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.\(^\text{[1]}\)

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,\(^\text{[2,3]}\) 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.\(^\text{[4]}\)

Thresholding method can be classified into two categories: The first category includes methods that find the optimal threshold using image histogram analysis.\(^\text{[5]}\) The second category includes methods that find the optimal threshold using objective functions. Generally, the two methods of Kapur\(^\text{[6]}\) and Otsu\(^\text{[7]}\) 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,\(^\text{[8]}\) and particle swarm optimization (PSO),\(^\text{[9]}\) 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.\(^\text{[10]}\) 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 IHLS.\[^{11}\]

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, HSI, 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:\[^{14}\]

\[
F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}
\]

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:\[^{13}\]

\[
i = \frac{1}{3} (R + G + B), \quad s = \max(R, G, B) - \min(R, G, B),
\]

\[
h = \arctan \left( \frac{\sqrt{3}(G - B)}{2R - G - B} \right)
\]

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

\[
R = i + \frac{2}{3} c_1, \quad G = i - \frac{1}{3} c_1 + \frac{1}{3\sqrt{3}} c_2, \quad B = i - \frac{1}{3} c_1 - \frac{1}{3\sqrt{3}} c_2
\]

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

\[
c = \frac{\sqrt{3}s}{2\sin(120 - (H - k \times 60^\circ))}
\]

**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>
<thead>
<tr>
<th>Method</th>
<th>IHLS</th>
<th>HSI</th>
<th>RGB</th>
<th>nRGB</th>
<th>YCbCr</th>
<th>CIELAB</th>
</tr>
</thead>
<tbody>
<tr>
<td>AdaBoost</td>
<td>0.320</td>
<td>0.300</td>
<td>0.260</td>
<td>0.250</td>
<td>0.270</td>
<td>0.276</td>
</tr>
<tr>
<td>BayesianNet</td>
<td>0.590</td>
<td>0.570</td>
<td>0.321</td>
<td>0.370</td>
<td>0.490</td>
<td>0.560</td>
</tr>
<tr>
<td>J48</td>
<td>0.684</td>
<td>0.680</td>
<td>0.662</td>
<td>0.626</td>
<td>0.680</td>
<td>0.660</td>
</tr>
<tr>
<td>MLP</td>
<td>0.650</td>
<td>0.591</td>
<td>0.590</td>
<td>0.569</td>
<td>0.627</td>
<td>0.600</td>
</tr>
<tr>
<td>NaiveBayes</td>
<td>0.460</td>
<td>0.450</td>
<td>0.255</td>
<td>0.408</td>
<td>0.427</td>
<td>0.454</td>
</tr>
<tr>
<td>Random forest</td>
<td>0.745</td>
<td>0.741</td>
<td>0.710</td>
<td>0.700</td>
<td>0.705</td>
<td>0.740</td>
</tr>
<tr>
<td>RBF</td>
<td>0.467</td>
<td>0.430</td>
<td>0.389</td>
<td>0.420</td>
<td>0.490</td>
<td>0.510</td>
</tr>
<tr>
<td>SVM</td>
<td>0.503</td>
<td>0.471</td>
<td>0.360</td>
<td>0.370</td>
<td>0.385</td>
<td>0.400</td>
</tr>
<tr>
<td>Hist.</td>
<td>0.409</td>
<td>0.408</td>
<td>0.418</td>
<td>0.399</td>
<td>0.390</td>
<td>0.400</td>
</tr>
</tbody>
</table>

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 \( t \)th gray level can be defined as Eq. 5:

\[
P_t = \frac{h(t)}{N} \quad \text{for} \quad (0 \leq t \leq (L - 1))
\]

where \( h(t) \) 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. 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:

\[
C_0 : \frac{p_0}{\omega_0(t)}, \ldots, \frac{p_{t-1}}{\omega_0(t)} \quad \text{and} \quad C_1 : \frac{p_t}{\omega_1(t)}, \ldots, \frac{p_L}{\omega_1(t)}
\]

where \( \omega_0(t) = \sum_{i=0}^{t-1} p_i \) and \( \omega_1(t) = \sum_{i=t}^{L} p_i \).

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

\[
\mu_0 = \frac{\sum_{i=0}^{t-1} i p_i}{\omega_0(t)}, \quad \mu_1 = \frac{\sum_{i=t}^{L} i p_i}{\omega_1(t)}
\]

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

\[
\omega_0 \mu_0 + \omega_1 \mu_1 = \mu_j \quad \text{and} \quad \omega_0 + \omega_1 = 1
\]

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

\[
J(t) = \omega_0 (\mu_0 - \mu_j)^2 + \omega_1 (\mu_1 - \mu_j)^2
\]

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. Now, the entropy resulted from the segmented histogram is defined in Eq. 10:

\[
H_0 = - \sum_{i=0}^{t-1} \frac{p_i}{\omega_0} \ln \frac{p_i}{\omega_0} \quad \text{and} \quad H_1 = - \sum_{i=t}^{L} \frac{p_i}{\omega_1} \ln \frac{p_i}{\omega_1}
\]

where \( \omega_0 \) and \( \omega_1 \) in Eq. 6 are expressed the same as in Eq. 11:

\[
\omega_0(t) = \sum_{i=0}^{t-1} p_i \quad \omega_1(t) = \sum_{i=t}^{L} p_i
\]

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

\[
J(t) = H_0 + H_1
\]

**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.

**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 \( J(\theta) \), \( \theta \in \mathbb{R}^s \). Consider \( \theta \) 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 \( \theta \), then \( J(\theta) < 0 \) and, if the amount of food is not sufficient in location \( \theta \), then \( J(\theta) > 0 \). If the food in location \( \theta \) is neutral, then \( J(\theta) = 0 \).

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

\[
\theta'(j+1, k, l) = \theta'(j, k, l) + C(i)\phi(i)
\]

where \( \theta'(j, k, l) \) indicates the \( j \)th bacterium in \( k \)th chemotactic, \( k \)th reproduction, and \( k \)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 \( \theta'(j+1, k, l) \) is less than its magnitude in \( \theta'(j, k, l) \), 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 \( J(i, j, k, l) \) decreases and it can continue to the maximum number of permitted swimming stages \( N_j \). This demonstrates that the bacterium continues in its direction as long as sufficient food is found in that direction.

**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 \( P(j, k, l) = \{\theta'(j, k, l)|i = 1, 2, \ldots, s\} \) is considered as a set of bacteria
locations, then swarming can be modeled as in Eq. 14:[15]

\[ J_{sw} = J(i, j, k, l) = \sum_{l=1}^{L} f_{jl}^{l}(\theta, \theta') + \sum_{l=1}^{L} [J_{health}(i, j, k, l)] + \sum_{l=1}^{L} [J_{sw}(i, j, k, l)] + \sum_{l=1}^{L} [J_{health}(i, j, k, l)] + \sum_{l=1}^{L} [J_{sw}(i, j, k, l)] \]  

(14)

where \( J_{sw}(i, j, k, l) \) is a time-dependent function and depends on the collective movement of bacteria and \( f(i, j, k, l) \) is added to the cost function. Therefore, the bacteria start 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. \( d_{attract}, h_{repellant}, \theta_{attract}, \theta_{repellent} \), and \( \phi \) 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 \((S) \).\(^{[15]}\)

### 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) \( f(i, j, k, l) \) is calculated and then the effect of swarming is added to it (Eq. 15).

\[ J_{sw} = J(i, j, k, l) + J_{ic}(j, k, l) \]

(15)

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

\[ J_{sw} = J(i, j, k, l) \]

(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 \( \phi(i) = \frac{\Delta(i)}{\sqrt{\Delta(i) \Delta(i)}} \) and \( \theta' = \theta'(i, j, k, l) + C(i) \phi(i) \) 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 \( J_{sw} < J_{sw} \), then \( J_{sw} = f(i, j+1, k, l) \) and \( J_{sw} = f(i, j+1, k, l) \) are calculated; otherwise, \( m = N_{s} \).

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

Step 5: If \( j < N_{s} \), then, step 3 and the chemotactic stage are repeated for all the bacteria.

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

Step 7: If \( k < N_{s} \), 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 \( l < N_{s} \), 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 by the designed orthogonal camera system at Sahand University of Technology, (2) 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.

Nonuniformity

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

Relative Foreground Area Error

The comparison of object properties such as area and shape, as obtained from the segmented image with respect
to the reference image, has been used in relative foreground area error. We modified this measure for the area feature \( A \) as follows:

\[
RAE = \begin{cases} 
\frac{A_o - A_t}{A_o} & \text{if } A_t < A_o \\
\frac{A_t - A_o}{A_t} & \text{if } A_t \geq A_o
\end{cases}
\]

(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...
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.

**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.
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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

Mohamad Amin Bakhshali was born in Mashad, Iran, in 1987. He graduated from high school (major: Mathematics-Physics) in Mashad, in 2005. He passed the university entrance examination for engineering studies in Iran in 2003, and joined Amirkabir University of Technology(Polytechnic Tehran). He received his B.Sc. degree in Biomedical Engineering (major: Bioelectric) from Amirkabir University of Technology, in 2010. In 2010, he joined the Sahand University of Technology, Tabriz, Iran. He received his M.Sc. degree in Biomedical Engineering (major: Bioelectric) from this university in 2012. His research interests are medical image processing and bio-inspired algorithms.

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Mousa Shamsi was born in Tabriz, Iran, in 1972. He graduated from high school (major: Mathematics-Physics) in Tabriz, Iran, in 1990. He passed the university entrance examination for engineering studies and joined Tabriz University, Tabriz, Iran, in 1990. He received his B.Sc. degree in Electrical Engineering (major: electronics) from Tabriz University, in 1995. In 1996, he joined the University of Tehran, Tehran, IRAN. He received his M.Sc. degree in Electrical Engineering (major: Biomedical Engineering) from this university in 1999. From 1999 to 2002, he taught as a lecturer at the Sahand University of Technology, Tabriz, Iran. In 2002, he entered the University of Tehran as a PhD Candidate. From 2002 to 2008, he was a PhD student at the University of Tehran in Bioelectrical Engineering. In 2006, he was granted with the Iranian government scholarship as a visiting researcher at the Ryukyus University, Okinawa, Japan. From December 2006 to May 2008, he was a visiting researcher at this University. He received his PhD degree in Electrical Engineering (major: Biomedical Engineering) from University of Tehran in December 2008. From December 2008, he is an assistant professor at Faculty of Electrical Engineering, Sahand University of technology, Tabriz, Iran. His research interests include medical image and signal processing, pattern recognition and facial surgical planning.

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