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Multi-domain Collaborative Reputation Evaluation Mechanism Based on SFLA for IOT

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ABSTRACT

The IOT as a rapid development of large scale networks, which is widely used in various fields, its complexity, uncertainty and fuzzy lead to the intelligent property of IOT has become a key attribute of its development. We introduce the cognitive elements into the IOT, and constitute the cognitive IOT. And according to the property of IOT and QoS requirements of users, proposes a reputation evaluation model based on shuffled frog leaping algorithm (SFLA) and the idea of multi-domain cooperation, through mutual cooperation between autonomous regions, filtering to obtain reliable nodes and autonomous domain as cooperative neighbors, thereby enhancing the accuracy of reputation evaluation, simulation results show the accuracy and the feasibility of the model.

Key words : Cognitive networking, reputation model, shuffled frog leaping algorithm (SFLA), multi-domain cooperation.

1. INTRODUCTION

IOT as a kind of heterogeneous, mixed and uncertain ubiquitous network is developing rapidly in the field of ecological protection, energy saving, food safety and other modern intelligent services. The participation of a large number of heterogeneous network nodes, the distributed existence of massive information in the network, the dynamic and instability of wireless networks and the limitation of node resource, made the information interaction requires many nodes, mutual cooperation, distributed execution to finish**.**
Self-recognition and intelligent decision mechanism is the key to intelligent property of IOT. So we refer to a new concept --the cognitive Internet of things by integrating the intelligence into IOT. In recent years, cognition and cooperation have become the focus of research. Since the concept of Dr.Mitola [1] proposed cognitive radio, cognitive radio network and cognitive network has attracted a lot of attention of researchers, and has made many achievements, which greatly promoted the development of the intelligence network. In these researches, collaborative thinking is often used to solve the intelligence of heterogeneous networks, multi user networks, multi agent networks, multi hop networks, biological inspired networks, autonomous systems and other networks.

2. RELATED WORK

With the emergence of large-scale dynamic distributed applications such as cross-domain resource sharing integration, heterogeneous network cooperation and multi-agency business cooperation, the cooperation problem in multi-autonomous environment poses a great challenge to traditional authentication and authorization mechanism. [2] Especially in the grid computing in the proposed virtual organization, multi-autonomous domain using group communication mechanism to form a virtual collaborative environment based on the network, domain members can dynamically join, exit collaboration, which requires a Safe and reliable group communication environment. In the literature [4], an electronic mail reputation management system based on the mutual cooperation between the autonomous domains is proposed, which can effectively improve the reliability and efficiency of the e-mail system. An adaptive cross layer scheme is proposed to balance the performance and security of the routing in the network when the network perceives the malicious behavior of a dangerous nodes in [5]. The network topology of IOT is shown in Figure 1.

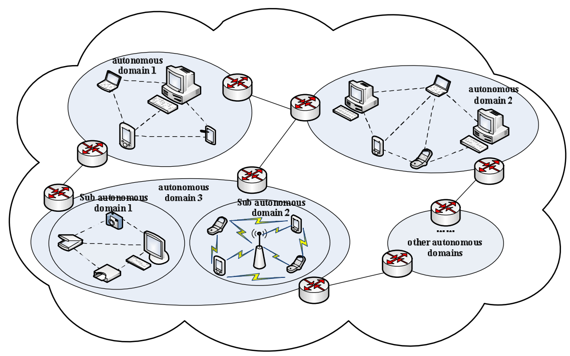

Figure 1: IOT Multi - autonomous Domain Network Topology

Trust management technology can be better used to support multi-domain security operations, so as to ensure the security and reliability of the network environment. Trust management links the inter-node and inter-domain trust relationships with operational history, behavioral results, reputation and even social network, and derives the final trust quantification index from these trust factors using a specific mathematical model .

At present, the reliability of the distributed system is mainly focused on two aspects: trusted management and trusted evaluation. The essence of trusted management is a model or method of access control based on authentication and authorization. Trust evaluation model is based on the recommendation trust relationship between entities, combined with their own experience of the entity to make evaluation, and then making decision based on the credibility. Classic reputation management technology has the average value of reputation, the Bayesian network and cluster filtering [6]. A trust model based on Markov chain is proposed for vehicle Ad Hoc networks (VANETs) [7]. Each vehicle can monitor and update the trust degree according to the behaviors of its neighbors' vehicles in the network. PeerTrust-Like mechanism is analyzed for the malicious nodes in P2P networks and the mathematical description is given in [8], and the similarity between nodes is used to calculate the trust value. In [9], a trust evaluation model is proposed to evaluate the credibility of the information and the information source node by the path similarity and information similarity, which is used as feedback to adjust the trust value of the nodes in the network.

Generally speaking, the level of trust can be evaluated by the behavior of neighbor nodes and the information they generate about the corresponding events [10]. However, nodes are vulnerable to attack, and then provide unreliable or malicious feedback, affecting the credibility of the true value of the node [3]. So we introduce the shuffled frog leaping algorithm (SFLA) to optimize the reputation evaluation system. We build model among the intra domain node based on clustering method by using SFLA, only trusted neighbor nodes can participate in the calculation process. Therefore, we propose a multi-domain cooperation reputation evaluation model based on Shuffled Frog Leaping Algorithm, which is as shown in Figure 2.

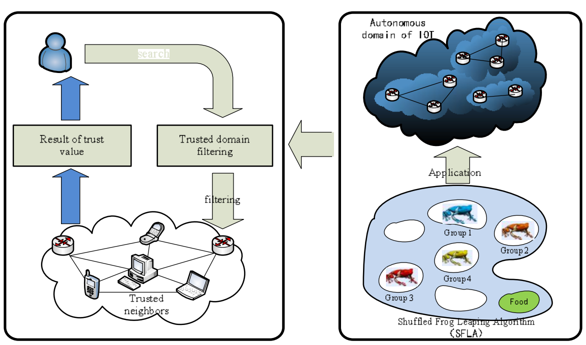

Figure 2: A Multi-domain Cooperation Reputation Evaluation Model Based on Shuffled Frog Leaping Algorithm (SFLA)

3. THE MATHEMATICAL DESCRIPTION

3.1 Related Definitions

Usually the reputation level evaluation needs to consider two factors: subjective and objective, such as the evaluation of the user's trustworthiness is determined not only by the direct reputation obtained locally, but also need to consider the indirect recommendation (reputation) collected from the calculation agency [11]. And the evaluation of the node reputation is decided not only by the users who use the node, but also need to consider the node's reputation recommendation of other domain users. Comprehensive consideration of the user, the node's reputation and the reputation of the evaluation process of the subjective and objective factors, to do the following definition:

Definition 1. In the cognitive Internet of things P, there is an autonomous domain S, $S \subset P$, and there must be an element o, such that $o \in P$, such that $\forall s \in S$, has operations such that $S \to o$. The S is called the principal domain, the set of o called the object domain is denoted as O. The model user belongs to the subject, and the node belongs to the object.

Definition 2. The direct reputation evaluation of the main body expressed as $\Delta s(o,t)$. A node gives a general evaluation of the user's reputation based on the historical records of the user; The direct reputation evaluation of the object expressed as $\Delta o(s,t)$, The overall evaluation of a user to a node is based on the historical situation of the completion of the calculation request submitted by the user to the node.

Definition 3. The indirect reputation of the subject refers to the sum of the direct reputation of the user, given the direct contact with the user, but not in direct contact with the user during this operation, expressed as $\Omega s(O_i,t)$. The object's indirect reputation refers to the sum of the nodes' direct reputation, which is denoted as $\Omega o(S_i,t)$, when a user applies for a node, and those who have direct contact with the node (not the user of this application). And $S_i \subset S, O_i \subset O, s \in S, o \in O, i \in n$.

Definition 4. $\Gamma s(o,t)$ as the overall reputation of the user, that is, after the evaluation of the trust value, at time t, the node should give the final reputation assessment for the user who visited it; $\Gamma o(s,t)$ means after a reputation evaluation, at time t, the node is evaluated by all users who have visited it. O and s respectively represent any entity that has a direct behavioral contact, and $s \in S, o \in O$.

Axiom 1. $\forall o \in O, \exists s \subset S$, at time t, the current subject, object overall reputation level $\Gamma(t)$ expressed as:

$$\begin{cases} \Gamma s(o,t) = \gamma_s \Delta s(o,t) + (1-\gamma_s)\sum_{i=1}^{n} \lambda_i \left(\Omega_s(o_i,t)\right), \\ \Gamma o(s,t) = \gamma_o \Delta o(s,t) + (1-\gamma_o)\sum_{i=1}^{n} \lambda_i \left(\Omega_o(s_i,t)\right), \end{cases}$$

And, $o < \gamma_s, \gamma_s < 1, i \in n, \Sigma_i^n \lambda_i = 1, 0 < \lambda_i < 1$;
If $\Gamma(t) \in [N, N+1)$, then $\Gamma(t) = N$.

3.2 Shuffled Frog Leaping Algorithm(SFLA)

The Shuffled frog leaping algorithm(SFLA) proposed by Eusuff and Lansey in 2003 is a meta-heuristic algorithm to find the global optimal solution by heuristic search. The algorithm is based on the evolution of meme and the global information exchange of the population. The local optimization is carried out through the meme evolution in the subgroup, and then the different subgroups are mixed to realize the global information exchange. So as to achieve the purpose of global search [12].

SFLA working process is described as follows: Randomly generated groups containing F frogs $P=\{X_1,X_2,X_3,...X_n\}$, the solution for the t-dimensional problem, the location of the i frog is $X_i=\{X_{i1},X_{i2},...,X_{it}\}$. After generating the population, the fitness of each frog location is calculated by $f(X_i)$, sort it from large to small. After sorting the frogs according to type (1) evenly distributed to m groups, each group has n frogs, so there is F=mn.

$$M_i=\left\{X_{i+m(l-1)}\in \mathrm{P}\,|\,1\le l\le \mathrm{n}\right\},1\le i\le m \qquad (1)$$

Among them, M_i is the ith group. The position of the frog with the smallest fitness function in the population is represented by X_w and updated by formula (2) and Formula (3).

$$D=rand\cdot\left(X_b-X_w\right) \qquad (2)$$

$$X_w^{'}=X_w+D,\ D_{min}\le D\le D_{max} \qquad (3)$$

Among them, X_b is the best frog position for the current ethnic groups; rand is the random number in [0,1]; D is the frog moving distance; $D_{\min}$ and $D_{\max}$ are the maximum and minimum values of the allowable travel distance for the frog location, respectively. After the update, if the fitness is better than the original fitness value, then replace X_w with $X_w^{'}$. Otherwise, replace (2) with (4).

$$D=rand\cdot(X_b^{'}-X_w) \qquad (4)$$

Among them, $X_b^{'}$ is the best frog position for the current entire population. If there is no improvement after the update, the random generation of a feasible solution instead of X_w. This operation is repeated within an ethnic group until the number of iterations is set. Then the frogs of all groups are re-mixed and sorted, the best frog position $X_b^{'}$ is updated, and then the population is subdivided and the local depth search is carried out, so that the final condition is satisfied [13].

3.3 Multi-Domain Collaborative Reputation Evaluation Mechanism

Under the premise of the above research, we can get the reputation of a domain by combining the local and remote node history database, called multi-domain collaborative reputation evaluation. Only the local database is available for initialization, in which case the derivation of reputation is simplified to a good reputation rate for each domain from the local database. The reputation in the remote database derived domain can also be used after the information is fed back with other domains. However, information from other cooperating domains may not be entirely reliable, so a reputation database is introduced for each remote database to be optimized. The domain reputation score is a weighted average of the good reputation rates of the local and remote databases.

Algorithm 1: computing domain reputation

1: Input: DNH_c and all collected remote DNH_r
2: Output: reputation score for every node in DNH_c and DNH_r.
3: **for** each remote DNH_r **do**
4: compute trustworthiness score P.
5: **end for**
6: for each node X in DNH_c and those DNH_r that contain it do.
7: compute the reputation score of X.
8: **end for**

There are two steps to calculating a domain's reputation. The first step (3-5) calculates the score of each remote history database DNH_r, and in step 2 (6-8) calculates the reputation value recorded by each node through the local or remote history database.

4. EXPERIMENTAL SIMULATION

Because the generation of the reputation value of the cognitive Internet of things is a multi-user participation and requires long-term accumulation, the trust experience is inevitable deviation in a short time, and the short-term collection of actual feedback data in the cognitive environment of Internet of things is difficult, so we focuses on the selection of reputation nodes and the process of evaluation and recommendation, as far as possible to reflect the real user evaluation of the credibility of the node behavior.

Experiments using Core i3-2130 3.40GHz processor, 4GB RAM PC, based on Java and Access to design a simulation program to simulate the interaction behavior between multiple nodes and the user. Experiment contains 200 nodes and 50 users. Each user scores at least 10 nodes. The whole experimental data set needs to be further divided into training set and test set, including 80% as the training set and 20% as the test set. The predicted node score set is $\{p_1, p_2, \ldots p_N\}$. The corresponding actual score set is $\{q_1, q_2, \ldots q_N\}$. The average absolute deviation is as follows.

$$\text{MAE} = \frac{\sum_{i=1}^{N} | p_i - q_i |}{N}$$

Firstly, the SFLA-based reputation node filtering method and the traditional K-means [15] and IBCF filtering method are discussed. Figure 3 describe the average absolute deviation obtained for the model with different number of nodes. We can see that the SFLA model reduces the average absolute deviation by about 20% compared to the traditional method.

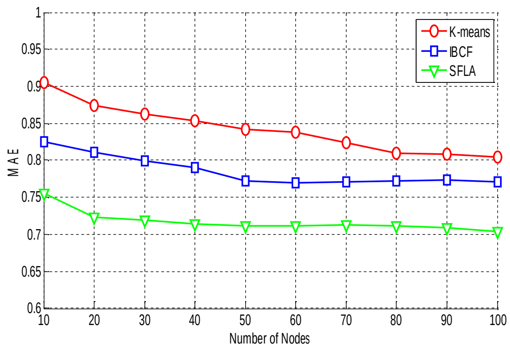

Figure 3: Comparison of Reputation Model Based on SFLA and K - means and IBCF

5. SUMMARY

In this paper, a multi-domain collaborative reputation evaluation model based on shuffled frog leaping algorithm is proposed, which takes into account the problem that the traditional reputation evaluation system may not interfere with the evaluation results. The main contributions of the model are: Through the historical behavior of the nodes and the collaboration between the autonomous domains, the multi-domain collaborative reputation evaluation mechanism of IOT is established to meet the security requirements of complex heterogeneous Internet of Things. The shuffled frog leaping algorithm is used to filter the nodes, which ensures the accuracy of the neighbor nodes in the credit rating, and thus improves the reliability of the reputation assessment as a whole. The simulation results show that the proposed model has a better global search capability than the traditional reputation model, and the reputation evaluation is more accurate and more consistent with the current security requirements of the IOT.

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