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Study and Implementation of the detection of Multilevel Segmentation for MR Images using HSO and PSO framework

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ABSTRACT: In this paper, a multilevel thresholding (MT) algorithm based on the harmony search optimization (HSO) is introduced and compared with PSO. HSO is an evolutionary method which is inspired in musicians improvising new harmonies while playing. Different to other evolutionary algorithms, HSO exhibits interesting search capabilities still keeping a low computational overhead. The proposed algorithm encodes random samples from a feasible search space inside the image histogram as candidate solutions, whereas their quality is evaluated considering the objective functions that are employed by the Otsu's or Kapur's methods. Guided by these objective values, the set of candidate solutions are evolved through the HSO operators until an optimal solution is found. PSO is effectively a better techniques as it optimises the search to obtain the global best solution. Experimental results demonstrate the high performance is obtained is using the PSO method for the segmentation of digital images.

KEYWORDS: Multi Level thresholding, Harmony search optimization, Particle swarm optimization, MR images.

I. INTRODUCTION

Segmentation is the most widely studied topic in computer vision. There are two types of approaches to deal with this problem: model-free methods (bottom-up fashion) and knowledge-based methods (top-down fashion). Model-free methods are often based on clustering, aiming at grouping together pixels with consistent visual properties according to a certain similarity criterion. Knowledge-driven methods, on the other hand, assume that the space of admissible solutions is constrained, and they seek a solution that is a compromise between the one produced from the observations and the one expressed in the model space.

Popular examples in the context of model-free segmentation refer to the mean-shift algorithm [Comaniciu 2002], variational formulations such as the Mumford-Shah framework [Mumford 1989] and its level set variant [Chan 2001, Paragios 2002], or graph-based methods including normalized cuts [Shi 2000], graph-cuts [Boykov 2006] etc. Due to the lack of assumptions on the geometric form of the object of interest, these methods are free in terms of admissible solutions, which is a desired property in certain cases but also an undesirable one since it can lead to erroneous results due to intensity variability, occlusions, noise presence, etc.

Knowledge-based methods are either manifold constrained or manifold enhanced. The former class of methods models geometric variation of the object of interest and then seeks an instance of this model in the image. Active shape [Cootes 1995] and active appearance models [Cootes 2001] are popular examples. Manifold enhanced methods aim at minimizing the distance of the solution from the learned manifold. Active contours/surface solutions [Staib 1996] are some examples. Both groups of knowledge-based methods inherit a severe limitation with respect to pose, since the sought solution should be brought to the same referential as the ones used in learning. The manifold constrained methods are rather robust to noise, but it cannot cope with examples not seen during training, while the manifold enhanced methods is often a compromise (to a certain extent) between model free and manifold constrained methods. There is another type of knowledge-based approaches widely used in medical imaging, namely atlas-based methods. The underlying idea of this approach is to achieve segmentation by registering an atlas to the target image. The atlas is a

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reference image associated with a ground truth segmentation. The segmentation of the target image is obtained by warping the atlas segmentation based on the deformation field from registration. In this context, choosing the atlas used as prior for the segmentation is very important. Thus, multi-atlas segmentation approaches with more sophisticated atlas construction techniques have been developed to capture shape variations of the object of interest. Since atlas-based segmentation is highly dependent on registration which is another active topic in computer vision, we will not discuss this type of approaches in details and we refer the reader to [Rohlfing 2005].

In recent years image processing has been applied to different areas as engineering, medicine, agriculture, and so forth. Since most of such implementations use a TH methodology, several techniques had been studied. Generally, TH methods are divided into parametric and nonparametric [2–5]. Parametric approaches need to estimate values of a probability density function to model each class. The estimation process is time consuming and computationally expensive.

On the other hand, the TH nonparametric employs several criteria such as the between-class variance, the entropy, and the error rate [6–8] in order to verify the quality of a th value. These metrics could also be used as optimization functions since they result as an attractive option due their robustness and accuracy. There exist two classical thresholding methods. The first, proposed by Otsu in [6] that maximizes the variance between classes while the second method, submitted by Kapur et al. in [7], uses the maximization of the entropy to measure the homogeneity among classes. Their efficiency and accuracy have been already proved for a bi-level segmentation [4]. Although they can be expanded for MT, their computational complexity increases exponentially when a new threshold is incorporated [5].

As an alternative to classical methods, the MT problem has also been handled through evolutionary optimization methods. In general, they have demonstrated to deliver better results than those based on classical techniques in terms of accuracy, speed, and robustness. Numerous evolutionary approaches have been reported in the literature. Hammouche et al. in [9] provides an interesting survey of how different evolutionary algorithms are used to solve the Kaptur's and Otsu's problems. The study uses four classical evolutionary algorithms to test their efficiency in MT. Such methods include differential evolution (DE) [10], simulated annealing (SA) [11], and tabu search (TS) [12]. Genetic algorithms (GA) [13], inspired on the biological evolution, have been also used for solving segmentation tasks. One interesting example is presented in [14], where a GA-based algorithm is combined with Gaussian models for multilevel thresholding. Other similar works, such as that of Yin [15] proposes an improved GA for optimal thresholding. In the approach, it is used as a learning strategy to increase the speed of convergence.

Evolutionary approaches inspired on swarm behavior, such as particle swarm optimization (PSO) [16] and artificial bee colony (ABC) [17], have been employed to face the segmentation problem. In [18], both methods are used to find the optimal multilevel threshold points by using the Kapur's entropy as fitness function.

Finally, in [19], the optimal segmentation threshold values are determined by using the bacterial foraging algorithm (BFA). Such method aims to maximize the Kapur's and Otsu's objective functions by considering a set of operators that are based on the social foraging behavior of the bacteria *Escherichia Colli*. On the other hand, the harmony search optimization (HSO) introduced by Geem et al.

II. IMAGE MULTILEVEL THRESHOLDING (MT)

Thresholding is a process in which the pixels of a gray scale image are divided in sets or classes depending on their intensity level (L). For this classification it is necessary to select a threshold value (th) and follow the simple rule of

$$C_1 \leftarrow p \quad \text{if } 0 \leq p < th,$$

$$C_2 \leftarrow p \quad \text{if } th \leq p < L - 1$$

where p is one of the $m \times n$ pixels of the gray scale image I_g that can be represented in L gray scale levels $L = \{0, 1, 2, \dots, L-1\}$. C_1 and C_2 are the classes in which the pixel p can be located, while th is the threshold. The rule in (5) corresponds to a bilevel thresholding and can be easily extended for multiple sets:

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$$C_1 \leftarrow p \quad \text{if } 0 \leq p < \text{th}_1,$$

$$C_2 \leftarrow p \quad \text{if } \text{th}_1 \leq p < \text{th}_2,$$

$$C_i \leftarrow p \quad \text{if } \text{th}_i \leq p < \text{th}_{i+1},$$

$$C_n \leftarrow p \quad \text{if } \text{th}_n \leq p < L - 1$$

where $\{\text{th}_1, \text{th}_2, \dots, \text{th}_i, \text{th}_{i+1}, \text{th}_k\}$ represent different thresholds. The problem for both bilevel and MT is to select the th values that correctly identify the classes. Although, Otsu's and Kapur's methods are well-known approaches for determining such values, both propose a different objective function which must be maximized in order to find optimal threshold values, just as it is discussed below.

A. Between-Class Variance (Otsu's Method)

This is a nonparametric technique for thresholding proposed by Otsu [6] that employs the maximum variance value of the different classes as a criterion to segment the image. Taking the L intensity levels from a gray scale image or from each component of a RGB (red, green, and blue) image, the probability distribution of the intensity values is computed as follows:

$$Ph_i^c = \frac{h_i^c}{NP}, \quad \sum_{i=1}^{NP} Ph_i^c = 1$$

$$c = \begin{cases} 1, 2, 3, & \text{if RGB Image,} \\ 1, & \text{if Gray scale Image,} \end{cases}$$

where i is a specific intensity level ($0 \leq i \leq L - 1$), c is the component of the image which depends if the image is gray scale or RGB, whereas NP is the total number of pixels in the image. i (histogram) is the number of pixels that corresponds to the i intensity level in c . The histogram is normalized within a probability distribution Ph_i^c . For the simplest segmentation (bilevel) two classes are defined as

$$C_1 = \frac{Ph_1^c}{\omega_0^c(\text{th})}, \dots, \frac{Ph_{\text{th}}^c}{\omega_0^c(\text{th})}, \quad C_2 = \frac{Ph_{\text{th}+1}^c}{\omega_1^c(\text{th})}, \dots, \frac{Ph_L^c}{\omega_1^c(\text{th})},$$

where $\omega_0(\text{th})$ and $\omega_1(\text{th})$ are probabilities distributions for C_1 and C_2 , as it is shown by

$$\omega_0^c(\text{th}) = \sum_{i=1}^{\text{th}} Ph_i^c, \quad \omega_1^c(\text{th}) = \sum_{i=\text{th}+1}^L Ph_i^c.$$

It is necessary to compute mean levels μ_0^c and μ_1^c that define the classes using (10). Once those values are calculated, the Otsu variance between classes σ_2^c is calculated using (11) as follows:

$$\mu_0^c = \sum_{i=1}^{\text{th}} \frac{i Ph_i^c}{\omega_0^c(\text{th})}, \quad \mu_1^c = \sum_{i=\text{th}+1}^L \frac{i Ph_i^c}{\omega_1^c(\text{th})},$$

$$\sigma^{2^c} = \sigma_1^c + \sigma_2^c.$$

Therefore, the optimization problem is reduced to find the intensity level (th) that maximizes (13). Otsu's method is applied for a single component of an image. In case of RGB images, it is necessary to apply separation into single component images. The previous description of such bilevel method can be extended for the identification of multiple thresholds. Considering thresholds, it is possible separate the original image into classes using (6); then it is necessary

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to compute the variances and their respective elements. The objective function (th) in (13) can thus be rewritten for multiple thresholds as follows:

$$J(\text{TH}) = \max(\sigma^{2^c}(\text{TH})), \quad 0 \leq \text{th}_i \leq L - 1, \quad i = 1, 2, \dots, k,$$

where $\text{TH} = [\text{th}_1, \text{th}_2, \dots, \text{th}_{(k-1)}]$, is a vector containing multiple thresholds and the variances are computed through

$$\sigma^{2^c} = \sum_{i=1}^k \sigma_i^c = \sum_{i=1}^k \omega_i^c (\mu_i^c - \mu_T^c)^2.$$

$$\omega_0^c(\text{th}) = \sum_{i=1}^{\text{th}_1} \text{Ph}_i^c,$$

$$\omega_1^c(\text{th}) = \sum_{i=\text{th}_1+1}^{\text{th}_2} \text{Ph}_i^c,$$

⋮

$$\omega_{k-1}^c(\text{th}) = \sum_{i=\text{th}_{k-1}+1}^L \text{Ph}_i^c.$$

And, for the mean values

$$\mu_0^c = \sum_{i=1}^{\text{th}_1} \frac{i \text{Ph}_i^c}{\omega_0^c(\text{th}_1)},$$

$$\mu_1^c = \sum_{i=\text{th}_1+1}^{\text{th}_2} \frac{i \text{Ph}_i^c}{\omega_0^c(\text{th}_2)},$$

⋮

$$\mu_{k-1}^c = \sum_{i=\text{th}_{k-1}+1}^L \frac{i \text{Ph}_i^c}{\omega_1^c(\text{th}_k)}.$$

Similar to the bilevel case, for the MT using the Otsu's method, c corresponds to the image components, RGB $c = 1, 2, 3$, and gray scale $c = 1$.

B. Entropy Criterion Method (Kapur's Method)

Another nonparametric method that is used to determine the optimal threshold values has been proposed by Kapur et al. [7]. It is based on the entropy and the probability distribution of the image histogram. The method aims to find the optimal th that maximizes the overall entropy. The entropy of an image measures the compactness and separability among classes. In this sense, when the optimal th value appropriately separates the classes, the entropy has the maximum value. For the bilevel example, the objective function of the Kapur's problem can be defined as

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$$J(\text{th}) = H_1^c + H_2^c,$$

$$c = \begin{cases} 1, 2, 3, & \text{if RGB Image,} \\ 1, & \text{if Gray scale Image} \end{cases}$$

where the entropies H1 and H2 are computed by the following model:

$$H_1^c = \sum_{i=1}^{\text{th}} \frac{Ph_i^c}{\omega_0^c} \ln \left(\frac{Ph_i^c}{\omega_0^c} \right),$$

$$H_2^c = \sum_{i=\text{th}+1}^L \frac{Ph_i^c}{\omega_1^c} \ln \left(\frac{Ph_i^c}{\omega_1^c} \right)$$

Similar to the Otsu's method, the entropy-based approach can be extended for multiple threshold values; for such a case, it is necessary to divide the image into classes using the similar number of thresholds. Under such conditions, the new objective function is defined as:

$$J(\text{TH}) = \max \left(\sum_{i=1}^k H_i^c \right),$$

$$c = \begin{cases} 1, 2, 3, & \text{if RGB Image,} \\ 1, & \text{if Gray scale Image,} \end{cases}$$

Each entropy is computed separately with its respective th value, so (21) is expanded for entropies:

$$H_1^c = \sum_{i=1}^{\text{th}_1} \frac{Ph_i^c}{\omega_0^c} \ln \left(\frac{Ph_i^c}{\omega_0^c} \right),$$

$$H_2^c = \sum_{i=\text{th}_1+1}^{\text{th}_2} \frac{Ph_i^c}{\omega_1^c} \ln \left(\frac{Ph_i^c}{\omega_1^c} \right),$$

⋮

$$H_k^c = \sum_{i=\text{th}_{k-1}+1}^L \frac{Ph_i^c}{\omega_{k-1}^c} \ln \left(\frac{Ph_i^c}{\omega_{k-1}^c} \right)$$

III. MULTILEVEL THRESHOLDING USING HARMONY SEARCH ALGORITHM (HSMA)

A. Harmony Representation.

Each harmony (candidate solution) uses k different elements as decision variables within the optimization algorithm. Such decision variables represent a different threshold point the that is used for the segmentation.

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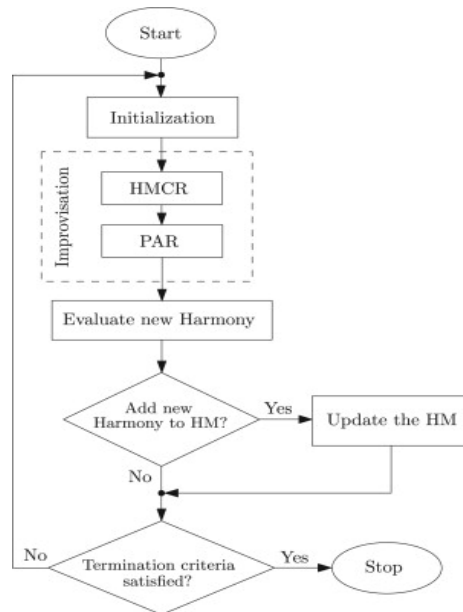


Fig 1. HSA Frame work

Therefore, the complete population is represented as

$$HM = [x_1^c, x_2^c, \dots, x_{HMS}^c]^T,$$

$$x_i^c = [th_1^c, th_2^c, \dots, th_k^c],$$

where T refers to the transpose operator, HMS is the size of the harmony memory, x_i is the i_{th} element of HM , and $c = 1, 2, 3$ is set for RGB images while $c = 1$ is chosen for gray scale images. For this problem, the boundaries of the search space are set to $l = 0$ and $u = 255$, which correspond to image intensity levels.

B. Swarm Intelligence: Swarm intelligence (SI) is the collective behavior of decentralized, self-organized systems, natural or artificial. The concept is employed in work on artificial intelligence. The expression was introduced by Gerardo Beni and Jing Wang in 1989, in the context of cellular robotic systems. SI systems consist typically of a population of simple agents or boids interacting locally with one another and with their environment. The inspiration often comes from nature, especially biological systems. The agents follow very simple rules, and although there is no centralized control structure dictating how individual agents should behave, local, and to a certain degree random, interactions between such agents lead to the emergence of "intelligent" global behavior, unknown to the individual agents. Examples in natural systems of SI include ant colonies, bird flocking, animal herding, bacterial growth, fish schooling and microbial intelligence.

Working of PSO: PSO is initialized with a group of random particles (solutions) and then searches for optimal by updating generations. Particles move through the solution space, and are evaluated according to some fitness criterion after each time step. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far (the fitness value is also stored). This value is called $pbest$. Another "best" value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the population. This second best value is a global best and called $gbest$.

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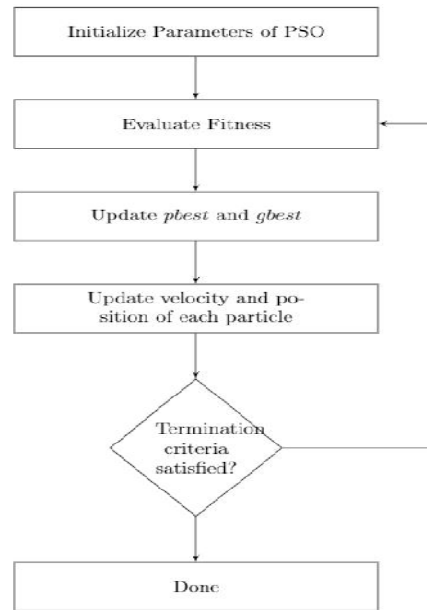


Fig 2. Flow Chart of PSO Optimization

When a particle takes part of the population as its topological neighbors, the second best value is a local best and is called **lbest**. Neighborhood bests allow parallel exploration of the search space and reduce the susceptibility of PSO to falling into local minima, but slow down convergence speed.

IV. RESULTS AND DISCUSSION

The HSMA has been tested under a set of 11 benchmark images. Some of these images are widely used in the image processing literature to test different methods (Lena, Cameraman, Hunter, Baboon, etc.) [3, 9]. All the images have the same size (512×512 pixels), and they are in JPGE format. For the sake of representation, only five images which are presented in Figure 1 have been used to show the visual results; however, the numerical outcomes are analyzed considering the complete set. Since HSMA is stochastic, it is necessary to employ an appropriate statistical metrics to measure its efficiency. Hence, the results have been reported executing the algorithm 35 times for each image. In order to maintain compatibility with similar works reported in the literature [14, 15, 18, 19], the number of thresholds points used in the test are $th = 2, 3, 4, 5$. In the experiments, the stop criterion is the number of times in which the best fitness values remain with no change. Therefore, if the fitness value for the best harmony remains unspoiled in 10% of the total number of iterations (NI), then the HSA is stopped. To evaluate the stability and consistency, it has been computed the standard deviation (STD) from the results obtained in the 35 executions. Since the STD represents a measure about how the data are dispersed, the algorithm becomes more instable as the STD value increases [19]. Equation (23) shows the model used to calculate the STD value:

$$STD = \sqrt{\sum_{i=1}^{NI} \frac{(bf_i - av)^2}{Ru}}$$

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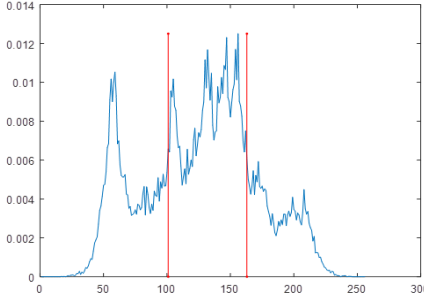
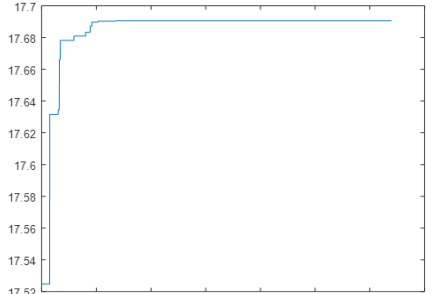
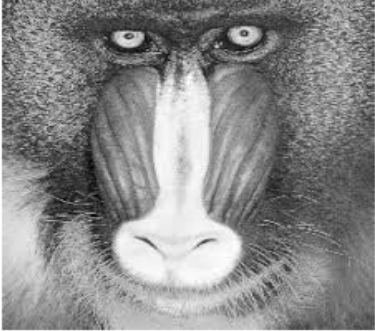
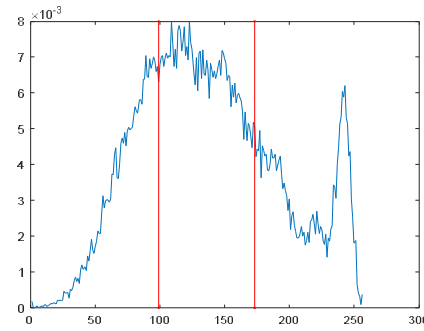
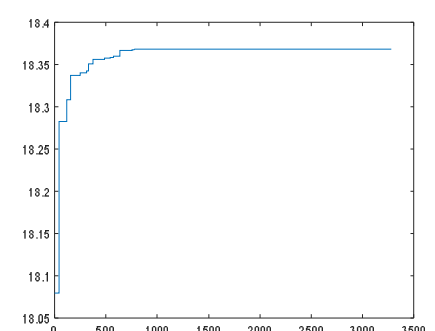
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$$PSNR = 20 \log_{10} \left(\frac{255}{RMSE} \right), \quad (dB)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{ro} \sum_{j=1}^{co} (I_o^c(i, j) - I_{th}^c(i, j))^2}{ro \times co}},$$

HSO Kapur :

The resultant image obtained after applying the HSO using kapur method	Histogram of image after applying 2 thresholds values on original image(Gray level on X-axis & Frequency on Y-axis)	Convergence curve for hso using kapur method (Number of iterations on X-axis & Objective function values on Y-axis).
	<p>th = 101 & 163</p> 	
	<p>th = 99 & 173</p> 	
	<p>th = 128 & 196</p>	

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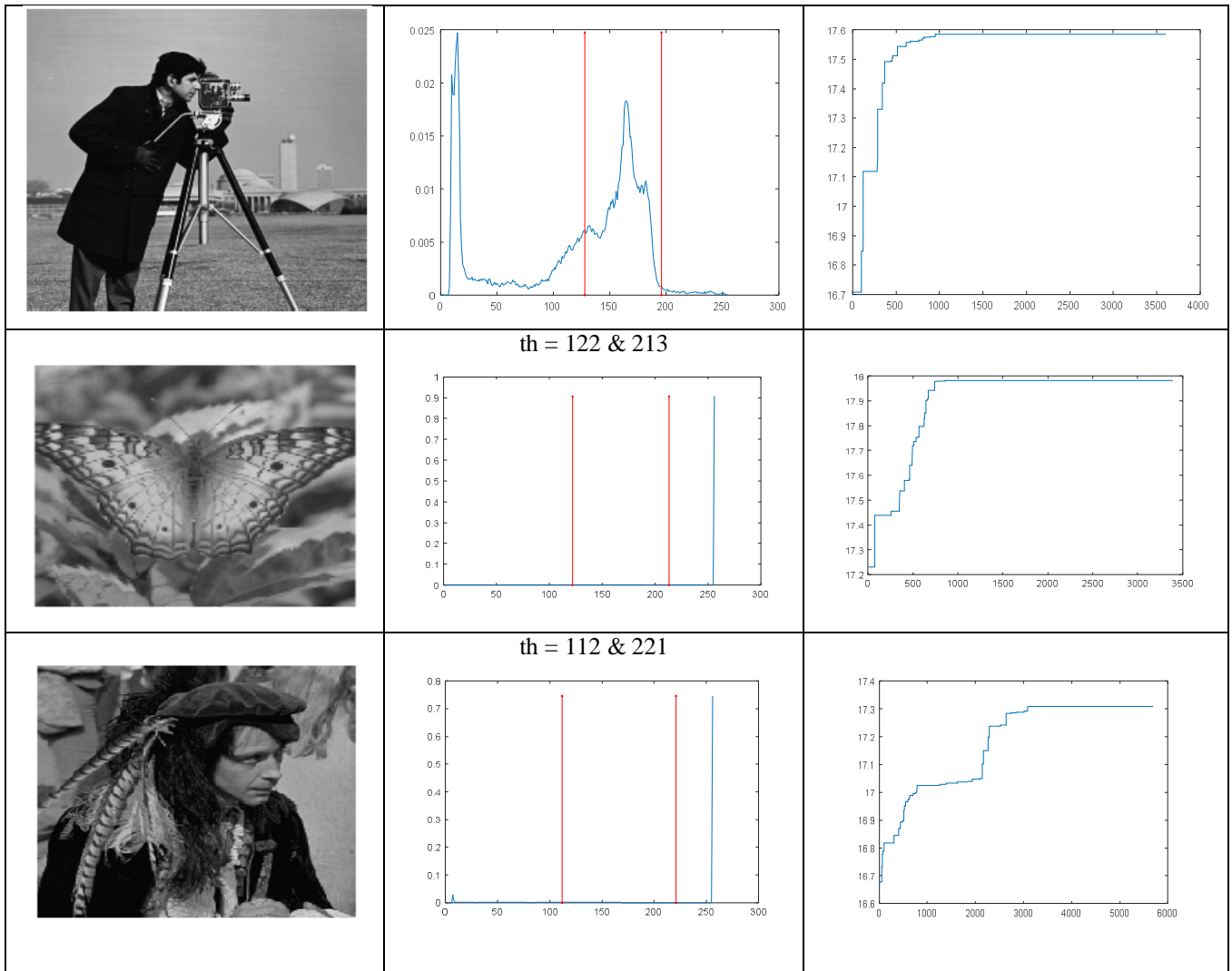


Table 1: Results obtained after applying HSO using Kapur's over Lena, Baboon, Camera man, Butterfly and Hunter images


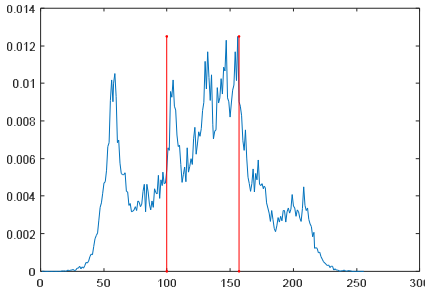
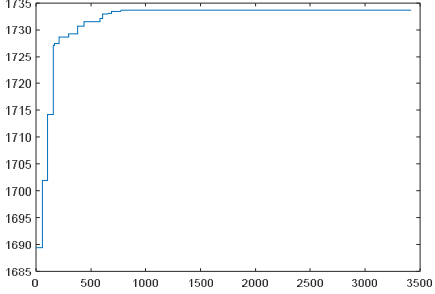

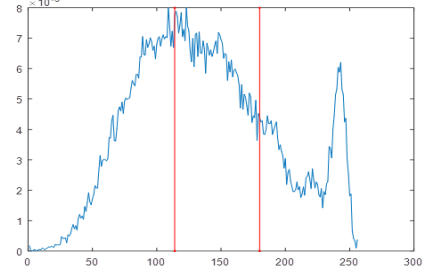
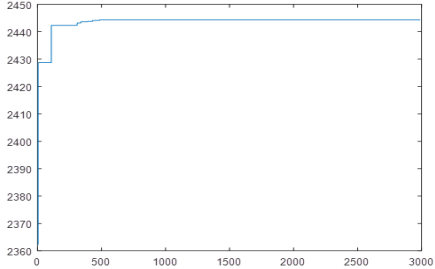

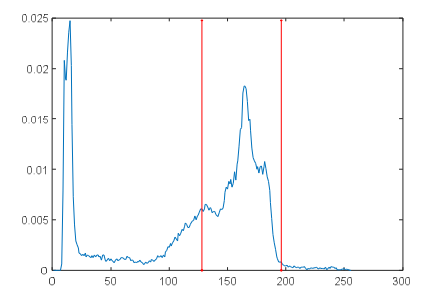
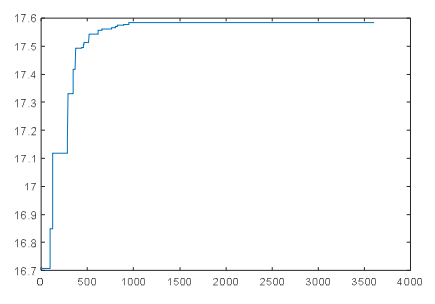
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HSO Otsu:

The resultant image obtained after applying the HSO using otsu method	Histogram of image after applying 2 threshold values on original image(Gray level on X-axis & Frequency on Y-axis)	Convergence curve for hso using otsu method (number of iterations on X-axis & Objective function values on Y-axis).
	<p>th =100 & 157</p> 	
	<p>th = 114 & 180</p> 	
	<p>th =128 & 196</p> 	

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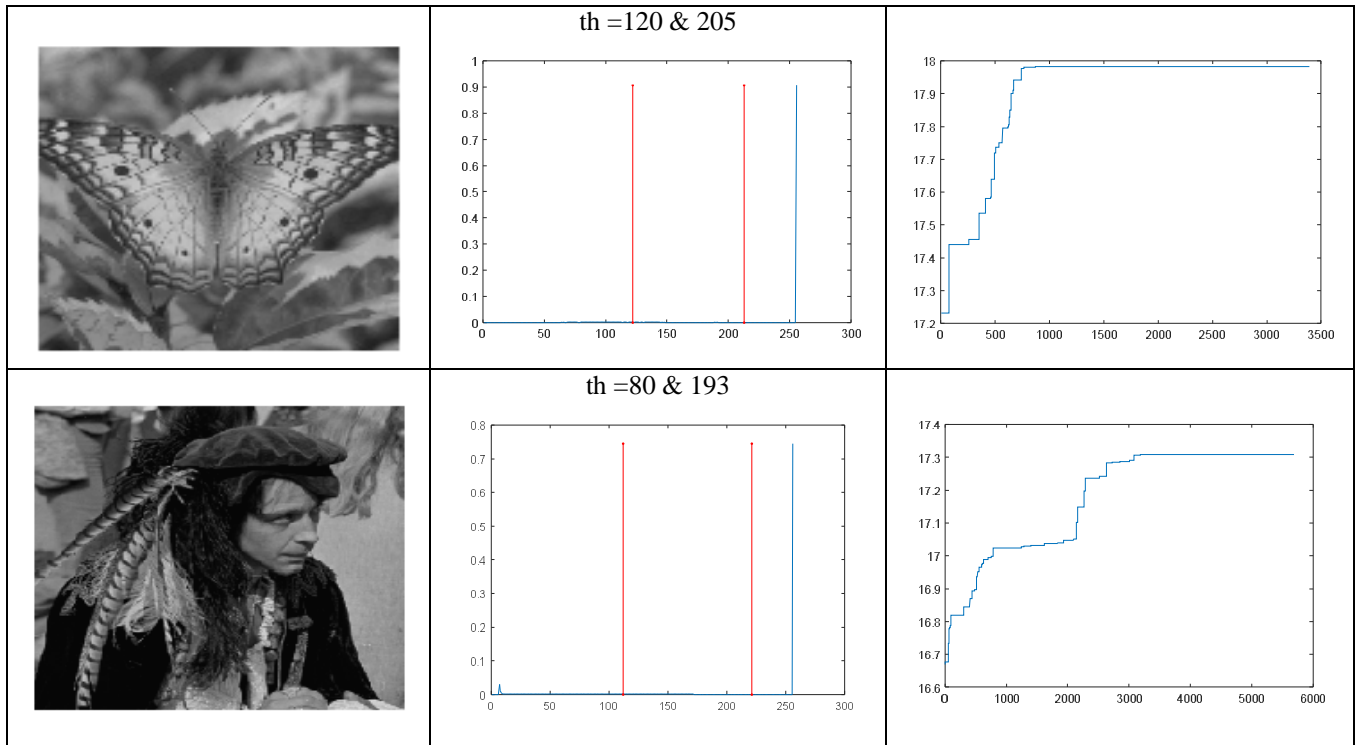


Table 2: Results obtained after applying HSO using Otsu over Lena, Baboon, Camera man, Butterfly and Hunter images

PERFORMANCE ANALYSIS TABLE USING HSO:

HSO	STD	MEAN	PSNR
KAPUR CASE 1(Lena)	0.0263	17.68	14.4167
KAPUR CASE 2(Baboon)	0.0364	18.35	13.6241
KAPUR CASE 3(Camera man)	0.1791	17.5231	13.625
KAPUR CASE 4(Butterfly)	0.1928	17.8947	14.9466
KAPUR CASE 5(Hunter)	0.1666	17.1730	16.324
OTSU CASE 1(Lena)	7.067	1.7317e+03	14.64

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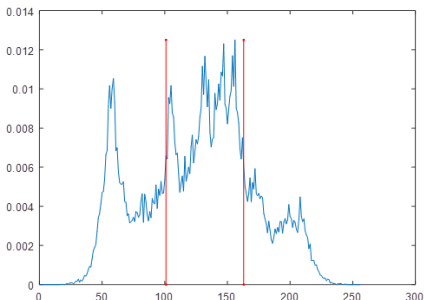
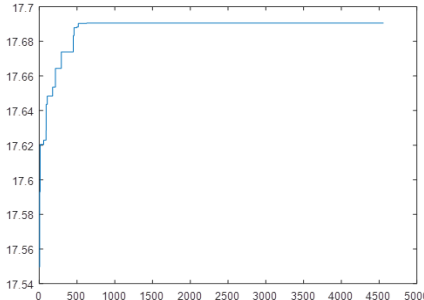
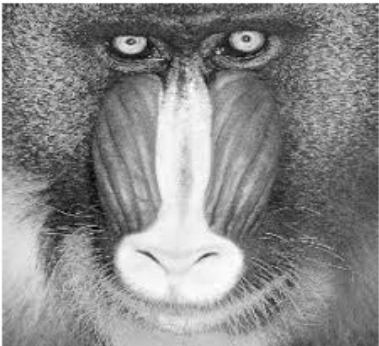
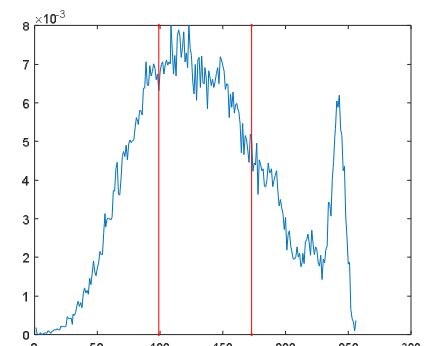
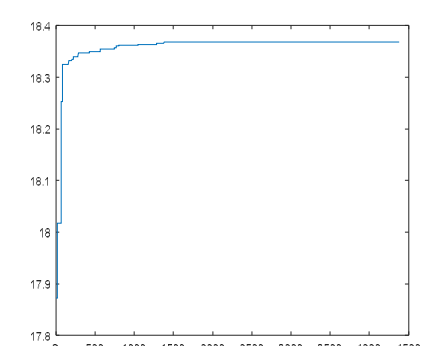
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OTSU CASE 2(Baboon)	4.14	2.4430e+03	12.546
OTSU CASE 3(Camera man)	2.3025	3.6514e+03	17.24
OTSU CASE 4(Butterfly)	0.6378	1.7486e+03	13.764
OTSU CASE 5(Hunter)	0.386	6.6196e+03	12.776

PSO Kapur:

The resultant image obtained after applying the PSO using kapurs method	Histogram of image after applying 2 threshold values on original image(Gray level on X-axis & Frequency on Y-axis)	Convergence curve for pso using kapurs method (Number of iterations on X-axis and Objective function values on Y-axis).
	<p>th =101 & 163</p> 	
	<p>th =99 & 173</p> 	
	<p>th =128 & 196</p>	

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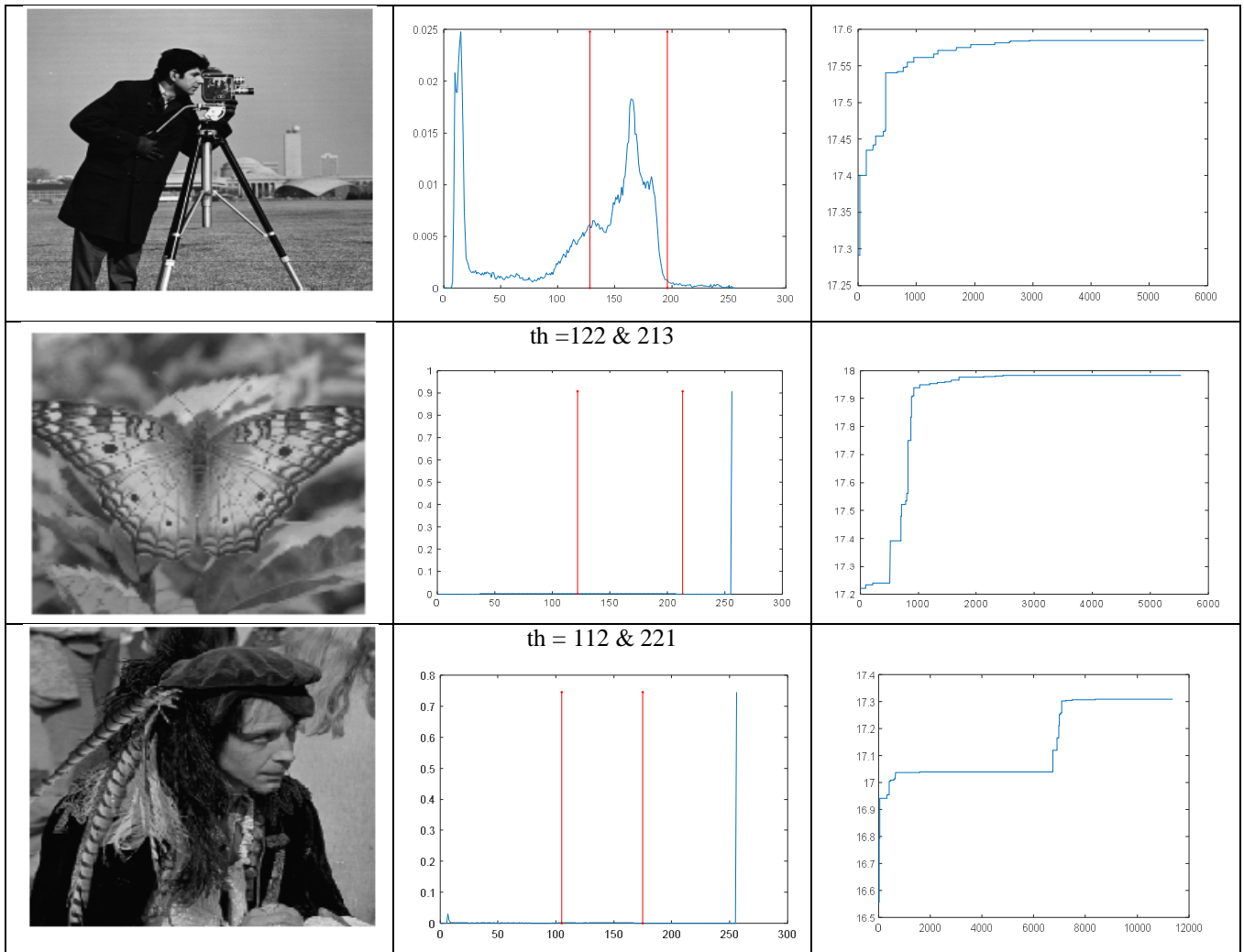


Table 3: Results obtained after applying PSO using Kapur's over Lena, Baboon, Camera man, Butterfly and Hunter images


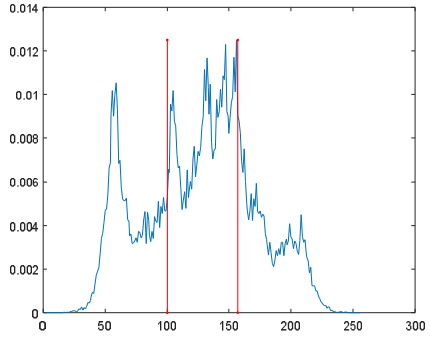
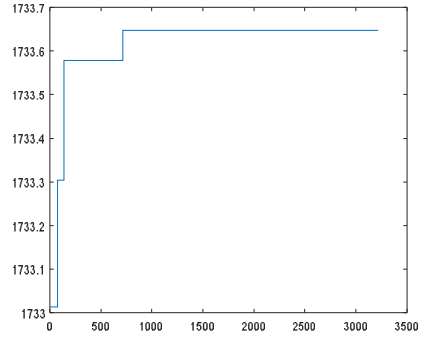
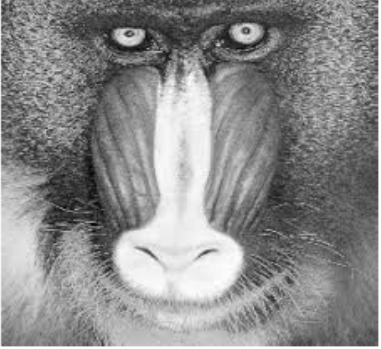
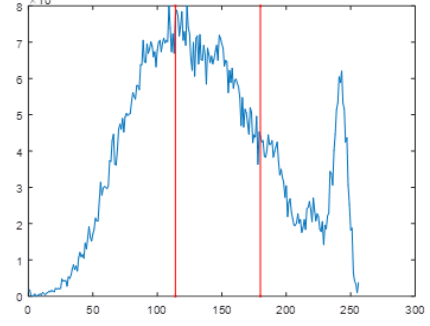
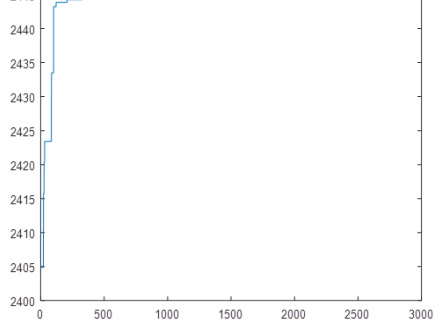

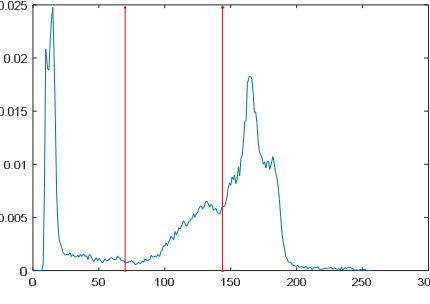
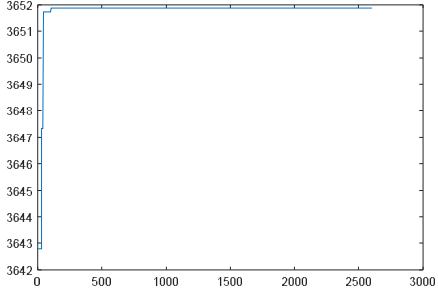
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PSO Otsu:

The resultant image obtained after applying the PSO using otsu method	Histogram of image after applying 2 threshold values on original image(Gray level on X-axis & Frequency on Y-axis)	Convergence curve for pso using otsu method with number of iterations on X-axis and Objective function values on Y-axis.
	<p>th = 100 & 157</p> 	
	<p>th = 114 & 180</p> 	
	<p>th = 70 & 114</p> 	

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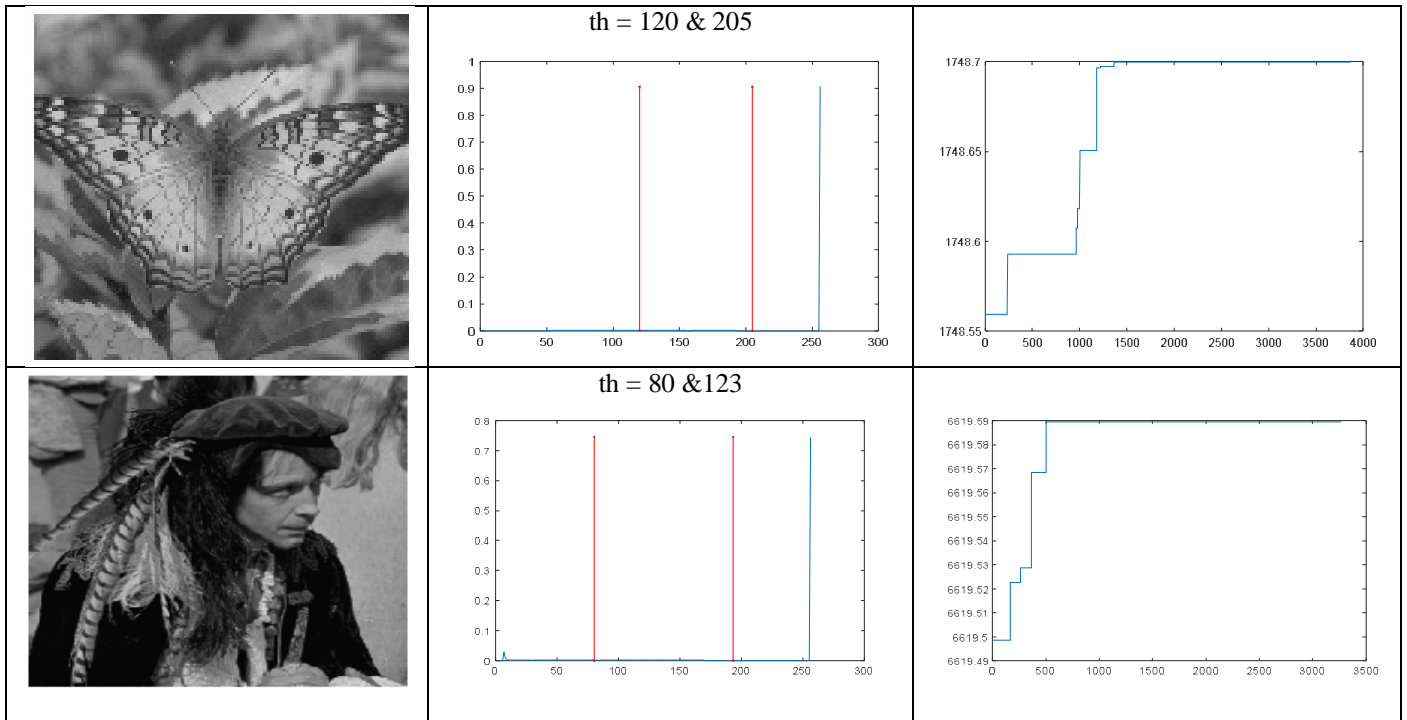


Table 4: Results obtained after applying PSO using Otsu over Lena, Baboon, Camera man, Butterfly and Hunter images

PERFORMANCE ANALYSIS TABLE USING PSO:

PSO	STD	MEAN	PSNR
KAPUR CASE 1 (Lena)	0.8521	18.9350	15.0300
KAPUR CASE 2 (Baboon)	0.4193	20.093	13.9126
KAPUR CASE 3(Camera man)	0.0459	19.0980	14.7366
KAPUR CASE 4(Butterfly)	0.2028	17.9868	16.8880
KAPUR CASE 5(Hunter)	0.1826	17.6546	18.241
OTSU CASE 1(Lena)	7.245	1.7434e+03	15.66
OTSU CASE 2(Baboon)	4.5120	2.4446e+03	13.4507
OTSU CASE 3(Camera man)	2.405	3.6523e+03	18.55
OTSU CASE 4(Butterfly)	0.7364	1.7597e+03	15.1349
OTSU CASE 5(Hunter)	0.7623	6.6297e+03	13.516

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VI. CONCLUSION

The proposed approach has been compared to other techniques that implement different optimization algorithms like GA and BF. The efficiency of the algorithm has been evaluated in terms of the PSNR index and the STD value. Experimental results provide evidence on the outstanding performance, accuracy, and convergence of the proposed algorithm in comparison to other methods. Although the results offer evidence to demonstrate that the standard HSO method can yield good results on complicated images, the aim of our paper is not to devise an MT algorithm that could beat all currently available methods, but to show that harmony search algorithms and Particle swarm optimization algorithm is compared and, PSO can be effectively considered as an attractive alternative for this purpose.

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