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Compression and Enhancement of Medical Images Using Opposition Based Harmony Search Algorithm

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Abstract

The growth of telemedicine-based wireless communication for images—magnetic resonance imaging (MRI) and computed tomography (CT)—leads to the necessity of learning the concept of image compression. Over the years, the transform based and spatial based compression techniques have attracted many types of researches and achieve better results at the cost of high computational complexity. In order to overcome this, the optimization techniques are considered with the existing image compression techniques. However, it fails to preserve the original content of the diagnostic information and cause artifacts at high compression ratio. In this paper, the concept of histogram based multilevel thresholding (HMT) using entropy is appended with the optimization algorithm to compress the medical images effectively. However, the method becomes time consuming during the measurement of the randomness from the image pixel group and not suitable for medical applications. Hence, an attempt has been made in this paper to develop an HMT based image compression by utilizing the opposition based improved harmony search algorithm (OIHSA) as an optimization technique along with the entropy. Further, the enhancement of the significant information present in the medical images are improved by the proper selection of entropy and the number of thresholds chosen to reconstruct the compressed image.

Keywords

Entropy, Harmony Search Algorithm, Image Compression, Multi-Thresholding, Optimization

1. Introduction

Due to the recent advancements in the hospitals, the amount of generation of the digital images for telemedicine-based applications has rapidly increased. But, they have many limitations at the time of analyzing the medical images as well as storing images for future references. Some of them are limited power resources, lack of storage space, bandwidth availability, and computational complexity. To address the above mentioned concerns, an effective image compression scheme is needed to ensure a significant size reduction without affecting the diagnostic information of the image. But, the selection of appropriate image compression with a high compression ratio possess a great challenge. A number of image compression techniques have been proposed so far in the field of medical imaging technology [1].

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Among them, lossless compression techniques are especially preferred to compress medical images. However, most of the lossless compression algorithms able to achieve better results at a low compression ratio only and also the storage and computation time are yet to be a big problem. Thus, dealing with the high compression ratio without losing critical medical information is the main challenging task for medical based image compression. To alleviate this limitation, it is important to develop a perfect and simple compression technique for medical images in order to consume less memory space for processing the image. The image compression techniques used for medical images are commonly classified into two categories such as transform-based and prediction-based [2]. Depending upon their own pros and cons, they can be utilized for compressing different medical images.

In recent years, many meta-heuristic algorithms are combined with different image compression techniques to enhance the compression rate and reduce memory demand [3]. Usually, the meta-heuristic optimization algorithms are grouped into physics inspired based, swarm intelligence based and evolutionary based methods. Among them, swarm intelligence based meta-heuristic optimization algorithms perform better to solve the different classes of problems such as image retrieval and near optimum solution problem. From the literature survey [4,5], most of the recent compression algorithms such as block truncation coding, fractal-based coding and multi-level thresholding (MLT) based compression utilize the meta-heuristic algorithm as an optimization technique for efficient image compression. Though the above methods show very good results in terms of image quality and performance metrics such as peak signal-to-noise ratio (PSNR) and compression rate, the time required to compute the algorithm is large. Hence, the selection of the optimization algorithm is a major key factor to decide the computation time. Unlike other meta-heuristic methods, it is obvious that there has been continuous interest in one method of the heuristic algorithm for image processing called harmony search algorithm. Various modifications and improvements over optimization algorithm have been carried out since then. However, bandwidth (BW) is one of the prime factors to increase the efficiency of the algorithm.

In this paper, instead of using transform based and spatial based technique, a histogram based multi-level thresholding (HMT) is utilized. The incorporation of the HMT with the innovative opposition based improved harmony search algorithm (OIHSA) [6-8] yield the better result in terms of less computational time and high compression rate. Further, to improve the effectiveness of the HMT based compression, several entropies such as Shannon, Tsallis, Fuzzy and Renyi entropies are considered and tested. Finally, to improve the measurement of the randomness, the chosen entropy based on the simulation results is appended with the proposed algorithm. In order to evaluate the performance, various metrics of the proposed method are determined and compared with the existing optimization techniques such as differential evolution (DE) and simple harmony search algorithm in terms of computation time and image quality.

The rest of the paper is organized as follows: Section 2 represents the existing medical image compression techniques in detail. Section 3 briefly explains the methodologies considered for the proposed algorithm and its working steps. Section 4 discusses the working model of the proposed method by using the flowchart. Simulation results and the performance comparison of the proposed medical image compression algorithm with the existing compression technique are dealt in Section 5. Finally, Section 6 concludes the paper with the future work.

2. Existing Medical Image Compression Techniques Using Optimization

In the medical community, two image compression techniques are very popular, they are JPEG and wavelet. The usage of wavelet transform for medical image compression provides better results in terms of compression rate and image quality than that of JPEG. In related to, Alhanjouri [9] has examined the coding properties of multi-resolution analysis techniques such as wavelet, curvelet and wave-atom. He has stated that the wave-atom is one of the best multi-resolution analysis for medical image compression technique. In the meantime, the properties of fractal coding such as self-similarity and high compression ratio have created an interest in applying fractals for medical image compression. However, this demands large encoding time and introduces a high computational complexity. Hence, Bhavani and Thanushkodi [5] has addressed a new quasi-lossless fractal algorithm based on machine learning to avoid the aforementioned problems. This technique has reduced the encoding time up to a certain extent and improves the image quality along with the PSNR and compression rate of the high-resolution fundus image.

Block-based Principal Component Analysis compression algorithm [10] is another method which is developed for medical image compression with negligible degradation in image quality. Then, a set of hierarchical trees are used to improve the PSNR of medical image coding [11]. Bruylants et al. [12] has developed a new generic code framework to support JPEG2000 for volumetric medical image compression. This technique improves the performance of JPEG2000 for handling medical images. Though the performances of the existing coding techniques are excellent in terms of compression ratio and PSNR, the computational complexity problem is not yet solved.

On the other hand, instead of compressing the whole image, it is sufficient to improve the quality of the image only in the region of interest (ROI), i.e., in diagonally important regions. In [13], the biomedical images are compressed by using predictive based image compression with the help of ROI. Recently in [14], a new technique has been introduced for medical image compression based on discrete wavelet transform and thresholding. It offer reduced mathematical and structural complexity than that of other techniques. The major role of using thresholding technique in image compression is, it discriminated the image into a number of classes such as background and the objects of interest depending upon the distribution of pixels. From the comprehensive surveys, found in [15-17], MLT is one of the simple method and utilized in different image compression techniques for the past two decades. Actually, the concept of the entropy based algorithm for picture thresholding was first developed by Pun [18] in 1980. Followed by Kapur et al. [19] has proposed an entropy based algorithm for better performance using the global and objective property of the histogram.

To enhance the performance of the MLT based image compression further, many entropy based algorithms are used to measure the randomness of each class in MLT. Some of the entropies, practically used with MLT are Shannon, Tsallis, Renyi, and Fuzzy entropies. But, the demerits such as longer computation time and complexity of the image compression algorithm is still to be rectified. Because of this reason, a powerful meta-heuristic optimization algorithms such as gravitational search algorithm, genetic algorithm, ant colony optimization, stimulated annealing, particle swarm optimization, DE, etc., are used with different image compression algorithms to obtain fast convergence and less computational time.

Vijayvargiya et al. [20] has introduced a new technique by hybridizing the particle swarm optimization with the integer wavelet transform to provide better medical image compression. But, it takes much time for searching the similar and dissimilar packets from the transformed output. Generally, in medical field more attempts have been done by combining the segmentation with optimization when compared to the image compression with optimization. Recently, many researchers have concentrate on processing the meta-heuristics algorithms with image compression schemes in order to reduce the search time [21,22]. From that, DE with MLT based image compression technique [23], reduces the computation time effectively for a grayscale image and the performance of the compression is independent of the size of the image. But, the slow convergence rate and trouble in local search performance cause trouble in computation time.

Later, Bansod and Jain [24], provided an overview of incorporation of HSA in block truncation coding and fractal-based image compression. Although, these techniques gave better compression ratio with acceptable encoding time, it addresses the problem of poor image quality. Due to this, Mahdavi et al. [25] has developed the new improved HSA by modifying the fixed parameters such as BW, distance and pitch adjusting rate (PAR) into dynamically reducing variables. After several research, Hasancebi et al. [26] in 2009 has done some changes in harmony memory consideration rate (HMCR) and PAR. This time complexity is reduced to a certain extent only. Hence, instead of using BW as a selection parameter, dynamically varying BW is utilized in the following proposed method. The opposition based learning method is also utilized to minimize the objective function of the optimization for effective computation time reduction. The enhancement of the OIHSA for multilevel thresholding based medical image compression is explained in detail in the following sections.

3. Methodologies Used in the Proposed Method

The following two concepts are considered as major key factors to decide the effectiveness of the proposed method.

3.1 Opposition Based Improved Harmony Search Algorithm

From the literature review, several meta-heuristic algorithms are utilized for image compression. Among them, improved harmony search algorithm (IHSA) needs very less memory space for image compression. The link between playing music and selecting an optimal solution leads to the creation of the harmony search algorithm. Harmony search was derived from the natural phenomena of the musician's behavior when they play their musical instruments (population members) to come up with a fantastic harmony (global optimal solution). This state is further determined by an aesthetic standard (fitness function). A fine performance of the IHSA algorithm depends on the careful selection of parameters. But, the trouble in local search performance and the slow convergence rate provide large computation time. Hence, new IHSA is developed by modifying the parameter BW into dynamically reducing BW variable. The dynamic BW for a particular decision variable is modified as a function of the current iteration that relies on the total number of iterations (NI), the field of the decision variables and the desired level of precision in the objective function. The following steps are implemented to search for the best harmony:

Step 1: In IHSA, the initialization of the harmony memory is always based on the concept of a random guess because there is no prior information about the solution vector. One approach to solve the selection of solution vector is by employing an opposition based learning method [27]. It provides the chance to find the initial (fitter) solution closer to the global optimum by simultaneously checking the opposite solution. At first, initialize the global optimization problem by minimizing the objective function $f(x)$ for each set of decision variable x. Each decision variable $x(j)$ can be determined by using lower and upper bounds. The upper and lower bounds can be identified by $u(j)$ and $l(j)$ respectively. Where j=1, 2… n and R^n is nothing but a Schwartz space that consists of smooth, rapidly decreasing functions.

$$f(x),\ x = (x(1), x(2),\ldots\ldots, x(\mathrm{n})) \in R^n \tag{1}$$

$$x(j) \in [l(j), u(j)] \tag{2}$$

The key mechanism of the opposition based learning is described as follows.

Let the opposite number $\bar{x}$ is defined as,

$$\bar{x} = l(j) + u(j) - x$$

To find the fitter solution, the following condition has to be checked simultaneously,

$$f(\bar{x}) \leq f(x)$$

If the above condition is true, the real number x can be replaced by $\bar{x}$; otherwise, it will continue with the same x value as a fitter solution. IHSA algorithm basically considers the objective function only. The parameters used to construct the algorithm are harmony memory (HM), PAR, the distance BW, HMCR, and NI.

Step 2: After setting the parameter values properly, random tuning process is performed by generating the random vectors $x(1)$ to $x(\mathrm{n})$,

$$HM = \begin{vmatrix} x(1) \\ : \\ x(n) \end{vmatrix} \tag{3}$$

Step 3: New harmony is generated based on three values such as HMCR, PAR and random selection. To reduce the iteration count significantly and improve the performance of the HSA, the values of the following parameters PAR, BW and HMCR need some modifications as mentioned in literature survey [28-31]. Typical values of HMCR {0, 1} and PAR {0.2, 0.9} are generally considered from [32,33]. HMS is the number of harmonics stored in HM. It should be high enough to maintain diversity in the harmonics. However, a larger HMS has a deteriorating effect on the performance of the algorithm. Typical dimensions of HMS discussed in the paper [34] are {10, 150}.

$$PAR = PAR_{MIN} + \frac{PAR_{MAX} - PAR_{MIN}}{NI} \times gn \tag{4}$$

$$HMCR = HMCR_{MAX} - \left[\frac{(HMCR_{MAX} - HMCR_{MIN}) \times gn}{NI}\right] \tag{5}$$

where PAR_{MAX} and PAR_{MIN} are the maximum and the minimum pitch adjustment rate, respectively. gn is the iteration for which PAR is to be calculated, and NI is the total number of iterations.

BW is one of the deciding parameters for the time complexity and the performance of the algorithm. A larger BW value is required to search within a large space, whereas a smaller BW value is suitable for fine tuning of the best solution vector. If the BW value is maintained consistently high throughout the algorithm, close convergence to the best harmony may not be achieved. Conversely, if the BW value is maintained consistently low, exploration of the search space may take a large number of iterations. Hence, the selection of the BW will decide the performance of the optimization. By using the dynamically varying BW as shown in Eq. (6), the convergence rate is improved and also, the algorithm reached the optimal solution with less computation time. The estimation of the BW is given as,

$$BW(i) = \begin{cases} \dfrac{BW_{MAX}}{1+K\left(\dfrac{i}{NI}\right)^3}, & i < \dfrac{NI}{2} \\ BW_{MIN}, & i \geq \dfrac{NI}{2} \end{cases} \tag{6}$$

$$\text{where, } K = \ln\frac{BW_{MAX}}{BW_{MIN}}$$

where BW_{MAX} and BW_{MIN} are the maximum and the minimum adjustment rate of the BW, respectively.

The dynamic variation of BW must provide the optimum number of iterations with maximum BW value as well as minimum BW value. In addition, this variation has to be a continuously decreasing function, which ensures a considerable number of steps at all levels of BW between the maximum permissible limit and the convergence limit. The dynamic BW for a particular decision variable is designed as a function of the current generation or iteration that relies on NI.

Step 4: Then, the HM is updated by comparing the new harmony with stored harmony. The new harmony is included in the HM if it is better than the previous harmony value. Otherwise, the old value is retained in HM.

Step 5: Once the termination condition (NI) is reached then the best harmony is selected. If not, step 3 and step 4 is repeated until the termination condition is reached.

3.2 Histogram Based Multi-level Thresholding

For the past two decades, thresholding is considered as the most desired procedure, used for image segmentation as well as image compression. This can be classified into bi-level thresholding and multi-level thresholding. For compressing the image, multi-level thresholding is the best choice. In [18], the author explained the concept of multi-level thresholding, i.e., the separation of the image into several objects by analyzing the profile characteristics of the image histogram or by optimizing a certain objective function. There are different entropy based methods have been proposed for multi-level global thresholding. Depending upon the number of thresholds chosen, the image is first segmented into a number of bins using the histogram. Then the approximation of the histogram is done by maximizing the entropy. With an increase in the number of thresholds, the process becomes complicated and hence the computational time increases almost exponentially. For this reason, optimization algorithms are used in multilevel thresholding. The basic working principle of multilevel thresholding is given below,

Let, *L* gray levels are to be assumed in a given image *I* and these gray levels are in the range *0,1,2........L-1*, the threshold value (*H)* of each level are obtained by using the following Eq.(7) to Eq. (10),

$$H_0 = \{(x, y) \in I \mid 0 \le f(x, y) \le t_1 - 1\} \tag{7}$$

$$H_1 = \{(x, y) \in I \mid t_1 \le f(x, y) \le t_2 - 1\} \tag{8}$$

$$H_2 = \{(x, y) \in I \mid t_2 \le f(x, y) \le t_3 - 1\} \ldots\ldots\ldots\ldots \tag{9}$$

$$H_k = \{(x, y) \in I \mid t_k \le f(x, y) \le L - 1\} \tag{10}$$

where $f(x, y)$ is the gray level of the point (x, y), t_i (i=1,2.....k) is the i^{th} threshold value and k is the number of the thresholds. The selection of the optimal threshold using bi-level thresholding is not computationally expensive. On the other hand, selecting more than a few optimal threshold values for multi-level thresholding requires a high computational cost. In order to find the correct threshold values, the entropy concept is utilized. The entropies of each group of gray levels are,

$$\begin{aligned} H_1 &= -\sum_{i=0}^{T_1} \frac{p_i}{p_1} \ln \frac{p_i}{p_1}, \\ H_2 &= -\sum_{i=T_1+1}^{T_2} \frac{p_i}{p_2} \ln \frac{p_i}{p_2} \ldots\ldots\ldots, H_{n+1} = -\sum_{i=T_n+1}^{L-1} \frac{p_i}{p_n} \ln \frac{p_i}{p_n} \end{aligned} \tag{11}$$

where, the probability of occurrence (p) can be calculated by using,

$$p_1 = \sum_{i=0}^{T_1} h_i\, , p_2 = \sum_{i=T_1+1}^{T_2} h_i\, , \ldots\ldots\ldots\ldots, p_{n+1} = \sum_{i=T_n+1}^{L-1} h_i$$

Then the total entropy will be

$$H(T) = H_1 + H_2 + \ldots\ldots\ldots\ldots + H_{n+1}. \tag{12}$$

4. Proposed Method

In this paper, the thresholds from the gray level histogram of the medical image is accomplished by implementing the non-parametric approach, i.e., the threshold values of the image can be obtained by maximizing the entropy within each histogram bin. Also, the variation in pixel values of the image is reduced by increasing the number of thresholds. When the number of thresholds is increased, then the approximation of histogram is more accurate. In this way, the compression of the medical image can be achieved. Due to the selection of more threshold values, the computational complexity of the compression algorithm also increased. Hence, meta-heuristic optimization called OIHSA is incorporated with the entropy to obtain optimal threshold. The working model of the proposed method is clearly depicted in Fig. 1.

The medical image compression using OIHSA is mainly based upon the probability distribution of the image histogram and selection of the number of thresholds. This method aims to reduce the compression error by increasing the number of optimal thresholds. The entropy of each group from the normalized histogram is maximized to obtain the optimal threshold. The total global entropy H(T) of the medical image can be defined as,

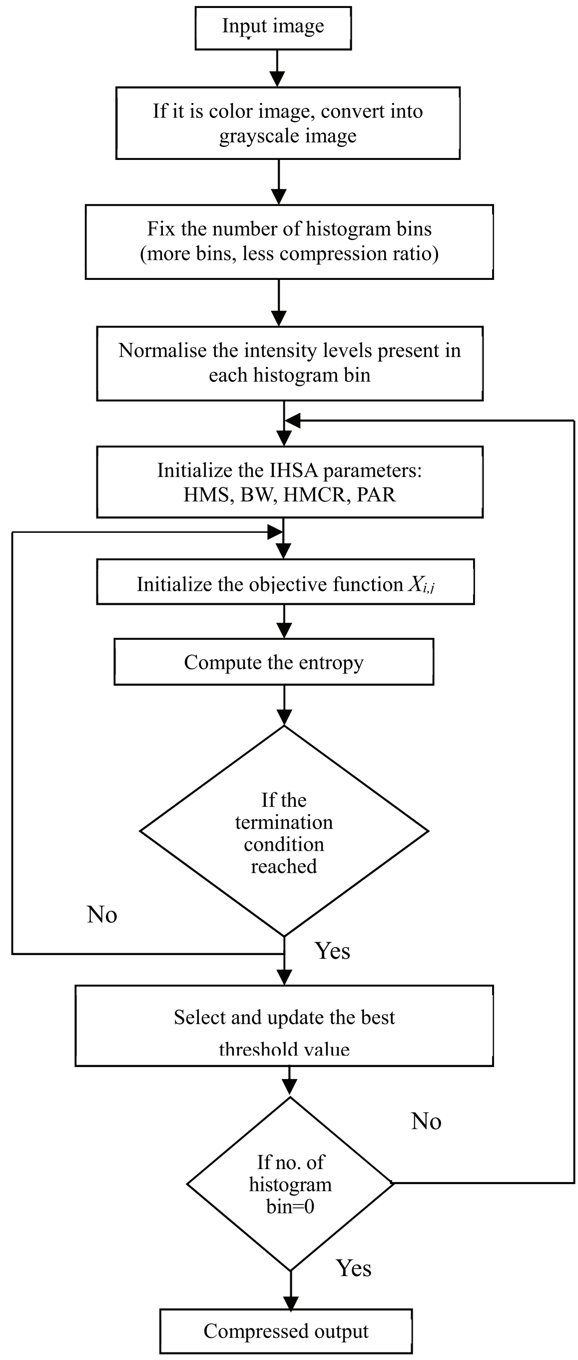


Fig. 1. Working model of OIHSA based image compression.

$$H(T)=H_0 + H_1 + H_2 + \ldots\ldots\ldots\ldots\ldots\ldots + H_K \tag{13}$$

where the entropies H_0,…, H_k are computed by using entropy. Some of the entropies tested with the optimization algorithm are Shannon entropy, fuzzy entropy, Tsallis entropy, Renyi entropy, etc. Among them, Shannon entropy was the first entropy as a measure of uncertainty. The H(X) of the information using Shannon entropy is expressed as,

$$H(X) = -\sum_{i=0}^{n} p(x_i) * \log_2 p(x_i) \tag{14}$$

where n is total number of states. Actually, the Shannon entropy is the limiting case of both the Tsallis entropy and the Renyi entropy and this can be formulated below,

$$H_q(X) = \frac{1}{q-1} - \sum_{i=1}^{n} \frac{p(x_i)^q}{q-1} \tag{15}$$

$$H_q(X) = \frac{1}{1-q} \ln \sum_{i=1}^{n} p(x_i)^q \tag{16}$$

By considering the property of the entropies, fuzzy entropy which is a measure of fuzzy information is quite different. Because, there is no need for probabilistic concepts due to its ambiguity uncertainty whereas Shannon contains the probabilistic uncertainty. The general expression for a fuzzy entropy is given below,

$$H(X) = -\sum P(x_i)\boldsymbol{\mu}_i * \ln(\mathrm{P}(x_i)\mu_i) \tag{17}$$

where μ_i is a member function used to estimate the membership of the number of states 'n'.

Then the total entropy can be maximized by using OIHSA. Before computing the process, the boundaries of the harmony search space are set as l=0 and u=255, which corresponds to image intensity levels. The objective function $x(i)$ is the i^{th} element of harmony memory HM which contains multiple thresholds (th), represented as,

$$x(i) = [\mathrm{th}_1, \mathrm{th}_2, \ldots\ldots, \mathrm{th}_k]. \tag{18}$$

5. Performance Analysis

There are several image compression techniques so far used to compress the image sizes. Out of that, histogram based multi-thresholding using entropy has shown better results in terms of qualitatively and quantitatively. But, for high compression ratio, the compressed images are poorly affected by the blurring effect and large computation time. Hence, to reduce the computation time of the HMT based image compression, a optimization algorithm called OIHSA is utilized. Also, to improve the effectiveness of the compression algorithm, several entropies such as Shannon, fuzzy, Tsallis, and Renyi entropies are considered and tested for different medical images. To investigate the performance of the proposed method the commonly used parameters namely compression ratio (CR), PSNR, structural similarity index measure (SSIM) and computation time are used.

The simulations of the proposed and the existing methods are done by using MATLAB R2014a in a workstation with Intel Core i7 2.6 GHZ processor. For demonstration purpose, the magnetic resonance imaging (MRI) and computed tomography (CT) image of the brain with the size of 225×273 are collected from medical image dataset. The initial set up for OIHSA is very important to compute better performance. The effective performance of the OIHSA is mainly depended on the allocation of minimum and maximum values of the parameters: PAR, HMCR and dynamically varying BW. After several iterations, the parameters of the OIHSA are fixed as mentioned in Table 1. The parameters values of the DE, given in Table 2 are very well explained in [23]. In this paper, the result analysis consists of two parts. The first part intends to test the proposed algorithm with different entropies and compare the performance with the existing techniques. The second part mainly focuses on texture and detailed information of the compressed medical image.

Table 1. Parameters of OIHSA

$HMCR_{MAX}$	$HMCR_{MIN}$	HMS	PAR_{MAX}	PAR_{MIN}	BW_{MAX}	BW_{MIN}	NI
0.95	0.4	150	0.8	0.4	0.5	0.2	100

Table 2. Parameters of DE

Differential weight (F)	Crossover probability (CR)	Population size (NP)	Lower and upper bound
0.5	0.95	≥4	[0, 255]

5.1 Quantitative Analysis

To justify the performance of the proposed algorithm, different combinations of the entropies are incorporated with the proposed (OIHSA) and the existing (DE, HAS, and IHSA) image compression techniques. For demonstrating purpose, the CT and MRI medical images are considered. For a valuable comparison, the performance metrics such as PSNR, SSIM and computation time are considered respectively. Here, the compression ratio is fixed as 2.6. Table 3 shows the comparison of different optimization based image compressions for different entropies with respect to the average computation time. From observations, the proposed OIHSA based image compression using Shannon entropy have significantly lesser computation time than that of the other algorithms. Also, it is clearly visible that the overall computation time of the HMT using OIHSA with the combination of different entropies took very lesser time than other existing techniques. Though the computation time of the image compression using HSA stood a second place in the comparison table, the PSNR and SSIM of the HSA are not good. It is noted from Table 4 that the PSNR of the proposed image compression using OIHSA is nearly 2 dB better than the IHSA and far better than that of the other compression algorithms. Further, the quality of the images are mainly determined by the SSIM value, if it is close to 1, then the compressed image is almost equal to the input image. It is inferred through the SSIM results from Table 5, that the proposed algorithm has high SSIM than that of the other compression algorithms. It is also noted from the Tables 3–5, that the optimization methods used in HMT based image compression shown not much difference in PSNR and SSIM values for fuzzy, Renyi, and Tsallis entropies. But, there is a huge difference when it comes to the proposed method with the Shannon entropy combination. Moreover, the overall performance of the HSA and DE based image compressions produce worst results compared to that of the other techniques. Apart from the computation time, the performance of the HSA is poorer than IHSA. Hence, IHSA based image compression is only considered and HSA combination is excluded for further analysis.

Table 3. Performance comparison of medical images in terms of computation time (in sec)

Entropy	DE [23]		HSA		IHSA		OIHSA	
	CT	MRI	CT	MRI	CT	MRI	CT	MRI
Shannon	7.08	7.68	1.654	1.697	1.713	1.81	1.41	1.47
Fuzzy	73.1	31.89	1.807	2.22	2.357	1.78	1.53	1.62
Renyi	10.5	14.04	1.81	1.87	2.86	1.74	1.51	1.58
Tsallis	24.21	50.32	8.562	1.91	3.86	1.82	1.60	1.67

Table 4. Performance comparison of medical images in terms of PSNR (dB)

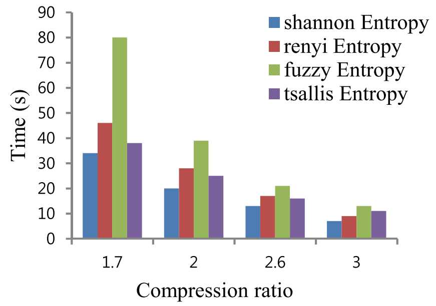
Entropy	DE [23]		HSA		IHSA		OIHSA	
	CT	MRI	CT	MRI	CT	MRI	CT	MRI
Shannon	37.75	37.52	34.49	40.10	41.90	41.58	43.61	42.19
Fuzzy	34.17	30.73	36.75	39.74	40.25	39.02	40.87	40.46
Renyi	38.91	37.73	36.65	39.37	40.79	37.89	40.86	40.57
Tsallis	37.78	20.36	36.4	37.57	41.09	38.79	41.52	39.02

Table 5. Performance comparison of medical images in terms of SSIM

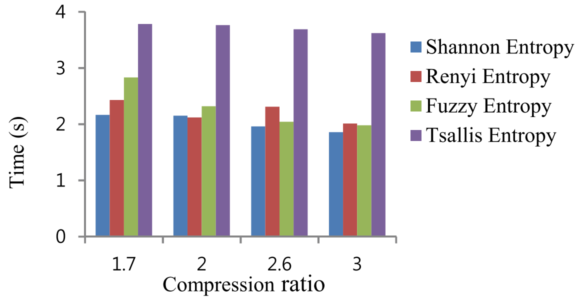
Entropy	DE [23]		HSA		IHSA		OIHSA	
	CT	MRI	CT	MRI	CT	MRI	CT	MRI
Shannon	0.938	0.946	0.915	0.981	0.977	0.987	0.990	0.990
Fuzzy	0.983	0.891	0.927	0.975	0.966	0.975	0.972	0.986
Renyi	0.946	0.968	0.925	0.963	0.976	0.956	0.975	0.979
Tsallis	0.987	0.81	0.991	0.944	0.978	0.958	0.987	0.981

The performance of the HMT using different entropies and optimization algorithms is also carried out in terms of the PSNR and computation time by increasing the compression ratio. For analyzing the algorithms for different compression ratio, CT image is considered. It is noted from Fig. 2, for all optimization, as the compression ratio increases, the computation time decreases drastically. From Fig. 2(a), the HMT using DE and Shannon have lesser computation time than other entropy combinations such as fuzzy, Renyi, and Tallis entropies. But, the Shannon combination itself took more time to compute the DE based image compression algorithm. The HMT based image compression with the combination of IHSA and different entropies shown in Fig. 2(b) have better computation time than DE. For the proposed OIHSA based image compression using Shannon entropy illustrated in Fig. 2(c), indeed needs very less computation time than the previous methods.

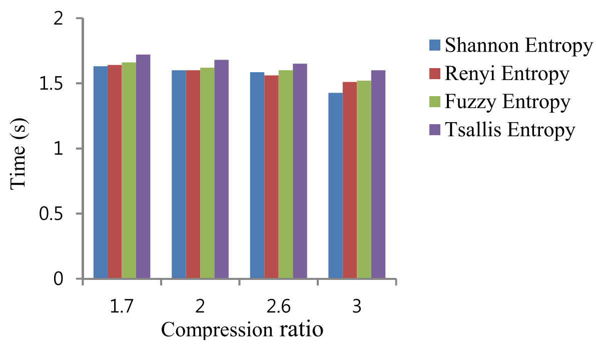
Overall, from the different entropies, Shannon entropy stood a better place when it combined with the HMT based image compression using OIHSA. Moreover, the results from Fig. 3(a) illustrated that the proposed OIHSA using Shannon entropy based compression has very less computation time for different compression ratio compared to that of the existing techniques. The medical-based applications mostly concentrate on the quality of the medical image for further diagnosis. Hence, the comparison of the different optimization based image compression algorithms are also done by using PSNR. For better results with high PSNR, the compression ratio is taken up to 3. It is noted from Fig. 3(b), that the OIHSA based image compression using Shannon entropy has high PSNR and shown very good performance with high compression ratio.



(a)

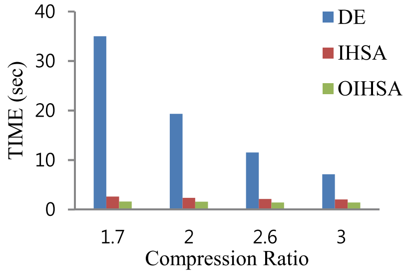


(b)

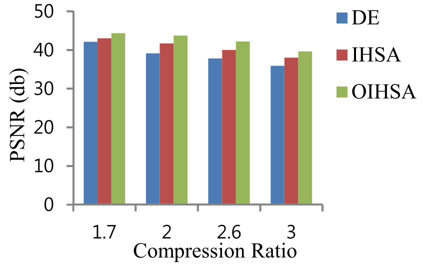


(c)

Fig. 2. Comparison of various entropies for different optimization techniques (a) Compression ratio with respect to Time for DE (b) Compression ratio with respect to Time for IHSA, (c) Compression ratio with respect to Time for OIHSA.



(a)



(b)

Fig. 3. Comparison of various optimization methods for HMT based image compression (a) Compression ratio with respect to time (b) Compression ratio with respect to PSNR.

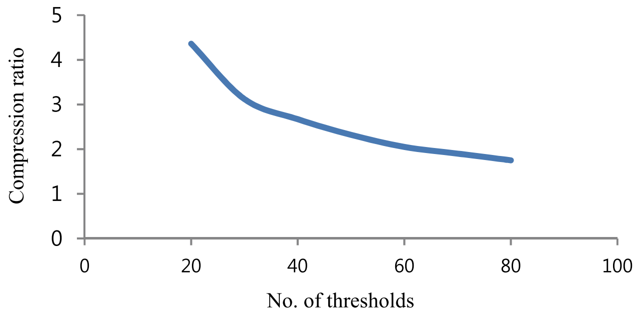
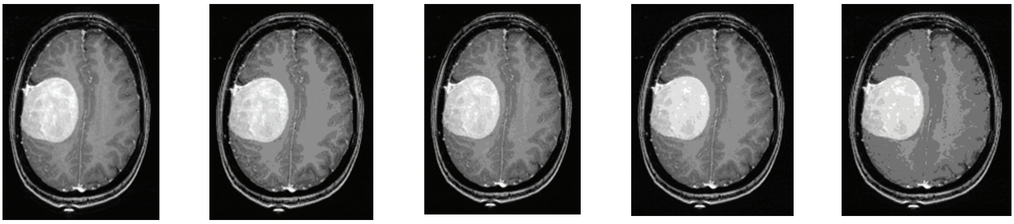


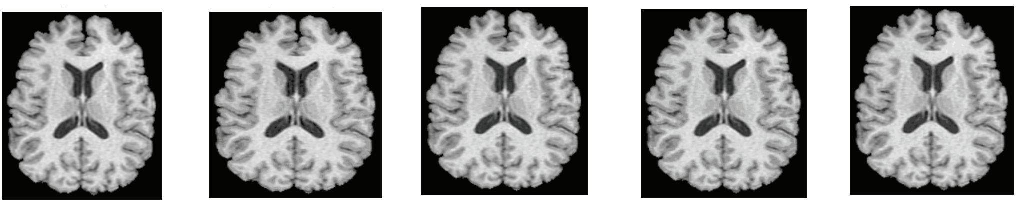
Fig. 4. Number of thresholds vs. compression ratio of HMT with the combination of OISHA and Shannon entropy based image compression for CT medical image.

The effect of the proposed compression technique with different entropies is also investigated in terms of varying the number of thresholds. From Fig. 4, it is noted that the selection of number of thresholds always decides the amount of compression ratio. The minimum limit for choosing the number of thresholds is 16. Because, if it is less than 16 then there is no guaranty for the perfect reconstructed image and the compressed image would be lost most of their fine details. Hence, it is safer to choose the number of thresholds more than 40 for medical images.



(a) (b) (c) (d) (e)

Fig. 5. The HMT based image compression using OIHSA: (a) the input CT medical image and the compressed output for different entropies such as (b) Shannon entropy, (c) Renyi entropy, (s) fuzzy entropy, and (e) Tsallis entropy.



(a) (b) (c) (d) (e)

Fig. 6. The HMT based image compression using OIHSA: (a) the input MRI medical image and and the compressed output for different entropies such as (b) Shannon entropy, (c) Renyi entropy, (s) fuzzy entropy, and (e) Tsallis entropy.

5.2 Qualitative Analysis

In the telemedicine field, medical images are the important inputs in determining the medical diagnosis and treatment. Particularly, during medical image acquisition, compression and display, there are many parameters involved and that have an impact on the observer's ability to make sure that diagnosis has done accurately. From the development and evaluation of the medical imaging systems, one always wishes to adjust the relevant system parameters to optimize observer performance. Likewise, an image acquisition, pre-processing, and display methods are developed, an assessment regarding the efficacy of the potential innovations is often desired. These kinds of determinations are based upon an assessment of the "quality" of the images. Thus the quality of the image is the major part to diagnose the disease for further treatment.

Generally, the estimation of the performance metrics such as PSNR and IQI is not enough to analyze the efficiency of the compressed output. Therefore, visual inspections are necessary to judge the amount of recovered information and artifacts. The qualitative comparison of the proposed method with different entropies is shown in Figs. 5 and 6. From the figures, the visual quality of the Tsallis entropy combination is very poor when compared with the other combinations. It is also observed that the proposed algorithm with the combination of the Shannon entropy has more details and have sharp edge details than other entropy combinations. Although, the performance of the fuzzy entropy combination is good, it fails to recover the fine details or features when the compression rate increases.

6. Conclusions

In this paper, a novel HMT based image compression algorithm is developed by appending OIHSA with different entropies. By applying the dynamically varying BW as a selection parameter and extracting the best threshold values from each region of the image histogram, efficient image compression was achieved. Further, the overall computation time of the proposed compression method is reduced to some extent by using opposition based learning concept. The various performance metrics such as PSNR, SSIM and computation time of the proposed method are determined and compared with the existing optimization based compression techniques. Also, the visual quality of the output images are taken into account for comparison. The combination of HMT based image compression with OIHSA overcomes the limitations of high computational time and compression ratio at a limited memory space for medical based digital images. Although, the compression introduced by the proposed OIHSA with different entropies reduces the computational time to a great extent, it is observed from the simulation that the proposed algorithm with Shannon entropy undisputedly performs well. This work can be extended further by hybridizing the different optimization techniques to improve the local search of OIHSA and also to improve the performance of the compression algorithm with respect to the PSNR and SSIM.

References

[1] M. Rehman, M. Sharif, and M. Raza, "Image compression: a survey," *Research Journal of Applied Sciences, Engineering and Technology*, vol. 7, no. 4, pp. 656-672, 2014.

[2] B. Alagendran and S. Manimurugan, "A survey on various medical image compression techniques," *International Journal of Soft Computing and Engineering*, vol. 2, no. 1, pp. 425-428, 2012.

[3] K. Hammouche, M. Diaf, and P. Siarry, “A comparative study of various meta-heuristic techniques applied to the multilevel thresholding problem,” *Engineering Applications of Artificial Intelligence*, vol. 23, no. 5, pp. 676-688, 2010.
[4] K. Uma, P. G. Palanisamy, and P. G. Poornachandran, “Comparison of image compression using GA, ACO and PSO techniques,” in *Proceedings of 2011 International Conference on Recent Trends in Information Technology*, Chennai, India, 2011, pp. 815-820.
[5] S. Bhavani and K. G. Thanushkodi, “Comparison of fractal coding methods for medical image compression,” *IET image Processing*, vol. 7, no. 7, pp. 686-693, 2013.
[6] D. Oliva, E. Cuevas, G. Pajares, D. Zaldivar, and M. Perez-Cisneros, “Multilevel thresholding segmentation based on harmony search optimization,” *Journal of Applied Mathematics*, vol. 2013, article ID. 575414, 2013.
[7] S. Bansod and S. Jain, “Recent image compression algorithms: a survey,” *International Journal of Advanced Research in Computer and Communication Engineering*, vol. 2, no. 12, pp. 4815-4820, 2013.
[8] J. Kalivarapu, S. Jain, and S. Bag, “An improved harmony search algorithm with dynamically varying bandwidth,” *Engineering Optimization*, vol. 48, no. 7, pp. 1091-1108, 2016.
[9] M. A. Alhanjouri, “Multi-resolution analysis for medical image compression,” *Multi-Resolution Analysis For Medical Image Compression*, vol. 3, no. 6, pp. 215-228, 2011.
[10] S. T. Lim, D. F. W. Yap, and N. A. Manap, “Medical image compression using block-based PCA algorithm,” in *Proceedings of 2014 International Conference on Computer, Communications, and Control Technology (I4CT)*, Langkawi, Malaysia, 2014, pp. 171-175.
[11] T. Kanumuri, M. L. Dewal, and R. S. Anand, “Progressive medical image coding using set of hierarchical trees,” in *Proceedings of 2015 2nd International Conference on Computing for Sustainable Global Development (INDIACom)*, New Delhi, India, 2015, pp. 1973-1978.
[12] T. Bruylants, A. Munteanu, and P. Schelkens, “Wavelet based volumetric medical image compression,” *Signal Processing: Image Communication*, vol. 31, pp. 112-133, 2015.
[13] S. Singh, M. Mishra, and P. Gupta, “Image compression on biomedical images using predictive coding with the help of ROI,” in *Proceedings of 2015 2nd International Conference on Signal Processing and Integrated Networks (SPIN)*, Noida, India, 2015, pp. 120-125.
[14] D. Ravichandran, R. Nimmatoori, and M. R, Ashwin Dhivakar, “Medical image compression based on daubechies wavelet global thresholding and huffman encoding algorithm,” *International Journal of Advanced Computer Engineering and Communication Technology*, vol. 5, no. 1, pp. 7-12, 2016.
[15] P. K. Sahoo, S. Soltani, and A. K. C. Wong, “A survey of thresholding techniques,” *Computer Vision, Graphics, and Image Processing*, vol. 41, no. 2, pp. 233-260, 1988.
[16] Y. Jiang, P. Tsai, Z. Hao, and L. Cao, “Automatic multilevel thresholding for image segmentation using stratified sampling and Tabu Search,” *Soft Computing*, vol. 19, no. 9, pp. 2605-2617, 2015.
[17] Q. B. Truong and B. R. Lee, “Automatic multi-thresholds selection for image segmentation based on evolutionary approach,” *International Journal of Control, Automation and Systems*, vol. 11, no. 4, pp. 834-844, 2013.
[18] T. Pun, “A new method for grey-level picture thresholding using the entropy of the histogram,” *Signal Processing*, vol. 2, no. 3, pp. 223-237, 1980.
[19] J. N. Kapur, P. K. Sahoo, and A. K. C. Wong, “A new method for gray-level picture thresholding using the entropy of the histogram,” *Computer Vision, Graphics, and Image Processing*, vol. 29, no. 3, pp. 273-285, 1985.
[20] G. Vijayvargiya, S. Silakari, and R. Pandey, “A novel medical image compression technique based on structure reference selection using integer wavelet transform function and PSO algorithm,” *International Journal of Computer Applications*, vol. 91, no. 11, pp. 9-13, 2014.

[21] K. Hammouche, M. Diaf, and P. Siarry, "A comparative study of various meta-heuristic techniques applied to the multilevel thresholding problem," *Engineering Applications of Artificial Intelligence*, vol. 23, no. 5, pp. 676-688, 2010.

[22] M. H. Horng, "Honey bee mating optimization vector quantization scheme in image compression," in *Artificial Intelligence and Computational Intelligence*. Heidelberg: Springer, 2009, pp. 185-194.

[23] S. Paul and B. Bandyopadhyay, "A novel approach for image compression based on multi-level image thresholding using Shannon Entropy and Differential Evolution," in *Proceedings of the 2014 IEEE Students' Technology Symposium*, Kharagpur, India, 2014, pp. 56-61.

[24] S. Bansod and S. Jain, "harmony search algorithm for color image compression," *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 2, no. 6, pp. 1669-1672, 2014.

[25] M. Mahdavi, M. Fesanghary, and E. Damangir, "An improved harmony search algorithm for solving optimization problems," *Applied Mathematics and Computation*, vol. 188, no. 2, pp. 1567-1579, 2007.

[26] O. Hasancebi, F. Erdal, and M. P. Saka, "Adaptive harmony search method for structural optimization," *Journal of Structural Engineering*, vol. 136, no. 4, pp. 419-431, 2009.

[27] A. Banerjee, V. Mukherjee, and S. P. Ghoshal, "An opposition-based harmony search algorithm for engineering optimization problems," *Ain Shams Engineering Journal*, vol. 5, no. 1, pp. 85-101, 2014.

[28] W. S. Jang, H. I. Kang, and B. H. Lee, "Hybrid simplex-harmony search method for optimization problems," in *Proceedings of 2008 IEEE Congress on Evolutionary Computation (IEEE World Congress on Computational Intelligence)*, Hong Kong, China, 2008, pp. 4157-4164.

[29] M. Mahdavi, M. Fesanghary, and E. Damangir, "An improved harmony search algorithm for solving optimization problems," *Applied Mathematics and Computation*, vol. 188, no. 2, pp. 1567-1579, 2007.

[30] R. R. M. Daga and J. P. T. Yusiong, "Image compression using harmony search algorithm," *International Journal of Computer Science Issues*, vol. 9, no. 5, pp. 16-23, 2012.

[31] D. Manjarres, I. Landa-Torres, S. Gil-Lopez, J. Del Ser, M. N. Bilbao, S. Salcedo-Sanz, and Z. W. Geem, "A survey on applications of the harmony search algorithm," *Engineering Applications of Artificial Intelligence*, vol. 26, no. 8, pp. 1818-1831, 2013.

[32] X. S. Yang, "Harmony search as a metaheuristic algorithm," in *Music-Inspired Harmony Search Algorithm*. Heidelberg: Springer, 2009, pp. 1-14.

[33] J. Greblicki and J. Kotowski, "Analysis of the properties of the harmony search algorithm carried out on the one dimensional binary knapsack problem," in *Computer Aided Systems Theory – EUROCAST 2009*. Heidelberg: Springer, 2009, pp. 697-704.

[34] M. G. Omran and M. Mahdavi, "Global-best harmony search," *Applied Mathematics and Computation*, vol. 198, no. 2, pp. 643-656, 2008.

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