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Segmentation of Fetal Images using Kernel Fuzzy C Means Clustering with Whale Optimisation Algorithm

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AbstractImage segmentation is considered as a critical process in medical imaging that are facilitated using automated computation. The segmentation process partitions the images into subsets based on its location or intensity. However, segmentation of fetal images faces poor segmentation due to the presence of noise and poor spatial intensities. In this paper, the study decomposes the fetal image into several parts for the purpose of segmentation and then performs the change in representations. The segmentation process is improved in this method using Kernel Fuzzy C Means (KFCM) based Whale Optimisation Algorithm (WOA). The segmentation process uses modified KFCM, where the centroid values are estimated using WOA. The segmentation method segments the input fetal image into appropriate regions using KFCM-WOA. The simulation result shows that the proposed method attains improved performance than other kernel based methods. The results of the performance metrics shows that the proposed method attains a sensitivity of 99.8273%, specificity of 99.7350%, accuracy of 99.9385%, positive predictive value (PPV) of 99.3964, Negative Predictive value (NPV) of 0.3805, Dice Coefficient of 48.5518, Rand Index (RI) of 0.9983 and Global consistency error (GCE) of 0.0460, which are higher than other kernel based methods.

***Keywords:** WOA, Segmentation, KFCM, Centroid estimation.*

I. INTRODUCTION

Image segmentation is the procedure for dividing the fetal image pixels into subsets. Biomedical images segmentation is a key step in many medical imaging studies. Automated segmentation can be extremely beneficial because large-scale studies are needed to identify subtle changes and the effects of disease.

Several approaches have been proposed to segment the medical image [1,3]. If a large training dataset of a certain image class is available with ground-truth labels, supervised segmentation can produce accurate results. However, the creation of training data sets calls for manual label delineation by experts, which is labor intensive and expensive for a dataset large enough to be trained. New image types are constantly being developed, which makes it ongoing task to create the manual training sets needed for controlled segmentation. Finally, for an unusual type of data, it can be challenging to provide a large sufficient data set for the label.

In contrast, unattended segmentation has the advantage that training data is not needed in segment images and is therefore helpful if a manually marked dataset is absent. Unattended segmentation methods apply to atypical and invisible situations more broadly and are more robust [2,4-6,8,10-12]. Furthermore, the results of these methods can lead to manual segmentation, which accelerates the development of training data sets. Since it is important to explore new methodologies to expand suitable options for unattended segmentation of different classes of medical images, even an unexploited segmentation algorithm can be effective for the segmentation of certain but not all image classes.

The main objectives of the proposed work is to decompose image into several parts for the purpose of segmentation and finally it performsthe change in representations. To achieve this objective and to improve the quality of segmentation, the proposed method uses two different stages of operation that includes both pre-processing and segmentation operations. The pre-processing stage reads the input image and resizes it in desirable format. The segmentation process uses modified KFCM, where the centroid values are estimated using WOA.

The outline of the paper is given below: Section 2 provides the literature survey. Section 3 discusses the proposed method. Section 4 evaluates the proposed method with other kernel based techniques and finally section 5 concludes the entire work.

II. PROPOSED METHOD

The proposed method involves two different stages of operation that includes 1) pre-processing and 2) segmentation. The former reads the input image and resizes it in desirable format. The latter uses KFCM, where the centroid values are estimated using WOA [7], which is different from the conventional initialization of centroid values in KFCM [9].

1.1. KFCM

Prioritizing kernel based FCM methods is appropriate and inappropriate test cases. The various kinds of KFCM algorithm expand the KFCM method by a variety of kernel-based learning settings. Depending on the coverage measure resemblance, the proposed method uses kernel fuzzy c means the clustering process for clustering the already prevalent test cases. FCM is the clustering method that allows information centered on the group's proximity to identify the pattern. The objective function of the projected c-mean algorithm of multiple kernels is defined effectively by,

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$$F(u,z)=\sum_{m=1}^{M}\sum_{n=1}^{c}u_{mn}^{i}\big(1-G(I_m,z_n)\big)$$

The KFCM is used in advance to detect an error. The end of the process is to find the source of the error. This method clusters the classification of suitable and inappropriate test cases. The test cases are clustered and the relevant test cases are taken to prioritize the test. The aim of test case priority is to review the test case arrangement which increases the probability of the failures in the input data being identified.

1.2. Whale Optimization

This algorithm operates on two phases. At the first phase i.e. the exploitation phase: encircling prey and spiral updating position operations are implemented.In the second phase i.e. exploration phase, the preys are searched randomly.

Due to the arbitrary nature of the optimization algorithm, the process for achieving an adequate balance of exploitation and exploration to improve a metaheuristic algorithm is a major challenge. In comparison with the various optimization approaches, WOA has the highest significance:

(1) Exploitation ability
(2) Exploration ability
(3) Ability to get rid of the local minima

Because of the position updating mechanism of whales, the WOA has a significant exploration capacity. This equation forces the whales to move around randomly throughout the initial step of the algorithm. In the next steps, the whales quickly update their positions and move along a spiral-like path towards the best path found so far. Since both phases are completed independently and in half-iteration, the WOA avoids local optimum and achieves simultaneous convergence by means of iterations. But most other optimisation algorithms don't have an operator who uses only one format to upgrade search agents' position to dedicate a particular iteration to exploitation, which increases the probability of falling into local optimum.

Segmentation (WOA-KFCM) Algorithm

Initially find the weight of the pixel

Step 1: Find the Local Variance coefficient$lvc_m=\frac{\sum_{t\in M_m}(I_t-I_m)^2}{M_R*(\bar{I}_m)^2}$ where I_t is a grayscale image, I_m is a mean grayscale, M_m represents window size, $M_R$represents cardinality ofM_m.

Step 2: Compute exponential for lvc_m to find weight within the local window$\tau_m=\exp\left(\sum_{t\in M_m,m\neq t}lvc_m\right)$

Step 3: Calculate the every pixel weight$p_m=\frac{\tau_m}{\sum_{t\in M_m}\tau_t}$

Step 4: Compute the final weight$\vartheta_m=\begin{cases}2+p_m, & \bar{I}_m<I_m\\ 2+p_m, \bar{I}_m>I_m & \\ 0, \bar{I}_m=I_m & \end{cases}$

Step 5: New formed weighted image $\bar{\mathcal{E}}_m=\frac{1}{2+\max(\vartheta_m)}\left(I_m+\frac{1+\max(\vartheta_m)}{M_R-1}\sum_{m\in M_m}I_m\right)$

Step 6: Compute Centroid by using WOA

Declare the population $\bar{\mathcal{E}}_m(m=1,2\ldots\ldots\ldots n)$

Compute the fitness function for every agent by using

$l_{bound}=\min(\bar{\mathcal{E}}_m)$;

$l_{upper}=\mathrm{man}(\bar{\mathcal{E}}_m)$;

$dim=30$;

$u_0=rand_{m*n,clus_{no}-1}*\frac{1}{clus\_no}$

$u_{m*n,clus_{no}}=0$

$obj_{func}=\max|\bar{\mathcal{E}}_m|$;

To initialize the first population of search agents

$p_{posistion}=rand_{sa:dim}*\left(l_{upper}-l_{bound}\right)+l_{bound}$

While(y< iteration)

For k=1: sa

If ($p_{posistion}<0.5$)

If(A < 1)

$p_{posistion}=|\mathbb{C}*p_{posistion_y}-p_{posistion_y}|$

$p_{posistion_{y+1}}=p_{posistion}-A*p_{posistion}$

Where

$A=2ar-a$

$\mathbb{C}=2.r$

$a=2-y\frac{-1}{iteration}$

r->random value between 0 to 1

else if($|A|\geq 1$)

Chose search agent randomly x_r

$p_{posistion_{y+1}}=x_r-A.p_{posistion}$

End if

Else if ($p_{posistion}\geq 0.5$)

$p_{posistion_{y+1}}=p_{posistion_y}-p_{posistion}*\exp(bl)*\cos(2\pi l)+p_{posistion_y}$

End if

End for

$best_{score}=p_{posistion}$

End while

$c_{centoid}=best_{score}$;

Step 7: Compute the kernel width δ

$$\delta=\left[\frac{\sum_{m=1}^{M}\left(d_m,\bar{d}\right)^2}{M-1}\right]^{1/2}$$

Step 8: While ($\max(u_0-u))>e$; $u=u_0$

Step 9: Compute Gaussian kernel

$$G(I_m, z_n) = \exp\left(-\frac{\|I_m, z_n\|}{2\delta^2}\right)$$

$$u = u.\hat{\ } i$$

$$final\_val(iteration) = 2\left[\sum_{m=1}^{M}\sum_{n=1}^{c} u_{mn}^{i}\left(1 - G(I_m, z_n)\right) + \sum_{m=1}^{M}\sum_{n=1}^{c} \vartheta_m z_{mn}^{i}\left(1 - G(\bar{I}_m, z_n)\right)\right]$$

$$z_{mn} = \frac{\left(\left(1 - G(I_m, z_n)\right) + \vartheta_m\left(1 - G(\bar{I}_m, z_n)\right)\right)^{-1/(i-1)}}{\sum_{t=1}^{c}\left(1 - G(I_m, z_t) + \vartheta_m\left(1 - G(\bar{I}_m, z_t)\right)\right)^{-1/(i-1)}}$$

$$Z_n = \frac{\sum_{m=1}^{M} z_{mn}^{i}\left(G(I_m, z_n)I_m + \vartheta_m G(\bar{I}_m, z_n)\bar{I}_n\right)}{\sum_{m=1}^{M} z_{mn}^{i}\left(G(I_m, z_n) + \vartheta_m G(\bar{I}_m, z_n)\right)}$$

End while

Step 10: Replace the original pixel with segmented part

Proposed Segmentation Algorithm

1. Find the pixel weight for the input image (see the coding PixWgt.m)

Find the Local Variance of every pixel
Find the local variance coefficient
Find the sum of local variance coefficient
Compute weight for every pixel
Calculate the final weight

2. Apply the average filter on the input image (see the modified_kfcm)
3. To compute the centroid by using WOA algorithm

Initialize the required parameter for WOA
Find the fitness function
Set the leader position as zero with dimension of 'dim'.
Set the leader score as infinity
Position initialization (see initialization.m)
Set Convergence curve as zeros with number iteration
Loop is starting
Update the best leader position and best score
Compute the best score

4. Set the best score value as centroid value
5. Compute the kernel width for both input image and filtered image (see kerWidth.m)
6. Compute the Gaussian kernel (see gauss Kernal. m)
7. Repeat the process until max no. of iteration
8. It gives the segmented part in the form of binary

III. RESULTS AND DISCUSSIONS

The performance of the proposed method is compared with other existing segmentation techniques that includes: Markov Random Field (MRF), Adaptive K-Mean Clustering (AKCM) and Expectation Maximization (EM). The proposed and other existing segmentation methods are evaluated in terms of various metrics that includes: True Positive Rate (TPR) or Sensitivity, True Negative Rate (TNR) or Specificity, positive predictive value (PPV), Negative Predictive value (NPV), Dice Coefficient, Rand Index (RI) and Global consistency error (GCE).

The images acquired after pre-processing and segmentation from the input fetal image is given in Figure 3.

(a) Original Image

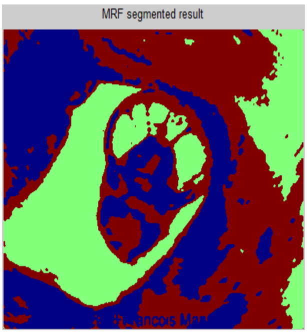
(b) Resized Image

(c) Noisy Image

(d) Noise removed Image

(e) Segmented Image

Figure 1: Results of Segmentation (Image 1)



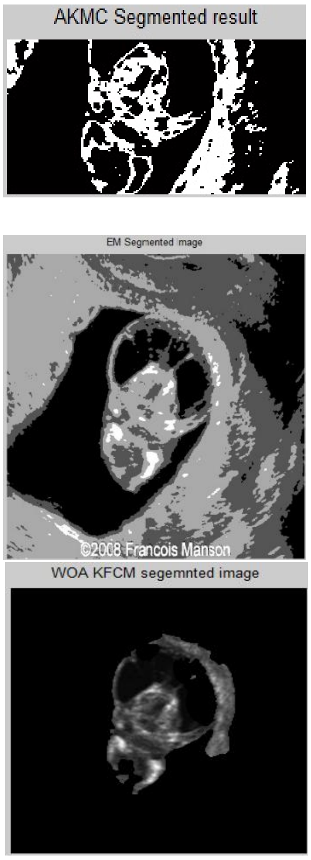


Figure 2: Segmentation results of various methods (Image 2)

It is seen that from Table 1, the accuracy of proposed method is invariably higher than the other techniques like MRF, AKCM and EM. Similarly, the other metrics from Table1 shows that the proposed algorithm shows improved segmentation and reduced execution time than the existing kernel based techniques. It is seen that the Sensitivity and Specificity of KFCM-WOA is higher than other methods. PPV and NPV are contrast with each other, so as the PPV increases the NPV reduces. The result shows that PPV of KFCM-WOA is higher than other methods and NPV of KFCM-WOA is lesser than EM but higher than MRF and AKCM. Similarly, Dice Coefficient and RI is higher in KFCM-WOA segmentation technique than other kernel based segmentation. Finally, GCE of KFCM-WOA segmentation technique is lesser than other method but marginally higher than EM. The Figure 4 shows the results of segmentation results of various methods for image 2. The result shows that the proposed method attains improved segmentation accuracy than other existing methods.

Table.1. Performance Evaluation

Technique	MRF	AKCM	EM	KFCM-WOA Image 1	KFCM-WOA Image 2
Sensitivity	89.456	90.025	91.2876	99.8273	99.8307
Specificity	90.178	91.112	92.0431	99.7350	96.1541
Accuracy	91.876	93.282	94.6520	99.9385	99.8110
PPV	90.467	90.421	94.1223	99.3964	84.9839
NPV	0.3450	0.2342	0.41670	0.3805	0.2652
Dice	0.4210	0.4515	42.9822	48.5518	49.8347
RI	0.1230	0.1340	0.81020	0.9983	0.9615
GCE	0.4560	0.3450	0.02200	0.0460	0.1502

IV. CONCLUSIONS

In this paper, the study decomposes the fetal image into several parts for the purpose of segmentation and then performs the change in representations. The segmentation process is improved in this method using KFCM-WOA. The segmentation process uses modified KFCM, where the centroid values are estimated using WOA. The segmentation method segments the input fetal image into appropriate regions using KFCM-WOA using improved centroid selection than existing random centroid selection methods. The simulation result shows that the proposed method attains improved performance than other kernel based methods.

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