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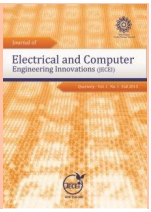

A Clustering Approach by SSPCO Optimization Algorithm Based on Chaotic Initial Population

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ABSTRACT

Assigning a set of objects to groups such that objects in one group or cluster are more similar to each other than the other clusters' objects is the main task of clustering analysis. SSPCO optimization algorithm is a new optimization algorithm that is inspired by the behavior of a type of bird called see-see partridge. One of the things that smart algorithms are applied to solve is the problem of clustering. Clustering is employed as a powerful tool in many data mining applications, data analysis, and data compression in order to group data on the number of clusters (groups). In the present article, a chaotic SSPCO algorithm is utilized for clustering data on different benchmarks and datasets; moreover, clustering with artificial bee colony algorithm and particle mass 9 clustering technique is compared. Clustering tests have been done on 13 datasets from UCI machine learning repository. The results show that clustering SSPCO algorithm is a clustering technique which is very efficient in clustering multivariate data.

1. Introduction

Optimization is the process of making better results or, in other words, the optimization of input setup process or the characteristics of a device, mathematical processes or experiments to find the minimum, maximum output or results [1]. Several nature-inspired algorithms to solve optimization problems came to the aid of human science, algorithms such as birds [2], ant colony algorithm [3], Firefly algorithm [4,5], Artificial bee colony algorithm [6], bees algorithm [7] which are many complex issues in various fields. SSPCO optimization algorithm [31] is also one of the newest algorithms based on the behavior of chickens and a type of bird called see-see partridge. Knowledge discovery process is introduced as the clustering and is one of the data mining techniques, [8], [9]. Furthermore, clustering and classification are two basic tasks of data mining [10]. Analyzing the data to understand various phenomena plays an essential role. Cluster analysis with no or little previous knowledge comprises the developed research in a range of communities [11]. The purpose of clustering a data set without label is the separation in a discrete finite set of natural [12], [13]. Unanticipated clustering is a mental process in nature that prevents absolute judgment as a relative effect on all clustering techniques [14]. Clustering in all sciences and researches play a decisive role, sometimes subtle, having prompted researchers to try to make more efforts in this area. In this paper solved the clustering problem by a new algorithm. Initialization population was created with Chaos Theory. Clustering tests on 13 datasets from UCI machine learning repository have been done. The results show that proposed method is a clustering

technique which is very efficient in clustering multivariate data. Proposed method compared with 12 clustering technique that in the proposed method is better than other methods in most of tests. In Section 2 of this article, we will discuss the issue of clustering, and Section 3 will be dedicated to introducing the related works. In Section 4, we present the chaos SSPCO algorithm and the experimental study is discussed in Section 5. Finally, Section 6 concludes the present study.

2. THE CLUSTERING PROBLEM

Clustering divides data into subsets of similar data so that the same data can be grouped together, while the different species remain in different groups [15]. In general, the evaluation criterion is the distances between the patterns that are alike. And when the N object is present and objects are assigned to the K clusters, clusters to minimize the Euclidean distance of the object from the center of the object are the main issue. Equation 1 is as follows [16]:

$$j(w,z) = \sum_{i=1}^{N}\sum_{j=1}^{K} w_{ij} \left\|x_i - z_j\right\|^2 \quad (1)$$

where, K is the number of clusters, N number of models, $x_i(i = 1, \dots, N)$is the ith pattern location, and $z_j(j = 1, \dots, K)$that is the jth cluster center and based on Equation (2) shall be regulated as:

$$z_j = \frac{1}{N_j}\sum_{i=1}^{N} w_{ij} x_i \quad (2)$$

N_j in this equation is the number of patterns in the jth cluster, and w_{ij} weight $x_i$is the pattern with the jth cluster which will be one or zero. Cost in this research would be to model is according to Equation 3:

$$f_i = \frac{1}{D_{Train}}\sum_{j=1}^{D_{Train}} d(x_j, P_i^{CL_{know(x_j)}}) \quad (3)$$

In which D_{Train} is the number of training patterns, and$P_i^{CL_{know(x_j)}}$is the class definition.

3. RELATED WORK

Bayes Net [20] of Bayesian, the target of the classification is to attribute an instance based on the values of variables of different attributes to a class. Many classification procedures are trying from Collection dependent to attribute values create a class to a label. Class in learning Bayesian mean is estimate of the probability distribution, After was made such an estimate, the values has been classification and class that with more likely has been identify. Multilayer Perceptron neural networks or MLP[21] show the non-linear relationships between input and output vectors. They operate through neurons connecting each node to the next one, and the previous layer is created. The output of each neuron is multiplied by weighting coefficients, and non-linear excitation function is given as input.

The training is given to the perception of information occurs, and then the weights are adjusted so that the error between the output current and target reaches their least amount of training or the number of preset. Afterward, to evaluate the accuracy of the training process, a series of analytical inputs is applied to the network. The inputs are chosen from the inputs used in the training process of the network. Generally, complex neural network training and an optimization problem have many variables [29].Artificial Neural Networks Radial Basis Function, RBF, [22], unlike the MLP network with several successive layers, comprises three fixed layers: an input layer, a hidden layer, and an output layer.

Dissimilar to MLP, the neurons of the hidden layer in RBF networks have anon-linear Gaussian function. The relationship between the neurons of the input layer and the hidden layer are not as simple as MLP network.

RBF training done in both section of supervised and unsupervised. This is a learning process for the first time with a clustering method; the parameters of Gaussian function hidden layer, hidden layer, and output are set, and then the relationship between weight, using a supervised learning algorithm such as the slope of the standard error propagation and conjugate gradient method or procedure, and Marquardt, is regulated [30]. Engineering K-STAR [23], that is the nearest neighbor method, is based on a conversion of the public by the distance from the general function.

Engineering Bagging [24] is used to incorporate the anticipated classification of several models. Suppose that you are going to do the prediction model for rating and make the desired data set small. You can select examples from the collection of data and samples obtained for trees category use (for example, C&RT and CHAID). Generally, for example, several different trees will arrive.

Then to predict using different trees obtained from the samples, do a simple voting. Final classification, that is a category, predicts that there will be different tree limitations. MultiBoostAB technique [25], the concept for the production of multiple models (for prediction or classification), is therefore used. In boosting the RT&C or CHAID methods, the sequence of the classifier will be produced. NBTree technique [26], a technique that creates such an atmosphere and a decision tree classifier of Bayes N, can be combined. Ridor technique [27] is a technique in which the basic rules are first generated and then for any exception the best exception is generated. The exception to this rule will be based on the lowest classification error and then expand the tree as an exception, which

leaves only the default rule to no exception. VFI clustering technique introduced by [28] is another clustering technique in this study which is used to compare performance. In 2007, clustering algorithms were used in studying particle mass, and velocity equations of motion of the particle mass were used for data clustering [19].

In the present study, for compare the performance of clustering algorithms we use a clustering approach based on the artificial bee colony algorithm presented by Karabuga et al. The clustering of the three phases of the optimization algorithm for clustering artificial bee has been used [17]. Many approaches have been proposed for data clustering.

This section have a review on recent research works related to data clustering based on KM, FKM, and hybrid algorithms. For more details, the interested reader can also refer to pre-vious surveys in the area, among which we point out Nayak et al. [39] that have been presented a comprehensive review on FKM and its applications from 2000 to 2014. Nayak et al. [40] have developed an improved firefly-based fuzzy c-means algorithm (FAFCM) for data clustering. They show the effectiveness and reliability of the proposed method by testing the algorithm with various real-world datasets. Wu et al. [41] have been developed a hybrid fuzzy K-harmonic means (HFKHM) clustering algorithm based on improved possibilistic c-means clustering (IPCM) and K-harmonic means (KHM). HFKHM solves the noise sensitivity problem of KHM and improves the memberships of IPCM by combining the merits of KHM and IPCM.

The performance of HFKHM is compared with those of KHM and IPCM on several datasets. In addition, experimental results indicate the superiority of HFKHM. Shamshirband et al. [42] proposed a density-based fuzzy imperialist competitive clustering algorithm (D-FICCA) for detecting the malicious behavior in wireless sensor network.

4. SSPCO Algorithm

The basic idea of this optimization algorithm is taken from the behavior of the chicks of a type of bird called see-see partridge [31]. The chicks of this type of bird at the time of danger are located in a regular queue to reach a safe place and they start to move behind their mother to reach a safe point.

In order to simulate the behavior of the chicks of this bird in the form of an optimization algorithm, each chick is considered as a particle of the suboptimal problem.

Particle's state should be according to the behavior of this type of chicks in a regular queue that we know takes us to the best optimal point, and this does not mean that it is minimizing the search space, but it is converging particles after some searches in a regular queue to the best point answers (bird mother).

In the algorithm, consider a variable for each particle entitled as priority variable. For particle i, priority variable is defined according to Equation 4:

$$X_i.priority \tag{4}$$

In every assessment, when a particle is better than the best personal experience or local optimum, a unit is added to the priority variable of that particle:

$$if \quad X_i.cost > P_{best} \rightarrow P_{best} = X_i.position \quad and \quad X_i.priority = X_i.priority + 1 \tag{5}$$

$X_i.cost$ is cost of each particle in the benchmark, P_{best} is the best personal experience of each particle, and $X_i.position$ is the location of each particle.

In each time of assessment, if the local optimum is better than the global optimum and vice versa, the particle's priority variable goes higher, and a unit is added to it:

$$if \quad P_{best} > G_{best} \rightarrow G_{best} = P_{best} \quad and \quad X_i.priority = X_i.priority + 1 \tag{6}$$

G_{best} is the global optimum. The motion equation of each particle is set almost similar to the particle swarm algorithm in the form of equation 7:

$$X_i.position = X_i.position + X_i.velocity \tag{7}$$

$X_i.velocity$ is the velocity of each particle or chick. Now the particle velocity equation is calculated based on Equation 8:

$$X_i.velocity = w * X_i.velocity + c * rand() * [position(X_{i+1}.priority)] - X_i.position \tag{8}$$

where, $X_i.velocity$ is the velocity of the particle, w is the coefficient impact of the previous velocity in the current velocity equation of particle, c is the coefficient impact of position of particle with upper priority in the current velocity equation of particle, $rand()$ is a random number between 0 and 1 to create a random movement for particles, $[position\ (X_i.priority + 1)]$ is the location of the particle with one level higher priority than the current particle adjusts its velocity according to the particle, and $X_i.position$ is the current location of the particle.

It can be seen that, according to Equation 7, each particle adjusts its movement based on a particle with one level higher priority.

In this way, it does not matter the local and global optimums and at any point in time it only moves to find a particle which is a unit ahead of that particle; and for this reason, the calculation number and time

in this algorithm has a great benefit compared to the previous optimization algorithm.

According to this equation, particles move until they conduct a particle which is the mother particle to the optimum solution, and remaining particles move behind the particle to the optimum solution

1.//initialize all chicken accidentally

2.Initialize by accidentally

3.Repeat

4. For each chicken $\boldsymbol{i}$

5. //update the chicken's best position and priority

6. If $\boldsymbol{f(x_i) > f(pbest_i)}$ *then*

7. $\boldsymbol{pbest_i = x_i}$

8. $\boldsymbol{prioirity_i = prioirity_i + 1}$

9. End if

10. //update the global best position and priority

11. If $\boldsymbol{f(pbest_i) > f(gbest)}$ *then*

12. $\boldsymbol{gbest = pbest_i}$

13. $\boldsymbol{prioirity_i = prioirity_i + 1}$

14. End if

15. End for

16. //update chicken's velocity and position

17. For each chicken $\boldsymbol{i}$

18. For each dimension $\boldsymbol{d}$

19. $\boldsymbol{X_i.velocity = w * X_i.velocity + c * rand() * [position(X_{i+1}.priority)] - X_i.position}$

20. $\boldsymbol{x_{i,d} = x_{i,d} + v_{i,d}}$

21. End for

22. End for

23. //advance iteration

24. $\boldsymbol{itetation = itetation + 1}$

25.Until $\boldsymbol{it > MaxIterations}$

Figure 1: Pseudo code of SSPCO algorithm [31].

4.1. Chaotic Theory

Simulation dynamic behavior of nonlinear systems called chaos. It has raised enormous interest in different fields. such as synchronization, chaos control, optimization theory, pattern recognition and so on [35].

In optimization algorithms based on the chaos theory, the methods using chaotic variables instead of random variables are called chaotic optimization algorithm (COA). COA is a stochastic search methodology that differs from any of the existing swarm intelligence methods and evolutionary computation. COA can carry out overall searches faster than stochastic searches that depend on probabilities [36].

There are several popular chaotic sequences such as chaotic sequences in logistic maps that are considered in this paper.

Logistic maps are frequently used chaotic behavior maps and chaotic sequences can be quickly generated and easily stored.

For this reason, there is no need for storage of long sequences [37]. In this study, we substitute the random parameters in PSO with sequences generated by the logistic map. The random parameters are modified by the logistic map based on the following equation:

$$Cr_{(t+1)} = k \times Cr_{(t)} \times (1 - Cr_{(t)}) \quad (9)$$

In Eq. (5), k =4 and for each independent run, Cr(0) is generated randomly, out of {0, 0.25, 0.5, 0.75, 1}.

4.2. SSPCO Applied to Clustering

Given a database with C classes and N parameters, the classification problem can be seen as that of finding the optimal positions of C center in an N-dimensional space i.e. that of determining for any center its N coordinates, each of which can take on, in general, real values.

With these premises, the i-th individual of the population is Encoded as it equation 10:

$$(p_i^{\rightarrow 1}, \dots, p_i^{\rightarrow C}, v_i^{\rightarrow 1}, \dots, v_i^{\rightarrow C}) \quad (10)$$

where $p_i$the position of the j-th center is constituted by N real numbers representing its N coordinates in the problem space:

$$p_i^{\rightarrow j} = \{p_{1,i}^j, \dots, p_{N,1}^j\} \quad (11)$$

And similarly the velocity of the j-th center is made up of N real numbers representing its N velocity components in the problem space:

$$v_i^{\rightarrow j} = \{v_{1,i}^j, \dots, v_{N,1}^j\} \quad (12)$$

Then, each individual in the population is composed of 2*C*N components, each represented by a real value.

1.//initialize all chicken by $\boldsymbol{k} \times \boldsymbol{Cr}_{(t)} \times (\boldsymbol{1} - \boldsymbol{Cr}_{(t)})$*(input is a clustering form according chaotic theory)*

2.Initialize by $\boldsymbol{k} \times \boldsymbol{Cr}_{(t)} \times (\boldsymbol{1} - \boldsymbol{Cr}_{(t)})$

3.Repeat

4. For each chicken $\boldsymbol{i}$

5. //update the chicken's best position and priority

6. $(\boldsymbol{p_i^{\rightarrow 1}}, \dots, \boldsymbol{p_i^{\rightarrow C}}, \boldsymbol{v_i^{\rightarrow 1}}, \dots, \boldsymbol{v_i^{\rightarrow C}})$

$$\boldsymbol{p_i^{\rightarrow j}} = \{\boldsymbol{p_{1,i}^{j}}, \dots, \boldsymbol{p_{N,1}^{j}}\}$$

$$\boldsymbol{v_i^{\rightarrow j}} = \{\boldsymbol{v_{1,i}^{j}}, \dots, \boldsymbol{v_{N,1}^{j}}\}$$

7. If $\boldsymbol{f(x_i) > f(pbest_i)}$ *then*

8. $\boldsymbol{pbest_i = x_i}$

9. $\boldsymbol{prioirity_i = prioirity_i + 1}$

10. End if

11. //update the global best position and priority

12. If $\boldsymbol{f(pbest_i) > f(gbest)}$ *then*

13. $\boldsymbol{gbest = pbest_i}$

14. $\boldsymbol{prioirity_i = prioirity_i + 1}$

15. End if

16. End for

17. //update chicken's velocity and position

18. For each chicken $\boldsymbol{i}$

19. For each dimension $\boldsymbol{d}$

20. $\boldsymbol{X_i.velocity = w * X_i.velocity + c * rand() * [position(X_{i+1}.priority)] - X_i.position}$

21. $\boldsymbol{x_{i,d} = x_{i,d} + v_{i,d}}$

22. End for

23. End for

24. //advance iteration

25. $\boldsymbol{itetation = itetation + 1}$

26.Until $\boldsymbol{it > MaxIteration}$*s*

27. clustering form=gbest(index of cluster-heads and members)

Figure 2: Pseudo code of Proposed Method.

In the flowchart of Figure 2, input is a clustering form according chaotic theory, and output is the best clustering form that introduced by proposed algorithm.

4.3. Fitness Function

The fitness function is computed in one step. It is the sum on all training set instances of Euclidean distance in N-dimensional space between generic instance $x_j^{\rightarrow}$ and the centroid of the class according to database ($p_i^{\rightarrow CL_{known}(x_j^{\rightarrow})}$). This sum is normalized with respect to D_{Train}. In symbols, i-th individual fitness is given by equation 13:

$$(i) = \frac{1}{D_{Train}} \sum_{j=1}^{D_{Train}} d(x_j^{\rightarrow}, p_i^{\rightarrow CL_{known}(x_j^{\rightarrow})}) \quad (13)$$

When computing distance, any of its components in the N-dimensional space is normalized with respect to the maximal range in the dimension, and the sum of distance components is divided by N. With this choice, any distance can range within [0.0,1.0].

5. Experimental Study

In this article, we compare the clustering algorithm with a two-clustering algorithm introduced earlier in this context. PSO clustering algorithm, in which the collective behavior of birds when flying was inspired by these parameters, has solved the problem of clustering [19]: n = 50, $T_{\max}$=1000, $v_{\max}$=. 05,$v_{\min}$ = -. 05, C_1= 2, C_2= 2, $w_{\max}$= .09, $w_{\min}$= .04. Artificial bee colony clustering algorithm has the following parameters [17]: the size of the colony is 20, the maximum ring is 1000, and a total of 20,000 is assessed. SSPCO algorithm has been exactly set according to PSO algorithm parameters. In this study, 13 datasets of known database UCI are tested for clustering problem [18]. Clustering of the 13 benchmark criteria is similar to and consistent with all algorithms, and the techniques are compared with SSPCO algorithm. 75% of the data for each data set is dedicated to education and 25% to testing. First, to briefly discuss data collections in this study, all the attributes are expressed and presented in Table 1 [17]:

Table 1
Properties of the Problems [17]

	Data	Train	Test	Input	Class
Balance	625	469	156	4	3
Cancer	569	427	142	30	2
Cancer-Int	699	524	175	9	2
Credit	690	518	172	51	2
Dermatology	366	274	92	34	6
Diabetes	768	576	192	8	2
E. coli	327	245	82	7	5
Glass	214	161	53	9	6
Heart	303	227	76	35	2
Horse	364	273	91	58	3
Iris	150	112	38	4	3
Thyroid	215	162	53	5	3
Wine	178	133	45	13	3

5.1. Results and Discussions

Benchmark comparison clustering techniques are based on the percentage error, and the percentage of models is sorted incorrectly. Each pattern should be part of the cluster closest to Euclidean distance with the cluster's center. The data is divided into two pieces, 75% of the training data and 25% of the final test data. Margins of error classification criteria are compared in this paper based on Equation 14 and set to be [17]:

$$CEP(Classification\ Error\ Percentage) = 100 \times \frac{misclassification\ examples}{size\ of\ test\ data\ set} \quad (14)$$

It can be seen that the clustering algorithm PSO in 6 data sets from ABC and PSO margins of error has fewer statistically significant errors in the data set compared to the other two algorithms, and the other data collection is ranked second on the error in the 4 clusters and only 3 of the data collection errors are higher than the other two algorithms.

The average margin of error for all 13 data sets shows that the clustering algorithm is SSPCO that has the lowest percentage of error.

The average margin of error on the full data set for clustering algorithm is with 10.71%, while the percentage errors of ABC and PSO are 13.13% and 15.99%, respectively.

Table 2
Classification Error Percentages of the Techniques [17]

	SSPCO	ABC	PSO	BayesNet	MlpAnn	RBF	KStar	Bagging	MultiBoost	NBTree	Ridor	VFI
Balance	15.36	15.38	25.74	19.74	9.29	33.61	10.25	14.77	24.20	19.74	20.63	38.85
Cancer	4.15	2.81	5.81	4.19	2.93	20.27	2.44	4.47	5.59	7.69	6.63	7.34
Cancer- Int	4.49	0.00	2.87	3.42	5.25	8.17	4.57	3.93	5.14	5.71	5.48	5.71
Credit	15.92	13.37	22.96	12.13	13.81	43.29	19.18	10.68	12.71	16.18	12.65	16.47
Dermatology	16.11	5.43	5.76	1.08	3.26	34.66	4.66	3.47	53.26	1.08	7.92	7.60
Diabetes	16.66	22.39	22.50	25.52	29.16	39.16	34.05	26.87	27.08	25.52	29.31	34.37
E. coli	13.89	13.41	14.63	17.07	13.53	24.38	18.29	15.36	31.70	20.73	17.07	17.07
Glass	13.56	41.50	39.05	29.62	28.51	44.44	17.58	25.36	53.70	24.07	31.66	41.11
Heart	14.03	14.47	17.46	18.42	19.46	45.25	26.70	20.25	18.42	22.36	22.89	18.42
Horse	12.22	38.26	40.98	30.76	32.19	38.46	35.71	30.32	38.46	31.86	31.86	41.75
Iris	4.48	0	2.63	2.63	0.00	9.99	0.52	0.26	2.63	2.63	0.52	0.00
Thyroid	3.31	3.77	5.55	6.66	1.85	5.55	13.32	14.62	7.40	11.11	8.51	11.11
Wine	5.12	0	2.22	0.00	1.33	2.88	3.99	2.66	17.77	2.22	5.10	5.77

Table 3
Average Classification Error Percentages and Ranking of the Techniques [17]

	SSPCO	ABC	PSO	BayesNet	MlpAnn	RBF	KStar	Bagging	MultiBoost	NBTree	Ridor	VFI
Average	10.71	13.13	15.99	13.17	12.35	26.93	14.71	13.30	22.92	14.68	15.38	18.89
Rank	1	3	9	4	2	12	6	5	11	7	8	10

5.1. T-Test

The statistics t-test allows us to answer this question by using the t-test statistic to determine a p-value that indicates how likely we could have gotten these results by chance, if in fact the null hypothesis were true (i.e. no difference in the population)[32]. By convention, if there is less than 5% probability for getting the observed differences randomly, the null hypothesis will be rejected and a statistically significant difference between the two groups can be found.

See Statistical Data Analysis for more information about hypothesis testing [33], [34]. In this study H_1 is defined as follow: the obtained results are based on the random nature of the problem. If the value of the significant level for the example is zero, then it indicates that the probability of H_1 being incorrect will be zero. Therefore, in this particular example, it is safe to say that the obtained results are independent of the random circumstances of the problem.

TABLE 4
T-TEST RESULTS FOR CLASSIFICATION ERROR OF SSPCO ALGORITHM

Dataset	Confidenceinterval 95%		Test Value	p-value	H_1 or H0
	Low	upper			
Balance	9.29	24.95	17	0	H1
Cancer	0.747	5.203	3	0	H1
Cancer-Int	2.18	7.227	4.5	0	H1
Credit	5.31	25.02	15.5	0	H1
Dermatology	7.33	22.77	15.5	0	H1
Diabetes	3.49	27.36	16	0	H1
E. coli	3.49	27.36	12.5	0	H1
Glass	5.10	22.22	13	0	H1
Heart	1.61	23.92	13	0	H1
Horse	14.00	27.00	22	0	H1
Iris	2.404	6.146	4.5	0	H1
Thyroid	2.11	3.627	3	0	H1
Wine	1.518	5.909	3	0	H1

6. CONCLUSION

Given the crucial role of clustering in various sciences and the need for progress in this area, in this paper by using a chaotic optimization algorithm, a clustering technique was presented at 13 benchmark tests which were compared with 11 other clustering algorithms on the benchmarks. Chaotic SSPCO clustering algorithm was to simulate the behavior of a type of bird called see-see partridge and was compared with ABC and PSO clustering techniques and other known techniques. The technique measures the performance of similar clustering patterns, which are classified in a cluster with other clusters, as well as the diversity and specific clustering of error, as compared to the techniques of clustering index, defining that the proposed algorithm in 5 sets with the lowest error clustering in clustering techniques were compared between 12 techniques and 5 other data collections have been good, and a total of 13 benchmarks have had the lowest average error. The results of Friedman's test proposed the accuracy and reliability of the clustering algorithm. And the results of simulations showed the effectiveness of the algorithm for clustering data.

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