An Adaptive Bayesian Network Inference Algorithm for Network Situation Awareness

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Abstract—**The traditional Bayesian network is relatively fixed, the set of nodes, and intensity dependence relationships are rarely change, thus, it is unable to reflect changes in the actual network state. Such an inaccurate network model is also difficult to inference subsequent network. In order to solve the problem of inference is not accurate enough in traditional model, in this paper, the Markov changes of node parameters with time based on Bayesian network is studied. Next, an adaptive inference sampling strategy is put forward and an adaptive inference model based on Bayesian network is designed, then proposes an adaptive Bayesian network Inference algorithm. Finally, simulation results show the effectiveness of the proposed algorithm compared with other algorithms.**

Keywords- cognitive network; bayesian network; inference; adaptive

I. INTRODUCTION

Cognitive network adjusts the corresponding internal configuration to adapt to changes in the external environment by sensing the external environment and their own understanding and learning. The improvement of cognitive network's performance is focus on the entire network end-to-end QoS (Quality of Service). As a result, cognitive network is able to provide better QoS guarantee using the above characteristics[1]. It owns the basic characteristics of self-awareness, self-learning, self-optimizing, self-configuration or re-configuration[2]. At present, the QoS of cognitive network has become a hot research in the world.

Their research are focused in the following areas: (1) cognitive network architecture; (2) cognitive network environment sensing technology [3] ; (3) cognitive network QoS intelligent decision-making[4]; (4) adaptive configuration of cognitive network[5] and the dynamic self-configuration of QoS [6] . Then an ant colony-based spectrum aware routing algorithm is proposed, which is a cognitive wireless network routing algorithm that inspired by biology[7] .

It can be seen that the main research of cognitive network focus on the QoS of the cognitive network. However, these methods mostly are a local, specific control method, it is difficult to rise with global significance and mechanism. Lacking of existing research on the global assessment of the cognitive network situation and understanding of the cognitive ability, knowledge level of personality traits on the network level (learners), and thus the current methods can't fully meet the different needs of users, and they also can't provide learners with the support and guidance of personalized configuration data .

So in this paper, a Bayesian network theory is applied to the cognitive network and in order to accurately reflect the level and particle relationship among the network parameters and improve the accuracy of the Bayesian network inference, a Bayesian network learning adaptive inference algorithm (Bayesian network adaptive inference algorithm BAA) is proposed, next, the key technical points in this algorithm is analyzed. Simulation results verify the validity and accuracy of the algorithm .

II. BAYESIAN NETWORK MODEL

Bayesian networks (BN)[8] is a directed acyclic graph that is comprised of nodes, edges, Bayesian network structure diagram and the conditional probability distribution table (CPT). Each node corresponding a variable; the conditional probability to identify the dependent intensity among nodes, and it is a probability of a range of values[9].

Bayesian network inference is to use Bayesian network structure and its conditional probability tables to calculate the probability of an event occurring after the given evidence. The joint probability distribution of the random vector corresponding to the Bayesian network nodes, can be decomposed into the product of random variable marginal distribution , that is:

$$\mathrm{P}(\boldsymbol{x_1},\boldsymbol{x_2},\ldots,\boldsymbol{x_\infty}|\mathbf{B})=\prod_{\mathrm{i}=1}^{\mathrm{N}}\mathrm{P}(\mathrm{x_i},\pi_\mathrm{i})=\frac{\sum_{\mathrm{A}-\{\mathrm{x}_1\}\cup\pi_\mathrm{i}}\mathrm{P}(\boldsymbol{x_1},\boldsymbol{x_2},\ldots,\boldsymbol{x_\infty})}{\sum_{\mathrm{A}-\{\mathrm{x}_1\}}\mathrm{P}(\boldsymbol{x_1},\boldsymbol{x_2},\ldots,\boldsymbol{x_\infty})} \quad (1)$$

In the equation: $\boldsymbol{x_1},\boldsymbol{x_2},\ldots,\boldsymbol{x_\infty}$ represent a node in the network, A=$\{\boldsymbol{x_1},\boldsymbol{x_2},\ldots,\boldsymbol{x_\infty}\}$ means that the network node set. $\boldsymbol{\pi_i}$:i=1,2,…, ∞ means that a network parent node set of the *i*th the network node, **B** is Bayesian networks .

In this paper, the principle of minimum description length Bayesian Information Criterion (BIC) is used as the scoring function. BIC mainly to solve the problem of model selection to find the best balance between model complexity and model description of the data set. Let $\boldsymbol{y_1}, \boldsymbol{y_2}, \ldots, \boldsymbol{y_m}$ are an independent and identically distributed variables, the posterior probability function F(• | θ), where F is a function model with k parameters. Definition of M(k) as follows[10]:

$$M(k): \{F(\cdot \mid \theta) \mid \theta = (\boldsymbol{\gamma_1}, \boldsymbol{\gamma_2}, \cdots \boldsymbol{\gamma_k}),\ \theta \in \vartheta_k\} \qquad (2)$$

Where ϑ_k is the model space. Assuming the number of free parameters in the model k, $\boldsymbol{\gamma_i}$ is the *i*th free parameters. The model selection problem is how to select one F from the M(k)that best reflects the model function F to the given sample information. In addition, in arbitrary candidate model the FM(k), the BIC 's are defined as follows :

$$B(F) = \ln L_{\hat{\theta}}(X) - k * \ln n \qquad (3)$$

In the formula (3), $\ln L_{\hat{\theta}}(X)$ is any candidate model, F(• |θ)in the sample set X on the maximum a posteriori likelihood, $k * \ln n$ is the model complexity penalty term, In the case of the number of dimensions is too large and relatively small training data, it can effectively avoid the dimensions disaster excessive phenomenon. In the formula (3), the BIC values of the largest model is the optimal model. It is defined as follows [11]

$$\widehat{F} = \operatorname{argmax}_{F \in M(k), k=1,2,\cdots} B(F) \qquad (4)$$

In practical application, by a combination of Bayesian networks and statistical techniques, it will have many advantages in data analysis, and achieve good results in a large number of applications [12].

III. DESCRIPTION OF THE PROBLEM

The problem that solved in this paper can be understood as a machine learning problem on the basis of the sampled data set of cognitive network parameters. Suppose in a cognitive network, the network parameters that need for modeling and inference analysis is N, perception S sampling data obtained for each parameter, the range of each parameter is [1,M] is the reasoning data sets. These existing data sets can be used to establish a Bayesian network model and assessment algorithm parameter values, and to justify the inference algorithm performance compared with other algorithms .

Bayesian inference model and optimize is constructed on base of a sample data set. First of all, according to the data set to build a probability model and optimization objectives. Assuming that the data set is a total of N * S data matrix, N represents the network nodes of cognitive network, S represents the total number of samples. i is the *i*th parameters of the data set, the range is [1,M]. In order to obtain the a priori probability of each parameter value, we adopt the frequency of occurrence in the data set to represent its priori probability. The probability of the *m*th value of the *i*th parameter, defined as follows : $p_i(m)=H_i(m)/(n*S)$, where $H_i(m)$ means that the total number of this parameter in the data set , i.e. $H_i(m)=\Sigma$ i(1->S)(m). Different values for each parameter in the inference data set corresponds to the a priori probability value. All parameters set inference probability model is composed by their prior probabilities. Wherein the inference probability for each parameter corresponding to the maximum value is the optimum value , i.e. argmax(i)=max(p_i).

All parameters corresponding to the maximum inference probability value set to the optimal value of the dataset is the reasoning, which means argmax(U)=max(p_i)(where i 1: n), U is the optimal value of inference dataset. The target is to try to find optimal inference corresponding to the maximum probability value for each network parameter. Thus, the optimal solution of the problem is unique.

As we can see from the description of the problem, when the network total number of samples N and the number of network parameters S is too large, the size of the problem space for N^S, which changes into an NP-hard problem. Using mathematical formulas to describe this problem as follows:

$$P = \operatorname{argmax}_{p_i \epsilon p(k), \boldsymbol{k=1,2,\cdots m}}(U), \quad i \in \{\boldsymbol{1}, \boldsymbol{2}, \cdots, \boldsymbol{n}\} \text{ and } m \in \{\boldsymbol{1}, \boldsymbol{2}, \cdots, \boldsymbol{M}\} \qquad (5)$$

subject to：

$$U = \operatorname{argmax}_{p_i \epsilon p(k), \boldsymbol{k=1,2,\cdots m}}(P), \qquad (6)$$

$$p = \frac{H_i(m)}{n*S}, \quad n \in \{n, (N-n)\}, \quad H \in \{H, H'\} \qquad (7)$$

$$H = \sum_{j=1}^{S} h(m), m \in \{\boldsymbol{1}, \boldsymbol{2}, \cdots, \boldsymbol{M}\} \qquad (8)$$

IV. BAYESIAN NETWORK ADAPTIVE INFERENCE ALGORITHM (BAA)

Bayesian network can accurately and clearly capture the dependent and independent relationships among these variables, thus, it owns an efficient and reliable solution to the more difficult optimization and data mining problems. However, traditional algorithms build Bayesian probability model requires a lot of credible sampling data, while the increase in the amount of data also means that the execution time of the algorithm significantly extended and its efficiency is also greatly reduced [13]. Therefore, it is not desirable to create a Bayesian network probability model based on a large number of trusted data. By small-scale data to build a probability model is a feasible way, but it can only approximate reflect the dependence and in dependence of the relevant variables. However, Approximate model inference results will be inaccurate [14]. Thus, with in-depth understanding of the problem, the Bayesian network structure often needs to adjust, so that the inference model has good adaptability.

In order to overcome these shortcomings, this paper adds an adaptive strategy to improve the performance, then proposes an adaptive Bayesian network inference algorithm (BAA). BAA not only makes full advantage of the established Bayesian network probability model for inference, but also explores some new unknown areas, thus, it can improve the global and local optimization ability and get an effectiveness and reliability results without a large number of credible data. In addition, cognitive network parameters considered in this paper is static, the cognitive network structure, random variables and parameters remain unchanged .

Further details of the description, in this paper, using $\boldsymbol{X_1}, \boldsymbol{X_2}, \dots, \boldsymbol{X_n}$ represent discrete random variables, referred to as random variables, $\boldsymbol{x_1}, \boldsymbol{x_2}, \dots, \boldsymbol{x_n}$ set is its specific values in a certain time, $\boldsymbol{\theta_1}, \boldsymbol{\theta_2}, \dots, \boldsymbol{\theta_n}$ set is its possible set of parameters, wherein $x \in \boldsymbol{\theta}$, i.e. the value of the variable at the present time is a specific value of its parameter set, n represents the number of random variables. In this paper, structure learning of Bayesian network model by far the most widely used K2 algorithm. The adaptive inference learning algorithm BAA includes two cases, that is, increased variable parameter learning and less variable parameter learning , $\boldsymbol{\theta}$、$\boldsymbol{\theta_I}$and $\boldsymbol{\theta_R}$, are Bayesian network variable parameters, the growth variable parameter learning and less variable the parameter learning Bayesian network variable parameters, I expresses increase, and R expresses reduce. The following will introduce both cases in static cognitive network environment :

In the increase variable parameter learning case, it is assumed that the original Bayesian network (G， $\boldsymbol{\theta}$), G represents the current Bayesian network graph structure, $\boldsymbol{\theta}$ is the variable set of parameters of the Bayesian network. Assuming that the existing instances of the number of data L, denoted as $\boldsymbol{D_1}, \boldsymbol{D_2}, \dots, \boldsymbol{D_l}$, they constitute a real data set D, while the $\boldsymbol{D_{l+1}}, \boldsymbol{D_{l+2}}, \dots, \boldsymbol{D_n}$ means that this variable $\boldsymbol{l+1}$ is no corresponding data in the real data set , resulting in " missing data " , constitutes a " missing" data set D' . Due to the Bayesian network probabilistic inference model is constructed in accordance with the existing data set, its accuracy will depend on the existing data, but the data in the data set did not appear in Bayesian network probability might be interested in the inference model generates a very significant impact. If you can determine the values of these variables to compensate for these "missing " data can be estimated based on more complete data instance variable parameters, probabilistic inference. Based on Bayesian network model and adaptive adjusted Bayesian network model to predict, inference and sampling, as accurately as possible to determine the value of these new variables, missing data set D'. $\boldsymbol{D_{l+1}}, \boldsymbol{D_{l+2}}, \dots, \boldsymbol{D_n}$ value based on the sampled data values adaptive iterative correction until the alignment value. Let $\mathbf{D_{im}}$ means $\mathbf{X_i}$ variable in the data set the value of the *m*th record, $\mathbf{D_{i(m+1)}}$ means that the correction variable $\mathbf{X_{im}}$ record in the dataset value $\boldsymbol{\theta_{im}}$ and $\boldsymbol{\theta_{i(m+1)}}$ corresponding to the parameter vector t th iteration , the adaptive iterative algorithm , a new set of data will be generated $\mathbf{D_{im}^t}$. Therefore, in each iteration, it will correct the data , and form a data sequence of sets :

$$D_i^t = D_{i1}^t，D_{i2}^t，\cdots，D_{iT}^t，D_{i(T+1)}^t = D_i^{(t+1)} \quad (9)$$

Correspondingly also produced a variable parameter vector sequence :

$$\theta_i^t = \theta_{i1}^t，\theta_{i2}^t，\cdots，\theta_{iT}^t，\theta_{i(T+1)}^t = \theta_i^{(t+1)} \quad (10)$$

In theory, all other variable data information should be used to correct the value of the variable $\boldsymbol{X_i}$ and parameters, but many of the variables are redundant variables and their parameters are also redundant, and there is a lot of noise, which will tend to enlarge the influence of the noise, reduce the effect of the correction, and therefore it is necessary to remove the redundant variables. Thus, the Bayesian network can be obtained:

$$p(\boldsymbol{x_1}, \boldsymbol{x_2}, \dots, \boldsymbol{x_{j-1}}, \boldsymbol{x_{j+1}}, \cdots, \boldsymbol{x_n}) = p(\boldsymbol{x_j}, \boldsymbol{m_j}, \boldsymbol{G_I}) = \alpha p(\boldsymbol{x_j}, \boldsymbol{\pi_j}, \boldsymbol{G_I}) \prod_{x_j \in \pi_k} p(\boldsymbol{x_j}, \boldsymbol{\pi_k}, \boldsymbol{G_I}) \quad (11)$$

Of which $\boldsymbol{\pi_j}(\boldsymbol{\pi_k})$ is the variable $\mathbf{X_j}$ parent nodes set value, the $\mathbf{m_j}$ is variable $\mathbf{X_j}$'s Markov chain value, $\boldsymbol{\alpha}$ is has nothing to do with the variable $\mathbf{X_j}$, thus we can see that just use $p(\boldsymbol{x_j}, \boldsymbol{\pi_j}, \boldsymbol{G_I}) \prod_{x_j \in \pi_k} p(\boldsymbol{x_j}, \boldsymbol{\pi_k}, \boldsymbol{G_I})$ can correct variable values, then can eliminate the redundant variables .

In the case of less variable parameter learning, through multiple iterations of adaptive learning in BAA, some of variables has been basically converge to its optimal value, these variables can be removed from the Bayesian network structure, thus, BAA will focus only on a few promising value or the value of certain variables, most of other variables will no longer be selected. Assume that the original Bayesian network variables $\mathbf{X_i}$ parent node is $\boldsymbol{F} = (\boldsymbol{X_1}, \boldsymbol{X_2}, \dots, \boldsymbol{X_s})$, After multiple iterations of BAA, in the new Bayesian network structure, variable $\mathbf{X_i}$ parent nodes are $\boldsymbol{F} = (\boldsymbol{X_1}, \boldsymbol{X_2}, \dots, \boldsymbol{X_t})$, $t < s$, new parameter learning can determine new conditional probability distribution :

$$p(X_i, \boldsymbol{F} = (\boldsymbol{X_1}, \boldsymbol{X_2}, \dots, \boldsymbol{X_t})) = \frac{\sum_{(\boldsymbol{x_1}, \boldsymbol{x_2}, \dots, \boldsymbol{x_n}) - (X_i, \boldsymbol{F} = (\boldsymbol{X_1}, \boldsymbol{X_2}, \dots, \boldsymbol{X_t}))} \prod_{i=1}^{n} p(X_i, \pi_i, G, \theta)}{\sum_{(\boldsymbol{x_1}, \boldsymbol{x_2}, \dots, \boldsymbol{x_n}) - (F = (\boldsymbol{X_1}, \boldsymbol{X_2}, \dots, \boldsymbol{X_t}))} \prod_{i=1}^{n} p(X_i, \pi_i, G, \theta)} \quad (12)$$

In which $\mathbf{G}$、$\mathbf{G_I}$ and $\mathbf{G_R}$ are original Bayesian network structure, increasing the parameter learning and less parameter learning Bayesian network structure.

The following specific description of the steps of BAA algorithm , the algorithm process is as follows :

The flow of BAA is shown in Figure 1:

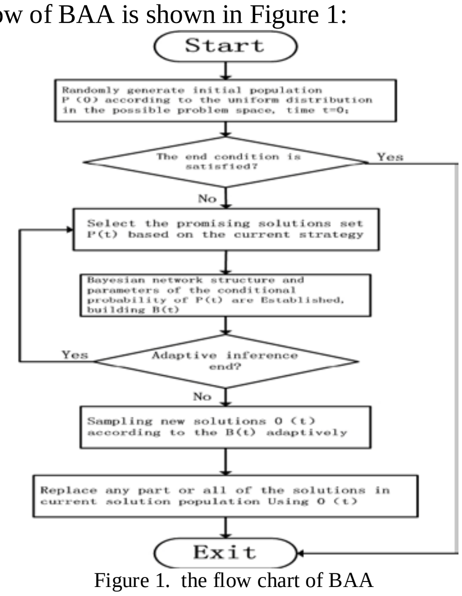

Figure 1. the flow chart of BAA

TABLE 2 THE FINAL RESULTS OF ALL ALGORITHMS

problem	BAA			HS			PSO		
	Mavg	*Mstd*	*Mmin*	*Mavg*	*Mstd*	*Mmin*	*Mavg*	*Mstd*	*Mmin*
scene1	**0.2801**	**0.0023**	**0.2758**	0.3826	0.0399	0.3109	0.3048	0.0244	0.2759
scene2	**0.4779**	**0.0017**	**0.4731**	0.5996	0.0498	0.5267	0.5407	0.0585	0.4745
mean	**0.3790**	**0.0020**	**0.3744**	0.4911	0.0449	0.4188	0.4228	0.0415	0.3752

In order to better and more accurate utilize Bayesian network and establish the conditional probability model, BAA uses an adaptive strategy to sample the new generation solutions. Traditional Bayesian network sampling method is strictly accordance with the conditional probability tables. Although such an approach in line with the inference of the order, but in the reality optimization problem, this method may cause BAA falls into local optimal. In order to more fully utilize the process of sampling the new solution, it is necessary to adopt an adaptive sampling strategy in the solution space, and then, with the increase of the number of iterations, BAA with this conditional probability model will enter into local search, eventually converge to an optimal solution. Adaptive sampling strategy is controlled according to the best fitness value and the current number of iterations, the formula is M/K, where M denotes populations in the recent evolution of L is the generation relative rate of change of the best fitness value, K is the algorithm adaptive inference iterations . M is defined as follows :

$$M = \frac{|f(t)-f(t-L)|}{f(t-L)} \tag{13}$$

$f(t)$ is the promising fitness value of population at t generation, $f(t-L)$ on behalf of the promising fitness values in subsection (t-L), M indicates that the relative change rate of population in the evolution of the best fitness value of in the L generation. When the optimal value of the rand<(M/K), population in the early evolution of iterative and evolutionary process, the population at the exploratory stage, in the beginning of BAA, the algorithm in a larger solution space to sample, it is conducive to the convergence of BAA; then, with the optimal fitness value of becomes small and the increase of the number of iterations in the process of evolution, BAA will enter into exploitation stage, the algorithm gradually convergence in local search and it is beneficial to get an accurate solution.

V. SIMULATIONS AND ANALYSIS

The simulation experiments using NS3 [15] to simulate network scenarios and sample network parameter values, Matlab toolbox BNT is used to build Bayesian Networks and evaluation. This paper simulates a wireless network, including an AP node and 40 user nodes. User nodes can communicate each other through the wireless AP access network. Different levels own 10 kinds of network parameters are really operating in continuous communication and sampling network protocol stack. For a more realistic effect and fully reflect the performance of BAA, we have sampled twice under 100ms and 1000ms interval respectively, the number of samples is 50000, which constitute two different network simulation data scenarios. Then, we select 20% of the total amount of data collected for Bayesian network learning inference model and the probability table statistics; The rest of 80% data are used to assessment established learning inference model and BAA .

Learning Bayesian network structure is an NP-hard problem. In order to improve the operating efficiency of BAA, which does not learn Bayesian network structure at the end of each iteration, but only after a certain number of iterations that is set a fixed number of iteration interval, which is 100 in this paper. In addition, the following strategies are used to update the current population promising solutions: At beginning of sampling a new solution, half of the total number of population promising solution are reserved, then BAA adaptive inference based on Bayesian network, Half promising solutions are produced and incorporated into the original population, constituting a new population of the next iteration. Finally, in order to verify the effectiveness of BAA, we compare it with the traditional hill-climbing algorithm and particle swarm optimization. The number of iterations of all algorithms is same, it is 1000, and the parameters used by each algorithm as shown in Table 1:

TABLE 1 ALGORITHM AND ITS PARAMETERS

Algorithm / Parameter	BAA	HS	PSO
Basic parameters	Population：50 Interval：100 Adaptive parameters: 0.5 The number of samples：25	Population：20 Control parameters: 0.3	Population：50 Inertial coefficient:0.9 C1：2.05 C2：2.05

The final results are shown in Table 2. The first column in the table is the scene name; Mavg, Mstd and Mmin denote the average values of the corresponding algorithm, the mean square error of results and find the optimal solution respectively. Each algorithm is run 15 times .

From the table 2, we can see that all of the algorithms run for a fixed number of iterations, the running time is almost the same. However, the performance proposed BAA algorithm is better than other comparable algorithms, in the scene of the two kinds of problems, the mean values and variance of BAA are 0.2801 and 0.4779, 0.0023 and 0.0017 , the mean values and variance of HS are 0.3826 and 0.5996 , 0.0399 and 0.0498; the mean values and variance of PSO are 0.3048 and 0.5407, 0.0244 and 0.0585. In scene 1, the mean of BAA increases 26.8 % and 8.1%, the variance increases 94.23% and 90.57% ; scene 2, the mean of BAA increases 20.30% and 11.64%, variance increases 96.58% and 97.09%. Thus, the variance of BAA is significantly better than the other algorithms, which shows that BAA algorithm has better robustness than other algorithms, it more suitable for solving the model 's inference accuracy problem.

Algorithm the mean results of BAA comparison with other algorithms shown in Figure 2.

VI. CONCLUSION

Firstly, a model inference accuracy NP-hard problem is put forward. Then, in order to overcome inaccuracy of the Bayesian network model inference, a new Bayesian network adaptive inference algorithm (BAA) is proposed, which owns an adaptive inference sampling strategy to ensure the inference of Bayesian Network is accurate enough.

In related experiments, we find that different adaptive functions will affect the choice of the optimal Bayesian network structure. Next, we will solve how to select more efficient adaptive function through the density and the number of iterations in-depth study.

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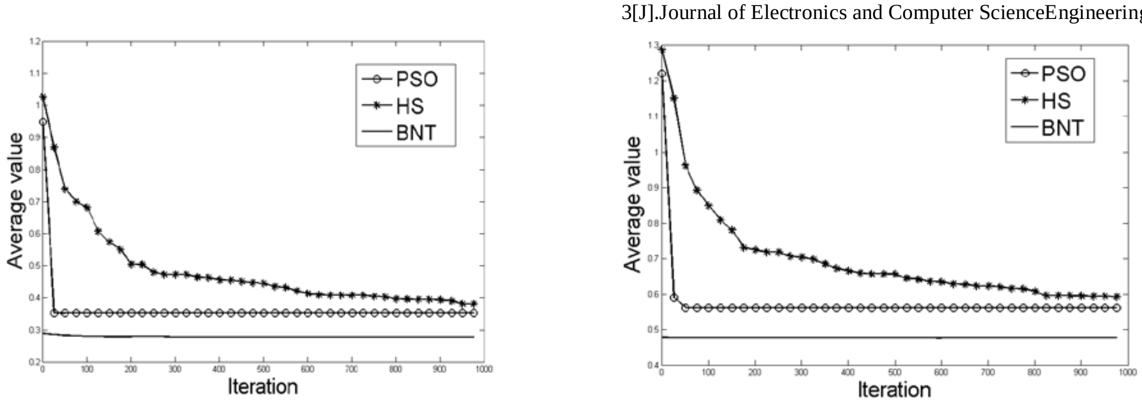

Figure 2. The mean results of BAA and other algorithms in scene 1 and 2