Using Artificial Intelligence Techniques for Image Compression

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ABSTRACT

Image compression helps in storing the transmitted data in proficient way by decreasing its redundancy. This technique helps in transferring more digital or multimedia data over internet as it increases the storage space. This research presents some methods to compress digital images using Artificial Intelligence Techniques(AITs) that include from fuzzy logic, swarm intelligent technique, and artificial neural networks. Traditional clustering algorithm k-means and AITs were used, such as Gath-Geva fuzzy clustering algorithm, and Particle Swarm Optimization Technique(PSO), and combined Gath-Geva with backpropagation neural network to produce a new method which is called Fuzzy BackPropagation Network (FBPN) algorithm, by applying these methods on gray level and color images and then applying compression algorithm RLE on it to obtain compressed image. Image quality measures have done by Peak Signal to Noise Ratio(PSNR), Mean Square Error(MSE), and Bitperpixel(bpp), compression ratio (CR) have been computed. Finally, a comparison between results after applying these algorithms on the images data set was obtained.

Keyword: *K-means algorithm, Gath-Geva (GG) fuzzy clustering algorithm; Particle Swarm Optimization Technique(PSO); Fuzzy Backpropagation Neural Network (FBPNN).*

باستخدام تقنيات الذكاء الاصطناعي لضغط الصور

بيداء خليل

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الملخص

يساعد كبس الصور في خزن البيانات المنقولة بطريقة ماهرة عن طريق تقليصها. وتساعد هذه التقنية في نقل بيانات رقمية كثيفة او بيانات وسائط متعددة عبر الانترنيت مما يؤدي الى زيادة مساحة الخزن. قدم هذا البحث بعض الطرائق لكبس بيانات الصور الرقمية باستخدام التقنيات الذكائية الاصطناعية والتي تشمل المنطق المضبب، وتقنية ذكاء السرب الاصطناعية، والشبكات العصبية الاصطناعية. وتم استخدام خوارزمية العنقدة التقليدية K-means وتقنيات ذكائية اصطناعية مثل خوارزمية العنقدة المضببة G-G وخوارزمية سرب الطيور PSO ، كما تم دمج خوارزميةG-G مع شبكة الانتشار الخلفي BP لتنتج طريقة جديدة و سميت خوارزمية شبكة الانتشار الخلفي المضببة FBPN ، وطبقت هذه الطرائق على الصور الملونة لعنقدتها ومن ثم تطبيق خوارزمية الكبس RLE للحصول على صورة مكبوسة. وتم حساب المقاييس النوعية للصور وهيCR, bpp, MSE, PSNR. واخيرا تمت المقارنة بين النتائج التي تم الحصول عليها بعد تطبيق هذه الخوارزميات على مجموعة بيانات الصور.

الكلمة المفتاحية: خوارزمية K-mean ، خوارزمية Gath-Geva (GG) التجميعية المبهمة ؛ تقنية تحسين سرب الجسيمات (PSO) ؛ غامض Backpropagation الشبكة العصبية (FBPNN).

1. Introduction

Digital image presentation requires a large amount of data and its transmission over communication channels is time consuming. Numerous image compression techniques have been developed in the past years[1]. Image compression is a result of applying data compression to the digital image. The main objective of image compression is to decrease the redundancy of the image data which helps in increasing the capacity of storage and efficient transmission. Image compression aids in decreasing the size in bytes of a digital image without degrading the quality of the image to an undesirable level[2]. K-means is one of the common partitioning techniques which has large number of applications in the fields of image and video compression, image segmentation, pattern recognition and data mining. Though the K-means algorithm always converge, it does not guarantee to yield the most optimal clustering as it is significantly sensitive to the randomly selected initial cluster centroids[3]. Fuzzy systems have been successfully applied to various areas such as classification, simulation, data mining, pattern recognition, image compression[4], Gath-Geva (G-G) fuzzy clustering algorithm takes the size and density of the clusters into account[5]. Swarm intelligence (SI) as an innovative artificial intelligence technique inspired by intelligent behaviors of insect or animal groups in nature, such as ant colonies, bird flocks, bee colonies bacterial swarm, and so on. In recent years, many SI algorithms have been proposed[6], such as Particale Swarm Optimization(PSO) is a kind of evolutionary computation techniques developed by Kennedy and Elberhart in 1995 based on social behaviour metaphor. PSO is a simple, but powerful search technique; it has been applied successfully to a wide variety of search and optimization problems, including some image processing problems such as image compression [7].

A neural network represents a highly parallelized dynamic system with a directed graph topology that can receive the output information by means of reaction of its state on the input nodes. The ensembles of interconnected artificial neurons generally organized into layers of fields include neural networks. The behavior of such ensembles varies greatly with changes in architectures as well as neuron signal functions [8]. Artificial neural networks have been applied to many problems, one such application is far data compression. In this research was combined Gath-Geva fuzzy clustering method with backpropagation neural network to produce Fuzzy Backpropagation Neural Network (FBPNN).

2. Previous Works

Numerous compression research studies examine the use of compression in different file types and different application domains, as well as by using different algorithms. In 2010, Singh V., Rajpal N., Murthy K.[1], described practical and effective image compression system based on neuro-fuzzy model which combines the advantages of fuzzy vector quantization with multi layered neural network and wavelet transform. Boopathi G, Arockiasamy S.[2], present the proposed technique for the image compression by using modified Self-Organizing Map(SOM) based vector quantization. Somasundarad K., Rani M.[3], used K-means algorithm and proposed a new approach to generate codebook used in Vector Quantization for the image compression. Al-Hashemi R., Kamal I.[9], presented an efficient lossless image compression approach based on a well-known error correcting BCH codes. Khashman A., Dimililer K.[10], presented Haar wavelet transform, and used a supervised neural network based on the back propagation learning algorithm for the image compression. Sahoolizadeh H., Abolfazl A.[11], the perceptron networks to compress images were used and tried by using the adaptive network based on the amount of information presented in blocks of the image. Chaabouni I., Fourati W., Bouhlel M.[12], presented four wavelets families used in incremental self organizing map ISOM based on the image compression technique. Four families of wavelets were considered:1) Bi-orthogonal, 2) Daubechies, 3) Coiflet and 4) Symlet. Wang A., Zhang Y., and Feng Gu Y.[13], were used of multiwavelets in Synthetic aperture radar (SAR) images denoising and compression. Vasmatkar1 R., Biradar S., Shivashankar P.[14], were using a parallel structure of Multilayer Feed-forward Networks and the concept of Discrete Wavelet Transform DWT for the image compression.

3. Image Quality Measures

A number of quality measures [4] are evaluated for color image compression. They are all bivariate, exploiting the differences between corresponding pixels in the original and the degraded images. Image quality assessment is an important, but difficult issue in image processing applications such as compression coding and digital watermarking. For a long time, root mean square error (RMSE) and peak signal-to-noise ratio (PSNR) are widely used to measure the image compression[15]. The $RMSE_R$, $RMSE_G$, $RMSE_B$ can be calculated by the following equation[15][16]:

$$RMSE = \sqrt{\frac{1}{N^2}\sum_{x=1}^{N}\sum_{y=1}^{N}\left[f(x,y)-\hat{f}(x,y)\right]^2} \qquad \ldots(1)$$

Then, the RMSE can be found for the color image by equation (2):

$$RMSE_T = \sqrt{\frac{1}{3}(RMSE_R^2 + RMSE_G^2 + RMSE_B^2)} \qquad \ldots(2)$$

Where, $RMSE_R$, $RMSE_G$, $RMSE_B$, represent the RMSE value for the Red, Green, and Blue colors for an image.

The Peak Signal to Noise Ratio (PSNR) in decibel (dB) for the three color can be calculated by the following equations[17]:

$$PSNR_{(color)} = 10\log_{10}\left(\frac{255^2}{MSE_{(color)}}\right)dB \qquad \ldots(3)$$

Where,

$$MSE_{(color)} = \frac{1}{N}\left(x_{jk} - y_{jk}\right)^2 \qquad \ldots(4)$$

The average PSNR can be calculated as follows:

$$PSNR = \frac{PSNR_{(red)} + PSNR_{(green)} + PSNR_{(blue)}}{3} \qquad \ldots(5)$$

To find the BitPerPixel, this equation can be used[18]:

$$BitsPerPixel = \frac{NumberofBits}{NumberofPixels} = \frac{(8)(Numberofbytes)}{N * N} \qquad \ldots(6)$$

4. Digital Image Background

A digital image is a rectangular array of dots, or pixels, arranged in m rows and n columns. A digital image is represented by a two-dimensional array of pixels, which are arranged in rows and columns. Hence, a digital image can be presented as M×N array.

$$f(x,y) = \begin{bmatrix} f(0,0) & f(0,1) & \ldots\ldots f(0,N-1) \\ f(1,0) & f(1,1) & \ldots\ldots f(1,N-1) \\ . & . & . \\ . & . & . \\ f(M\text{-}1,0) & f(M\text{-}1,1) & f(M\text{-}1,N\text{-}1) \end{bmatrix}$$

Where, f(0,0) gives the pixel of the left top corner of the array that represents the image and f(M-1,N-1) represents the right bottom corner of the array. A Grey-scale image, also referred to as a monochrome image contains the values ranging from 0 to 255, where 0 is black, 255 is white and values in between are shades of grey. In color images, each pixel of the array is constructed by combining three different channels (RGB) which are R=red, G=green and B=blue. Each channel represents a value from 0 to 255. In digital image, each pixel is stored in three bytes, while in a Grey image is represented by only one byte. Therefore, color images take three times the size of Gray images [19].

5. Image Compression

The main idea in the image compression is to reduce the data stored in the original image to a smaller amount. According to scientific revolution in the internet and the expansion of multimedia applications, the requirements of new technologies have been grown. Recently, many different techniques have been developed to address these requirements for both lossy and lossless compression. Modern computers employ graphics extensively. Window-based operating systems display the disk's file directory graphically. The progress of many system operations, such as downloading a file, may also be displayed graphically. Now-a-days, most of the applications working under windows provide a graphical user interface (GUI), which makes it easier to use the program. Many areas of life use computer graphics to change the type of the problem from information to a digital image. Thus, images are important, but they tend to be big! Modern hardware can display many colors, which is why it is common to have a pixel represented internally as a 24-bit number, where the percentages of red, green, and blue occupy 8 bits each. Such a 24-bit pixel can specify 16.78 million colors. As a result, an image at a resolution of 512×512 that consists of such pixels occupies 786,432 bytes. At a resolution of 1280×800 it gives 3,072,000 bytes as a total for 3 bytes for each pixel which makes it four times as big as 512×512. Therefore, an image compression arises to solve this problem[19].

6. Run Length Encoding

Run Length Encoding is a compression technique that replaces consecutive occurrences of a symbol with the symbol followed by the number of times it is repeated. For example, the string 111110000003355 could be represented by 15063252. Clearly, this compression technique is most useful where symbols appear in long runs, and thus can sometimes be useful for images that have areas where the pixels all have the same value, cartoons for example[20].

7. K- Means Algorithm

K-means algorithm was originally introduced by McQueen in 1967. It is a non-fuzzy clustering method, whereby each pattern can only belong to one
center at any one time. Let $X = \{x_1, x_2, ..., x_n\}$ represents a set of data, where n is the number of data points. $V = \{v_1, v_2, ..., v_c\}$ is the corresponding set of centers, where c is the number of clusters. The aim of K-means algorithm is to minimize the objective function *J (V),* in this case a squared error functions[21]:

$$J(V) = \sum_{i=1}^{c}\sum_{j=1}^{ci}\left\| x_{ij} - v_j \right\|^2 \qquad \ldots(7)$$

Where $\left\| x_{ij} - v_j \right\|$ is the Euclidean distance between x_{ij} and v_j, c_i is the number of data points in the cluster i.

The ith center v_i can be calculated as :

$$v_i = \frac{1}{c_i}\sum_{j=1}^{c_i} x_{ij} \qquad i = 1,....c \qquad \text{...(8)}$$

The procedure of this algorithm can be described as follows:

1) Randomly select *c* cluster centers.
2) Calculate the distance between all of the data points and each center.
3) Data is assigned to a cluster based on the minimum distance.
4) Recalculate the center positions using (8).
5) Recalculate the distance between each data point and each center. And
6) If no data was reassigned, then stop, otherwise repeat (3)[21][22].

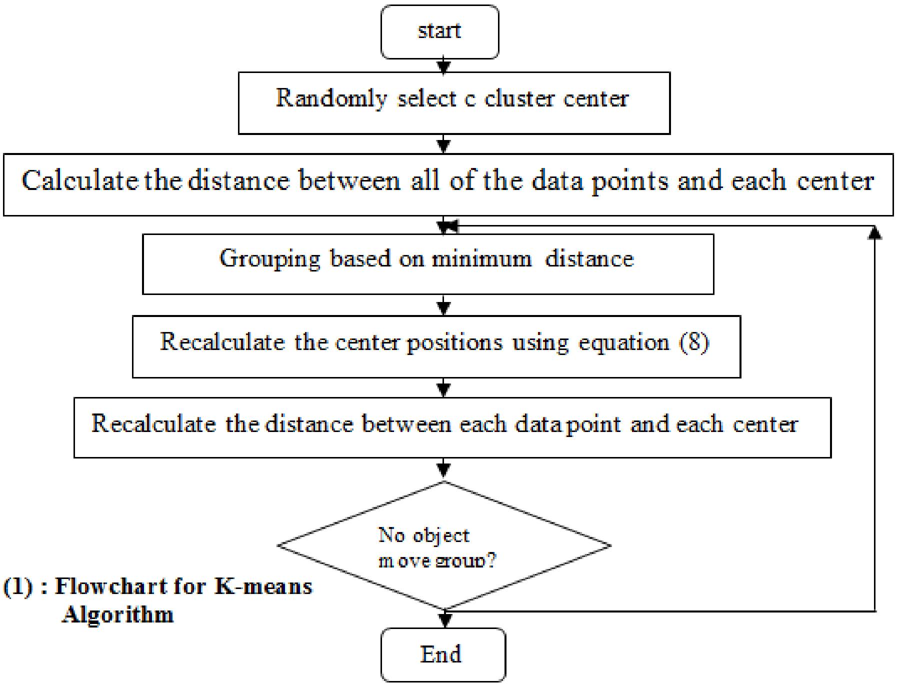

Figure (1) : Flowchart for K-means Algorithm

8. Gath-Geva Fuzzy Clustering Algorithm

Gath-Geva (GG) can be used to detect ellipsoidal clusters with varying size[23]. G-G fuzzy clustering algorithm takes the size and density of clusters for classification[5]. The objective function based on the minimization of the sum of weighted squared distances between the data points and cluster centers is described in the following[4][23]:

$$J\,(Z,U,V) = \sum_{i=1}^{c}\sum_{k=1}^{N}(\mu_{ik})^m\, D_{ik}^2 \qquad \text{...(9)}$$

Where Z is the set of data, $U = [\mu_{ik}]$ is the fuzzy partition matrix, $V = [V_1, V_2, ..., V_c]^T$ is the set of centers of the clusters, c is the number of clusters, N is the number of the data, m is the fuzzy coefficient, μ_{ik} is the membership degree between the i-th cluster and k-th data, which satisfies conditions:

$$\mu_{ik} \in [0,1]; \sum_{i=1}^{c}\mu_{ik} = 1 \qquad \text{...(10)}$$

The minimum of (U,V) is calculated as follows:

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c} (D_{ik} / D_{jk})^{2/(m-1)}} \qquad \ldots(11)$$

$$v_i = \frac{\sum_{k=1}^{N} (\mu_{ik})^m \, X_k}{\sum_{k=1}^{N} (\mu_{ik})^m} \qquad \ldots(12)$$

The norm of distance between i-th cluster and k-th data is :

$$D_{ik}(X_k, V_i) = \frac{\sqrt{\det(F_{mi})}}{P_i} * \exp\left(\frac{1}{2}(X_k - V_i)^T F_{mi}^{-1}(X_k - V_i)\right) \qquad \ldots(13)$$

$$F_{mi} = \frac{\sum_{k=1}^{N} (\mu_{ik})^m (X_k - V_i)(X_k - V_i)^T}{\sum_{k=1}^{N} (\mu_{ik})^m} \qquad \ldots(14)$$

Where, the F_{mi} is the fuzzy covariance matrix of the i-th cluster, μ_{ik} is the fuzzy partitioning matrix, m is the weighting exponent controls the 'fuzziness' of the resulting cluster and P_i is aprior probability of selecting the i-th cluster. The distance in Eq. (13) is used in the calculation of P_i, the probability of selecting the i-th cluster given the k-th data point, is given by:

$$P_i = \frac{1}{N} \sum_{k=1}^{N} \mu_{ik} \qquad \ldots(15)$$

The steps of the GG algorithm are listed as follows[4]:

Step1: determining the number of cluster; c and m value(let $m = 2$), given the converge error, $\varepsilon > 0$.

Step2: generate the matrix U randomly, U must satisfy the condition (10).

Step3: compute the parameters of the model using (12), (14), (15).

Step4: calculate the norm of distance utilizing (13).

Step5: update the partition matrix U using (11).

Step6: stop if $\left\| U^{(l)} - U^{(l-1)} \right\| \le \varepsilon$, else go to step 3.

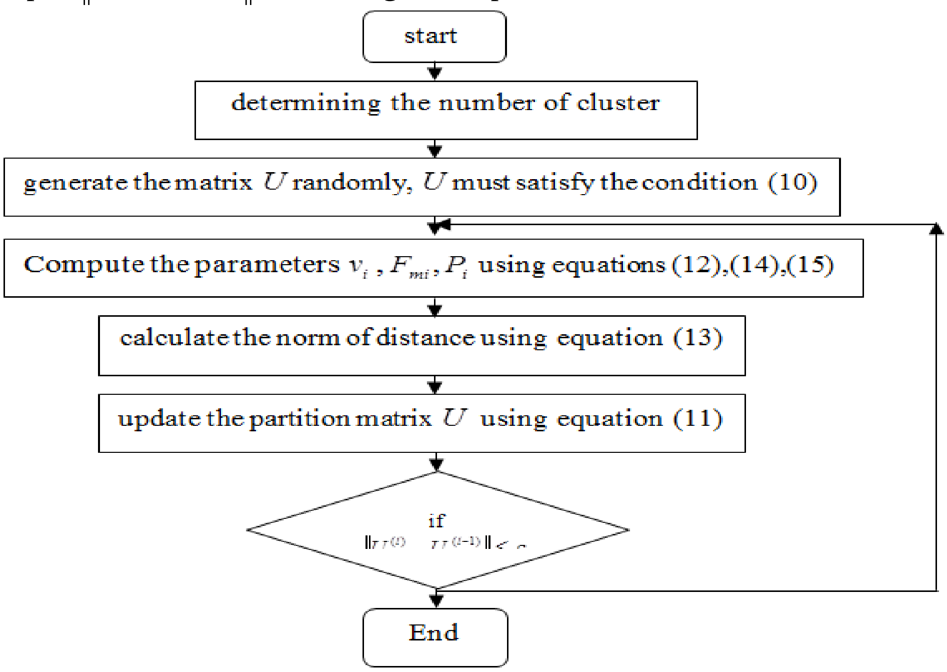

Figure (2) : Flowchart for Gath-Geva Fuzzy Clustering Algorithm

9. Particles Swarm Optimization (PSO)

A PSO is population-based optimization algorithms modeled after the simulation of social behaviour of bird in a flock. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. Each particle is flown through the search space, having its position adjusted based on its distance from its own personal best position and the distance from the best particle of the swarm. The performance of each particle. i.e., how close the particle is from the global optimum, is measured using a fitness function which depends on the optimization problem. Each particle i flies through the n-dimensional search R^n and maintains the following information:

- x_i, the current position of the particle i (x-vector).
- p_i, the personal best position of the particle i (p-vector).
- v_i, the current velocity of the particle i (v-vector).

The personal best position associated with a particle i is the best position that the particle has visited so far. If f denotes the fitness function, then the personal best of particle i at a time step t is updated as :

$$p_i(t+1)=\begin{cases} p_i(t) & if\ \ f(x_i(t+1))\geq f(p_i(t)) \\ x_i(t+1) & if\ \ f(x_i(t+1))< f(p_i(t)) \end{cases} \qquad \ldots(16)$$

If the position of the global best particle is denoted by gbest, then:

$$\begin{aligned} gbest &\in \{p_0(t), p_1(t), \ldots\ldots, p_m(t)\} \\ &= \min\{f(p_0(t)), f(p_1(t)), \ldots\ldots, f(p_m(t))\} \end{aligned} \qquad \ldots(17)$$

The velocity updates is calculated as a linear combination of position and velocity vectors. Thus, the velocity of particle i is updated by using equation 18 and the position of particle i is updated by using equation 19:

$$v_i(t+1)= wv_i(\mathrm{t})+\mathrm{c1r1}(\mathrm{p_i}(t)-x_i(t)+c2r2\ gbest-x_{i(t)}) \qquad \ldots(18)$$

$$x_i(t+1)=x_i(t)+v_i(t+1) \qquad \ldots(19)$$

In the formula, w is the inertia weight, c_1, and c_2 are the acceleration constants and r_1, r_2 are random numbers in the rang [0,1], v_i must be in a predefined range [$V_{\min}$, $V_{\max}$], where if $V_i > V_{\max}$ then $V_i = V_{\max}$, and if $V_i < V_{\min}$ then $V_i = V_{\min}$ [7]. And Figure (3) shows the flow chart for Particle Swarm Optimization [24].

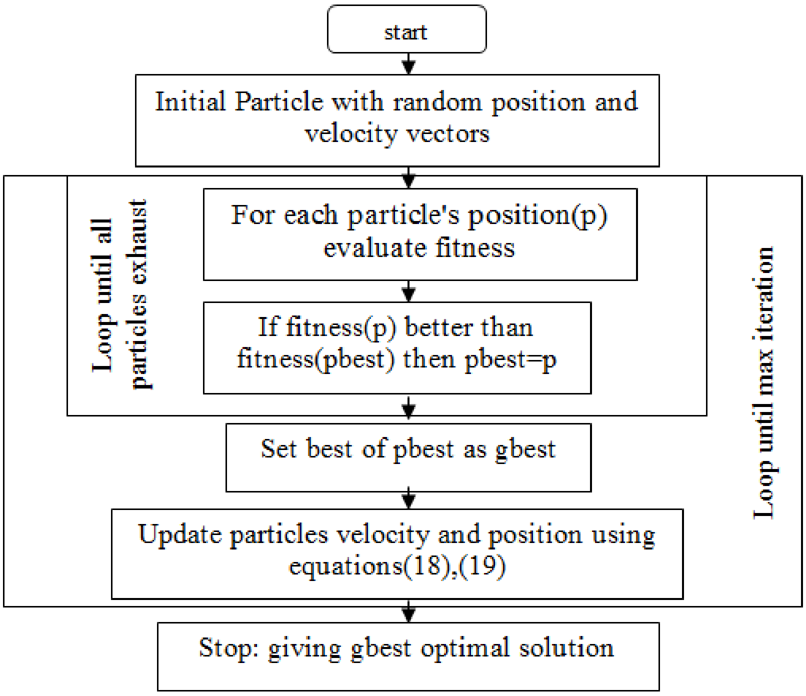

Figure (3) : Flow chart for Particle Swarm Optimization (PSO)

10. Fuzzy Backpropagation Network

Artificial neural networks are massively parallel adaptive networks of simple non-liner computing elements called neurons which are intended to abstract and model some of the functionality of the human nervous system in an attempt to partially capture some of its computational strengths. Neural networks are classified as feed forward and feedback networks. Back propagation network is of feed forward type. In BPNN the errors are back propagated to the input level[8]. By combining Gath-Geva fuzzy clustering algorithm with backpropagation network, Fuzzy backpropagation neural network was produced. The fuzzy backpropagation neural network (FBPNN) algorithm is as follows[8][25] and [26]:

Step 1: create initial random weights for network nodes .

Step 2: A vector pair $\lfloor X_p, T_p \rfloor$ of the training set, is selected in random.

calculate output for each node in each layer L in network.

$$net_{pj}^{L+1} = \sum_{i=1}^{n^L} w_{ij}^L \, out_i^L + bias_j^{L+1} \qquad \ldots(20)$$

$$out_{pj}^{L+1} = f\left(net_{pj}^{L+1}\right) = \frac{1}{1+e^{-\beta \, net_{pj}^{L+1}}} \qquad \ldots(21)$$

Step 3 : calculate the error between actual output out_{pj} and target output, and

use the actual output out_{pj}^{o} with target output t_{pj} to calculate δ

$$\delta_{pj}^{o} = \left(t_{pj} - out_{pj}^{o}\right) f'(net_{pj}^{o}) \qquad \ldots(22)$$

Step 4: calculate δ value for each hidden layer

$$\delta_{pi}^{L+1} = f'(net_{pi}^{L+1}) \left[\sum_{j=1}^{m^{L+2}} \delta_{pj}^{L+2} \, w_{ij}^{L+1} \right] \qquad \ldots(23)$$

And

Step 5: update the weights by adding z_i to the standard update weight equation for backpropagation network, then this equation becomes as follows:

$$w_{ij}^{new} = \mathrm{w}_{\mathrm{ij}}^{\mathrm{old}} + \Delta\, \mathrm{w}_{\mathrm{ij}}^{\mathrm{L}} \qquad \ldots(24)$$

$$\Delta w_{ij}^{L} = \mathrm{z}_{\mathrm{i}}\, \eta\, \delta_{pj}^{L+1}\ \mathrm{out}_{\mathrm{pi}}^{\mathrm{L}} \qquad \ldots(25)$$

Where, $z_i = (\mu_{ik})^m$

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c} \left(D_{ik} / D_{jk}\right)^{2/(m-1)}} \qquad \ldots(26)$$

Step 5 : return to step 2 , repeated for each pattern of training set.

Figure (4) shows the structure of FBP network, The number of the input nodes in FBP is (256 nodes) in input layer for image that have resolution (256 x 256), and equal(300 nodes) in input layer for image that have resolution (300 x 250) , and 6 nodes in hidden layer which randomly selected, the output is 15 nodes which are equal to number of cluster center.

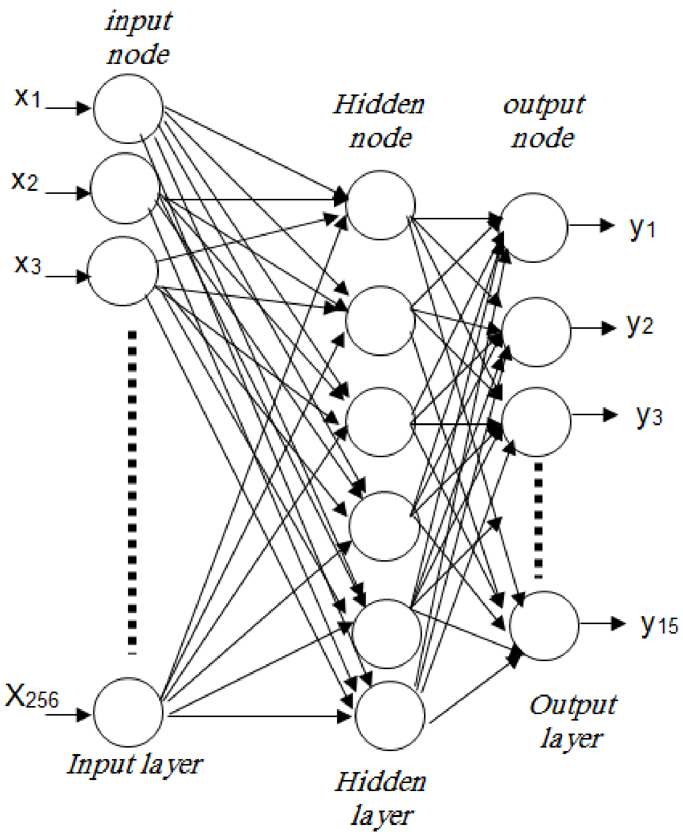

Figure (4): structure for Fuzzy BackPropagation Network (FBPN)

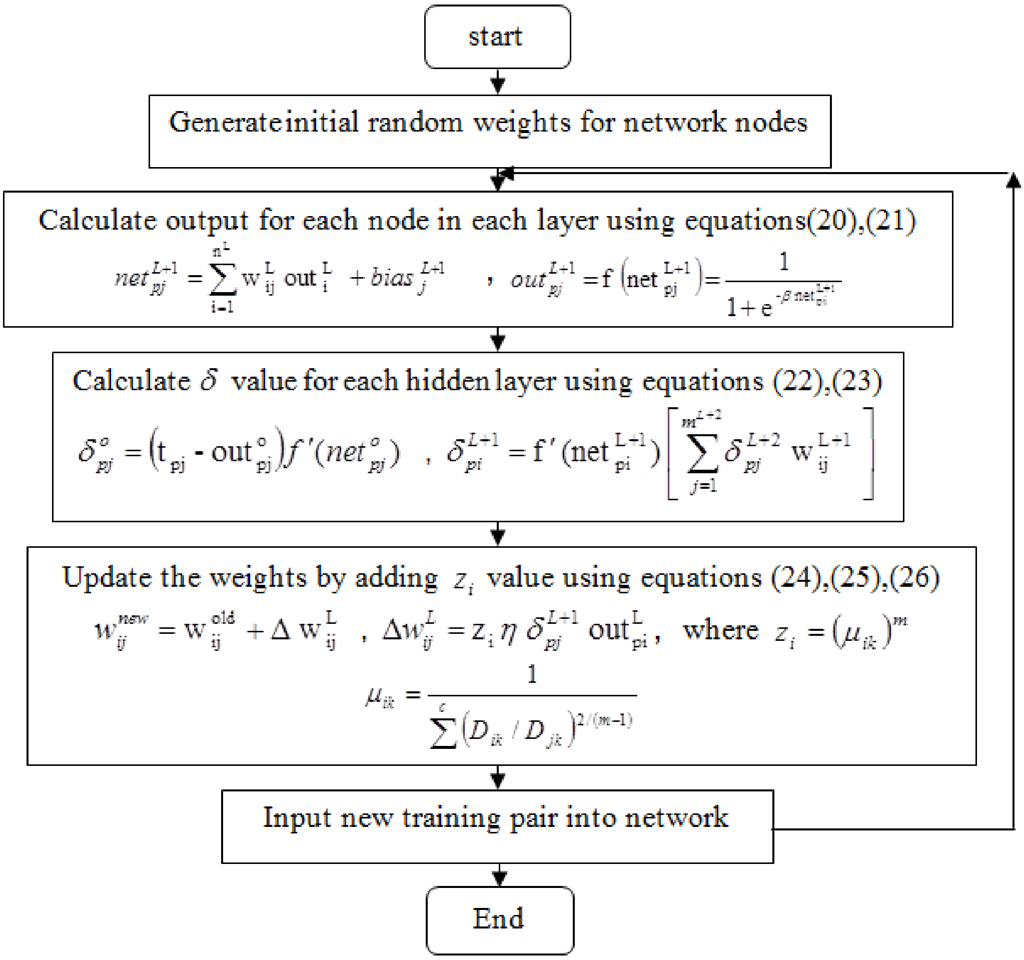

Figure (5) : Flowchart for Fuzzy BackPropagation Network (FBPN) Algorithm

11. Experimental Results

In this research, four methods were used K-means, Gath-Geva Fuzzy Clustering Algorithm (G-G FCA), and PSO, and then combined backpropagation network with G-G FCA to produce Fuzzy BP method, to evaluate the performance of these methods, experiments are conducted by using these methods on different images of size (256 x 256), and (300 x 250) pixels to obtain clustered images, and then compress these images by using RLE algorithm to obtain efficiently compressed images with less number of bits. Compression was measured in bits per pixel(BPP), and also compression ratio was calculated by this equation[18]:

$$compression\ ratio = \frac{uncompressed\ \ file\ size}{compressed\ file\ size} \quad \ldots(27)$$

The computed values for bpp, PSNR, and compression ratio(CR)for color images pepperd_red, strawberry, and for gray level tulips image using these four methods which are given in tables 1- 3. From these tables, we observe that the fuzzy BP method accomplishes enhanced bit per pixel bpp rate, and compression ratio comparable image quality than (k-means, G-G FCA, and PSO) methods. Figures 6-8 show the result for the four methods were used, and the reconstructed images of pepperd_red, strawberry, and tulips image by using these four methods.

Table (1) shows results pepper_red image(256x256) and original point number (196608) 192 KB

Pepper_red image	k-means	G-G FCA	PSO	Fuzzy BP
Points number	27108	10280	3550	224
Bit rate(bpp)	1.103027	0.418294	0.144450	0.009115
$PSNR_{red}$ in dB	16.615177	69.228069	50.098396	61.071770
$PSNR_{green}$ in dB	17.594070	67.302221	53.565543	72.352903
$PSNR_{blue}$ in dB	18.332654	64.255607	57.259514	61.600636
PSNR in dB	17.513967	66.928632	53.641151	65.608437
File size after compressed	63.5 KB	22.85 KB	8.23 KB	2.39 KB
Compression ratio (CR)	3.02	8.40	23.33	80.33

Table (2) shows results strawberry image(300x250) and original point number (225000) 219 KB

strawberry image	k-means	G-G FCA	PSO	Fuzzy BP
Points number	40146	18846	9992	777
Bit rate(bpp)	1.427413	0.670080	0.355271	0.027627
$PSNR_{red}$ in dB	16.205393	69.322573	47.687673	56.916362
$PSNR_{green}$ in dB	18.358513	69.229709	57.100923	63.709687
$PSNR_{blue}$ in dB	15.908691	69.205020	61.142413	62.485772
PSNR in dB	16.824199	69.252434	55.310337	61.037274
File size after compressed	97.5 KB	40.07 KB	21.94 KB	2.74 KB
Compression ratio (CR)	2.25	5.47	9.98	79.93

Table (3) shows results tulips image(256x256) gray level image and original point number (65536) 65 KB

tulips image	k-means	G-G FCA	PSO	Fuzzy BP
Points number	12528	10192	5956	722
Bit rate(bpp)	1.529297	1.244141	0.727051	0.0881348
PSNR in dB	16.983647	66.596139	54.952200	66.091711
File size after compressed	29.4 KB	21.7 KB	12.9 KB	1.73 KB
Compression ratio (CR)	2.21	2.99	5.04	37.57

Table (4) shows the comparison between K-means, G-G FCA, PSO, and Fuzzy BP for image compression. The FBP is better than other methods were used in this research (K-means, G-G FCA, and PSO), because FBP method obtained higher compression ratio CR, and lower BitPerPixels BPP.

Table (4) shows comparison between (K-means, G-G FCA, PSO, and Fuzzy BP)

Gray level and color Images	Measures	K-means	G-G FCA	PSO	Fuzzy BP
tulips image	Bit rate(bpp)	1.529297	1.244141	0.727051	0.0881348
	Compression ratio (CR)	2.21	2.99	5.04	37.57
strawberry image	Bit rate(bpp)	1.427413	0.670080	0.355271	0.027627
	Compression ratio (CR)	2.25	5.47	9.98	79.93
Pepper_red image	Bit rate(bpp)	1.103027	0.418294	0.144450	0.009115
	Compression ratio (CR)	3.02	8.40	23.33	80.33

Table (5) compares results between (K-means, G-G FCA, PSO, and Fuzzy BP)

With previous works

Images	methods	Bit rate(bpp)	Compression ratio (CR)	PSNR
Lena	Neuro-wavelet model and fuzzy vector quantization technique[1]	0.296 bpp	-	22.132
Cameraman	Counter Propagation Neural Networks[27]	-	9.4	29.84
Lena		-	9.7	29.01
Pepper		-	9.8	29.14
Fruits		-	9.8	29.98
Lena	Self Organizing Feature Map (SOM)[28]	-	19.75	27.7
Einstein image		-	22.63	26.0
Couple image		-	29.69	28.2
tulips image	k-means	1.529297	2.21	16.983647
	G-G FCA	1.244141	2.99	66.596139
	PSO	0.727051	5.04	54.952200
	Fuzzy BP	0.0881348	37.57	66.091711
strawberry image	k-means	1.427413	2.25	16.824199
	G-G FCA	0.670080	5.47	69.252434
	PSO	0.355271	9.98	55.310337
	Fuzzy BP	0.027627	79.93	61.037274
Pepper_red	k-means	1.103027	3.02	17.513967
	G-G FCA	0.418294	8.40	66.928632
	PSO	0.144450	23.33	53.641151
	Fuzzy BP	0.009115	80.33	65.608437

12. Conclusions

In this research, we have presented K- MEANS method and some of artificial intelligent techniques such as, Gath-Geva fuzzy clustering algorithm G-G FCA, Particle Swarm Optimization PSO, and a proposed method Fuzzy backpropagation neural network FBPNN that obtained by the combination of G-G FCA with standard BPNN. Real images were used to compare the performance of these four methods. Various experiments were conducted on (300 x 250), (256 x 256) images. The proposed method FBPNN is proved to be highly efficient in compression and reconstruction of gray level and color images. The proposed FBPNN method shows better performance in terms of points number, bits per pixel rate (bpp) , and compression ratio (CR), when compared with the other methods (k-means, G-G FCA, and PSO) were used in this research.

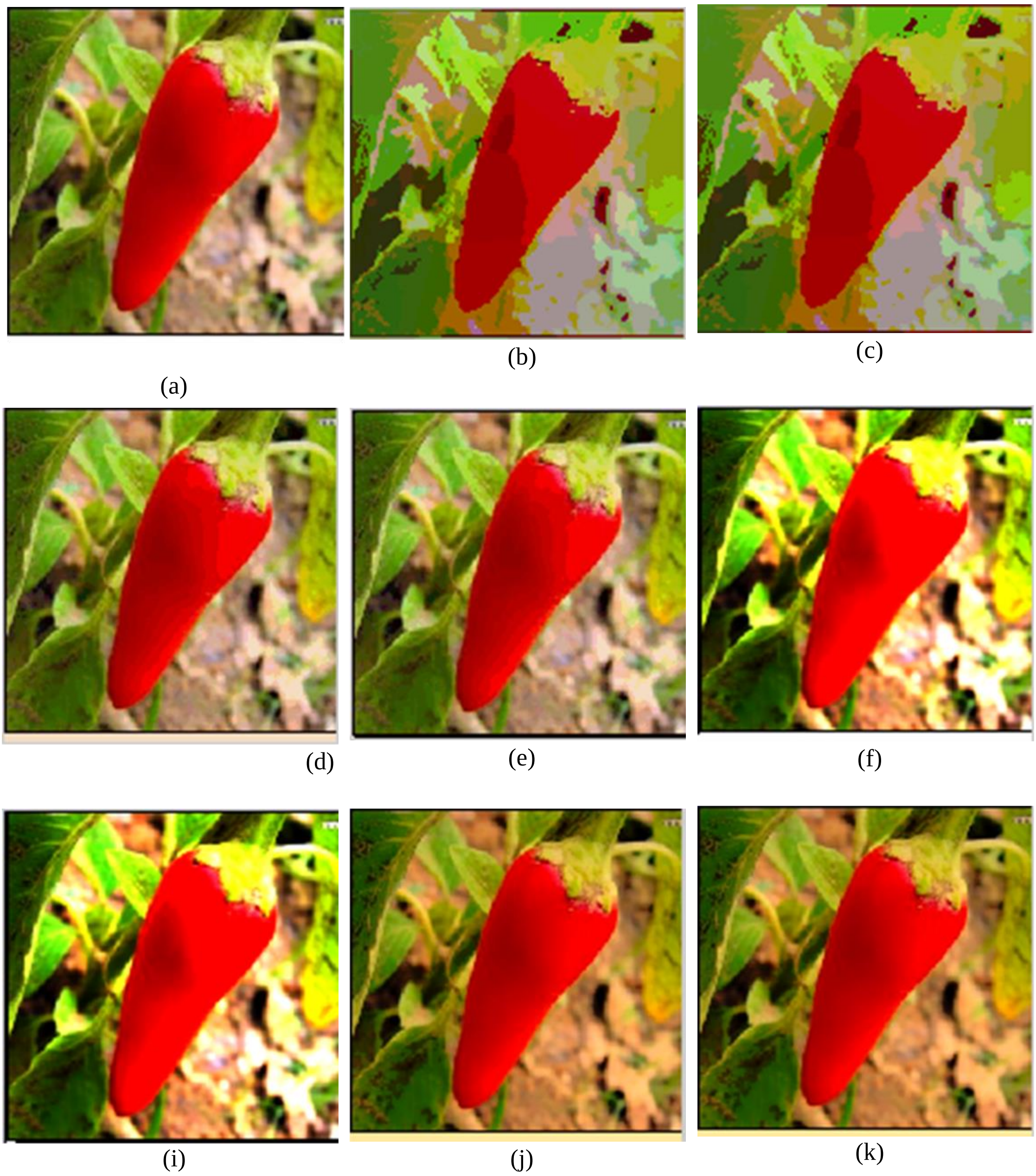

Figure (6): original pepper_red image and the results of K-means, G-G FCA, PSO, Fuzzy BP methods
(a) original image, (b) k-means result, (c) k-means reconstructed image, (d) G-G FCA result, (e) G-G FCA reconstructed image, (f) PSO result, (i) PSO reconstructed image, (j) Fuzzy BP result, (k) Fuzzy BP reconstructed image

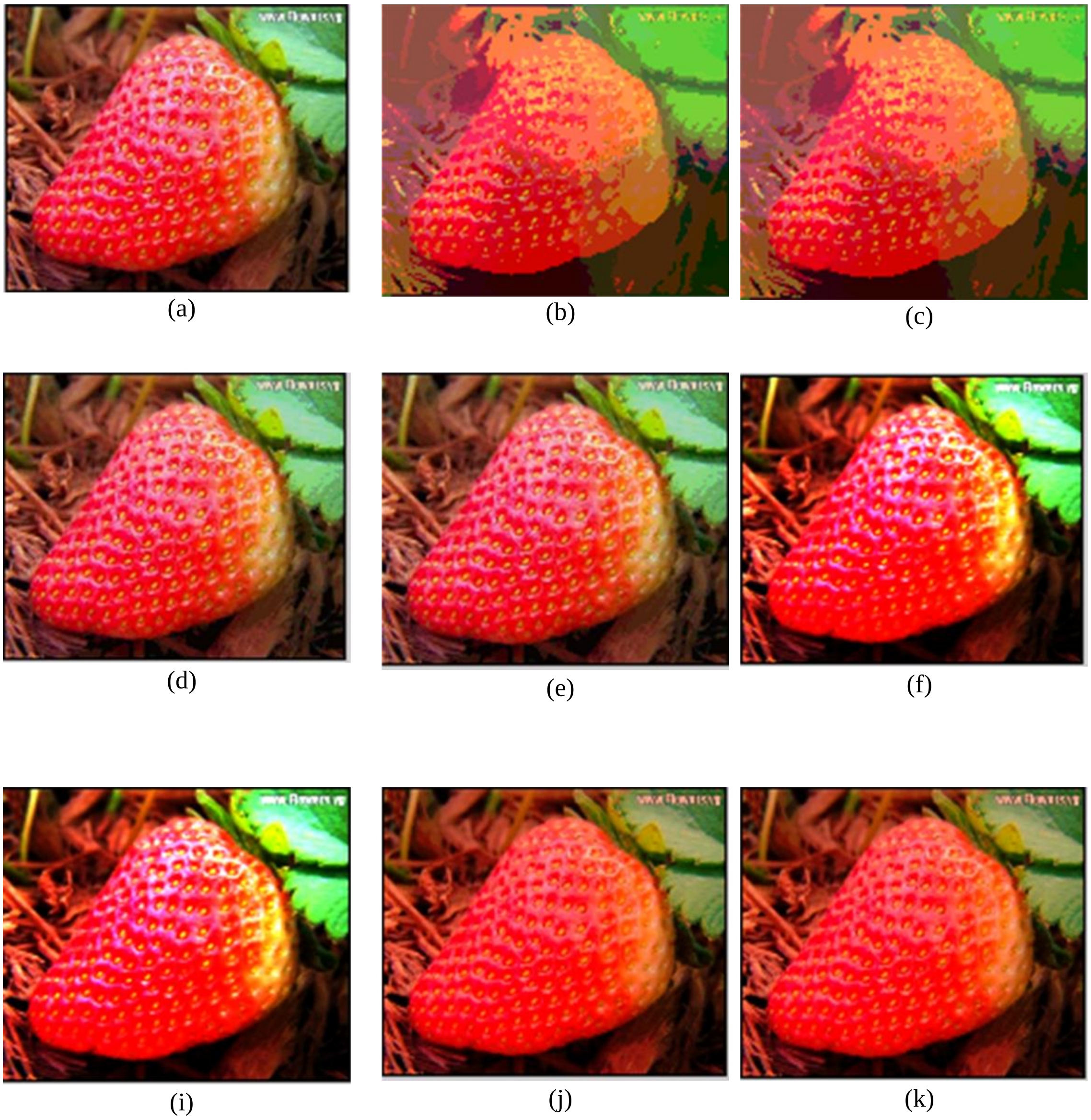

Figure (7): original strawberry image and the results of K-means, G-G FCA, PSO, Fuzzy BP methods
(a) original image, (b) k-means result, (c) k-means reconstructed image, (d) G-G FCA result, (e) G-G FCA reconstructed image, (f) PSO result, (i) PSO reconstructed image, (j) Fuzzy BP result, (k) Fuzzy BP reconstructed image

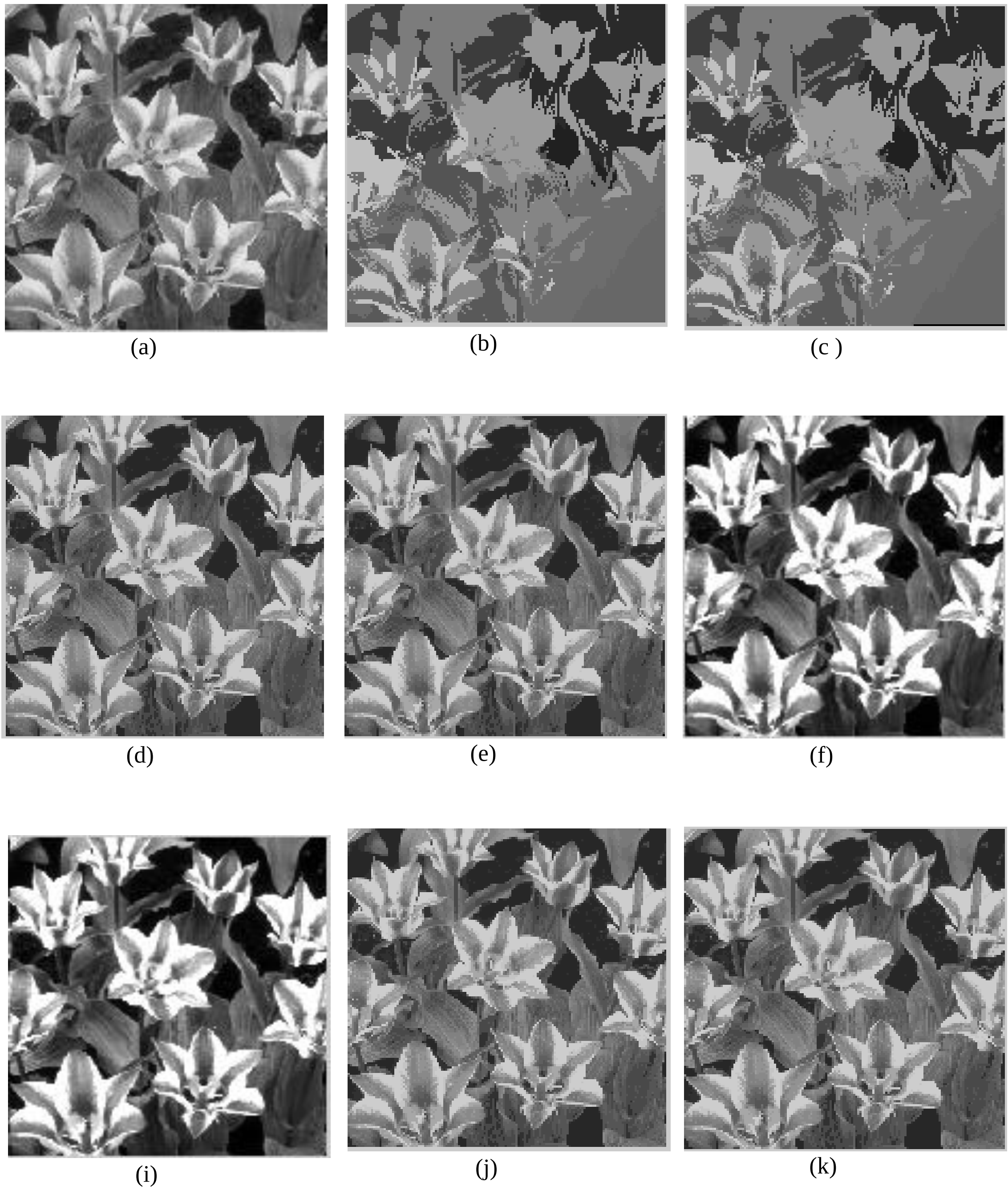

Figure (8): original tulips image and the results of K-means, G-G FCA, PSO, Fuzzy BP methods (a) original image, (b) k-means result, (c) k-means reconstructed image, (d) G-G FCA result, (e) G-G FCA reconstructed image, (f) PSO result, (i) PSO reconstructed image, (j) Fuzzy BP result, (k) Fuzzy BP reconstructed image

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