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An Effective Hybrid Harris Hawk Optimization for Facial Skin Segmentation under Varying Illumination

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ABSTRACT

The segmentation of facial color images is an essential step for facial analysis purposes such as face recognition, identification, and planning of facial reconstruction surgeries. The varying illumination has a notable effect on it. One of the applications of facial skin segmentation is contour extraction in the analysis of facial plastic surgeries, which is a challenging problem under varying illumination. Therefore, in this paper, a modified version of the Fuzzy c-Means (MFCM) algorithm with adding varying illumination parameter is presented to segment frontal and profile facial color images. MFCM algorithm is sensitive to the initial value and may cause this algorithm to fall in a local minimum. In this paper, to overcome the mentioned problems, we proposed a hybrid optimization method, which combines Grey Wolf Optimization (GWO) and Harris Hawk Optimization (HHO). The main goal of using GWO is to improve the exploration phase in HHO. Also, the same weight coefficient is used for all three alpha, beta, and delta wolves. The ranking of wolves for selecting these coefficients is not considered. To improve the location update, weight coefficient is updated based on the rank of each wolf. Experimental results demonstrate that the proposed algorithm has high efficiency and is robust to the varying illumination effect in the segmentation of facial color images. Also, it shows that the proposed algorithm has a suitable performance in facial skin segmentation compared to other image segmentation methods.

1. Introduction

The human face plays a significant role in social interactions. Nowadays, facial skin segmentation has become an important topic for purposes such as face tracking, face recognition, human face

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animation, identification, and planning of facial surgeries [1-3]. Facial skin segmentation can be classified into two main approaches: (1) pixel-based and (2) region-based methods. In pixel-based methods, features such as color are extracted from information contained in a pixel while in region-based methods; features such as texture are extracted from information in a pixel and its neighborhoods [4]. The presented methods for human skin detection can be divided into 4 categories: (1) Explicit Classifiers (EC), (2) Parametric Classifiers (PC), (3) Non-Parametric Classifiers (NPC), and (4) Dynamic Classifiers (DC). EC use thresholding-based methods to discriminate between skin and non-skin pixels. PC use parametric models such as the Gaussian Mixture Model (GMM) or the Elliptic Boundary Model (EBM) to detect the skin. Due to the pixel-by-pixel processing, these methods is usually slow with a low accuracy. NPC require a set of training data to estimate the statistical model of skin color distribution. The advantage of these methods is that they are quickly trained and independent of the skin distribution shape. DC methods use neural network-based methods to detect human skin [5]. Shamsi et al. [6] presented a method based on the Expectation-Maximization (EM) algorithm for facial skin segmentation under varying illumination. In the presented method, it was first assumed that a face image could be expressed as a product of the reflection component in the illumination component. In the EM algorithm, the probability distribution function has been considered as a Gaussian function with variable mean and standard deviation parameters. Then, using the EM algorithm, three desired parameters were estimated. Experiment results showed that the accuracy of the presented method in considering the varying illumination compared to the absence of varying illumination gives better performance in the facial skin segmentation. Bakhshali and Shamsi [1] used the meta-heuristic algorithm based on Bacterial Foraging Optimization (BFO) to optimize Otsu and Kapoor thresholdings to segment face images in IHLS color space. Alaei et al. [7] presented the Possibilistic Fuzzy C-means (PFCM) method for facial skin segmentation to evaluate in facial surgeries. Francisco et al. [8] introduced a method based on skin color segmentation using fuzzy entropy to detect the face. To recognize face, Lou et al. [9] presented the reconstruction of the color space by optimizing the luminance and chrominance components. Cuevas et al. [10] presented a Learning Vector Quantification (LVQ) method for face segmentation to use in face tracking. Naji et al. [4] used a method based on multi-pixel clustering models to segment the skin. The presented method has no sensitivity to changes in lighting conditions and background complexity. Hani et al. [5] presented a hybrid neural network and k-means clustering method for skin detection. In the presented method, a multilayer perceptron neural network was used to train the network. Also, to improve the performance of the presented method in skin detection, Differential Evolution (DE) algorithm was used to optimize the neural network. Xu et al. [11] introduced GMM method and the Support Vector Machine (SVM) for face color classification. The desired features were extracted using the GMM method. Paracchini et al. [12] presented a facial skin detection method using a Deep Learning Architecture (DLA). The presented method can detect skin pixels in low resolution grayscale images. Salah et al. [13] presented a novel method for human skin detection based on Convolutional Neural Network (CNN). Sahnoune et al. [14] presented a rule-based skin detection method in the Cyan Magenta Yellow Key (CMYK) color space. In this method, two thresholding models were presented which are based on the relation between CMYK components.

The k-means algorithm is one of the simplest clustering methods in data mining. This method is quick and easy to implement but not suitable for finding cluster centers in complexly distributed data. Fuzzy C-means (FCM) is a soft segmentation method that is widely used in medical applications and face analysis. FCM is an unsupervised method used for model reconstruction and data analysis. In this method, based on the distance criterion, one membership degree is assigned to each data, so that the membership degree depends on the proximity of the data to the cluster centers. In other words, FCM algorithm divides n vectors into c fuzzy groups, calculates the cluster center for each group, and minimizes the dissimilarity function [15-22]. FCM is one of the most effective algorithms in image segmentation, but sensitivity to the initial value may cause this algorithm to fall at a local minimum. In other words, the main structure of the FCM algorithm is to apply the descending gradient method and find the optimal answer. As a result, we have a spatial optimization problem in which the convergence rate is affected by the initial values. To overcome this problem, meta-heuristic algorithms are used. FCM algorithm can be expressed as an optimization problem in two ways. (1) Considering the membership degree (u_{ij}) as the initial population for each search agent is a discrete optimization problem for the FCM algorithm. (2) Considering cluster centers (v_i) as the initial population for each search factor is a continuous optimization problem for the FCM algorithm. In discrete optimization mode, the problem dimension is high, and not every meta-heuristic algorithm can optimize the FCM algorithm in this mode. In recent years, extensive research has been conducted on the optimization of the FCM algorithm using meta-heuristic algorithms. Most of this work has focused on expressing the FCM algorithm as a continuous optimization problem. In this section, the related works to optimize the FCM algorithm are reviewed for image segmentation.

Rahman Ali et al [16] presented a method based on Fast Fuzzy C-means (FFCM) optimization based on Particle Swarm Optimization (PSO) to segment CT images. Compared to the FFCM method, the FFCMPSO method exhibited better results in the segmentation of CT images. Bose and Mali [20] presented a method based on FCM optimization using Artificial Bee Colony (ABC) to segment the gray image. Compared to the FCMGA, FCMPSO, and EM maximization methods, the FCMABC method was performed better in terms of convergence, computational complexity, robustness, and segmentation accuracy. Das and De [21] presented an improved version of the Genetic Algorithm (MGA) to express the FCM algorithm as an optimization problem. This method (FCMMGA) was used to segment MRI images. Compared to the FCMGA method, the improved version of GA showed better results in image segmentation and convergence speed. Li et al. [22] used an improved version of Grey Wolf Optimization (MGWO) to segment the SAR images to improve the performance of the FCM algorithm. In this method, the cluster primary centers are considered as the search agent for the GWO algorithm. Differential evolution (DE) was used to improve the performance of the GWO algorithm. Experimental results showed that both FCMGWO and FCMDEGWO methods performed better than the FCM method in terms of segmentation accuracy and convergence speed. Zhang et al. [19] presented another approach to image segmentation based on the FCM algorithm and Biogeography-Based Optimization (BBO). In this method, improved versions of the BBO algorithm were also used in combination with the FCM algorithm. Experimental results showed that FCMBBO method has better performance in image segmentation than FCMPSO, FCMABC and FCM methods. Also, improved versions of BBO (MBBO) performed better than FCMBBO. Verma et al. [15] used the meta-heuristic PSO algorithm to solve the shortcomings of the FCM algorithm. In the PSO algorithm, the optimal parameter is represented by a particle position, and this parameter is evaluated by the cost function during an iteration of the program execution. In this method, each particle vector shows the cluster center. Results showed that the FCMPSO hybrid method performed better than the FCMELPSO and FCMBBO methods in image segmentation accuracy. Also, results showed that the execution time of the program in the FCMPSO method is longer than other methods. Fred et al. [17] presented a hybrid method of Crow Search Algorithm (CSA) and FCM based on continuous optimization for segmentation of medical images. Experimental results showed that FCMCSA method has better performance in terms of Partition Coefficient (PC), Partition Entropy (PE), Sugeno Index (SI), CS index, and segmentation accuracy compared to FCMABC and FCMSA methods. Tongbram et al. [18] presented the Whale Optimization Algorithm (WOA) to segment MRI images in the presence of noise. WOA algorithm has a great ability to solve large-scale optimization problems. Experimental results showed that FCMWOA method has better performance in segmentation of MRI images and convergence speed than the FCM and FCMIPSO methods. In all presented methods [15-22], the FCM algorithm has been considered as a continuous optimization problem.

Regarding the background of research works, the FCM algorithm has been not considered as an optimization problem for facial skin segmentation under varying illumination. This parameter has a notable effect on facial skin segmentation applicable for contour extraction in the analysis of facial reconstruction surgeries. Therefore, in this paper, a modified version of the Fuzzy C-Means (MFCM) algorithm with adding varying illumination parameter is presented to segment facial color images. MFCM algorithm is sensitive to the initial value and may cause this algorithm to fall at a local minimum. In this paper, a hybrid optimization method is presented to overcome the mentioned problems, which combines Harris Hawk Optimization (HHO) with GWO algorithm to improve the exploration phase in the HHO algorithm. Also, the same weight coefficients are used in updating the position of prey for all three alpha, beta, and delta wolves. The ability of wolves for selecting these coefficients is not considered. To improve the location update, these coefficients are updated based on the ability of each wolf. The block-diagram of proposed algorithm has been shown in ***Figure 1***.

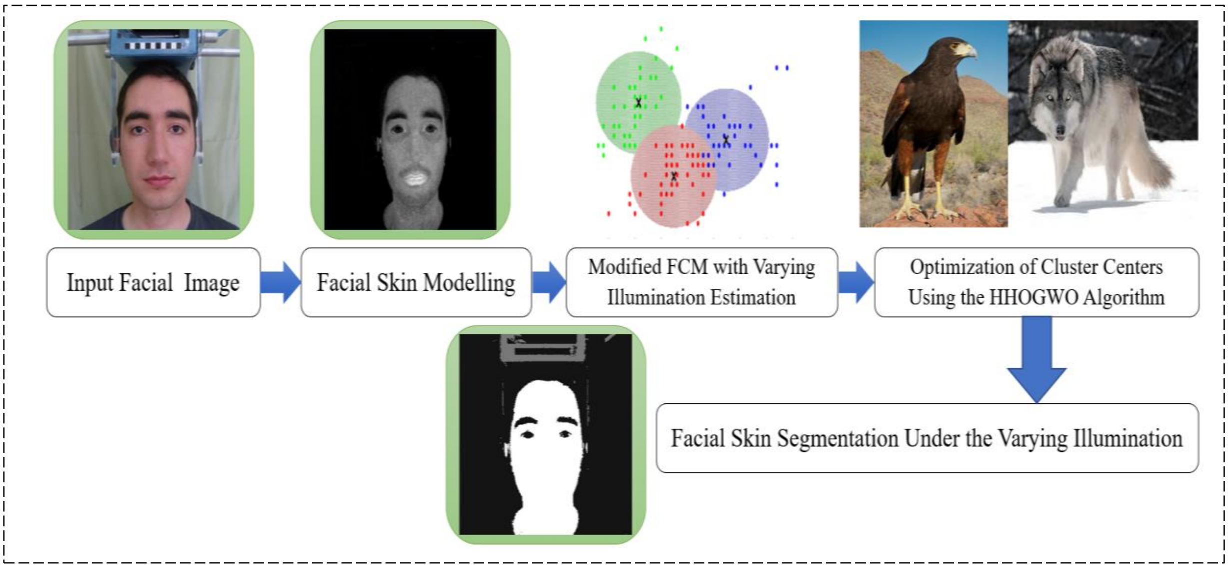

Figure. 1. Block-diagram of the proposed algorithm for facial skin segmentation under varying illumination.

The general structure of the article is as follows. In Section 2, a brief summary of HHO algorithm is presented. Section 3 presents a modified FCM algorithm for varying illumination estimation. The proposed hybrid Harris hawk optimization is presented in Section 4. Experimental results and discussion are described in Section 5. Finally, the conclusion and future works are presented in Section 6.

2. Harris Hawk Optimization

The HHO [23] is a new meta-heuristic algorithm that has been inspired by the participatory behavior and the pursuit style of the Harris hawk in hunting prey, in most cases rabbits. Harris hawk's main method in the hunting prey is known as the seven kills strategy. In this intelligence strategy, several hawks jointly try to attack from different directions and simultaneously converge on an identified escaping rabbit. When the best hawk or leader of the group loses prey, the hawks will use the substitution strategy. In this case, the pursuit process by one of the group members will continue. This method is suitable for confusing escaping rabbits.

In the HHO algorithm, at each stage, the hawks and the prey of the target are considered as the selected answers and the best-selected answer, respectively. When hawks cannot see prey, they peak at several locations and are detected by two approaches (1) the perching of the hawks based on the position of other family members and (2) the perching of the hawks based on the position of the rabbit (prey). As a result, the new position of the hawks will be updated as follows [23]:

$$x(t+1)=\begin{cases} x_{rand}(t)-r_1|x_{rand}(t)-2r_2x(t)|, q\geq 0.5 \\ x_{rabbit}(t)-x_m(t)-r_3\big(LB+r_4(UB-LB)\big), q<0.5 \\ x_m(t)=\frac{1}{N}\sum_{i=1}^{N}x_i(t) \end{cases} \quad \textbf{(1)}$$

where x_{rand}, x_{rabbit} and x_m are a randomly selected hawk from the current position, the position of the rabbit and the average position of the current position of hawks, respectively. (r_1, r_2, r_3, r_4) parameters are random numbers in interval [0,1]. Also, q parameter show an equal chance for each perching strategy.

In the HHO algorithm, the exploration and exploitation phases are controlled using the escaping energy of the prey (parameter E). When the $|E|\geq 1$ exploration phase occurs, while it will be $|E|<1$ in the exploitation phase. In the exploitation phase, the prey often tries to escape from dangerous situations; however different chasing strategies will occur in real situations. Based on the escape-chase behavior, there are 4 possible strategies (1) soft besiege, (2) hard besiege, (3) soft besiege with the gradual rapid attack, and (4) hard besiege with the gradual rapid attack. In this case, a soft besiege will occur when $|E|\geq 0.5$ and a hard besiege will occur when $|E|<0.5$. Also, parameter *r* is used to surround the prey softly or hard from different directions. Soft and hard besieges are modeled based on E and *r* parameters. When $r\geq 0.5$, and $|E|\geq 0.5$, the rabbit still has enough energy to escape through randomly confusing jumps and soft besiege behavior is modeled. Also, When $r\geq 0.5$ and $|E|<0.5$, the prey is exhausted and will not have enough energy to escape. In these conditions, the hard besiege will be modelled.

In the HHO algorithm, Levy Flight (LF) is used to model rabbit escape patterns. It is assumed that if the hawks take prey in competitive conditions, the hawks can gradually select the best possible attack on the rabbit. Then, the result of the current attack will be compared with the previous attack. If the result of the attack is not good, the hawks will continue their irregular, sudden, and fast attacks. It is assumed that the hawks want to carry out an attack based on LF patterns using the following rule [23]:

$$\begin{cases} Z=Y+S.LF(D) \\ Y=x_{rabbit}(t)-E|J.x_{rabbit}(t)-x(t)| \end{cases} \quad \textbf{(2)}$$

where *S* and *D* are the dimension of problem and a random vector by size 1×D, respectively.

When still $|E| \geq 0.5$ but $r < 0.5$, the hunt still has enough energy for a successful escape and a soft besiege is still applied before the surprise attack. The final strategy for updating the position of the hawks in the soft besiege phase will be as follows [23]:

$$x(t+1) = \begin{cases} Y, F(Y) < F\big(x(t)\big) \\ Z, F(Z) < F\big(x(t)\big) \end{cases} \quad \textbf{(3)}$$

when $|E| < 0.5$ and $r < 0.5$, the rabbit has not enough energy to escape and a hard besiege is applied before the surprise attack to kill the rabbit. In this process, the hawks try to decrease the distance of their average location with the escaping rabbit. For more information about HHO algorithm and the final strategy for updating the position of the hawks in the hard besiege phase, it can be referred to [23].

3. Modified Fuzzy c-Means with Varying Illumination Estimation

A facial color image can be modeled as a multiplying main signal (X_k) (reflectance component) and illumination component(VI_k):

$$Y_K = X_K \times VI_K, \forall K \in (1, 2, \dots, n) \quad \textbf{(4)}$$

Eq. (4) can be expressed as an additive term as follows:

$$Y_K = X_K + VI_K, \forall K \in (1, 2, \dots, n) \quad \textbf{(5)}$$

which Y_k is the *k*th observed logarithmic image and X_k is the *k*th true logarithmic image. Objective function of modified FCM algorithm can be expressed as follows:

$$J(U, C, VI) = \sum_{k=1}^{c} \sum_{i=1}^{n} {u_{ki}}^m \|y_i - VI_k - c_k\|^2 \quad \textbf{(6)}$$

To find varying illumination of face (VI_k) for the *k*th pixel, the objective function (*J*) is derived respect to VI_k and set the result to zero. The varying illumination coefficient is expressed by ***Eq. (7)***:

$$VI_k = \frac{\sum_{i=1}^{n} {u_{ki}}^m (y_i - c_k)}{\sum_{i=1}^{n} {u_{ki}}^m} \quad \textbf{(7)}$$

To obtain the cluster centers, the objective function (*J*) is derived relative to C_k and then set to zero. The center of each cluster is updated by ***Eq. (8)***:

$$C_k = \frac{\sum_{i=1}^{n} {u_{ki}}^m (y_i - VI_k)}{\sum_{i=1}^{n} {u_{ki}}^m} \quad \textbf{(8)}$$

To obtain the membership matrix, the new objective function subject to the constraints $\sum_{\mathrm{i}=1}^{\mathrm{c}} u_{ki} = 1$ is defined using the Lagrange multiplier method:

$$L(U, C, VI) = \sum_{k=1}^{c} \sum_{i=1}^{n} {u_{ki}}^m \|y_i - VI_k - c_k\|^2 + \lambda\left(1 - \sum_{i=1}^{c} u_{ki}\right) \quad \textbf{(9)}$$

To evaluate the membership matrix, the objective function (L) is derived relative to $\mathrm{u_{ki}}$ and then set to zero. Finally, the membership matrix is expressed by ***Eq. (10)***:

$$u_{ki} = \frac{1}{\sum_{j=1}^{c} \left(\frac{y_i - VI_k - {c_k}^2}{y_i - VI_k - {c_j}^2} \right)^{\frac{1}{m-1}}} \quad \textbf{(10)}$$

4. Proposed Hybrid Harris Hawk Optimization

Spatial variations of the imaging systems and inadequate lighting conditions in the hospital environment and medical centers cause varying illumination in facial images. The varying illumination effects is an important problem in facial skin segmentation and the analysis of facial plastic surgeries. The extraction of facial components and external contour of the profile view plays an important role in many applications such as planning of facial reconstruction surgeries, which it is a challenging problem under this effect. In this paper, the MFCM algorithm is presented to estimate and correct the varying illumination parameter. Also, this algorithm is sensitive to the initial value and may cause this algorithm to fall at a local minimum. HHO algorithm is used to prevent the MFCM algorithm from getting stuck at a local minimum. The algorithm starts with the initial population as the position of the hawks, and the goal is for the hawks to gradually move closer to the position of the prey (rabbit). In the HHO algorithm, the exploration phase can be improved. In this process, the search agents are randomly selected. The random location will cause the search agents to be either near to or far from the potential regions. To overcome this problem, the GWO is used to improve the ability of exploration process in the HHO. The GWO has proved its ability to optimize the problems with high dimension. Therefore, the proposed hybrid method (HHOGWO) is used to optimize the MFCM parameters. Also, in the original GWO algorithm, alpha, beta, and delta wolves are used for the updating the position of prey with same coefficient weight. In the presented method, these coefficients are updated based on the ability of each wolf. ***Figure 1*** shows a summary of the proposed hybrid algorithm for facial skin segmentation under varying illumination.

Grey wolves are more interested to live in groups. They have a very strict social dominant hierarchy. This ranking includes alpha (α), beta (β), delta (δ), and omega (ω) wolves, respectively. The assignment of the alpha wolf is to decide about hunting, sleeping place, and time to wake up. Also, they are the best in the management of a group. Beta wolves are subordinate wolves that help the alpha wolf in decision-making. The lowest ranking belongs to the omega wolf. Omega wolf plays the role of protection. Delta wolves do not belong to alpha, beta, or omega wolves [48]. Grey wolf hunting made of three main phases: (1) tracking, chasing, and approaching the prey; (2) pursuing, encircling, and harassing the prey until the prey stops moving; (3) attacking the prey. The mathematical model of the grey wolf hunting includes five main steps: (1) ranking the wolves; (2) encircling prey; (3) hunting; (4) attacking the prey (exploitation phase); (5) searching for prey (exploration phase). The behavior of encircling the prey by grey wolves is modelled using ***Eq. (11)*** [24]:

$$\begin{cases} D = \left|C.x_p(t) - x(t)\right| \\ x(t+1) = x_p(t) - A.D \end{cases} \tag{11}$$

where C, D, and $x_p(t)$ are coefficient vectors and the position vector of the prey. ***Eq. (12)*** is used to calculate the coefficient vectors [24]:

$$\begin{cases} A = 2a.r_1 - a \\ C = 2r_2 \end{cases} \tag{12}$$

where $\vec{a}$ is linearly decreased from 2 to 0 and (r_1, r_2) are random vectors in [0,1]. In order to model the hunting behaviour, it is supposed that α, β, and δ wolves have better knowledge about the location of prey. There is no knowledge about the location of prey $(x_p(t))$ in the search space.

Therefore, the position of prey is considered alpha (the best obtained position). Hunting prey is modelled as below [24]:

$$\begin{cases} D_\alpha(t) = |C_1.x_\alpha(t) - x(t)| \rightarrow x_1(t) = x_\alpha(t) - A_1.D_\alpha(t) \\ D_\beta(t) = |C_2.x_\beta(t) - x(t)| \rightarrow x_2(t) = x_\beta(t) - A_2.D_\beta(t) \\ D_\gamma(t) = |C_3.x_\gamma(t) - x(t)| \rightarrow x_3(t) = x_\gamma(t) - A_3.D_\gamma(t) \\ x(t+1) = \frac{x_1(t)+x_2(t)+x_3(t)}{3} \end{cases} \quad (13)$$

For more information about GWO, it can be referred to [24]. In Equation (13), the same weight coefficient has been used for all three alpha, beta, and delta wolves. To improve the location update, this coefficient is updated based on the ability of each wolf. In other words, the ability of three wolves are different, and their coefficients must also be different. Based on the ranking of wolves, weight coefficients are considered $W_1 = 0.7$, $W_2 = 0.2$, and $W_3 = 0.1$ for alpha, beta, and delta wolves, respectively. Since the lowest ranking belongs to the alpha wolf, the largest weight coefficient is assigned to the alpha wolf. ***Eq. (14)*** is used as a new formula for updating the position of prey:

$$\begin{cases} x(t+1) = W_1.X_1(t) + W_2.X_2(t) + W_3.X_3(t) \\ W_1 + W_2 + W_3 = 1 \end{cases} \quad (14)$$

The search agents are randomly selected in the exploration phase of HHO algorithm. To improve the efficiency of exploration phase in the HHO, the obtained position of the alpha wolf is replaced with the random position in each iteration. ***Eq. (15)*** is used as a new position for the hawks:

$$x(t+1) = x_\alpha(t) - r_1|x_\alpha(t) - 2r_2.x(t)|, q \geq 0.5 \quad (15)$$

Flowchart of the proposed algorithm has been shown in ***Figure 2***.

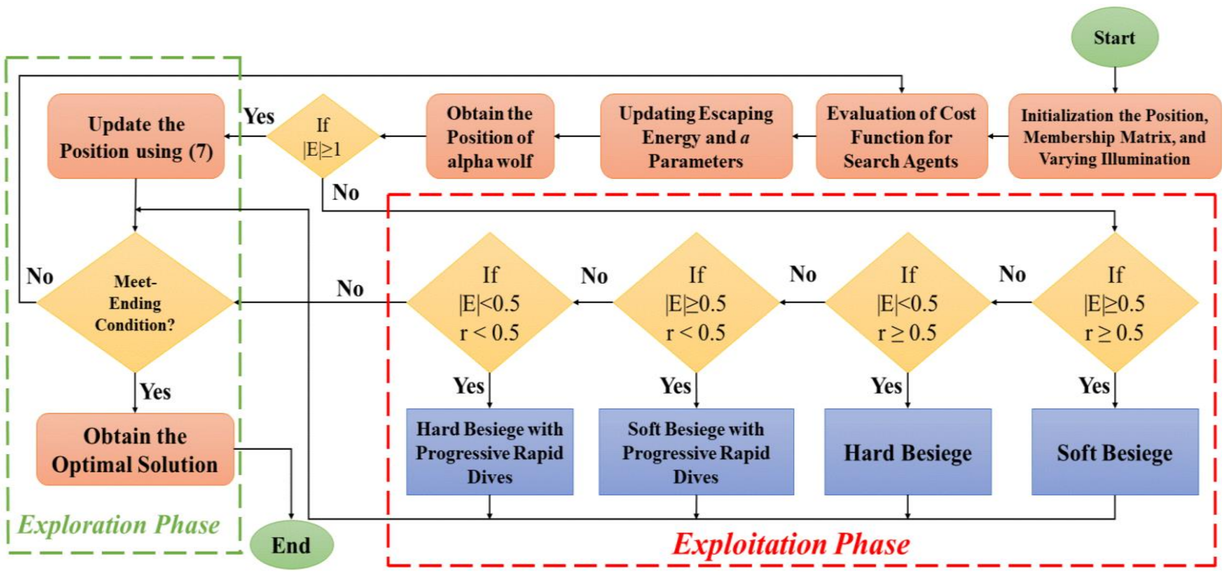

Figure. 2. Flowchart of the proposed hybrid method to improve the HHO algorithm.

5. Experimental Results

To evaluate the proposed algorithms, the SUT dataset [25] and facial images of patients referred to the ENT division of Emam Hospital, Tehran, Iran [6] are used. SUT dataset has a very important impact in facial surgery analysis due to using an orthogonal system. This system has a head-fixed structure that can increase the accuracy of imaging. The orthogonal imaging system has many advantages in facial surgery analysis. One of the important advantages is capturing three orthogonal images simultaneously. In this system, 100 facial color images from the frontal and profile views are used. All images were resized to 300×400. In this study, the YPbPr color space [26] is used to model the facial skin. This color space has a suitable performance in modelling non-skin pixels. The Pr channel of this color space has a good performance in modelling skin pixels. To verify the efficiency of the proposed algorithm, other methods for the optimization of FCM algorithm including FCMPSO [15], FCMCSA [17], FCMWOA [18], FCMBBO [19], and FCMGWO [22] are used for comparison. These methods have been introduced as an effective algorithms for image segmentation. Metaheuristic algorithms should provide a suitable balance between exploration and exploitation phases. This task need tuning parameters. The parameters of mentioned methods were set as suggested in the article. Also, all implementations were performed using the same simulation parameters. For all metaheuristic algorithms, we set the search agents $n = 12$, the maximum number of iterations to 40, and the fuzzy parameter m to 2. Also, the number of cluster centers was set to 3 for each image. The used constant parameters in optimization algorithms have been shown in ***Table 1***.

Table 1. Value of the constant parameters for the used meta-heuristic algorithms.

PSO	Value	CSA	Value	BBO	Value	GWO	Value	WOA	Value	HHO	Value
nPop	12	nPop	12	nPop	12	nPop	12	nPop	12	nPop	12
MaxItr	40	MaxItr	40	MaxItr	40	MaxItr	40	MaxItr	40	MaxItr	40
W	1.0	AP	0.1	$Keep_{rate}$	0.2	r_1	rand()	r_1	rand()	q	rand()
$\boldsymbol{C_1}$	2.0	FL	2	alpha	0.9	r_2	rand()	r_2	rand()	r	rand()
$\boldsymbol{C_2}$	2.0	-	-	mutation	0.1	-	-	P	rand()	-	-

5. 1. Evaluation Criteria

In this study, five main criteria including: *CE*, *PC* [27], *DSC*, *JSC*, and *CMS* [28] are used to quantitative evaluate the performance of the methods.

- ***Classification Entropy (CE):*** this index measures the fuzziness of the cluster partition. A clustering method has a suitable performance when the CE index value is low. This index is defined as follows:

$$CE = -\frac{1}{N}\sum_{i=1}^{C}\sum_{j=1}^{N} log\left({u_{ij}}^{q}\right) \quad \textbf{(16)}$$

- ***Partition Coefficient (PC):*** this index determines the amount of overlapping between clusters. A clustering method has a suitable performance when the PC index value is high. This index is defined as follows:

$$PC = \frac{1}{N}\sum_{i=1}^{C}\sum_{j=1}^{N}\left({u_{ij}}^{2}\right) \quad \textbf{(17)}$$

- ***Dice Similarity Coefficient (DSC):*** this index is used to measure the overlap degree between two images, including segmented image and manually segmented image. DSC index is defined as follows:

$$DSC(A,B) = \frac{2|A\cap B|}{|A|+|B|} \quad \textbf{(18)}$$

- ***Jaccard Similarity Coefficient (JSC):*** this index is used to compute the similarity between two images. JSC index is defined as follows:

$$JSC(A,B) = \frac{|A \cap B|}{|A \cup B|} \quad \textbf{(19)}$$

- ***Contour Matching Score (CMS):*** this index is used to compute the contour matching score between the segmented image and manually segmented image. This index is in the range [0,1], a score of 1 means that the contour of objects in the predicted image and ground-truth are the perfect match. CMS index is defined as follows:

$$CMS = \frac{2.P^c.R^c}{P^c + R^c} \quad \textbf{(20)}$$

where P^c and R^c are precision and recall, respectively. A clustering method has a suitable performance when the DSC, JSC, and CMS criteria value are high.

5. 2. Experimental Results

In this article, the FCM algorithm was optimized in three mods. (1) Optimization of FCM algorithm using HHO without varying illumination (FCMHHO). (2) Optimization of MFCM algorithm using HHO (MFCM+HHO). (3) Optimization of MFCM algorithm using the proposed hybrid algorithm (HHOGWO). Also, the MFCM algorithm was optimized using the GWO algorithm (MFCM+GWO) for comparison with proposed algorithm. ***Figure 3*** shows the convergence speed of these three algorithms for the four samples. It is clear that the obtained value of cost function for the proposed algorithm is smaller than MFCM+GWO and MFCM+HHO algorithms.

Figure 4 shows some results for facial skin segmentation under varying illumination on images of patients referred to the ENT division of *Imam Hospital, Tehran, Iran*. Clinics or hospitals often does not provide acceptable lighting conditions for taken facial images. As shown in ***Figure 4*** (the first row), these conditions cause intensity inhomogeneity. This condition causes shadows on the facial images (especially under the chin). The proposed algorithm has been able to accurately label the regions of intensity inhomogeneity to the class of facial skin tissue. Facial landmark detection requires the contour extraction. Facial skin segmentation for accurate extraction of facial contour and facial quantitative measurements in facial reconstruction surgeries is an important challenge under varying illumination conditions. ***Figure 4*** demonstrates that the proposed algorithm has high efficiency and is robust to the varying illumination effect in the segmentation of facial color images and can be used as a suitable method for the analysis of facial plastic surgeries.

Figures 5, 6 illustrate some results of the proposed algorithms on facial color images of SUT dataset. The second column shows the constructed model of facial skin based on Pr channel. Results of the conventional FCM algorithm have been demonstrated in the third column. It illustrates which conventional FCM algorithm does not suitable performance in segmentation of facial skin due to varying illumination effect. The extraction of facial components and external contour of the profile view plays an important role in many applications such as planning of facial reconstruction surgeries. As shown in ***Figures 5, 6*** (the third column), skin regions under the chin have incorrectly labeled. It makes the segmentation task difficult. Also, ***Figure 6(c)*** demonstrates that facial contour extraction from profile view is not correctly performed. It is obvious that the proposed algorithm has good performance for facial skin segmentation.

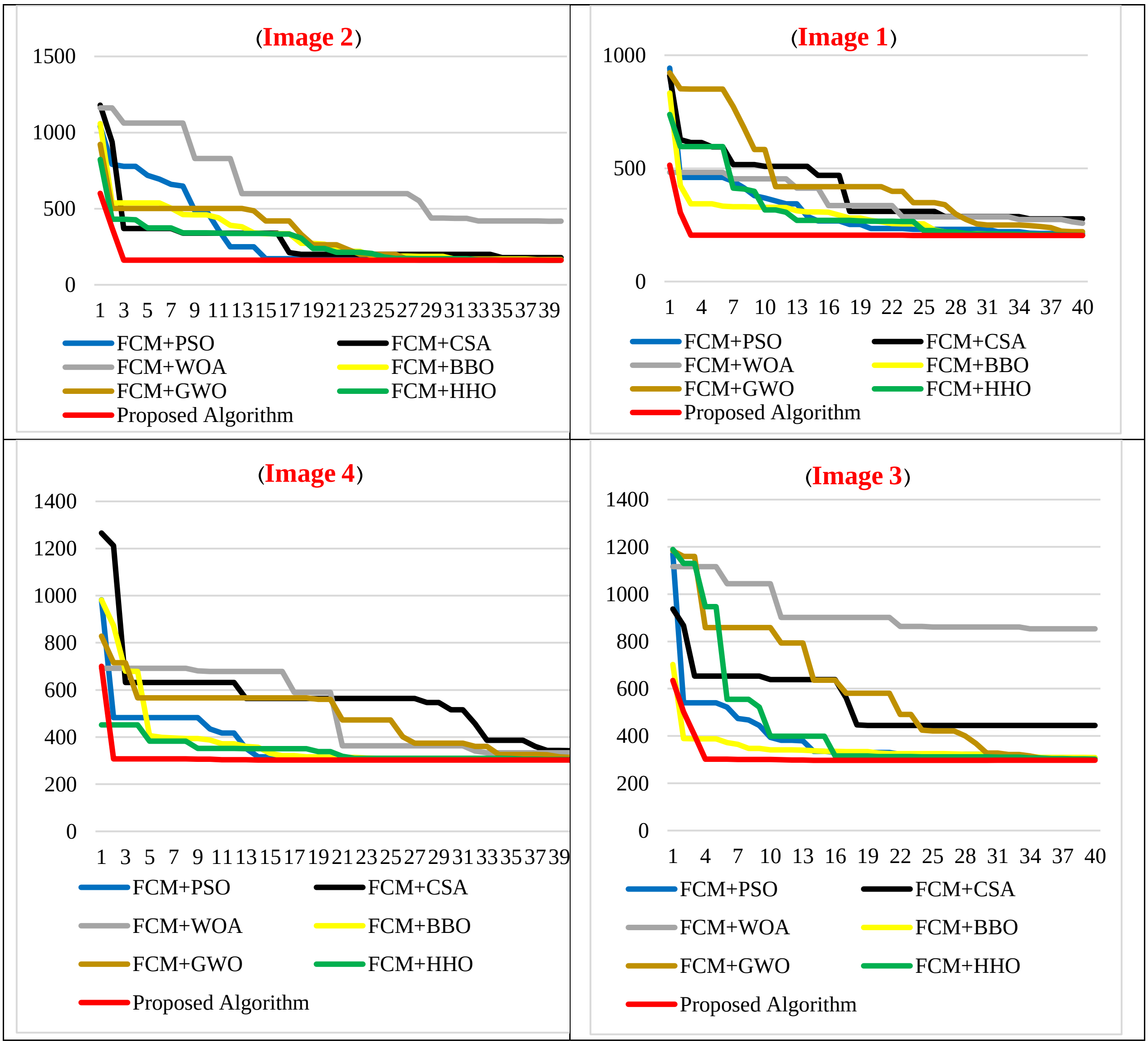

Figure. 3. Convergence Speed of Different Algorithms for MFCM Optimization.

Figure. 4. Illustrate the efficiency of proposed algorithm (HHOGWO) for facial skin segmentation under varying illumination on facial images of patients referred to the ENT division of *Imam Hospital, Tehran, Iran* [6]. **First row** Original facial color images. **Second row** Segmented facial images under varying illumination using the proposed algorithm.

Experimental results of the different methods to optimize the FCM algorithm are presented in ***Tables 2 and 3***. A descriptive statistical analysis including mean and standard deviation (S.D) is presented for facial skin segmentation from frontal and profile views. ***Table 2*** indicates that the proposed algorithms perform better than the other compared methods. CMS index manifests that the contour matching in the proposed algorithms is proper in facial skin segmentation. It is valuable to mention that the S.D index is low in more experimental results. Based on ***Table 3***, all criteria in the proposed algorithms are better than those of the other compared methods. Therefore, the proposed method illustrates a suitable performance in facial skin segmentation from profile view. Based on the obtained results, it can be concluded that the proposed algorithm is more robust to varying illumination effect. Also, it demonstrates that the integration of GWO in HHO is effective to improve the exploration phase.

Table 2. Comparison of the different methods for facial skin segmentation from the frontal view.

Criteria / Methods	CE Index		PC Index		DSC Index		JSC Index		CMS Index	
	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D
FCMPSO [15]	0.334^{5}	0.089^{6}	0.821^{6}	0.057^{6}	0.910^{4}	0.072^{4}	0.842^{4}	0.113^{4}	0.685^{5}	0.187^{5}
FCMCSA [17]	0.486^{8}	0.210^{8}	0.742^{7}	0.119^{8}	0.872^{8}	0.120^{7}	0.791^{8}	0.167^{7}	0.617^{8}	0.213^{8}
FCMWOA [18]	0.357^{7}	0.097^{7}	0.815^{5}	0.058^{7}	0.889^{7}	0.139^{8}	0.821^{7}	0.168^{8}	0.663^{7}	0.202^{7}
FCMBBO [19]	0.343^{6}	0.068^{4}	0.815^{5}	0.043^{4}	0.903^{5}	0.089^{5}	0.834^{5}	0.132^{5}	0.692^{4}	0.159^{4}
FCMGWO [22]	0.327^{4}	0.082^{5}	0.823^{4}	0.053^{5}	0.894^{6}	0.100^{6}	0.822^{6}	0.147^{6}	0.671^{6}	0.200^{6}
FCMHHO	0.325^{3}	0.067^{3}	0.825^{3}	0.042^{2}	0.925^{3}	0.065^{3}	0.867^{3}	0.103^{3}	0.730^{3}	0.147^{3}
MFCM+HHO	0.176^{2}	0.058^{2}	0.913^{2}	0.037^{1}	0.949^{2}	0.028^{1}	0.904^{2}	0.047^{2}	0.777^{2}	0.103^{1}
Proposed Algorithm	0.145^{1}	0.042^{1}	0.941^{1}	0.046^{3}	0.976^{1}	0.030^{2}	0.926^{1}	0.035^{1}	0.782^{1}	0.120^{2}

Table 3. Comparison of the different methods for facial skin segmentation from the profile view.

Criteria / Methods	CE Index		PC Index		DSC Index		JSC Index		CMS Index	
	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D
FCMPSO [15]	0.356^{7}	0.076^{3}	0.808^{7}	0.050^{4}	0.916^{4}	0.067^{3}	0.851^{3}	0.102^{3}	0.695^{3}	0.140^{3}
FCMCSA [17]	0.478^{8}	0.202^{8}	0.747^{8}	0.113^{8}	0.868^{8}	0.161^{7}	0.792^{8}	0.186^{8}	0.625^{8}	0.212^{8}
FCMWOA [18]	0.343^{6}	0.096^{6}	0.820^{6}	0.061^{5}	0.876^{7}	0.172^{8}	0.807^{5}	0.185^{7}	0.647^{6}	0.180^{5}
FCMBBO [19]	0.339^{5}	0.069^{2}	0.821^{5}	0.044^{2}	0.879^{6}	0.135^{6}	0.803^{7}	0.166^{6}	0.640^{7}	0.181^{6}
FCMGWO [22]	0.329^{4}	0.104^{7}	0.826^{4}	0.067^{7}	0.884^{5}	0.102^{5}	0.805^{6}	0.148^{5}	0.648^{5}	0.184^{7}
FCMHHO	0.305^{3}	0.067^{1}	0.840^{3}	0.042^{1}	0.918^{3}	0.086^{4}	0.832^{4}	0.127^{4}	0.671^{4}	0.150^{4}
MFCM+HHO	0.232^{2}	0.091^{5}	0.877^{2}	0.062^{6}	0.940^{2}	0.029^{1}	0.888^{2}	0.049^{1}	0.736^{2}	0.077^{1}
Proposed Algorithm	0.222^{1}	0.090^{4}	0.935^{1}	0.047^{3}	0.948^{1}	0.030^{2}	0.901^{1}	0.060^{2}	0.762^{1}	0.100^{2}

The FCMHHO algorithm has the best performance compared to the other methods. Crow Search Algorithm (CSA) has not satisfying performance on the optimization of the FCM algorithm. FCMCSA has the lowest values in all criteria. Experimental results of two meta-heuristic algorithms including: Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) are close to the results of the HHO algorithm, approximately. HHO algorithm has a high ability in optimizing the problem with high dimension. Experimental results confirm that adding the varying illumination effect to cost function and optimization of cluster centers by HHO (MFCM+HHO) has a suitable efficiency in facial skin segmentation. Also, it can be demonstrated that proposed algorithms including FCMHHO, MFCM+HHO, and MFCM+HHOGWO can be used as an effective method in the segmentation of facial color images and are robust to varying illumination condition applicable for analysis of facial plastic surgeries. The proposed algorithms have been performed by an Intel Core i7-9750H CPU with speed of 2.60 GHz and 16 GB of RAM.

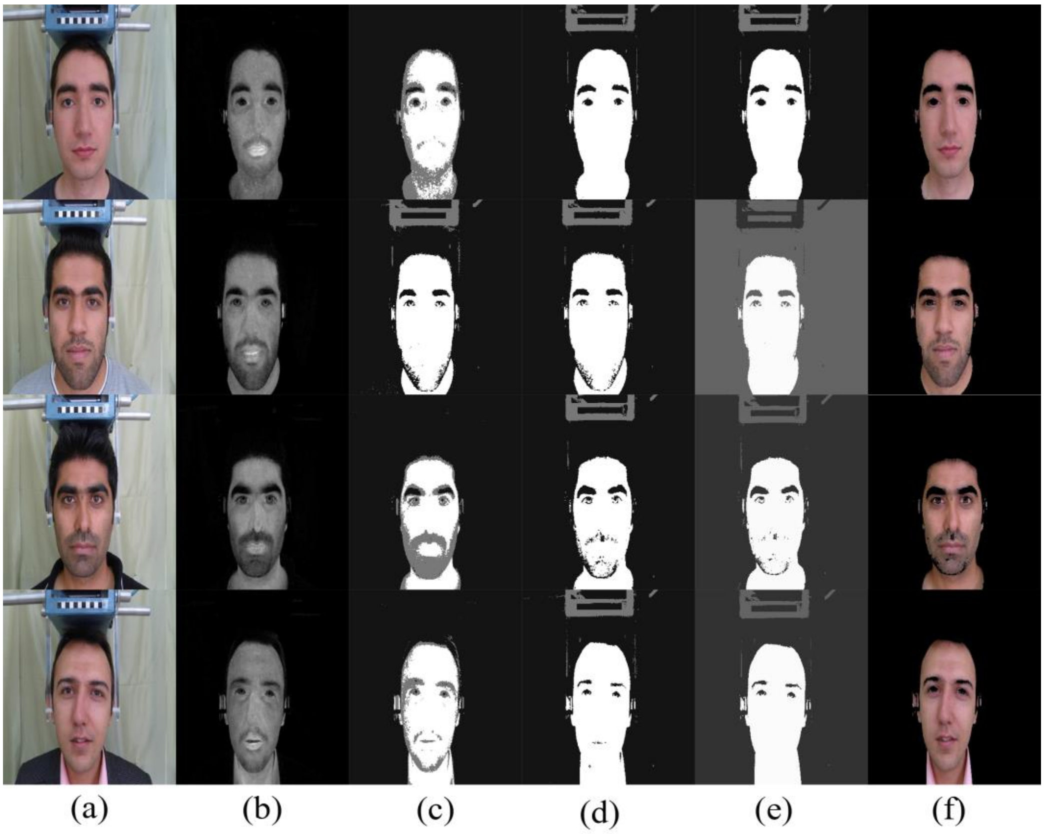

Figure. 5. Facial skin segmentation under varying illumination. (a): Frontal images. (b): Pr channel. (c): Skin segmentation based on conventional FCM algorithm. (d): Skin segmentation using the MFCM+HHO algorithm. (e): Skin segmentation using the proposed algorithm MFCM+HHOGWO (f): Facial mask.

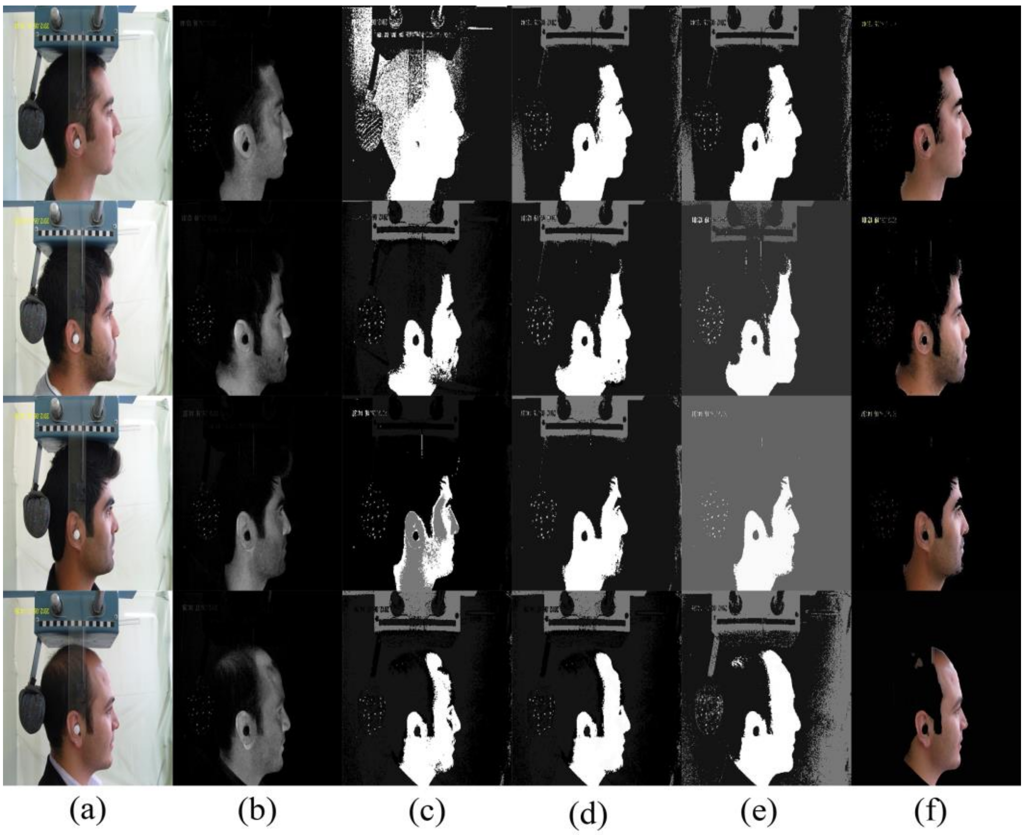

Figure. 6. Facial skin segmentation under varying illumination. (a): Profile images. (b): Pr channel. (c): Skin segmentation based on conventional FCM algorithm. (d): Skin segmentation using the MFCM+HHO algorithm. (e): Skin segmentation using the proposed algorithm MFCM+HHOGWO (f): Facial mask.

6. Conclusion and Future Works

The segmentation of facial color images plays a very important role in the contour extraction of facial components to use in the analysis of facial plastic surgeries. Spatial variations of the imaging systems cause varying illumination in facial images. Therefore, face segmentation is a challenging problem under varying illumination. In this study, we first proposed a modified FCM algorithm (MFCM) by adding a varying illumination condition to facial skin segmentation. MFCM algorithm is sensitive to the initial values and may fall in a local minimum. In the next step, Harris Hawk Optimization (HHO) was used to prevent the MFCM algorithm from getting stuck at a local minimum. In the HHO algorithm, the search agents are randomly selected. The random location will cause the search agents to be either near to or far from the potential regions. To overcome this problem, the Grey Wolf Optimization (GWO) is used to improve the ability of exploration process in the HHO. Finally, the same weight coefficient has been used to model the hunting prey for all three alpha, beta, and delta wolves. To improve the location update, this coefficient is updated based on the rank of each wolf. Experimental results confirmed that the proposed hybrid algorithm (MFCM+HHOGWO) is robust to facial skin segmentation under varying illumination and can be used in the analysis of facial surgical planning. Also, it indicated that the Pr channel of YPbPr color space can be used as a suitable preprocessing step for modeling facial skin. Therefore, the method introduced in this study is suitable for the segmentation of facial color images. However, like other clustering algorithms, there are obstacles in dealing with practical applications because the number of cluster centers is not adjusted automatically. Accordingly, as a suggestion, future studies should dedicate to automated estimation of the number of cluster centers. It can also be considered to examine the varying illumination for the FCM algorithm and optimize its parameters.

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