Original Article

Facial Skin Segmentation Using Bacterial Foraging Optimization Algorithm

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Submission: 28-08-2012 Accepted: 09-10-2012

ABSTRACT

Nowadays, analyzing human facial image has gained an ever-increasing importance due to its various applications. Image segmentation is required as a very important and fundamental operation for significant analysis and interpretation of images. Among the segmentation methods, image thresholding technique is one of the most well-known methods due to its simplicity, robustness, and high precision. Thresholding based on optimization of the objective function is among the best methods. Numerous methods exist for the optimization process and bacterial foraging optimization (BFO) is among the most efficient and novel ones. Using this method, optimal threshold is extracted and then segmentation of facial skin is performed. In the proposed method, first, the color facial image is converted from RGB color space to Improved Hue-Luminance-Saturation (IHLS) color space, because IHLS has a great mapping of the skin color. To perform thresholding, the entropy-based method is applied. In order to find the optimum threshold, BFO is used. In order to analyze the proposed algorithm, color images of the database of Sahand University of Technology of Tabriz, Iran were used. Then, using Otsu and Kapur methods, thresholding was performed. In order to have a better understanding from the proposed algorithm; genetic algorithm (GA) is also used for finding the optimum threshold. The proposed method shows the better results than other thresholding methods. These results include misclassification error accuracy (88%), non-uniformity accuracy (89%), and the accuracy of region's area error (89%).

Key words: *Bacterial foraging optimization algorithm, facial image, genetic algorithm, IHLS color space, thresholding*

INTRODUCTION

Nowadays, analysing human facial images has gained an ever-increasing importance due to its various applications. Among its applications, video conference analysis, police image recognition, human face animation, identity recognition, user interface with human facial image, and planning face surgeries can be named. As an instance, recent development in the field of human-related digital technologies in combination with graphics of supercomputers has opened exceptional opportunity for developing a new series of applications in the areas of facial aesthetic and reconstructive surgery.[1]

Image segmentation is required as a very important and fundamental operation for significant analysis and interpretation of images. So far, many segmentation methods have been proposed which include segmentation based on fuzzy clustering algorithms,[2,3] and Expectation maximization (EM) algorithm. Among the segmentation methods, image thresholding method is one of the most well-known methods due to its simplicity, robustness, and high precision.[4]

Thresholding method can be classified into two categories: The first category includes methods that find the optimal threshold using image histogram analysis.[5] The second category includes methods that find the optimal threshold using objective functions. Generally, the two methods of Kapur[6] and Otsu[7] are the best methods in thresholding based on optimizing the objective function. The goal is to find the exact threshold in images but the obstacle of all these methods is the complexity of calculation while optimizing the objective function.

In this area, evolutionary methods and algorithms are also used. Among these evolutionary methods are the genetic algorithm (GA), ant colony optimization (ACO) algorithm,[8] and particle swarm optimization (PSO),[9] which have been successful in thresholding. GA is a quick method because it uses parallel searching techniques. Particle swarm optimization has been also used in thresholding for image segmentation.

Bacterial foraging optimization (BFO) was first introduced as a new and innovative algorithm by Passino.[10] The concept

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of BFO algorithm is based on the fact that, in nature, animals with low sense of foraging are more probable to extinct in comparison with animals with high sense of foraging. *Escherichia coli* bacteria which lives in human intestine has foraging method based on four stages of (1) chemotactic, (2) swarming, (3) reproduction, (4) elimination and dispersal.[10]

Considering that color images are used for segmenting facial skin and also considering that human faces have different colors, precise selection of color space was one of the main parameters of this article. Various color spaces exist for marking skin pixels which include RGB, HSV, YCbCr, CIE XYZ, CIE LUV, and IHSL.[11]

In this paper, first, a new color space is introduced for facial skin segmentation and its features and advantages are reviewed in Section 2. In Section 3, thresholding based on optimization of the objective function is introduced. Section 4 explains the bacterial foraging optimization (BFO) algorithm. In Section 5, facial skin segmentation is presented using thresholding based on BFO algorithm in the new color space. Section 6 shows the experimental results for this algorithm and reviews its disadvantages and advantages and finally there is a conclusion section.

MATERIALS AND METHODS

Color Space

Recognizable colors are made up of a combination of three primary colors including red (R), Green (G), and blue (B). Brightness, hue, and saturation are properties that are used to distinguish a color from others. There are various color spaces in image processing like RGB, CMY, HIS, YIQ, and IHLS. These color spaces can convert to each other.[12]

Considering different color spaces and their span, a proper color space should be chosen for each image processing operation. The segmentation accuracy is improved in following image processing stages due to a proper color space. So noticing the application of different color spaces, we chose IHLS, a new color space which has an appropriate efficiency in image processing operations.

Improved lightness-hue saturation color space was first presented by Hanbury.[13] The IHLS model has been improved by brightness normalization, and color saturation, considering the likenesses to HLS, HIS, and HSV color spaces. This property has solved the numerical problems existing in color channels.[14]

This color space is the most accurate and efficient one compared with other color spaces in skin segmentation using different methods. For instance the F parameter for IHLS color space is measured as 0.650, using perceptron neural network and is measured as 0.467 using the radial basis function (RBF) method, which is the best values compared with other color spaces.[14] These values are shown in Table 1. F measure is harmonic mean of precision and recall and is calculated as Eq. 1:[14]

$$F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} \tag{1}$$

In pattern recognition and information retrieval, precision is the fraction of retrieved instances that are relevant, while recall is the fraction of relevant instances that are retrieved. Both precision and recall are therefore based on an understanding and measure of relevance.

This color space converts form RGB color space to IHLS color space using below equations. Considering the point that the RGB color space is made up of three R, G, and B color channel, we would have Eq. 2:[13]

$$i = \frac{1}{3}(\mathrm{R}+\mathrm{G}+\mathrm{B}), \quad s = \max(\mathrm{R},\mathrm{G},\mathrm{B}) - \min(\mathrm{R},\mathrm{G},\mathrm{B}), \quad h = \arctan\left(\frac{\sqrt{3}(\mathrm{G}-\mathrm{B})}{2\mathrm{R}-\mathrm{G}-\mathrm{B}}\right) \tag{2}$$

The equation for converting from RGB color space to IHLS color space is as Eq. 3:

$$\mathrm{R} = i + \frac{2}{3}c_1, \; \mathrm{G} = i - \frac{1}{3}c_1 + \frac{1}{\sqrt{3}}c_2, \; \mathrm{B} = i - \frac{1}{3}c_1 - \frac{1}{\sqrt{3}}c_2 \tag{3}$$

And then we have $c_1 = c\cos(h)$, $c_2 = c\sin(h)$ when c is defined as Eq. 4:

$$c = \frac{\sqrt{3}s}{2\sin(120 - (H - k \times 60°))} \tag{4}$$

Optimal Thresholding Methods

Optimal thresholding methods search types of thresholds in which classes with the desired features are segmented. This method is carried out by maximizing the objective function

Table 1: F measurement for three-dimensional color spaces using different color space modeling methods[15]

	IHLS	HSI	RGB	nRGB	YCbCr	CIELAB
AdaBoost	0.320	0.300	0.260	0.250	0.270	0.276
BayesianNet	0.590	0.570	0.321	0.370	0.490	0.560
J48	0.684	0.680	0.662	0.626	0.680	0.660
MLP	0.650	0.591	0.590	0.569	0.627	0.600
NaiveBayes	0.466	0.450	0.255	0.408	0.427	0.454
Random forest	0.745	0.741	0.710	0.700	0.705	0.740
RBF	0.467	0.430	0.389	0.420	0.490	0.510
SVM	0.503	0.471	0.360	0.370	0.385	0.400
Hist.	0.409	0.408	0.418	0.399	0.390	0.400

RBF – Radial basis function; SVM – Support vector machine; IHLS – Improved hue-luminance-saturation with parameters which are thresholds. In this section, two methods of thresholding are introduced: (1) entropy-based method (Kapur) and (2) inter-class variance method (Otsu). If L is considered the gray level in the image within the range of $\{0, 1,\ldots, L-1\}$, the probability of i^{th} gray level can be defined as Eq. 5:

$$P_i = \frac{h(i)}{N} \quad \text{for } (0 \le i \le (L-1)) \tag{5}$$

where $h(i)$ is the number of pixels with L gray level and N is the total number of image pixels.

Inter-class variance method was introduced by Otsu in order to determine the threshold values.[7] In this method, thresholding is done based on maximizing the inter-class variance to separate the segmented classes as much as possible. In two-level thresholding, an image is divided into two classes of C_0 and C_1. Threshold is equal to t and C_0 class includes pixels within the level range of 0 to $t-1$ and C_1 class includes pixels within the level range of t to L. Now, probability distributions of these two classes are according to Eq. 6:[7]

$$\begin{gathered} C_0 : \frac{p_0}{\omega_0(t)},\ldots,\frac{p_{t-1}}{\omega_0(t)} \quad \text{and} \quad C_1 : \frac{p_t}{\omega_1(t)},\ldots,\frac{p_{L-1}}{\omega_1(t)} \\ \omega_0(t) = \sum_{i=0}^{t-1} p_i \quad \text{and} \quad \omega_1(t) = \sum_{i=t}^{L-1} p_i. \end{gathered} \tag{6}$$

Mean values for C_0 and C_1 classes are as Eq. 7:

$$\mu_0 = \sum_{i=0}^{t-1} \frac{ip_i}{\omega_0(t)}, \quad \mu_1 = \sum_{i=t}^{L-1} \frac{ip_i}{\omega_1(t)} \tag{7}$$

Mean value for total image intensity is defined as shown in Eq. 8:

$$\omega_0\mu_0 + \omega_1\mu_1 = \mu_T \quad \text{and} \quad \omega_0 + \omega_1 = 1 \tag{8}$$

Objective function which should be optimized is defined as Eq. 9:

$$J(t) = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2 \tag{9}$$

Entropy-based method, or the Kapur method, is done in such a way that the entropy resulting from segmented histogram is maximized so that each segment can achieve a central distribution.[6] Now, the entropy resulted from the segmented histogram is defined in Eq. 10:[6]

$$H_0 = -\sum_{i=0}^{t-1} \frac{P_i}{\omega_0} \ln \frac{P_i}{\omega_0} \qquad H_1 = -\sum_{i=t}^{L-1} \frac{P_i}{\omega_1} \ln \frac{P_i}{\omega_1} \tag{10}$$

where ω_0 and ω_1 in Eq. 6 are expressed the same as in Eq. 11:

$$\omega_0(t) = \sum_{i=0}^{t-1} p_i \qquad \omega_1(t) = \sum_{i=t}^{L-1} p_i \tag{11}$$

The objective function which must be maximized is in the form of Eq. 12:

$$J(t) = H_0 + H_1 \tag{12}$$

Bacterial Foraging Optimization Algorithm

The concept of BFO algorithm is based on the fact that, in nature, animals with low sense of foraging are more probable to be extinct compared with those with high sense of foraging. After many generations, weak animals and weak foraging methods are either extinct or are modified into better forms. *E. coli* bacteria which live in human intestine have a foraging method based on four stages: (1) chemotactic, (2) swarming, (3) reproduction, (4) elimination and dispersal.[15]

Chemotactic

In this stage, bacteria start to tumble and swim. In fact, depending on the rotation of the bacterium tail, it tumbles and starts to move in a direction. If the amount of food is better in the new direction, the bacterium starts to swim in that direction. Suppose we intend to find the minimum value of $J(\theta), \theta \in \Re^p$. Consider θ as the location of the bacterium and $J(\theta)$ as the amount of food in that location or in fact the cost function. Therefore, if the bacterium finds the better amount of food in location θ, then $J(\theta) < 0$ and, if the amount of food is not sufficient in location θ, then $J(\theta) > 0$. If the food in location θ is neutral, then $J(\theta) = 0$.[15]

In order to perform the tumble, a unit vector named $\phi(i)$ is formed. This vector is used to define the new direction of bacterium movement after tumbling. New location of bacterium is defined as in Eq. 13:

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\phi(i) \tag{13}$$

where $\theta^i(j, k, l)$ indicates the i^{th} bacterium in j^{th} chemotactic, k^{th} reproduction, and l^{th} elimination and dispersal. $C(i)$ is chemotactic magnitude of the bacterium in the direction of $\phi(i)$. If the magnitude of $J(i, j, k, l)$ in $\theta^i(j+1, k, l)$ is less than its magnitude in $\theta^i(j, k, l)$, then another chemotactic step with the magnitude of $C(i)$ is done in the direction of $\phi(i)$ and the bacterium starts to swim in the direction of $\phi(i)$. This swimming is continued until the magnitude of $J(\theta)$ decreases and it can continue to the maximum number of permitted swimming stages (N_s). This demonstrates that the bacterium continues in its direction as long as sufficient food is found in that direction.[15]

Swarming

When a bacterium finds a better direction for foraging, it attracts other bacteria to that direction and other bacteria reach the main food source faster. Swarming causes collective movement of bacteria to the food. If $P(j, k, l) = \{\theta^i(j, k, l) | i = 1,2,\ldots, s\}$ is considered as a set of bacteria locations, then swarming can be modeled as in Eq. 14:[15]

$$J_{cc}(\theta, P(i,j,l)) = \sum_{i=1}^{s} J_{cc}^{i}(\theta, \theta^{i}(j,k,l)) = \sum_{i=1}^{s}[-d_{\text{attract}} \exp(-\omega_{\text{attract}} \sum_{m=1}^{P}(\theta_m - \theta_m^i)^2)] + \sum_{i=1}^{s}[-h_{\text{repeliant}} \exp(-\omega_{\text{repeliant}} \sum_{m=1}^{P}(\theta_m - \theta_m^i)^2)] \quad (14)$$

where $J_{cc}(\theta, P(i, j, l))$ is a time-dependent function and depends on the collective movement of bacteria and $J(i, j, k, l)$ is added to the cost function. Therefore, the bacteria starts to find food and evade foodless areas while attracting each other; but they never get too close to each other. S is the total number of bacteria and P is number of parameters that must be optimized and is considered as a bacterium position in the p-dimensional space. d_{attract}, $h_{\text{repellent}}$, ω_{attract}, and $\omega_{\text{repellent}}$ are coefficients that must be given a proper value depending on the problem.[15]

Reproduction

Half of the bacteria which have not found proper food would die and each bacterium in the other half which is healthy bacteria would be divided into two bacteria which are left in the same previous place. This process keeps the number of bacteria constant ($S_r = S/2$).[15]

Elimination and dispersal

Life of bacteria would change gradually because of food consumption or suddenly due to other factors. Accidents can kill or disperse bacteria. Although at first this may disturb the process of chemotactic stage, it can also have a positive effect on that because bacteria's dispersion might place them in areas with sufficient food. Elimination and dispersal stage prevents the bacteria from being trapped in the local optimum points. In this stage, the possibility of each bacterium in the group for elimination and dispersion is equal to P_{ed}. To keep the number of bacteria constant, in case a bacterium is eliminated, another bacterium is randomly placed in the search space.[15]

Summarized BFO algorithm

The summary of BFO is as follows:[16]
Step 1: Start (giving initial values to all parameters)
Step 2: Elimination and dispersion loop
Step 3: Reproduction loop
Step 4: Chemotactic loop

(1-4) i^{th} bacterium moves according to the following pattern:

(2-4) $J(i, j, k, l)$ is calculated and then the effect of swarming is added to it (Eq. 15).

$$J_{sw} = J(i,j,k,l) + J_{cc}(\Theta^{i}(j,k,l), P(j,k,l)) \quad (15)$$

(3-4) the current value is saved for later comparison (Eq. 16).

$$J_{\text{last}} = J_{sw}(i,j,k,l) \quad (16)$$

(4-4) Tumble: A random vector of $\Delta(i) \in \Re^{p}$ with values of $m = 1,2,\ldots, P$ is generated within the range of [-1,1].

(5-4) Chemotactic: The values of $\phi(i) = \frac{\Delta(i)}{\sqrt{\Delta^{T}(i)\Delta(i)}}$ and $\theta^{i}(j+1,k,l) = \theta^{i}(j,k,l) + C(i)\phi(i)$ are obtained. Then, the bacterium with the magnitude of $C(i)$ moves in the direction of $\phi(i)$.

(6-4) $J(i, j+1, k, l)$ is calculated and then the swarming effect is added to it.

(7-4) Swimming stage: First, $m = 0$. The following loop is continued until $m < N_s$.

$m = m + 1$

if $J_{sw}(i, j+1, k, l) < J_{\text{last}}$, then $J_{\text{last}} = J(i, j+1, k, l)$ and $J_{\text{last}} = J(i, j+1, k, l)$ are calculated; otherwise, $m = N_s$.

(8-4) If $i \neq s$, then, the loop is repeated for the next bacterium.

Step 5: If $j < N_c$, then, step 3 and the chemotactic stage are repeated for all the bacteria.

Step 6: Reproduction: First, for the specific values of k and l, $J_{health}^{i} = \min_{j\in\{1,2,\ldots,N_c+1\}}\{J_{sw}(i,j,k,l)\}$ is calculated for each bacterium and the bacteria are sorted in an increasing manner. Half of the bacteria with the highest values of J_{health}^{i} are eliminated and the other half are first transferred to a place where the value of $J(i, j, k, l)$ is equal to J_{health}^{i} and then a bacterium is reborn from each bacterium and is placed in the same position.

Step 7: If $k < N_{\text{re}}$, then Step 2 is repeated.

Step 8: Elimination and dispersion: Each bacterium is eliminated and dispersed using the probability value of P_{ed}. To do that, in case a bacterium is eliminated, another bacterium is randomly formed in the search space.

Step 9: If $l < N_{\text{ed}}$, then, Step 1 is repeated.

The Proposed Method

In the proposed method, first, the color facial image is converted from RGB color space to IHLS color space, as explained in Section 2. Then, the y component of IHLS that has a great mapping of the skin color is used. Considering that the color spectrum of color image of face was limited, two-level thresholding is used; i.e., a pixel is either related to the facial skin or is not related to facial feature at all.

To perform thresholding, the entropy-based method is applied. In order to find the optimum threshold, there are various optimization algorithms; here, a new algorithm called BFO is used. This algorithm was explained and its parameters were introduced in the previous section. In this paper, using BFO, an optimum threshold is found based on entropy criteria and proper segmentation of the facial skin is performed. Figure 1 shows a summary of the proposed algorithm.

Parameters of BFO algorithm that were used in this method are shown in Table 2. Each of these parameters was explained in Section 4 and, by changing them, the optimization process would also change. Parameters presented in Table 2 were obtained in the best segmentation case resulting from our data.

RESULTS

In order to analyze the proposed algorithm, color images of the database of Sahand University of Technology of Tabriz, Iran were used. This database contained three orthogonal facial images (for each person) which were taken simultaneously by the designed orthogonal camera system at Sahand University of Technology. This system is based on orthogonal placement and calibration of three cameras. These cameras are special and with specific technical characteristics for the simultaneous, fast, accurate and high quality imaging. This system contains a head fixer which increases the accuracy of imaging and sets the head in its best position. The use of strong and durable materials, has made it possible to place the system in any environment.

This system which has many advantages in the field of medical science and aesthetic surgery is used to facilitate surgeon's diagnosis. The advantages of this system include: (1) providing images of three orthogonal views simultaneously, (2) accurate calibration, (3) easy to use in the health care environment by training the nurses and doctors, (4) capability of remote control and adjustment, and information storage as dataset, (5) mechanical and physical strength and endurance, (6) noise robustness using the head fixer, (7) fast installation. All color images were taken from 150 volunteer students. All input images were re-sized to 350×200 pixels. Figure 2a shows the frontal view of two samples data.

Misclassification Error

This error is the percentage of the background pixels which are wrongly identified as the desired areas and also percentage of the pixels regarding the desired areas which are wrongly considered as the background pixels. To classify this error into two classes, Eq. 17 is used:[17]

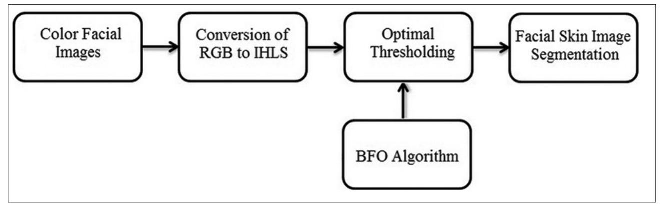

Figure 1: The proposed algorithm for segmentation of the facial skin

Table 2: Parameters of bacterial foraging optimization algorithm

Parameters of BFO	Value
Number of bacterium (s)	20
Number of chemotatic steps (N_c)	10
Swimming length (N_s)	10
Number of reproduction steps (N_{re})	4
Number of elimination of dispersal events (N_{ed})	2
Probability of elimination and dispersal (P_{ed})	0.02
Depth of attractant ($d_{attract}$)	0.1
Height of repellent ($h_{repellent}$)	0.1
Width of attract ($\omega_{attract}$)	0.2
Width of repellent ($\omega_{repellent}$)	10

BFO – Bacterial foraging optimization

$$ME = 1 - \frac{|B_0 \cap B_T| + |F_0 \cap F_T|}{|B_0| + |F_0|} \quad (17)$$

In this equation, B_0 and F_0 are the numbers of background pixels and pixels in the desired area for the original image, respectively. B_T and F_T are the numbers of background pixels and pixels in the desired area for the image resulted from the algorithm, respectively. The sign $\cap$ also denotes the common pixels between the two areas. ME ranges from 0 to 1, in which 0 is related to the best classification and 1 is related to the worst.

Nonuniformity

This measure, which does not require ground-truth information, is defined as Eq. 18:[18]

$$\mathrm{NU} = \frac{|F_T|}{|F_T + B_T|} \frac{\sigma_f^2}{\sigma^2} \quad (18)$$

where σ^2 represents the variance of the whole image, and σ_f^2 represents the foreground variance. It is expected that a well-segmented image will have a non-uniformity measure close to 0, while the worst case of NU = 1 which corresponds to an image for which background and foreground are indistinguishable up to the second order moments.

Relative Foreground Area Error

The comparison of object properties such as area and shape, as obtained from the segmented image with respect

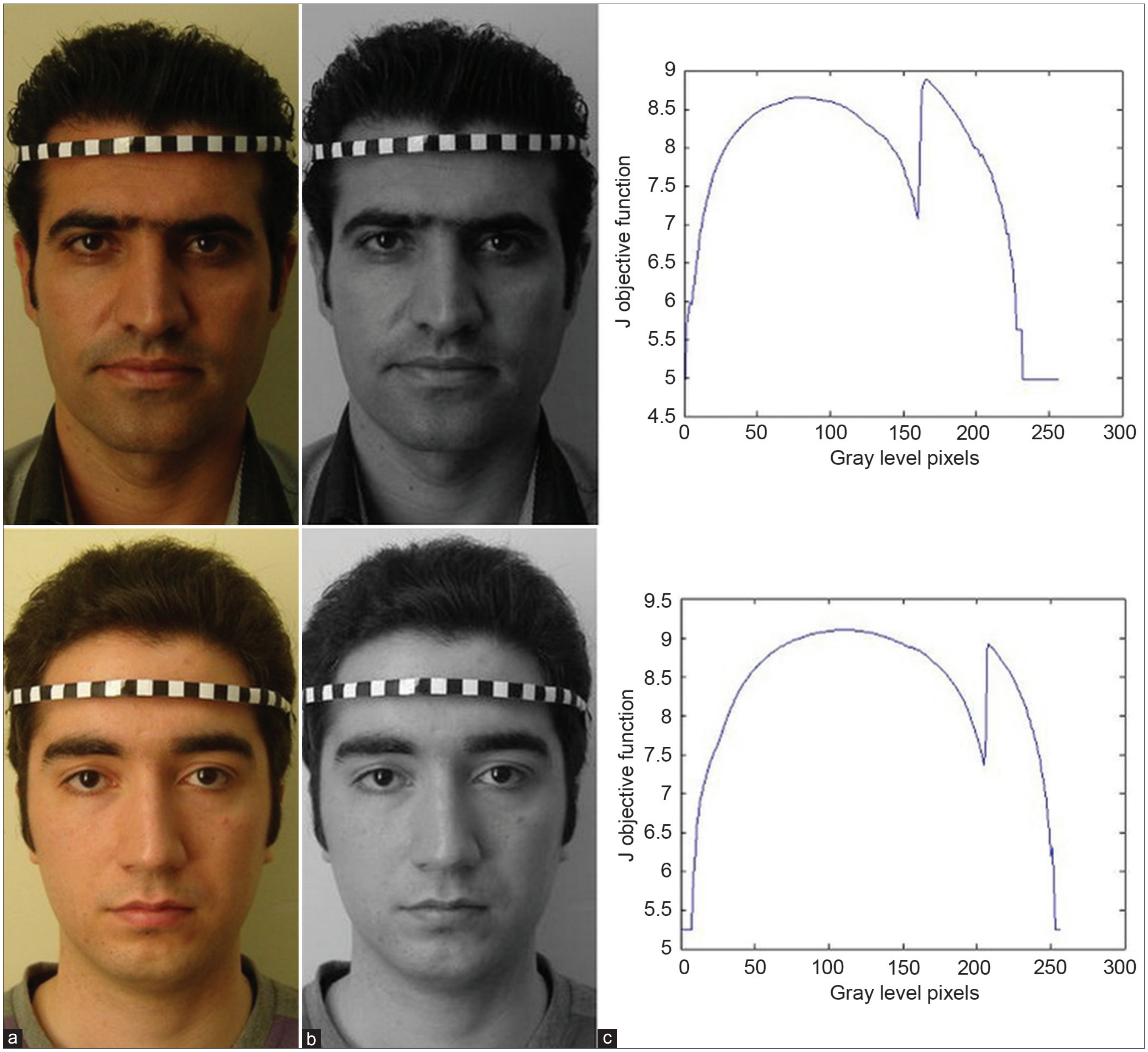

Figure 2: (a) Frontal view of facial color images, (b) image in one of IHLS color space channels, (c) diagram of the objective function

to the reference image, has been used in relative foreground area error. We modified this measure for the area feature A as follows:[18]

$$\mathrm{RAE} = \begin{cases} \dfrac{A_O - A_T}{A_O} & \text{if } A_T < A_O \\[2ex] \dfrac{A_T - A_O}{A_T} & \text{if } A_T \geq A_O \end{cases} \tag{19}$$

where A_O is the area of reference image, and A_T is the area of thresholded image. Obviously, for a perfect match of the segmented regions, RAE is zero, while if there is zero overlap of the object areas, the penalty is the maximum one.

Figure 2b demonstrates the conversion of color space of images to y component of IHLS.

Using Otsu and Kapur methods, thresholding was performed. Figure 3a is the image obtained from Otsu method and Figure 3b gives the image related to the Kapur method. These images were obtained using BFO algorithm. Figure 2c presents the objective function of each image, in which their optimum thresholds were specified using optimization algorithm.

In order to have a better understanding from the proposed algorithm, GA is also used for finding the optimum threshold and the results of skin segmentation are given in Figure 3c. Threshold points and the optimum values of objective functions are presented in Table 3. These values were

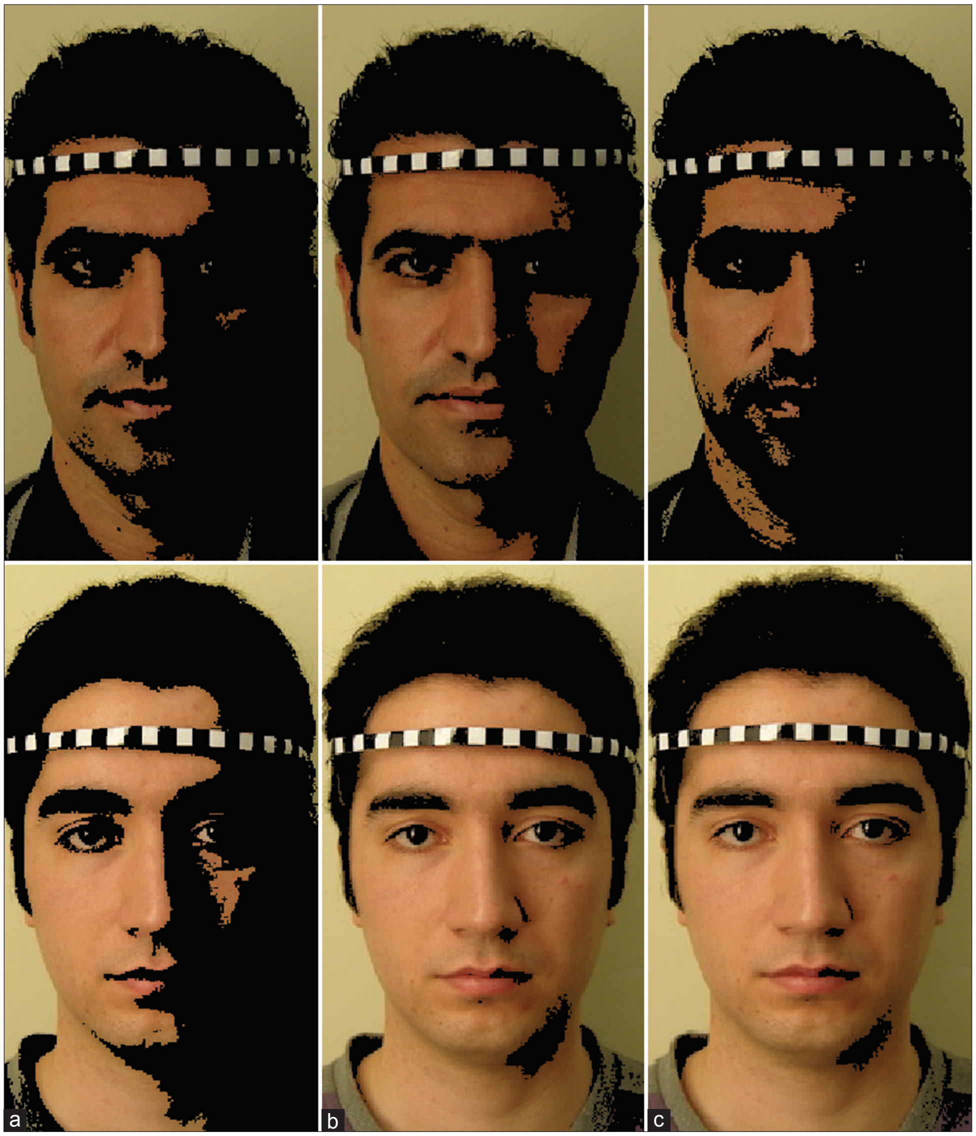

Figure 3: (a) Segmented image based on Otsu thresholding using BFO, (b) segmented image based on Kapur thresholding using BFO, (c) segmented image based on Kapur thresholding using genetic algorithm

Table 3: Optimum threshold points and values of the objective function in these points using different methods

RAE	NU	ME	Values of the objective function (mean)	Optimum threshold (mean)	Optimization methods
0.21	0.3	0.2	8.63	91	BFO with Otsu thresholding
0.25	0.3	0.2	7.86	75	Genetic algorithm
0.11	0.1	0.1	7.52	60	BFO with Kapur thresholding (proposed method)

RAE – Relative foreground area error; NU – Nonuniformity; ME – Misclassification error; BFO – Bacterial foraging optimization

obtained after an average of 20 repetitions for each image. As the results show, the proposed method contained the best results for the optimum value of the objective function and the best optimum threshold. Furthermore, using misclassification error measurement, the three methods were compared. The proposed method had the least error. Brightness of images was not the same and a lot of shadow was formed on skin; therefore, by considering this point, the proposed method had the highest performance in this regard.

DISCUSSION

This article tried to perform facial skin segmentation using thresholding method based on a new and efficient color space. In this regard, a new optimization method called BFO was used and a connection was formed between new biological optimization algorithms and color image segmentation. The proposed algorithm is a new research topic in facial skin segmentation.

REFERENCES

1. Shamsi M, Zoroofi RA, Lucas C, Sadeghi Hasanabadi M, Asharif MR. Automatic facial skin segmentation based on EM algorithm under varying illumination. IEICE Trans Inf Syst 2008;E91-D: 1543-51.
2. Bezdek JC. A convergence theorem for the fuzzy ISODATA clustering algorithms. IEEE Trans Pattern Anal Mach Intell 1980;2:1-8.
3. Li M, Staunton RC. A modified fuzzy C-means image segmentation algorithm for use with uneven illumination patterns. Pattern Recognit 2007;40:3005-11.
4. Sezgin M, Sankur B. Survey over image thresholding techniques and quantitative performance evaluation. J Electron Imaging 2004;13:146-65.
5. Pikaz A, Averbuch A. Digital image thresholding based on topological stable state. Pattern Recognit 1996;29:829-43.
6. Kapur JN, Sahoo PK, Wong AK. A new method for gray-level picture thresholding using the entropy of the histogram. Comput Vis Graph Image Process 1985;29:273-85.
7. Otsu N. A threshold selection method from gray level histograms. IEEE Trans Syst 1979;9:62-6.
8. Zhiwei Y, Zhaobao Z, Xin Y, Xiaogang N. Automatic threshold selection based on ant colony optimization algorithm. In: Proceedings of the International Conference on Neural Networks and Brain; Beijing, China; October 2006, p. 728-32.
9. Maitra M, Chatterjee A. A hybrid cooperative-comprehensive learning based PSO algorithm for image segmentation using multilevel thresholding. Expert Syst Appl 2008;34:1341-50.
10. Passino KM. Biomimicry of bacterial foraging for distributed optimization and control. IEEE Trans Control Syst Mag 2002;22: 52-67.
11. Yang MH, Kriegman DJ, Ahuja N. Detecting faces in images: A survey. IEEE Trans Pattern Anal Mach Intell 2002:24:34-58.
12. Robertson AR. The CIE 1976 color difference formulae. Color Res Appl 1977;2:7-11.
13. Hanbury A. Constructing cylindrical coordinate colour spaces. Pattern Recognit Lett 2008;29:494-500.
14. Khan R, Hanbury A, Stottinger J, Bais A. Color based skin classification. Pattern Recognit Lett 2012;33:157-63.
15. Sathya PD, Kayalvizhi R. Modified bacterial foraging algorithm based multilevel thresholding for image segmentation. Eng Appl Artif Intell 2011;24:595-615.
16. Sanyal N, Chatterjee A, Munshi S. An adaptive bacterial foraging algorithm for fuzzy entropy based image segmentation. Expert Syst Appl 2011;38:15489-98.
17. Yasnoff WA, Mui JK, Bacus JW. Error measures for scene segmentation. Pattern Recognit 1977;9:217-31.
18. Sezgin M, Sankur B. Survey over image thresholding techniques and quantitative performance evaluation. J Electron Imaging 2004;13:146-65.

How to cite this article: Bakhshali MA, Shamsi M. Facial skin segmentation using bacterial foraging optimization algorithm. J Med Sign Sens 2012;2:203-10.

Source of Support: Nil, **Conflict of Interest:** None declared

BIOGRAPHIES

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