transactions on Parallel and Distributed Systems*, 2007.

[17] H. G. Shakouri and M. B. Menhaj, A Systematic Fuzzy Decision-Making Process to Choose the Best Model Among a Set of Competing Models, *IEEE Transaction on Systems, Man and Cybernetics: Part A*, pp. 1118-1128, Sept. 2008.

[18] H. Chen and Z. Ye, Research of P2P Trust based on Fuzzy Decision-making, in *Proceedings of 12th International Conference on Computer Supported Cooperative Work in Design (CSCWD'08)*, pp. 793-796, 2008.

[19] N. Baldo and M. ZorzH, Cognitive Network Access using Fuzzy Decision Making, in *Proceedings of IEEE International Conference on Communications (ICC'07)*, pp. 6504-6510, 2007.