A Replication of Harmony Fuzzy Image Segmentation Algorithm

Eddie Yee Tak Ma

Abstract—**In this project, we have replicated previous work which combines the Harmony Search soft computing technique with the well known fuzzy c-means (FCM) algorithm. The resulting combination of the two is known as the Harmony Fuzzy Image Segmentation Algorithm (HFISA). This algorithm leverages the local optimization capability of the fuzzy c-means and also the global optimization capability of harmony search. Harmony Search is similar to Genetic Algorithm in that it is a stochastic search which creates prospective new solutions by the random recombination of elements found in a population of increasingly correct answers to the problem. Both the fuzzy c-means algorithm and the proposed algorithm are implemented and tested on the same batch of test images as used by the original authors. We repeat the use of the statistical values Partition Coefficient, Partition Entropy, Xie-Beni Index and PBMF in characterizing the performance of these two techniques. We verify the results of the original authors that the proposed algorithm does indeed provide some gain in grey-level segmentation performance over fuzzy c-means at the cost of increased computation. Contradicting the original results, we find that HFISA has reduced model stability as compared to FCM.**

I. Introduction

In this section, we overview some of recent ideas developed and proposed which utilize fuzzy set theory as a means of image segmentation. This task has been broadly categorized below into techniques that segment based on (1) the regions of an image, (2) extending fuzzy set theory in some meaningful way, (3) thresholding the global grey-levels of an image, and (4) an iterative clustering algorithm.

Region-based segmentation can be performed in a hierarchical fashion using a nested fuzzy c-means approach as in the work done by Rezaee et al. [12]. This approach took the form of a stack of fuzzy c-means classifiers such that each subsequent layer in the so called pyramid would refine the segmentation task at a different resolution. Redundantly representing the same image at different resolutions allowed the system to perform some planning on how final segmentation should take place. Another approach that considers spatial information is one evaluating the neighbourhood of each pixel in an image as in Beevi et al. [2]. In that work, the authors proposed a modified fuzzy c-means approach which was capable of mitigating artificial noise introduced into medical images. Knowledge about specific segmentation tasks can also be useful. In a study by Plissiti et al. [11], cell nuclei were segmented by first identifying darkened regions that are more likely to be cells as observed through a light microscope. The centroids of these darkened regions were considered candidate areas to find cell nuclei whereupon refinement was then conducted.

Work done by Pednekar and Kakadiaris [10] took advantage of fuzzy set theory in order to segment images based on a formalization of the perceived connectedness of an object. Given that the grey level of certain objects may vary from region to region, an approach using dynamic weights (DyW) to quantify the allowed change in greyscale is used. Furthermore, this DyW representation considers the direction in which the grey values change in order to assign appropriate memberships. Hasanzadeh et al. [6] performed a similar task by combining the notions of spatial connectedness and grey-level thresholding into the so called membership connectedness.

The work that is replicated in this project falls into the category of grey-level thresholding. In it, one considers the number of occurrences for each grey-level that occurs in an image. This relation can be thought of as a histogram. Recent work done by Deng et al. [4], introduces interval-valued fuzzy sets (an extension of set theory) to resolve ambiguities in membership of some observed grey values. This method does not change the way the grey-level histograms are created, but it does propose a different way to interpret them. Methods have also been developed to alter histograms as in Aarle and Sijbers [14]. In this method, the global histogram is calculated based on minimizing the inconsistencies within image segments and is applied to computed tomography images.

As well, the work replicated here utilizes a combination of iterative methods. Iterative methods which are based on K-means or fuzzy c-means clustering have also been developed as in Isa et al. [7], [13] who have innovated a method called *Adaptive Fuzzy Moving K-means Clustering*. The result is an algorithm that benefits from (1) the moving of unfit centroids to new clusters, (2) fuzzy set theory by permitting elements degrees of memberships in more than one cluster, and (3) the moving of members to clusters belonging to the nearest centroid.

II. Four Mathematical Objects

In this project, we replicate the work performed by Mandava et al. [1]. These authors created and investigated a novel strategy to perform grey-level-based image segmentation. This new method is dubbed Harmony Fuzzy Image Segmentation Algorithm (HFISA). HFISA is a combination of Harmony Search (HS) [5], [8] and fuzzy c-means clustering (FCM) [3]. FCM is characterized as a method that is particularly good at local solutions while HS is a method good at finding global solutions. The combination of the two allows for a versatile stochastic algorithm.

Eddie Ma is with the School of Computer Science, University of Guelph, Guelph, Ontario, Canada (email: ema@uoguelph.ca).

This work is submitted in partial fulfillment of course requirements for CIS 6050 – Artificial Neural Networks.

There are really only four mathematical objects that we need to consider in order to describe the logical components of HFISA. These objects are (1) the representation of the problem, (2) the representation of the centroid corresponding to each segment, (3) the fuzzy partition of the problem over each grey level, over each segment, and (4) the harmony memory. We discuss these components here and connect them together with the appropriate functions.

To represent the problem, a grey-level histogram is derived from the image as follows. Let x_i be a unique grey-level and h_i be the number of occurrences of that grey-level where there are q many different grey-levels in a given image ($i \in [1, q]$). For an image considered, this results in a tuple in the form $\{(x_1, h_1), ..(x_i, h_i), ..(x_q, h_q)\}$.

In order to make use of clustering algorithms for the purpose of segmentation, we can stipulate that each segment of the image according to a range of grey levels corresponds to a cluster in the solution. Each cluster has a centroid which is a real number. We can think of a centroid as a weighted average of the grey levels of a given segment. The number of clusters is arbitrarily defined based on the needs of the user; let us refer to this number with c. Given c clusters, the centroids can be expressed in a tuple of the form $\{v_1..v_j..v_c\}$.

Now that we have both a representation of the problem as well as a representation of the centroids along with an idea of their relationship to segments, we can complete the picture by describing the fuzzy partition U. A fuzzy partition describes how much each grey level belongs to each of the available clusters. This partition has several stipulations. First, it is a two-dimensional array of real-values; the number of rows are equal to the number of clusters c and the number of columns are equal to the number of grey-levels of the problem q (i.e. $|U| = c \times q$). The values in this fuzzy partition convey the membership of each grey-level x_i to each cluster j denoted as μ_{ji}. Notice that we must obey a rule of fuzzy set membership here and ensure that the sum of the memberships for each grey-level must be normalized to 1.0 over all clusters ($\sum_j^c \mu_{ji} = 1.0$); that is, we expect that no element may contribute more than one whole unit of membership in total over all clusters (nor less than one whole unit).

These three mathematical objects are all that we would need to discuss FCM. Let us complete our discussion of FCM before proceeding onto the final object that is only needed for HS.

FCM is a method that attempts to create partitions that will minimize the condition in (1).

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

The value $m \in [1.0, +\infty)$ is arbitrarily set by the user. We set it to 2.0 in accordance with the original study. The notation $|| \bullet ||$ indicates the inner product (Euclidean distance) between x_i and v_j. Note that this degenerates to the absolute difference of the two values because our clusters and elements to cluster are in greyscale (single dimension real numbers as opposed to vectors with more than one dimension).

In order to calculate the fuzzy partition from the problem and the tuple of centroids, equation 2 is used.

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

Note again that the inner products degenerate into the absolute difference for this particular task.

In order to calculate the centroids from the problem and the fuzzy partition, equation 3 is used.

$$v_j = \frac{\sum_{i=1}^{n} \mu_{ij}^m x_i}{\sum_{i=1}^{n} \mu_{ij}^m} \tag{3}$$

The FCM algorithm is essentially the repeated and alternating application of this pair of equations (2) (3). To start the algorithm, one needs an estimation of the initial clusters; and to end the algorithm, one needs a definition of convergence.

Convergence is defined as $||v_{\text{new}} - v_{\text{old}}|| < \epsilon$ where this inner product is the amount of change experienced between clusters given a present and previous iteration of the algorithm. We have set $\epsilon = 0.001$ in accordance to the original study.

Continuing on with our discussion of mathematical objects, we need only one more object in order to discuss the HS algorithm since all of the other objects needed are already defined and shared with FCM. The final object is the Harmony Memory which is just an array of fuzzy partitions. Each of the fuzzy partitions therein have the same number of clusters and the same number of grey levels as one another.

III. Harmony Fuzzy Search Algorithm

We will describe here a very focused, implementation-oriented version of Harmony Search as it applies to the grey-level thresholding problem. HS is a soft computing technique that resembles genetic algorithm (GA). HS has two operations; Improvise a New Harmony, Fitness Evaluation.

To start improvisation, a new blank fuzzy partition is generated. This new fuzzy partition is not part of the harmony memory. This new partition has the same dimensions as those partitions found in the harmony memory – the number of clusters times the number of grey-levels. To improvise a new harmony, each position of the new harmony memory is traversed. We index these positions given a cluster index and a grey-level index. A random decision is made for each position to either include an existing value from a random member of the harmony memory from the same index or to include a new randomly generated value. The probability that we will use an existing element is given by the Harmony Memory Consideration Rate (HMCR); the probability that we include a new random value is the complement (HMCR-1). Now that each of the elements of this new fuzzy partition is filled, we iterate over its elements once more. This time, each element may undergo a pitch adjustment given a random decision. This depends on the Pitch Adjustment

Rate (PAR) value which states the probability of such an adjustment. When an adjustment occurs, the value is tuned given a bandwidth (bw) as in $\mu_{ij} + \text{bw} \times \text{uniform}(-1, 1)$ where *uniform* returns a uniform random value.

Now that the new fuzzy partition is complete, a fitness function is used to decide how well it serves as a solution to the problem. In this application, some function which describes the clustering or segmentation effort is used. Each fuzzy partition of the harmony memory is also scored. If the new fuzzy partition is better than the worst fuzzy partition in the harmony memory (given the fitness function), then the new fuzzy partition replaces the worst partition.

This process is repeated until the number of allowed iterations (NI) is exhausted or some level of fitness is achieved for the best fuzzy partition in the harmony memory. This best scoring partition becomes the solution to the segmentation effort.

In creating the new partition, two stipulations arise. It should be noted that in generating random values, that the result must be in the range $[0.0, 1.0]$. Note also that normalization must occur at least before fitness is checked obeying the rule $\sum_j^c \mu_{ji} = 1.0$ as previous.

To augment the HS algorithm described above into the HFISA algorithm, the following change is made. After the new fuzzy partition is created, one round of FCM is applied on it. That is, the centroids of the new fuzzy partition are calculated, then the values of the new partition are modified given those centroids. The new partition then carries on in as before and undergoes fitness testing.

In total, HS (HFISA) requires four parameters. They are the harmony consideration rate (HMCR $= 0.98$), pitch adjustment rate (PAR $= 0.01$), bandwidth (bw $= 0.02$), and total allowed number of iterations (NI $=$ originally 5000, we use 250). The few parameters is one of the reasons the original authors chose this algorithm.

The fitness function used is the Xie-Beni (XB) index [15] as per the original work. The XB index is shown in 4.

$$XB = \frac{\sum_{j=1}^{c} \sum_{i=1}^{q} \mu_{ji}^2 h_i ||x_i - v_j||^2}{n \times \min_{j,k} ||v_j - v_k||^2} \tag{4}$$

This objective function is to be minimized. The factor $\min_{j,k}||v_j - v_k||$ returns the smallest inner product having considered each pair of centroids (all pairs of inner products are calculated, the smallest of these are returned).

IV. Clustering Validity Scores

In order to evaluate the results, the original authors chose the quantities Partition Coefficient (PC), Partition Entropy (PE) [3], XB [15] and (PBMF) [9].

V. Results

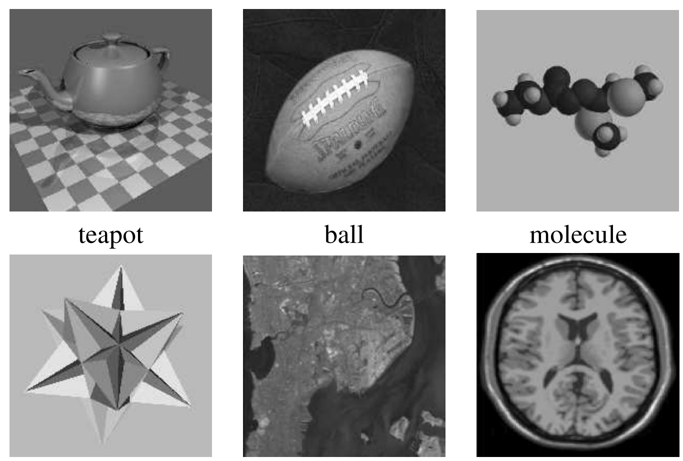
The experiments run are paired between FCM and HFISA. These experiments are of a head-to-head design given the intention to show which of the two methods performs better.

Figure 1 is a photo of a team member's cat with the application of the FCM grey-level segmentation technique as well as the HFISA technique. This is a representative result of these segmentation efforts; there is nearly no visually identifiable difference in quality.

Original FCM HFISA

Fig. 1. A photo of a team member's cat experiencing segmentation.

Figure 2 is a collection of the original six images used in the image segmentation task. These have been reduced in size and turned to grey-scale. Notice that each of these images has a different distribution of grey-levels.



teapot ball molecule

shapes Mumbai MRI brain

Fig. 2. The original six test images.

In repeating the experiment performed by the original authors, we used the six images included in the original paper and performed the segmenting task on each. The original authors performed thirty rounds of each FCM and HFISA. We performed ten rounds of each. The original authors varied the number of clusters used, whereas we kept all experiments to four clusters. Finally, the original authors performed 5000 training cycles of HFISA whereas we performed 250. These adjustments were made due to time constraints. All remaining parameters are as noted above.

Table I shows the average and standard deviation of the four scores obtained over the duration of the experiment.

The results in the original paper concluded that HFISA was far superior to fuzzy c-means. The numerical results seen here seem to indicate an agreement with the original paper. In both PC and PE, HFISA is better than FCM in five of the six cases where the exception, *molecule* is a tie. In XB, HFISA performed better on three of the six images, tied again in the image *molecule* and fared worse on the remaining two. In PBMF, HFISA fared better in four of six cases.

TABLE I
THE PERFORMANCE OF EACH METHOD GIVEN AS A (AVERAGE±STANDARD DEVIATION). SCORING FUNCTIONS ARE ANNOTATED WITH A SUPERSCRIPT $(+)$ TO INDICATE THAT A HIGHER SCORE INDICATES BETTER PERFORMANCE AND A $(-)$ TO INDICATE THAT A LOWER SCORE IS BETTER.

Image Name	Algorithm	PC$^+$	PE$^-$	XB$^-$	PBMF$^+$
teapot	HFISA	0.739 ± 0.015	0.503 ± 0.031	0.06 ± 0.006	1208.759 ± 351.924
	FCM	0.73 ± 0.0	0.526 ± 0.0	0.076 ± 0.0	986.911 ± 0.054
ball	HFISA	0.768 ± 0.003	0.444 ± 0.003	0.031 ± 0.001	2354.932 ± 19.624
	FCM	0.758 ± 0.0	0.46 ± 0.0	0.035 ± 0.0	2319.534 ± 0.003
molecule	HFISA	0.772 ± 0.0	0.44 ± 0.0	0.009 ± 0.0	3490.461 ± 3.789
	FCM	0.772 ± 0.0	0.44 ± 0.0	0.009 ± 0.0	3507.429 ± 0.01
shapes	HFISA	0.76 ± 0.003	0.462 ± 0.006	0.062 ± 0.023	3108.986 ± 299.924
	FCM	0.757 ± 0.0	0.464 ± 0.0	0.03 ± 0.0	3544.439 ± 0.01
Mumbai	HFISA	0.724 ± 0.027	0.527 ± 0.051	0.091 ± 0.021	1583.443 ± 510.513
	FCM	0.664 ± 0.0	0.644 ± 0.0	0.145 ± 0.0	547.111 ± 0.004
MRI brain	HFISA	0.703 ± 0.012	0.567 ± 0.022	0.067 ± 0.032	672.595 ± 242.711
	FCM	0.692 ± 0.0	0.58 ± 0.0	0.056 ± 0.0	649.609 ± 0.001

The amount of improvement gained from HFISA according to these numbers varies widely, with the amount of improvement proportional to the model instability given by the standard deviation. We say that a model with greater standard deviation is less stable as we are less certain about the precise value of the next score that we obtain from it. FCM on the other hand is remarkably stable and even under a random selection of initial clusters does not have a single standard deviation with a value in the tenth's magnitude. It should be noted that the value PBMF is in the correct magnitude as compared with the original paper (we estimate the value of $E1 = 5000.0$ given said magnitude – $E1$ was an unpublished parameter needed to calculate PBMF).

The model stability result is in stark opposition to that found of the original work. In it, the standard deviations of HFISA are zero for PC, PE and XB while the standard deviation of FCM varied in [0,1] for PC, PE and in [0,65] in XB. The stability for PBMF however was comparable.

VI. CONCLUSIONS AND DISCUSSION

The HFISA technique has been repeated and tested. While the visual quality of the segmented images are not vastly dissimilar, the numerical difference given the different cluster scores indicates that a detectable difference exists. In the original experiments, the authors additionally found that HFISA was a more stable model as well, able to reliably achieve the same values from trial to trial. We did not find this to be the case, and found that FCM was remarkably stable. In fact, in the preliminary work needed to establish some of the unknown parameters of the original work, we discovered that as long as the original centroids of the FCM are unique, that the FCM would tend to find the same solution within one hundred iterations for the same data (within a hundredth's precision of the XB score). The sub-optimal local optimum was simply not encountered in our implementation of FCM, whereas it was a major point in the original paper. Finally, the HFISA algorithm offers inspiration for future works that may require the strengths of both a global and local search heuristic.

REFERENCES

[1] Osama Moh'd Alia, Rajeswari Mandava, Dhanesh Ramachandram, and Mohd Ezane Aziz. A novel image segmentation algorithm based on harmony fuzzy search algorithm. In *Proceedings of the 2009 International Conference of Soft Computing and Pattern Recognition*, SOCPAR '09, pages 335–340, Washington, DC, USA, 2009. IEEE Computer Society.

[2] S. Zulaikha Beevi, M. Mohammed Sathik, and K. Senthamaraikannan. A robust fuzzy clustering technique with spatial neighborhood information for effective medical image segmentation. *Computing Research Repository*, 2010.

[3] James C. Bezdek. *Pattern Recognition with Fuzzy Objective Function Algorithms*. Kluwer Academic Publishers, Norwell, MA, USA, 1981.

[4] Tingquan Deng, Peipei Wang, Yuling Mei, and Wenjie Liu. Thresholding approaches with interval-valued fuzzy sets to image segmentation. In *Proceedings o f 2008 3rd International Conference on Intelligent System and Knowledge Engineering*, pages 1059 – 1064, 2008.

[5] Zong Woo Geem, Joong-Hoon Kim, and G. V. Loganathan. A new heuristic optimization algorithm: Harmony search. *Simulation*, 76(2):60–68, 2001.

[6] M. Kasaei Hasanzadeh and H. S. Mohseni. A new fuzzy connectedness relation for image segmentation. In *Information and Communication Technologies: From Theory to Applications, 2008. ICTTA 2008. 3rd International Conference on*, pages 1 – 6, 2008.

[7] Nor Mat Isa, Samy Salamah, and Umi Ngah. Adaptive fuzzy moving k-means clustering algorithm for image segmentation. *IEEE Transactions on Consumer Electronics*, 55:2145–2153, 2009.

[8] Kang S. Lee and Zong W. Geem. A new structural optimization method based on the harmony search algorithm. *Computers & Structures*, 82(9-10):781–798, April 2004.

[9] Malay K. Pakhira, Sanghamitra Bandyopadhyay, and Ujjwal Maulik. Validity index for crisp and fuzzy clusters. *Pattern Recognition*, 37(3):487 – 501, 2004.

[10] Amol Pednekar and Ioannis A. Kakadiaris. Image segmentation based on fuzzy connectedness using dynamic weights. *IEEE Transactions on Image Processing*, 15:1555–1562, 2006.

[11] Marina E Plissiti, Christophoros Nikou, and Antonia Charchanti. Automated detection of cell nuclei in pap smear images using morphological reconstruction and clustering. *IEEE Trans Inf Technol Biomed*, 15(2):233–41, 2011.

[12] M. Ramze Rezaee, Pieter M. J. Van Der Zwet, Boudewijn P. F. Lelieveldt, Rob J. Van Der Geest, and Johan H. C. Reiber. A multiresolution image segmentation technique based on pyramidal segmentation and fuzzy clustering. *IEEE Transactions on Image Processing*, 9:1238–1248, 2000.

[13] Siti Noraini Sulaiman and Nor Ashidi Mat Isa. Adaptive fuzzy-k-means clustering algorithm. *IEEE Transactions on Consumer Electronics*, 56(4):2661–2668, 2010.

[14] W van Aarle and J Sijbers. Optimal threshold selection for segmentation of dense homogeneous objects in tomographic reconstructions. *IEEE Trans Med Imaging*, 2011.

[15] Xuanli Lisa Xie and Gerardo Beni. A validity measure for fuzzy clustering. *IEEE Trans. Pattern Anal. Mach. Intell.*, 13:841–847, August 1991.