Development of an Enhanced Fuzzy C-Means algorithm for Medical Image Segmentation using Ant Colony Optimization

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Abstract

Modified Fuzzy C-Means (MFCM) algorithm, which is a combination of fuzzy c means and k means, for medical image segmentation, suffers from high computational time and noise which lead to high memory consumption and low accuracy. Therefore, this paper presents an Enhanced MFCM algorithm (ACOMFCM), which has better accuracy and low memory consumption for medical image segmentation. Thirty medical images used in this work were pre-processed using Gaussian filtering method. ACOMFCM algorithm was developed using Ant Colony Optimization techniques to minimise the Euclidean distance between the data point and centre coordinate in the K-means algorithm characterizing the existing MFCM. Segmentation of the thirty images were carried out using the MFCM and ACOMFCM algorithms in Matrix Laboratory 7.1 (R0011a) environment. Performance of the MFCM and the ACOMFCM was evaluated using segmentation accuracy, segmentation time and memory consumption.

The average result of MFCM algorithm for thirty images yielded segmentation accuracy, segmentation time and memory consumption of 7117992.29, 22.484s and 494161920bit, respectively while average result of the ACOMFCM algorithm for thirty images used yielded segmentation accuracy, segmentation time and memory consumption of 10590135.79, 6.649s and 502960128 bit, respectively.

Keywords: MFCM, ACOMFCM, Segmentation, Accuracy, Memory Consumption.

1. Introduction

Image segmentation is a means of dividing digital image into different regions to get useful information. The role of Segmentation cannot be underestimated in image analysis as it is one of the peculiar challenges in image processing technology because Clinicians and Patients always

desire quality images. The images are divided into non-overlapped and consistent regions which are similar with regard to some image properties such as intensity, color, texture and so on (Krishnan and Ramamoorthy, 2014).

Yu, Lee, Jeon (2014) reported that image segmentation has a wide range of applications such as image content analysis, object recognition and computer-assisted medical diagnosis. Research on image segmentation has delivered a considerable progress over the years, yet there have not been a perfect algorithm for segmentation. According to Dasgupta, 2012, the arrival of Computed Tomography (CT), Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI) and other peculiar medical image modalities has significantly improved the diagnosis of diseases in human beings. Medical imaging gives a dependable source of information of the human body, both to the Patient and clinician for use in fields like: reparative surgery, radiotherapy, stereotactic etc.

Hamed and Hadi, (2012) reported that minimizing the weighted vector within group sum of images is achievable through Fuzzy C means (FCM) algorithm as it produces a C-partitioning method in an iterative clustering format. FCM allows a pixel to be in multiple clusters with different degree of membership function. According to Krishnan and Ramamoorthy, (2014); Ghizlane, Amina and Khalid (2013), Ant Colony Optimization (ACO) is a meta-heuristic scheme which was used for solving discrete swarm optimization problems and handle the optimization and clustering problems. Due to its parallel searching capability, artificial ants implement a randomized construction heuristic which makes probabilistic decisions.

2. Literature Review

Segmentation is divided into different types with their unique peculiarities: According to Rubal Ahuja and Krishan Kumar, (2014); Nitesh et al, (2014); Joyjit et al, (2014); Sasibala and Sudhavani, (2016), Segmentation can be divided into Edge based, Model based, Thresholding, Region based and Clustering. Fuzzy c means, one of the methods under clustering has been modified by Ajala et al (2012) to overcome its inability to segment colour images.

2.1 Modified Fuzzy C-Means (MFCM) Algorithm

MFCM is an approach developed by Ajala et al (2012) where the data points are updated iteratively. It worked on colored images by the incorporation of K-means algorithm. The strength of K-means (ability to work on colored images) and FCM (allowing the member of one cluster to belong to another member) was combined to get MFCM algorithm. The step for the MFCM algorithm is shown as thus;

Step 1: Input the image to be segmented

Step 2: Get the number of colors in the image by looking for the $a*b*$ space

Step 3: Assign the number of colors to be cluster cluster no; that is $C=no$ of colors

Step 4: Choose an appropriate level of cluster fuzziness $f > 1$.

Step 5: Initialize the $N \times C \times M$ sized membership matrix U , at random,

Step 6: Determine the cluster centers CC_{jm} , for j th cluster and its m th dimension by using the expression given below:

$$\frac{\sum_{i=1}^N U_{ijm}^f x_{im}}{\sum_{i=1}^N U_{ijm}^f}$$

Step 7: Calculate the Euclidean distance between i th data point and j th cluster center using repetitive structure

Step 8: Update fuzzy membership grade point n according.

Step 9: Repeat from Step 6 to Step 8 until the changes a pre-specified termination criterion is reached

Step 10: Stop and output the image.

2.2 Ant Colony Optimization (ACO)

Ant colony algorithm used by Dohyeun Kim, (2016) and Cheraghali, et al (2014) was used in conjunction with modified MFCM algorithm that was developed by Ajala et al (2012) to form ACOMFCM. The ACO algorithm is presented as follows;

Step 1: Initialize all parameters, n fault symptom samples can be regarded as n classes.

Step 2: Compute weighted Euclidean distance between samples X_i and X_j .

$$d_{ij} = \|D(X_i - X_j)\|^2 = \sqrt{\sum_{k=1}^m P_k (X_{ik} - X_{jk})^2} \quad 3.6$$

P_k is weighted factor which can be defined according to every component's contribution in clustering.

Step 3: Compute the pheromone quantity of trail, r is described as cluster center and $\tau_{ij}(t)$ is intensity of the pheromone trail between X_i and X_j at time t , set the intensity of pheromone trail to 0 at time 0.

$$\tau_{ij}(t) = \begin{cases} 1 & \text{if } d_{ij} \leq r \\ 0 & \text{if } d_{ij} > r \end{cases} \quad 3.7$$

Step 4: Compute the probability of merging class X_i and X_j .

$$P_{ij} = \frac{\tau_{ij}(t)^\alpha \cdot \mu_{ij}(t)^\beta}{\sum_{is} \tau_{is}(t)^\alpha \cdot \mu_{is}^\beta} \quad 3.8$$

Where $S = \{s \mid d_{rs}, s = 1, 2, \dots, n\}$ is $\neq$ and $\eta_{ij}(t)$ is weight coefficient. It can reflect expectation of merging class X_i and X_j .

Step 5: If $P_{ij}(t) \geq P_0$ merging X_i and X_j , computing cluster center after merging.

$$\overline{C_j} = \frac{1}{j} \sum_{k=1}^j X_k (X_K \in C_j) \quad 3.9$$

Step 6: Compute the biased error of the *j*th clustering.

$$D_j = \sum_{k=1}^j \sqrt{\sum_{i=1}^m X_{ki} - C_{ji}}^2 \quad 3.10$$

Where c_{ji} is the *i*th component of the *j*th cluster center.

Step 7: Compute overall error

$$\epsilon = \sum_{j=1}^K D_j, \text{ if } \epsilon \leq \epsilon_0 \quad 3.11$$

The whole process will pause. Please output the number of clustering *m* and cluster center *j c* Otherwise, jump step 3 and continue iteration.

Step 8: Output image

Step 9: Stop

2.3 Related Work

Dasgupta (2012), performed demarcation of brain tumor using modified fuzzy c-means. The area of the segmented tumor generated from the modified fuzzy c-means segmentation was evaluated using Edge-adaptive clustering model. Despite this modification, the system still has the problem of Long Computational Time and Memory Consumption.

Ajala et al (2012) worked on Modified Fuzzy C-Means for Colored Image Segmentation (continuation of the Fuzzy k-c-means Clustering Algorithm for Medical Image Segmentation). The research describes FCM as a method of clustering which allows one piece of data to belong to two or more clusters. The results shows better performance than the existing fuzzy algorithm in terms of cluster centers, simulation time, iteration count and the outputted image. However, when applied to medical image analysis, it has important drawbacks such as long computational time and sensitivity to noise which lead to high memory consumption.

Lucia Ballerni, Leonardo Bocchi and Carina Johansson (2013) worked on Clustering algorithm for Color image segmentation. The classical Fuzzy C-Means algorithm was used with a Genetic algorithm (GA). From the result, segmentation of noise images is effectively improved. However, the limitation of the system occurs in long computational time.

3. Methodology

The methodology adopted were as follows

(a) Image Acquisition

Thirty medical images comprising of brain, eyes, finger, foetus, leg etc were used for the work Sample images were depicted in figure 3.1

(b) Image Pre-processing

Gaussian Filtering algorithm (GFA) was used to pre-process the acquired images and to prepare the images for further processing.

Figure 3.1: Samples of the medical images used

(c) Ant Colony Optimization with Modified Fuzzy C Means (ACOMFCM)

The Modified FCM algorithm method is optimized using Ant Colony Optimization (ACO) algorithm, known as ACOMFCM. ACO depicts an ant that move randomly from their colony in search of food and after gotten the food they create a marker or pheromone that forms the shortest distance between the Colony and the food source. This selection ability of ACO was employed in MFCM to get the shortest distance between cluster center and the data n point in each cluster. ACO helps to further reduce time and noise by its ability of picking through the shortest distance. The resulting algorithms (ACOMFCM) produces high quality segmented image. The step for the ACOMFCM algorithm is shown thus;

1. *Input the image to be segmented*
2. *If image = colored image goto 3 else goto 4*
3. *Load K means clustering segmentation and goto 4*
4. *Generate initial fuzzy partitioning /membership matrix*

$$n_{ij} = \frac{1}{\sum_{k=1}^c \frac{\|x_i - c_{j1}\|^{\frac{2}{m-1}}}{\|x_i - c_k\|^{\frac{2}{m-1}}}}$$

5. *Calculate initial fuzzy cluster*
6. *Calculate the cluster centroid*

$$C = \frac{\sum_{i=1}^n U_{ij}^m * x_i}{\sum_{i=1}^n U_{ij}^m}$$

7. *Locate the membership grade point (n) in the cluster*
8. *Start the iteration using Ant Colony Optimization (ACO) for selection process*
(Hint: ACO was used to find near optimal combination between c and n)
9. *Get the probability of ant movement from c to n that depends on attractiveness and trail level.*

$$P_{cn}^K = \frac{(T_{cn}^\alpha)(\eta_{cn}^\beta)}{\sum_{xy} (T_{xy}^\alpha)(\eta_{xy}^\beta)}$$

Where;

T_{cn} = amount of pheromone deposited for transition from c to n

η_{cn} = desirability of cluster transition for cn ($1/d_{cn}$, d=distance)

T_{zc} = attractiveness for other possible cluster transition

η_{zc} = trail level for other possible cluster transition

$0 \leq \alpha$ = parameter to control the influence of T_{cn}

$\beta \geq 1$ = parameter to control influence of η_{cn}

10. If $n=0$, go to 11, else go to 9

11. Update pheromone when ants have completed the solution using

$$(1-P)T_{cn} + \sum \Delta T_{cn}^k$$

Where

$$\sum \Delta T_{cn}^k = Q/L_k \text{ if ant uses curve c n in its tour, otherwise } 0$$

L_k = length of ant tour and Q = constant

12. Defuzzification process then takes place in order to achieve the crisp clusters

13. Output image.

(d) Performance Evaluation

The performance evaluations of the algorithms were carried out using the metrics by Lauren (2001), which are segmentation time, segmentation accuracy and Memory consumption.

Segmentation Time

This is the time taken to compute the segmentation including the running time of the algorithm or the time spent to perform interactive segmentation. The research was carried out using Compaq Presario CQ60 notebook PC with AMD Athlon Dual-core QL 62 2.00 GHz processor. It was computed in milli seconds using computer time.

Segmentation Accuracy

The accuracy of the segmentation algorithms is generally based on Volume measurement. This is the volume of segmented feature in the image domain. It is can be evaluated using segmented volume area;

$$\text{Segmented volume area} = \text{Number of pixel} * \text{volume of each pixel}$$

Memory Consumption

This depends highly on the computer memory. System performance is highly dependent on the memory being consumed. System memory is of paramount importance as it plays a major role in image processing. Obviously segmentation types with low memory consumption could be accepted, as low memory consumption would aid system performance.

4. Result

Table 4.1 gave the results of segmentation time, accuracy and memory consumption of thirty (30) medical images used to test the developed ACOMFCM segmentation algorithm. Also, Table 4.2 shows the average result of segmentation accuracy, segmentation time and memory consumption of the thirty (30) medical images used for the developed ACOMFCM segmentation algorithm.

Table 4.1: Results showing performance of thirty (30) medical images using ACOMFCM

	Segmentation Accuracy		Segmentation time(ms)	Memory consumption (bit)
Image 1	10590135.80		6.6490	561573888
Image 2	6128271.23		5.8444	563331072
Image 3	12386959.36	6.4993		564572160
Image 4	12381430.82	5.9288		566853632
Image 5	12385636.29	4.3902		569896960
Image 6	11745512.47	8.7860		571670528
Image 7	12051088.59	6.3189		574046208
Image 8	12319600.92	5.6506		578646016
Image 9	12149562.81	4.8701		580956160
Image 10	11745592.21	6.1048		582828032
Image 11	11686054.97	7.4773		585805824
Image 12	12382281.36	9.3358		587993088
Image 13	9635115.52	5.4453		592527360
Image 14	11701810.08	8.5429		594886656
Image 15	5779547.78	6.2660		589528448
Image 16	11749411.57	4.3806		600162304
Image 17	11749590.86	9.3522		602861568
Image 18	25319554.79	5.5716		607268864
Image 19	24472631.677.2044			609669120
Image 20	21144745.44	6.2651		611676160
Image 21	12095671.32	8.0836		614039552
Image 22	12386392.33	9.7321		616783872
Image 23	12386959.36	4.5167		619196416
Image 24	4592289.24	5.3353		623517696
Image 25	1238143.71	6.1340		626376704

Image 26	9569788.93	8.3511	628617216
Image 27	11679847.05	7.5672	631640064
Image 28	12325365.73	4.7214	633860096
Image 29	12363672.42	9.7812	596099072
Image 30	12381430.755.9288		693540064

Table 4.2: Average result of the thirty (30) medical images used for ACOMFCM

	Segmentation Accuracy	Segmentation time(ms)	Memory consumption (bit)
ACOMFCM	10590135.79	6.6490	502960128

5. Discussion of Results

The result obtained for ACOMFCM segmentation algorithm was compared with MFCM segmentation algorithm developed by Ajalaetal (2012). Both MFCM and ACOMFCM algorithms were tested using thirty medical images. In the analysis done, the values of segmentation accuracy, segmentation time and memory consumption were computed for both the MFCM and the ACOMFCM. Table 4.3 gave the results of segmentation time, accuracy and memory consumption of thirty (30) medical images used to test MFCM segmentation algorithm while Table 4.4 shows the average result of segmentation accuracy, segmentation time and memory consumption of the thirty (30) medical images used for MFCM and ACOMFCM segmentation algorithms and it can be deduced that ACOMFCM has increase segmentation accuracy of 20%, decrease segmentation time of 54% and increase memory consumption of 1% compared to MFCM.

Moreover, user interface designed for MFCM and ACOMFCM segmentation algorithms for three randomly selected samples of medical images; image 1, 15 and 30 were presented as shown in figure 4.1, figure 4.2 and figure 4.3. The bar chart of segmentation time, accuracy and memory consumption were presented in figure 4.4, figure 4.5 and figure 4.6. It was discovered that ACOMFCM has higher segmentation accuracy compared to MFCM and also, ACOMFCM has an increase memory consumption compared to MFCM because of the robustness of ACO algorithm.

Table 4.1: Results showing performance of thirty (30) medical images using MFCM

	Segmentation Accuracy	Segmentation time (ms)	Memory consumption (bit)
Image 1	71179924.29	22.4842	442568704
Image 2	5813119.67	17.6057	448299008
Image 3	11749949.44	14.1741	448704512
Image 4	11744705.21	30.3736	638954368
Image 5	11542761.38	20.6182	549265664
Image 6	11430639.64	12.7821	419433600
Image 7	11749008.17	15.1472	449613824
Image 8	11516827.62	25.7256	447242240
Image 9	11473641.14	18.5131	447188992
Image 10	10572345.23	32.3410	656892416
Image 11	11005107.25	19.3533	451350528
Image 12	11633007.54	35.1675	651452928
Image 13	9139621.51	15.7312	391274240
Image 14	9672336.92	31.8036	591233280
Image 15	54823296.34	34.7937	516284416
Image 16	10065066.02	27.4042	531222528
Image 17	11005107.25	20.7165	536039424
Image 18	12366924.31	29.5232	530395136
Image 19	12044756.76	16.8063	431664896
Image 20	12141199.11	30.1430	636940544
Image 21	11748425.48	21.2945	532828160
Image 22	10028653.38	27.4534	533164032
Image 23	6128271.23	15.3538	432844544
Image 24	1238535.78	20.4773	533401600
Image 25	1214191.11	17.1084	438329088
Image 26	4592289.24	28.8710	531267584
Image 27	11430639.45	14.5065	531230720
Image 28	10439160.25	19.7214	335527424
Image 29	10842809.27	25.7680	534339584
Image 30	11744706.28	30.3736	634793964

Table 4.4: Average result of the thirty (30) medical images used for MFCM and ACOMFCM

	Segmentation Accuracy	Segmentation time(ms)	Memory consumption (bit)
MFCM	7117992.29	22.484	494161920
ACOMFCM	10590135.79	6.6490	502960128

Figure 4.1: Image 1 interface for MFCM Figure 4.2: Image 15 interface for MFCM and ACOMFCM

Figure 4.3: Image 30 interface for MFCM and ACOMFCM

Figure 4.4: Segmentation time for MFCM and ACOMFCM

Figure 4.5: Segmentation accuracy for MFCM and ACOMFCM

Figure 4.6: Memory consumption for MFCM and ACOMFCM

6. Conclusion

This work combined Ant colony optimization (ACO) with existing modified fuzzy c means segmentation algorithm (MFCM) to develop Ant Colony Optimization with Modified Fuzzy CMeans segmentation (ACOMFCM) algorithm. Performance evaluation of the existing MFCM and the developed ACOMFCM was done using segmentation accuracy, segmentation time and memory consumption.

The result shows that ACOMFCM algorithm performed better than the existing MFCM algorithm because it produces higher segmentation accuracy and lower segmentation time. This work will assist the medical personnel in effective medical image diagnosis.

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