

LOCAL CONTRAST ENHANCEMENT USING INTUITIONISTIC FUZZY SETS OPTIMIZED BY ARTIFICIAL BEE COLONY ALGORITHM

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Abstract - In this research, the researcher presents the enhancement method of cells images. The first method used in the local contrast enhancement is Intuitionistic Fuzzy Sets (IFS). The proposed method is the IFS optimized by Artificial Bee Colony (ABC) algorithm. The ABC is used to optimize the membership function parameter of IFS. To measure the image quality, Image Enhancement Metric (IEM) is applied. The results of local contrast enhancement using both methods are compared with the results using histogram equalization method. The tests are conducted using two MDCK cell images. The results of local contrast enhancement using both methods are evaluated by observing the enhanced images and IEM values. The results show that the methods outperform the histogram equalization method. Furthermore, the method using IFS-ABC is better than the IFS method.

Keywords: Local contrast enhancement, Cell, Intuitionistic Fuzzy Sets, Artificial Bee Colony Algorithm

I. INTRODUCTION

Image quality is an essential element for the human vision in utilizing and analyzing the image. Image quality can be very crucial in some areas of utilization. One of the utilization areas is medical image analysis. There are several needs in medical image analysis, and one of them is the clarity of the image. In most cases, a little noise of the image will yield a difficulty for its users such as the doctor or other medical staffs in analyzing. Removal of noise in the image is not easy and effective in image handling. Therefore, in this case, the image enhancement plays an important role in medical image analysis. Image enhancement deals the converting of an image to another to make it significantly clearer for the human observers.

One of the tasks before utilizing or analyzing a noisy image is the enhancement of image information. An algorithm that is used widely to enhance an image is global histogram equalization (Nayak, 2016). However, there is a shortcoming in this technique; the global image properties may not be reasonably and effectively applied in a local neighborhood setting. In addition, for images with extensive spatial variety, global stretching and histogram equalization techniques do not always create great results. To overcome the issue, various techniques on local contrast enhancement have been proposed. These procedures can be separated into three general domains: spatial, frequency and fuzzy domain. The last one includes the utilization of learning base frameworks that are fit to imitate the human expertise.

Fuzzy set theory is utilized in image processing because of its ability to handle the imprecision in images effectively. Some researches are continuously undertaken in

this area to make improvement in the existing techniques. Fuzzy procedures have been applied in some areas of image handling such as thresholding (Al-Azawi, 2013), clustering (Selvy, Palanisamy, & Purusothaman, 2011), interpolation (Chen & Wang, 2009), and morphology (Nayak & Bhoi, 2014). In the area of local contrast enhancement, the utilization of fuzzy technique is also increasing that some fuzzy based techniques have been proposed. A method of generating the fuzzy if-then rules has been proposed to be applied specifically to a given image based on the available local information to be used by a fuzzy inference system (Jayaram, Narayana, & Vetrivel, 2011). Another research by Sharma and Bhatia (2015) presented image enhancement using modified fuzzy based algorithms with color normalization to reduce color artifacts. Fuzzy grayscale image enhancement technique is proposed to maximize the fuzzy measures contained in the image (Hasikin & Isa, 2012). However, fuzzy sets may not match the requirement of assigning degrees of membership to the elements of a set precisely. This constraint raises some of the flexibility of fuzzy sets theory to cope with data characterized by uncertainty. This observation leads the researcher to search more efficient ways to express and model imprecision, which leads to higher-order extensions of fuzzy set theory. Therefore, Intuitionistic Fuzzy Sets (IFS) theory is brought into image handling.

Atanassov (2012) has proposed an idea of Intuitionistic Fuzzy Sets (IFS) which is thought to be exceptionally valuable to manage ambiguity. The significantly preferred stand point of IFS over the fuzzy set is the capability of IFS to differentiate between the level of membership degree and the level of non-membership degree of an element in the fuzzy set (Nayak, 2016). More uncertainties can be taken into account in the form of membership function by the IFS compared to conventional fuzzy sets (Deng, Sun, Liu, Ye, & Zhou, 2016). IFS that was proposed by Atanassov (2012) described the intuitionistic fuzzy sets as a reasonable method to demonstrate the hesitancy emerging from uncertain or unclear information. The cause of the hesitation is the inadequate knowledge or the individual error in characterizing the membership function (Chaira, 2015). In IFS, the belongingness of an element to a set is characterized by two properties, the membership, and non-membership of that element.

In this research, the medical images which contain uncertainties need to be enhanced. One of the IFS properties is the capability of considering more number of uncertainties. Therefore IFS will be appropriate to be applied to enhance the medical images. One of the crucial needs for processing the medical images is the image improvement. When some the structures in the medical image are not highlighted appropriately, the improvement of that image is vital. In the case, after the image is improved appropriately, the

post handling results by the medical staff will be better and precise.

In enhancing the images, IFS has a constant parameter in determining the membership function and calculating the hesitancy degree. To obtain the best result, trial and error method is used. The result obtained is not always the best one, so a systematic procedure needs to be utilized to obtain an optimized result. Therefore, an optimization algorithm is required to do the task.

ABC algorithm is a new algorithm that is inspired by the behavior of honey bee colonies in searching food. This algorithm was first introduced by Karaboga and Akay (2009). ABC algorithm does not use crossover operators to create new or candidate arrangements from the present ones. Comparing to the other algorithms, the operators are utilized by the algorithm based on genetic programmings such as Genetic Algorithm (GA) and evolutionary algorithm such as Differential Evolution (DE). The operation to create candidate solution by ABC is based on its parent, which considers the distinction parts of the parent and the arbitrarily picked solutions from the population. Using this process, the velocity of convergence can be increased so that the duration of searching the local minimum is shortened (Karaboga & Akay, 2009).

In algorithm based on genetic programming technique (GA), the evolutionary algorithm (DE) as well as the well-known swarm-based algorithm such as Particle Swarm Optimization (PSO), the best solution so far is found residing in the population. It is further utilized to create the next solutions as a part of the instance of GA and DE. In the case of PSO, it is called the new velocities. On the other hand, in any case, the best solution found so far by ABC is not stored in the population. This is because the scout in ABC may be supplanted with an arbitrarily created solution. Therefore, this will not add to the creation of trial solutions (Karaboga & Akay, 2009). It has been studied that the execution of ABC calculation is superior to or like these algorithms despite the fact that it utilizes fewer control parameters. Therefore, among the optimization algorithm widely used nowadays, Artificial Bee Colony (ABC) algorithm is chosen in this research to optimize the IFS. Thus, the objective of this research is to enhance medical images using IFS that is optimized by ABC. The method used is by calculating the membership functions of each pixel in the original images using IFS. Then, the optimum values of the membership function, non-membership function, and hesitancy values are obtained by the ABC. The optimum values of pixel intensity are obtained by the ABC by applying the Image Enhancement Metric as the objective function.

This technique has two favorable contributions. First, the membership function of IFS is established by utilizing the ABC algorithm to find its optimum parameter value and further standardized to [0,1]. It is a reasonable technique to enhance distinctive parts of an image. Second, the fuzzification and defuzzification operations of IFS are sequentially implemented on each pixel of the image by implementing the Image Enhancement Metric. To evaluate the performance of the technique, it is suggested to compare it with the well-known image enhancement technique, histogram equalization.

II. METHODS

The theory of IFS defines that in a limited set of $X = \{x_1, x_2, \dots, x_n\}$, the fuzzy set can be mathematically

expressed as:

$$A = \{(x, \mu_A(x)) | x \in X\} \quad (1)$$

Where, $\mu_A(x): X \rightarrow [0,1]$ is the level of membership of element x in the limited set X . From (1) it can be mathematically analyzed that the degree of non-membership is $1 - \mu_A(x)$. To measure the hesitancy of membership of an element to an intuitionistic fuzzy set, Atanassov in Despi, Opris, and Yalcin (2013) defined that the degree of indeterminacy of x was to A . This hesitancy represents the membership degree emerging because of the insufficient knowledge. Using the presentation of hesitancy level, $\pi_A(x)$, non-membership degree is not the supplement of the membership degree as in the fuzzy set. It cannot be considered as equal or the same as the degree of membership complement. An intuitionistic fuzzy set A in a limited set X can be mathematically represented as (Chaira, 2015):

$$A = \{(x, \mu_A(x), \nu_A(x)) | x \in X\} \quad (2)$$

where, $\mu_A(x), \nu_A(x): X \rightarrow [0,1]$ is consecutively the membership and the non-membership function of elements x with the required condition (Chaira, 2015):

$$0 \leq \mu_A(x) + \nu_A(x) \leq 1 \quad (3)$$

and

$$\pi_A(x) + \mu_A(x) = 1 \quad (4)$$

Artificial Bee Colony Algorithm (ABC) is inspired by the behavior of bees in search of food. In ABC algorithm, some natural phenomena are simulated to search space to represent for aging process of bee colonies in real terms. Each solution obtained is referred to the source of food. The nectar from these food sources is represented as fitness (Karaboga & Akay, 2009). In the bee colony, there are three types of bees, namely, employee, onlooker, and scout. The duty of employee is to look for the food source and count nectar. Furthermore, the bees supply information to the onlooker bees. The duty of onlooker is to receive information about the quality of the food source and choose the best food source. Food source which contains more nectar has more opportunities to be chosen by the onlooker. After that, the employee who is in every food source goes to find a new food source in the neighborhood. Then, in the process of finding a new food source, the employee turns into scout (Karaboga & Akay, 2009). One of the parameters of the ABC algorithm is the number of bee population consisting of employee and onlooker. Every food source is occupied by an employee, so the amount of food source is equal to the number of employees and the number of onlookers (Karaboga & Akay, 2009).

In the ABC calculation, the quantity of the employed honey bees or the onlooker bees is equivalent to the number of arrangements in the population. At the initial step, the ABC creates an arbitrarily conveyed starting population P of SN arrangements (the positions of sustenance source), where SN indicates the span of the population. Every arrangement (nourishment source) $x_i (i = 1, 2, \dots, SN)$ is a D -dimensional vector. The number of inhabitants in the positions (arrangements) is according to rehashed cycles, $C = 1, 2, \dots, C_{max}$, of the determined procedures of the employed bees, onlooker bees, and scout bees. An artificial employed or onlooker honey bee probabilistically creates

a change in the position (arrangement) in the memory for finding another sustenance source and tests the nectar sum (wellness quality) of the new source (new arrangement) (Karaboga & Akay, 2009).

An artificial onlooker bee honey bee picks a sustenance source contingent upon the likelihood usefulness corresponds with that nourishment source, p_i , is computed by the following expression (Karaboga & Akay, 2009):

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \quad (5)$$

Where, fit_i is the wellness estimation of the arrangement i which is related to the nectar measure of the nourishment source in the position of i , and SN is the number of sustenance sources which is equivalent to the number of employed honey bees or onlooker bees. To deliver a candidate sustenance position from the old one in memory, the ABC utilizes the accompanying expression (Karaboga & Akay, 2009):

$$v_{ij} = x_{ij} + \Phi_{ij}(x_{ij} - x_{ij}) \quad (6)$$

Where, $k \in \{1,2, \dots, SN\}$ and $j \in \{1,2, \dots, D\}$ are randomly chosen indexes. Despite the fact that k resolve s randomly, it must be unique with i . $\Phi_{i,j}$ is an arbitrary number between $[-1,1]$. It controls the generation of neighbor sustenance sources around $x_{i,j}$ and determines the examination of two nourishment positions outwardly by a honey bee.

In ABC, if a position cannot be enhanced further through a foreordained number of cycles, then that sustenance source is considered to be relinquished. The estimation of predetermined number of cycles is a vital control parameter of the ABC calculation, which is called "limit" for deserting. The deserted source is x_i and $j \in \{1,2, \dots, D\}$ that the scout finds another nourishment source to be supplanted with x_i . This operation can be characterized as:

$$x_i^j = x_{min}^j + rand[0,1](x_{max}^j - x_{min}^j) \quad (7)$$

After every competitor of the source position ($v_{i,j}$) is delivered and assessed by the artificial honey bee, its execution is contrasted with the old one. If the new nourishment source has an equivalent or preferable nectar over the old source, it supplants the old one in the memory. Otherwise, the old one is held in the memory. The basic ABC defines three control parameters. The first is the number of food sources, which is equal to the number of employed or onlooker bees. The second is the value of the limit. Moreover, the third is the maximum cycle number.

The ABC algorithm is used to find the optimum parameter value of x in (2). A general structure of the ABC algorithm for optimization is given below (Karaboga, Gorkemli, Ozturk, & Karaboga, 2014):

Initialization Phase
REPEAT
Employed Bees Phase
Onlooker Bees Phase
Scout Bees Phase
Memorize the best solution achieved so far
UNTIL (Cycle = Maximum Cycle Number or a Maximum CPU time)

In this research, the objective function applied is

Image Enhancement Metric (IEM) which approximates the contrast and sharpness of an image by partitioning it into non-overlapping blocks. The average value of the total contrast between the inside pixel and its eight neighbors for every single nearby window in the reference and enhanced images will give a sign of the change in the contrast and sharpness. The window size of 3×3 is sufficient as the metric uses just eight neighbors.

The full-reference metric, IEM is characterized as the entirety proportion of total distinction estimations of every pixel from its 8-neighbors in the enhanced image and the reference image. It is represented by (Jaya & Gopikakumari, 2013) as:

$$IEM_{8n} = \frac{\sum_{m=1}^{k_1} \sum_{l=1}^{k_2} \sum_{n=1}^8 |I_{s,c}^{l,m} - I_{s,n}^{l,m}|}{\sum_{m=1}^{k_1} \sum_{l=1}^{k_2} \sum_{n=1}^8 |I_{r,c}^{l,m} - I_{r,n}^{l,m}|} \quad (8)$$

Where, the image is partitioned into $k_1 k_2$ squares of size 3×3 , and $I_{s,c}^{l,m}, I_{r,c}^{l,m}$ is the power of the inside pixel in block (l,m) of the improved and reference images respectively. $I_n^{l,m}, n = 1,2, \dots, 8$ demonstrates the 8 neighbors of the inside pixel.

When the reference image and improved images are indistinguishable, $IEM = 1$. $IEM > 1$ shows that the image has improved, or there is an impairment. The higher the estimation of IEM is, the better the change in image contrast and sharpness is (Jaya & Gopikakumari, 2013).

The images which need contrast enhancement are the ones consisting of similar values that are distributed in the narrow range, such as bright or dark values. This kind of images needs contrast enhancement which changes the image value s distribution to cover a wide range of values. The contrast of an image can be revealed by its histogram. The histogram of a monochrome image with L possible gray levels, $f = 0,1, \dots, L - 1$ can be expressed as $P(l) = \frac{nl}{n}$, where nl is the number of pixels with gray level l , and n is the total number of pixels in the image. The histogram equalization is used to transform an image with an arbitrary histogram to one with a flat histogram. If f has Probability Distribution Function ($p_f(t), 0 \leq f \leq 1$), this function will be transformed to $g(f) = \int_0^f p_f(t) dt$, where g is distributed in $(0,1)$ uniformly.

The proposed algorithm to utilize the IFS, ABC, and IEM in the local contrast enhancement of the images is defined in Algorithm 1. In this algorithm, the membership function of IFS is established to find its optimum parameter value and standardized to $[0, 1]$. In step 2.e, the fuzzification and defuzzification operations of IFS are sequentially implemented on each pixel of the image by implementing the Image Enhancement Metric. The Algorithm 1 can be seen as following:

Algorithm 1.

Step 1. Determine the Control Parameters of ABC algorithm

Step 2. Problem specific variables

Running Intuitionistic Fuzzy Set and the objective function

- Determine dimension of the image
- Computing Intuitionistic fuzzy membership function, fuzzification, and defuzzification
- Atanassov's operator to convert intuitionistic fuzzy image to fuzzy image
- Obtain enhanced image

- e. Calculate the Image Enhancement Metric for each pixel
- Step 3. All food sources are initialized
- Step 4. Employed Bee Phase
 - a. Calculate Probabilities
 - b. A food source is chosen with the probability which is proportional to its quality
- Step 5. Onlooker Bee Phase**
The best food source is memorized
Determine the food sources whose trial counter exceeds the "limit" value
- Step 7. Determine the global minimum**
- Step 8. Repeat iteration until the limit value is reached**

The implementation of proposed method was carried out using MATLAB software. The three different cell images were processed using the method. The first image is the populations of MDCK cells (Type 1) expressing C x 43 - GFP - 4C image with confocal microscopy by revealing the dynamic redistribution of C x 43 during mitosis (<http://ccdb.ucsd.edu/sand/main?mpid=7769&count=y&event=displayRaw>). The second is the image of MDCK cells (Type

2) expressing C x 43 - 4C309/337 (green) showing their rearrangement during and after mitosis (<http://ccdb.ucsd.edu/sand/main?mpid=7796&count=y&event=displayRaw>).

The different experiments were undertaken with the proposed method. The parameters used for the ABC are some variables (1), the maximum number of iterations (100), the number of population which is also the number of onlooker bees (100).

The result of local contrast enhancement process using IFS is compared with the one enhanced by using IFS optimized by ABC. Moreover, the images are compared with the result of enhancement using histogram equalization. The comparison is conducted by observing the images and comparing the IEM values.

III. RESULTS AND DISCUSSIONS

For the quantitative analysis, a particular part of the original image pixels is extracted and analyzed. The intuitionistic fuzzified membership function values of the original image for that part are presented in Table 1. The intensity values of pixels of the image part which correspond to the membership function values are displayed in Table 2.

Table 1 The Intuitionistic Fuzzified Membership Function Values of Pixels of the Original Image

Membership values of the image			Non-membership values of the image			Hesitancy values of the image		
0,5390	0,5390	0,5766	0,0002	0,0002	0,0001	0,4608	0,4608	0,4233
0,7010	0,4315	0	0,0000	0,0020	1,0000	0,2990	0,5665	0
0,5766	0,4769	0,3297	0,0001	0,0008	0,0123	0,4233	0,5223	0,6580
0,0757	0	0,1797	0,4206	1,0000	0,1132	0,5037	0	0,7071
0,1116	0,1116	0,4074	0,2720	0,2720	0,0032	0,6163	0,6163	0,5894
0,4984	0,6114	0,5943	0,0005	0,0000	0,0000	0,5011	0,3885	0,4056
0,4984	0,3018	0	0,0005	0,0192	1,0000	0,5011	0,6789	0
0,3297	0,3297	0,5943	0,0123	0,0123	0,0000	0,6580	0,6580	0,4056
0,5766	0,2119	0,5191	0,0001	0,0729	0,0003	0,4233	0,7153	0,4806
0,7915	0,9074	0,5390	0,0000	0,0000	0,0002	0,2085	0,0926	0,4608

Table 2 The Intensity Values of Pixels of The Image Part Corresponding to the Membership Function Values in Table 1

Intensity values of pixels		
75	75	82
106	58	0
82	65	43
9	0	22
14	14	54
69	88	85
69	39	0
43	43	85
82	27	72
126	161	75

Table 3 The Intuitionistic Fuzzified Membership Function Values of Pixels of the Enhanced Image

Membership values of the image			Non-membership values of the image			Hesitancy values of the image		
0,4993	0,4993	0,5360	0,0010	0,0010	0,0005	0,4996	0,4996	0,4635
0,6599	0,3962	0	0,0000	0,0067	1,0000	0,3400	0,5972	0
0,5360	0,4395	0,3005	0,0005	0,0032	0,0287	0,4635	0,5573	0,6708
0,0679	0	0,1622	0,4972	1,0000	0,1725	0,4349	0	0,6654
0,1003	0,1003	0,3734	0,3498	0,3498	0,0096	0,5499	0,5499	0,6170
0,4601	0,5702	0,5534	0,0022	0,0002	0,0003	0,5377	0,4295	0,4463
0,4601	0,2746	0	0,0022	0,0412	1,0000	0,5377	0,6842	0
0,3005	0,3005	0,5534	0,0287	0,0287	0,0003	0,6708	0,6708	0,4463
0,5360	0,1916	0,4800	0,0005	0,1208	0,0015	0,4635	0,6875	0,5184
0,7535	0,8807	0,4993	0,0000	0,0000	0,0010	0,2464	0,1193	0,4996

Table 4 The Intensity Values of Pixels of the Image Part Corresponding to the Membership Function Values in Table 3

Intensity values of pixels		
154	154	162
187	133	0
162	142	113
41	0	77
55	55	129
146	169	165
146	107	0
113	113	165
162	86	151
206	231	154

Then, the researcher presents the results of the enhanced image. The same particular part of the enhanced image pixels is also extracted and analyzed. The optimized intuitionistic fuzzified values of the enhanced image for that part are presented in Table 3.

It can be seen in Table 1 and Table 3 that the sum of membership, non-membership and hesitancy values of a pixel is equal to 1. It is because the fuzzified values are in the range of 0 to 1. The ABC algorithm optimized these values that the intensity values of the enhanced image are higher than the original image. This can be seen when the researcher compares the values of each pixel in Table 2 and Table 4. This shows that the membership function of IFS is established by utilizing the ABC algorithm to find out its optimum parameter value and further standardized to [0, 1]. The optimization performed by ABC is by utilizing IEM defined in (8). This technique is applied to enhance distinctive parts of an image. Therefore these results show that the fuzzification and defuzzification operations of IFS are sequentially implemented on each pixel of the image using Algorithm 1 by implementing IEM.

To analyze the local contrast enhancement method qualitatively, the original images are compared with the enhanced images. Figure 1 and Figure 2 show the original image of MDCK cells (Type 1) and MDCK cells (Type 2) respectively. Then, Figure 3 and Figure 4 depict the enhanced images obtained by applying the IFS and IFS - ABC respectively for MDCK cells (Type 1). While Figure 5 and Figure 6 illustrate the enhanced images of MDCK cells (Type 2) using IFS and IFS-ABC. Moreover, Table 5 shows the IEM calculated by using both methods.

For the first image (MDCK cells Type 1), Figure 3 shows that the local contrast enhancement using IFS is not significantly observable. This is also confirmed by the IEM value of 1,0652 in Table 5. The result in Figure 4 clearly depicts that the image is enhanced significantly. The IEM value of 2,2208 in Table 5 confirms it.

The second image is enhanced using IFS as shown in Figure 5. It shows that the image cannot be seen clearly, which is also confirmed by the IEM value of 1,6715. Figure 6 depicts that the image can be observable and enhanced. The IEM value of 6,7426 approves the enhancement performance.

It can be seen in Figure 1 to Figure 6 that the IFS-ABC method enhances the two images better than the IFS method. The IEM values of the two local contrast enhancements using IFS-ABC method are much higher than the values of the enhancement using only IFS.

The results in Figure 7 and Figure 8 show that the enhanced images using histogram equalization are not observable for both cells (MDCK Type 1 and Type 2). This

is also indicated by the IEM values of 0,0090 and 0,0094 for Figure 7 and Figure 8 respectively.

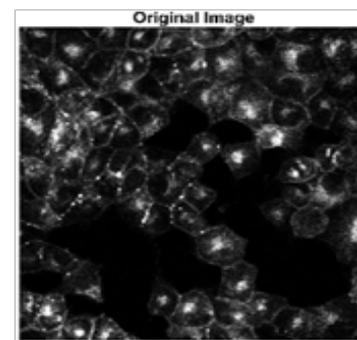


Figure 1 The Original Image of MDCK Cells (Type 1)

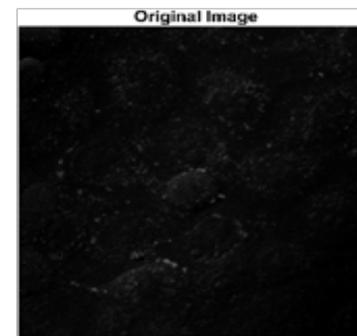


Figure 2 The Original Image of MDCK Cells (Type 2)

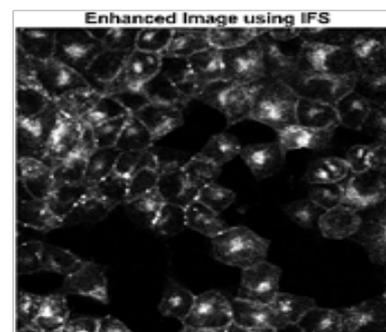


Figure 3 The Enhanced Image of MDCK Cells (Type 1) Using IFS

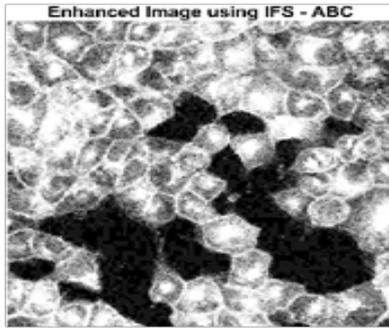


Figure 4 Enhanced image of MDCK cells (Type 1) Using IFS-ABC



Figure 8 The Enhanced Image of MDCK Cells (Type 2) Using Histogram Equalization

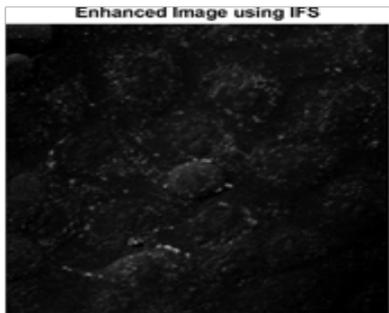


Figure 5 The Enhanced Image of MDCK Cells (Type 2) Using IFS

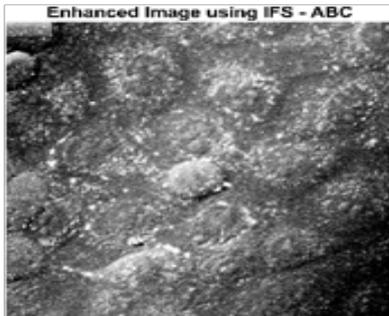


Figure 6 The Enhanced Image of MDCK Cells (Type 2) Using IFS-ABC

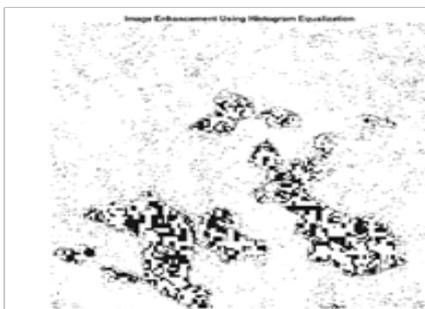


Figure 7 The Enhanced Image of MDCK Cells (Type 1) Using Histogram Equalization

Table 5 IEM of the IFS and IFS – ABC Method

Image	IFS	IFS - ABC	Histogram Equalization
MDCK (Type 1)	1,0652	2,2208	0,0090
MDCK (Type2)	1,6715	6,7426	0,0094

IV. CONCLUSIONS

The two local contrast enhancement techniques have been presented. The first method used is IFS and the second is IFS- ABC. In the first method, the IFS operations are implemented on each pixel of the image. In the second method, the membership function is set by utilizing the ABC algorithm to find its optimum parameter values. Then, the objective function used is Image Enhancement Metric (IEM). By applying such techniques on cell images, it can be noticed that both methods work effectively to enhance the cell images with observable results in separating distinctive parts of the images and descent enhancement results. Based on the quantitative and qualitative analysis, it is concluded that the proposed methods are superior compared to the histogram equalization method. Furthermore, it is visible that the IFS – ABC method is better than the IFS method.

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