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A Novel Image Segmentation Algorithm Based on Harmony Fuzzy Search Algorithm

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***Abstract*—Image segmentation is considered as one of the crucial steps in image analysis process and it is the most challenging task. Image segmentation can be modeled as a clustering problem. Therefore, clustering algorithms have been applied successfully in image segmentation problems. Fuzzy c-mean (FCM) algorithm is considered as one of the most popular clustering algorithm. Even that, FCM can generate a local optimal solution. In this paper we propose a novel Harmony Fuzzy Image Segmentation Algorithm (HFISA) which is based on Harmony Search (HS) algorithm. A model of HS which uses fuzzy memberships of image pixels to a predefined number of clusters as decision variables, rather than centroids of clusters, is implemented to achieve better image segmentation results and at the same time, avoid local optima problem. The proposed algorithm is applied onto six different types of images. The experiment results show the efficiency of the proposed algorithm compared to the fuzzy c-means algorithm.**

***Index Terms*—harmony search algorithm; image segmentation; fuzzy clustering; cluster validity index.**

I. INTRODUCTION

Image segmentation is the process of subdividing the digital image into their constituent regions, in which each region shares similar properties or features [1]. These features can be brightness, spatial coherence, color, texture, motion, mean, variance, etc. The level of subdivision depends on the problem to be solved. Since no single image segmentation algorithm can solve all types of image segmentation problems, many algorithms have been researched and presented, each of which uses a different induction principle. From the literature, many classifications were assigned to segmentation algorithms, such as thresholding methods, deformable models, clustering methods, histogram based methods, region based methods, graph partitioning methods, classification methods, and etc. [2], [3].

Image segmentation can be modeled as clustering problem [4]. Therefore, clustering algorithms have been applied successfully in image segmentation problems. They can be categorized into different groups, such as hierarchical algorithms, partitional algorithms, density-based clustering algorithms, fuzzy clustering, etc [1]. Fuzzy c-means algorithm (FCM) [5] is considered as one of the most popular algorithm used in clustering problems and at same time in image segmentation problems [6], [7], [8].

However FCM algorithm has serious limitations such as the tendency to become trapped in local optima and prone to initialization sensitivity [9], [10].

One approach to obtain a globally optimum solution and overcome these limitations is to use one of the metaheuristic algorithms to find the appropriate initial cluster centers and then feed these cluster centers into FCM algorithm. In this approach, the conventional way is to consider cluster centers as an optimization decision variables and find the appropriate values for them using the abilities of metaheuristic algorithms to exploring and exploiting the search space such as genetic algorithms [11], simulated annealing [12], tabu search algorithm [13], bees colony algorithm [14], particle swarm optimization algorithm [15], ant colony algorithm [16], [17], and recently harmony search (HS) algorithm [18], [19], [20], [21].

In this paper, we propose a novel approach to image segmentation called Harmony Fuzzy Image Segmentation Algorithm (HFISA). It is based on Harmony Search (HS) algorithm, where HS is also a new metaheuristic population based algorithm which was developed by Geem [22] and has been successfully tailored to different computational optimization problems [23]. In this paper, a new approach to select the decision variables for HS is proposed. This is done by using fuzzy memberships of image pixels to the predefined number of clusters as a decision variables, rather than centroids of clusters in this optimization problem.

The effectiveness of HFISA is demonstrated on six different types of images such as natural image, synthetic images, medical MR image and remote sensing image.

The rest of the paper is organized as follows: Section II describes the fundamentals of fuzzy clustering with FCM. Section III describes fuzzy cluster validity measures. Section IV discusses the proposed HFISA. Section V shows the experimental results and the final section, presents conclusion and future directions of our work.

II. FUNDAMENTALS OF FUZZY CLUSTERING

Clustering is a typical unsupervised learning technique for grouping similar data points (pixels) according to some

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measure of similarity that maximizes the intra-cluster similarity and minimizes the inter-cluster similarity [1]. Clustering algorithm of a fuzzy partitioning type is performed on a set of n objects (pixels) $X = \{x_1, x_2, \ldots, x_n\}$, each of which, $x_i \in \Re^d$, is a feature vector consisting of d real-valued measurements describing the features of the object represented by x_i. Fuzzy clusters c of the objects can be represented by a fuzzy membership matrix called fuzzy partition $U = [u_{ij}]_{(c\times n)}$, $U \in M_{fcn}$ as in Eq. 2. Where u_{ij} represents the fuzzy membership of the ith object to the jth fuzzy cluster. In this case, every data object belongs to a particular (possibly null) degree of every fuzzy cluster.

FCM is an iterative procedure which is able to locally minimize the following objective function:

$$J_m = \sum_{j=1}^{c}\sum_{i=1}^{n} u_{ij}^m \|x_i - v_j\|^2 \tag{1}$$

where $\{v_j\}_{j=1}^c$ are the centroids of the clusters c, $\|.\|$ denotes an inner-product norm (e.g. Euclidean distance) from the data point x_i to the jth cluster center, and the parameter $m \in [1, \infty)$, is a weighting exponent on each fuzzy membership that determines the amount of fuzziness of the resulting classification.

$$M_{fcn} = \left\{ \begin{matrix} U \in \Re^{c\times n} | \sum_{j=1}^{c} U_{ij} = 1, 0 < \sum_{i=1}^{n} U_{ij} < n \\ , and\ U_{ij} \in [0,1]\,; 1 \le j \le c; 1 \le i \le n \end{matrix} \right\} \tag{2}$$

FCM's steps can be summarized as follows [5]:

1) Select the number of fuzzy clusters, c .
2) Select initial cluster centers $v_1, v_2, \ldots, v_c$.
3) Compute the elements of the fuzzy partition matrix:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_i - v_j\|}{\|x_i - v_k\|}\right)^{\frac{2}{m-1}}} \tag{3}$$

4) Compute the cluster centers:

$$v_j = \frac{\sum_{i=1}^{n} u_{ij}^m \cdot x_i}{\sum_{i=1}^{n} u_{ij}^m} \tag{4}$$

5) Repeat steps 3 and 4 until the number of iterations t exceeds a given limit or a termination criterion is satisfied:

$$\|v_{new} - v_{old}\| < \varepsilon \tag{5}$$

where $\varepsilon < 0.001$

III. FUZZY CLUSTER VALIDITY MEASURES

Cluster validity index is normally used to evaluate the quality of different solutions provided by different settings of a given algorithm (or even by different algorithms) [24]. In other words, the discovery of the best fuzzy clustering solution among a set of candidates requires an accurate index to quantitatively measure the quality of the fuzzy partitions obtained. Several indices for fuzzy clustering assessment have been proposed (e.g. see [24], [25], [26] and references therein).

In this study, we used the validity index measurements in two ways. The first way is to use one validity index as fitness function as described in section IV-E, while the second way is to use 4 different types of validity indices in order to evaluate the performance of our proposed algorithm comparing it with FCM algorithm as detailed in experimental section.

These 4 algorithms have different properties. We describe them briefly as follows:

Bezdek's PC and PE indices: In [5], Bezdek defined two fuzzy cluster validity measures, Partition Coefficient (PC) and Partition Entropy (PE). These types of indices only use membership values and therefore the advantage is being easy to calculate. To achieve proper clustering results, PC index should be maximized while PE index minimized.

The indices were defined as follows:

$$V_{PC} = \frac{1}{n}\sum_{j=1}^{c}\sum_{i=1}^{n} u_{ij}^2 \tag{6}$$

$$V_{PC} = -\frac{1}{n}\sum_{j=1}^{c}\sum_{i=1}^{n} u_{ij}\ log_a\ u_{ij} \tag{7}$$

Xie_Beni (XB) index: XB index [27] is considered as a representative index of fuzzy clustering indices that uses both membership values and the dataset [24], [28]. XB index is defined as a ratio of the total variation (compactness) to the minimum separation of the clusters. The objective is therefore to minimize the XB index for achieving proper clustering.

The index is defined as follows:

$$XB = \frac{\sum_{j=1}^{c}\sum_{i=1}^{n} u_{ij}^2 \left\|x_i - v_j\right\|^2}{n\ min_{i,j} \left\|v_i - v_j\right\|^2} \tag{8}$$

PBMF-index: This index is recently developed by Pakhira et al. [29]. This index involves both the membership values and the dataset in its calculations. The maximum value of PBMF-index indicates correct clustering results.

The PBMF-index is defined as follows:

$$PBMF(c) = \left(\frac{1}{c} \times \frac{E_1}{E_c} \times D_c\right)^p \tag{9}$$

where c is the number of clusters. Here

$$E_c = \sum_{j=1}^{c}\sum_{i=1}^{n} u_{ij}^m \|x_i - v_j\| \tag{10}$$

and

$$D_c = max_{i,l}\|v_i - v_l\| \tag{11}$$

where the power p is used to control the contrast between the different cluster configurations and it is set to be 2. $E1$ is a constant term for a particular data set and it is used to avoid the index value from approaching zero.

IV. THE HFISA ALGORITHM

Harmony search [22] is a new metaheuristic optimization method imitates the music improvisation process where the musicians improvise their instruments' pitch searching for a perfect state of harmony. HS possess several advantages over traditional optimization techniques that increase the flexibility of the HS to produce better solutions such as: (1) it is a simple population based metaheuristic algorithm and does not require initial value settings for decision variables (2) uses stochastic random searches (3) no need for derivation information (4) has few parameters (5) can be easily adopted for various types of optimization problems [30]. For further explanation on HS algorithm and its steps see [31].

In the following sections we describe a model of HS that represents our proposed algorithm HFISA.

A. Representation of Solutions

Using fuzzy memberships as decision variables in the optimization problem could not be feasible when the decision variables are too large since there are $c \times n$ decision variables to be optimized [32]. However, in the field of image processing, the image can be represented in a different way; it can be simplified through any image simplification technique. In this study, the simplification process is based on finding the frequency of occurrence of each pixel in the tested image. Therefore, the image is represented in a model such as $X = ((x_1, h_1), \dots, (x_i, h_i), \dots, (x_q, h_q))$ where h_i is the frequency of occurrence x_i in the image, and q is the total number of distinct x value in the image with $(\sum_{i=1}^{q} h_i = n)$. As a consequence, the dimensions of partition matrix will be reduced. To illustrate this idea, assume a gray image with 8-bit resolution and size of 512×512. Typically there are only 256 possible values for each pixel. Therefore, the value of n becomes 256 instead of 262144 (i.e. 512×512) and the partitioning matrix becomes $U = c \times 256$ instead of $U = c \times 262144$.

B. Initialization of Harmony Memory

Harmony memory (HM) is initialized with randomly generated feasible solutions. Each row of harmony memory consists of one candidate fuzzy membership matrix corresponding to a specific clustering process, in which the value of the ith element in each row is actually a column that shows the membership values of each pixel belonging to c regions (clusters). This membership values will be randomly selected from $[0, 1]$ range. Each column values must satisfy the rule of ONE which is $\sum_{j=1}^{c} u_{jk} = 1$. A fitness function for each row is calculated and saved in harmony memory as explained in Section IV-E.

C. Improvise a New Harmony

The new harmony vector is a new candidate clustering matrix, and the values of this matrix will be generated depending on HS's improvising rules. This new HM (solution) will inherit the values of its components from harmony memory solution rows stored in HM with probability of Harmony Memory Consideration Rate (HMCR), otherwise, the value of the components of the new solution is selected from the possible range with probability (1-HMCR). Furthermore, the new solution components that selected out of memory consideration operator are examined to be pitch adjusted with probability of Pitch Adjustment Rate (PAR). After the new solution matrix is generated, the repair strategy is employed to satisfy the rule of ONE for the new solution. The new solution is compared with the worst HM solution in term of fitness function. If it is better the new solution is included into the HM and the worst harmony is removed.

D. Performance Improvement

With reference to [19], [33], the hybridization of a global based search algorithm such as HS with one of the local search based algorithm such FCM will improve the performance of the proposed algorithm since the above HS's processes is good at finding a promising area of the search space, while FCM algorithm performs better in localized based search within those areas. As such, the combination of two ideas can results in an algorithm that can outperform either one individually. Therefore, FCM algorithm is introduced a few times during the algorithm process. For further explanation, after a new clustering solution is generated (the new harmony) by applying harmony operations, FCM will be called with this new clustering solution, then the clusters centroids are calculated using Eq.(13) for the new solution. After that, each pixel is reassigned to the cluster with the nearest centroids. Then FCM will return back the new generated membership matrix to the HS algorithm. The fitness function for this solution is calculated and compared with the worst fitness function saved in harmony memory, if it is better; a replacement will take place. Otherwise this new FCM solution will be rejected.

E. Fitness Computation

The fitness value for each harmony memory row indicates the degree of goodness of the solution it represents. In this paper, we use the XB-index [27] in order to calculate the fitness function.

In order to include the simplification step mentioned in Section IV-A, XB index is modified as follows:

$$XB = \frac{\sum_{j=1}^{c} \sum_{k=1}^{q} u_{kj}^2 h_k \left\| x_k - v_j \right\|^2}{\sum_{k=1}^{q} h_k \ min_{i,j} \left\| v_i - v_j \right\|^2} \left(\sum_{k=1}^{q} h_k = n \right) \quad (12)$$

Also the cluster centers are computed as follows:

$$v_j = \frac{\sum_{k=1}^{q} u_{ik}^m \ h_k \ x_k}{\sum_{k=1}^{q} u_{ik}^m \ h_k} \quad (13)$$

V. EXPERIMENTAL RESULTS

To show the effectiveness of our proposed HFISA algorithm, a set of different types of images are tested. These images (shown in Fig.1) can be categorized into synthetic images, natural image, remote sensing image and medical MR image. All of these images cover different domain and posses different

TABLE I
HARMONY SEARCH ALGORITHM PARAMETERS VALUES

HMCR	0.98
HMS	6
PAR	0.01
NI	5000
bw	0.02

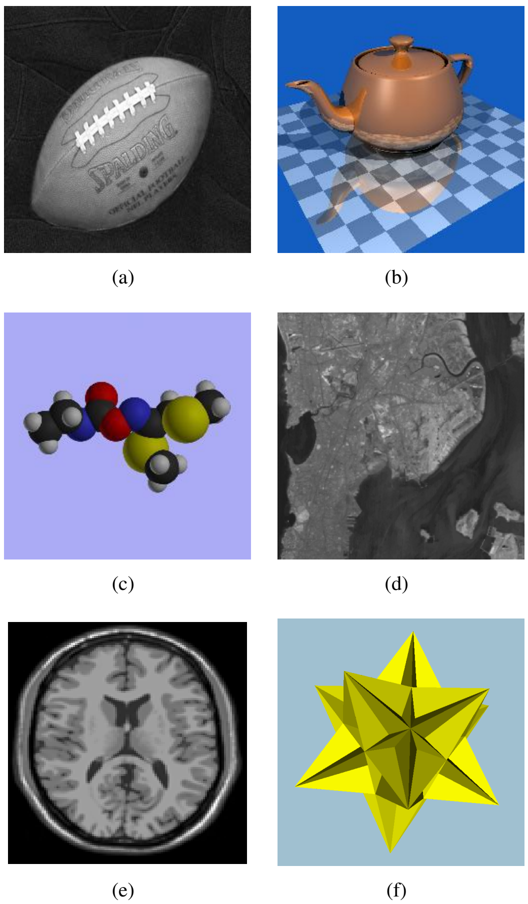


Fig. 1. Six different type images have been used to show the effectiveness of HFISA. (a) ball image, (b) teapot image, (c) molecule image, (d) Mumbai image, (e) MRI brain image, (f) shapes image.

characteristics. Furthermore, a comparison with a well known algorithm (FCM) is conducted. This is to show the ability of our HFISA algorithm over FCM in avoiding the local optima problem.

As an initial step, the appropriate parameter values of HFISA algorithm are selected. Table I describes these parameters and their values that were experimentally set. Note that the number of clusters (image regions) must be set prior to initializing the clustering process.

Fig.2 shows the effectiveness of NI parameter on the segmentation results on T1WI MR brain image obtained by our proposed algorithm with different iteration numbers.

In the next step, the performance of both HFISA and FCM algorithms are measured in terms of cluster validity index. Both HFISA and FCM algorithms segments those images

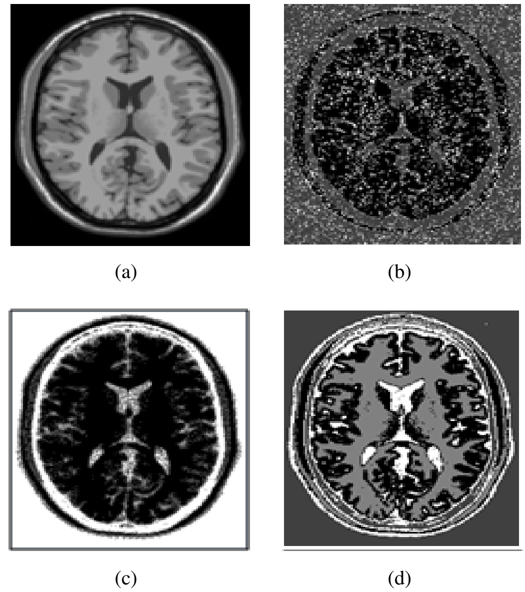


Fig. 2. Shows the effectiveness of NI values on the performance of HFISA. (a) Original brain MRI T1WI, (b) segmented image after 1000 iteration, (c) segmented image after 1500 iteration, (d) segmented image after 2000 iteration.

where each algorithm run for 30 times for each image. In each run, all of the cluster validity indices mentioned in Section III is calculated for each segmentation result.

Table II shows the mean and standard deviation of these 30 runs of both algorithms. It appears from this table that HFISA always finds good segmentation results while FCM, in some cases, gets stuck in local optima and as a result, fails to get good segmentation results (i.e. ball, teapot, shapes). For illustration, Fig.3(b) shows a good result that obtained from HFISA and Fig.3(c) shows a good result obtained by FCM, while Fig.3(d) shows FCM in its worst case (stuck in local optima).

Furthermore, and in order to compare the means of the results produced by HFISA and FCM algorithms, we used the unpaired t-tests for this purpose. Unpaired t-test assumes that the data have been sampled from a normally distributed population. From the concepts of the central limit theorem, it can be noted that when the sample sizes increase, the sampling distribution of the mean reaches a normal distribution regardless of the original distribution [34]. Tables III, IV, V, VI show the t-tests results for the means produced by HFISA compared with the means produced by FCM using PC,PE,XB,PBMF indices respectively. It can be seen from these tables that the mean clustering accuracy of all cases of HFISA is significantly better than that of the FCM algorithm.

These results clearly show the efficiency of our proposed HFISA over the state of the art FCM.

VI. Conclusion

In this paper the problem of finding a globally optimal partition of a given set of images into a specified number of

TABLE II
THE MEAN AND STANDARD DEVIATION OF 4 VALIDITY INDICES APPLIED ON SEGMENTATION RESULTS OF HFISA AND FCM.

Image name	No. of clusters	Algorithm name	PC	PE	XB	PBMF
teapot	6	HFISA	0.8315 ± 0.0	0.3403 ± 0.0	0.0737 ± 0.0	181.1989 ± 0.088
		FCM	0.8210 ± 0.015	0.3655 ± 0.030	0.1888 ± 0.0227	153.3924 ± 34.485
ball	5	HFISA	0.8894 ± 0.0	0.2341 ± 0.0	0.0397 ± 0.0	98.2247 ± 0.038
		FCM	0.8616 ± 0.051	0.2783 ± 0.081	0.2042 ± 0.303	91.5218 ± 12.332
molecule	6	HFISA	0.9488 ± 0.0	0.1029 ± 0.0	0.0288 ± 0.0	1438.1720 ± 0.012
		FCM	0.9488 ± 0.0	0.1029 ± 0.0	0.0288 ± 0.0	1430.9827 ± 0.390
shapes	11	HFISA	1 ± 0.0	0 ± 0.0	0 ± 0.0	3.24590E+96 $\pm$ 4.508E+94
		FCM	0.9017 ± 0.108	0.1588 ± 0.166	21.5611 ± 65.494	$5777736.3781 \pm 27382810.16$
Mumbai	6	HFISA	0.7521 ± 0.0	0.4928 ± 0.0	0.1185 ± 0.0	8.8447 ± 0.001
		FCM	0.7518 ± 0.0	0.4934 ± 0.0	0.1189 ± 0.0	8.8248 ± 0.002
MRI brain	4	HFISA	0.9205 ± 0.0	0.1563 ± 0.0	0.0268 ± 0.0	936.0049 ± 0.0
		FCM	0.9205 ± 0.0	0.1563 ± 0.0	0.0268 ± 0.0	935.9470 ± 0.019

TABLE III
UNPAIRED T-TEST RESULTS FOR THE PC INDEX

Image name	Standard error	t	95% confidence interval	Two-tailed P	Significance
teapot	0.003	3.9243	0.0051 to 0.0158	2.33E-04	Very significant
ball	0.009	2.9689	0.0090 to 0.0464	0.0043	Very significant
molecule	0.000	13.8001	-9.877E-7 to -7.375E-7	5.65E-20	Extremely significant
shapes	0.020	4.9908	- 0.0589 to - 0.1377	5.8097E-06	Extremely significant
Mumbai	0.000	22.6123	2.867E-4 to 3.424E-4	1.88E-30	Extremely significant
MRI brain	0.000	28.7747	2.892E-6 to -2.515E-6	4.97E-36	Extremely significant

TABLE IV
UNPAIRED T-TEST RESULTS FOR THE PE INDEX

Image name	Standard error	t	95% confidence interval	Two-tailed P	Significance
teapot	0.006	4.1816	-0.0372 to -0.0131	9.91E-05	Extremely significant
ball	0.015	2.9683	-0.0740 to -0.0144	0.0043	Very significant
molecule	0.000	3.4639	-1.028E-7 to -3.841E-7	0.001	Very significant
shapes	0.030	5.2295	-0.2196 to -0.0980	2.43E-06	Extremely significant
Mumbai	0.000	23.6518	-6.550E-4 to -5.528E-4	1.79E-31	Extremely significant
MRI brain	0.000	34.8302	3.772E-6 to 4.232E-6	1.40E-40	Extremely significant

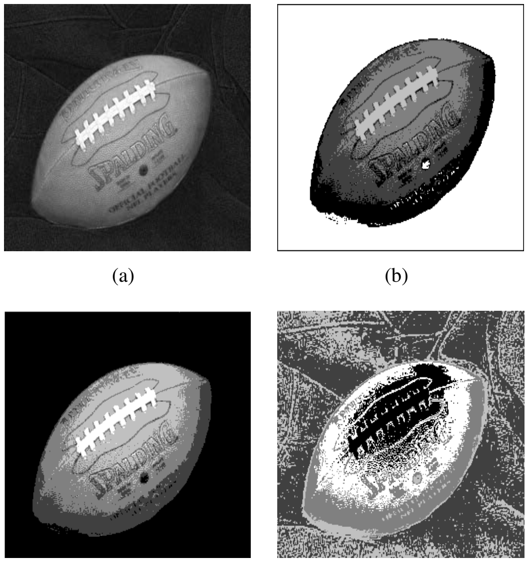
TABLE V
UNPAIRED T-TEST RESULTS FOR THE XE INDEX

Image name	Standard error	t	95% confidence interval	Two-tailed P	Significance
teapot	0.041	2.7773	-0.1981 to -0.0321	0.0074	Very significant
ball	0.055	2.9716	-0.2754 to -0.0537	0.0043	Very significant
molecule	0.000	1.961	-1.379E-5 to 1.4E-7	0.0547	Significant
shapes	11.958	1.8031	-45.4968 to 2.3745	0.0766	Significant
Mumbai	0.000	14.8147	-4.589E-4 to -3.496E-4	2.26E-21	Extremely significant
MRI brain	0.000	14.6667	-1.491E-6 to -1.133E-6	3.58E-21	Extremely significant

TABLE VI
UNPAIRED T-TEST RESULTS FOR THE PBMF INDEX

Image name	Standard error	t	95% confidence interval	Two-tailed P	Significance
Teapot	6.296	4.4165	15.2036 to 40.4094	4.44E-05	Extremely significant
Ball	2.252	2.977	2.1960 to 11.2099	0.0042	Very significant
molecule	0.071	101	7.0468 to 7.3318	6.87E-67	Extremely significant
shapes	8E+93	397.358	3.234E+96 to 3.266E+96	2.52E-101	Extremely significant
Mumbai	0.000	46.7796	0.0191 to 0.0208	9.34E-48	Extremely significant
MRI brain	0.004	16.4377	0.0509 to 0.0650	1.70E-23	Extremely significant

regions is considered and a novel algorithm, named HFISA, is proposed. In this paper the clustering problem is modeled as an optimization problem. In the proposed algorithm, a hybridization framework, which combines the harmony search algorithm with FCM algorithm, is employed. This hybridization strategy significantly improved the quality and speed of convergence of HFISA. Our experimental results on six different images showed that HFISA algorithm produces better solutions with high quality considering the PC, PE, XB and PBMF validity index measures in comparison with FCM algorithm. For future work, we will focus on exploring the hybridization of HS algorithm with other heuristic components



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

Fig. 3. Image segmentation results obtained from HFISA and FCM. (a) original image, (b) good results obtained by HFISA, (c) good results obtained by FCM, (d) bad results obtained by FCM (trapped in local optima).

in order to improve the performance of HFISA.

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