

MRI Brain Edge Detection Using GAFCM Segmentation and Canny Algorithm

Romesh Laishram, W.Kanan Kumar Singh, N.Ajit Kumar, Robindro.K, S.Jimriff

Department of Electronics and Communication Engineering

Manipur Institute of Technology

Imphal, Manipur, India

e-mail: romeshlaishram@gmail.com, wahengbam.kanankumar@gmail.com

ningombama@gmail.com, robindro.khangembam@gmail.com, jim_reevs2004@yahoo.co.in

Abstract— Over the past few decades we have seen tremendous growth in the field of Magnetic Resonance Imaging (MRI) Brain image processing. It requires various steps to ensure that the desired result is obtained. One of the constituent processes for the basic study of the brain parts is the edge detection, which is the initial module for all other post processing procedures. These edges characterize the abnormalities existing in the human brain. Hence it should be done with utmost care for obtaining worthy result. In this paper, a new approach to MRI brain edge detection problem is presented. It consists of two stages. First the original MRI image is passed through image segmentation block and in the second stage edge detection algorithm is applied to the segmented image. Image segmentation is done using Genetic algorithm incorporating Fuzzy C means clustering (GAFCM) and Canny edge detection Algorithm is used for edge detection. Although this approach has high computational complexity it greatly improves the accuracy of the segmentation on medical image that produces precise edge detected image of the Human Brain.

Keywords—Edge ,MRI,GAFCM,Canny,segmentation.

I. INTRODUCTION

Magnetic Resonance Imaging (MRI) is the medical imaging technology that allows cross sectional view of the human brain with an unprecedented tissue contrast. MRI provides a digital representation of tissue characteristic that can be obtained in any tissue plane. The images produced by an MRI scanner are best described as slices through the brain. MRI has the added advantage of producing images, which slices the brain images in both horizontal and vertical planes. For further processing these MRI images must be categorized and analyzed using edge detection.

One natural view of segmentation [1] is that we are attempting to determine which components of a data set naturally "belong together". Clustering is a process whereby a data set is replaced by clusters, which are collections of data points that "belong together". Thus, it is natural to think of image segmentation as image clustering i.e. the representation of an image in terms of clusters of pixels that "belong together". The specific criterion to be used depends on the application. Pixels may belong together because of the same colour or similarity measure. The result of this algorithm produced a better result to compare with other techniques.

This work is an enhanced form of edge detection methodology that aids to obtain the best results out of MRI brain images. The method uses fuzzy C means (FCM) [2] clustering algorithm for segmenting the image prior to edge detection process. The main purpose of using GA is to reach the Global minima of the clustering objective function. In [3] the application GA in image segmentation problem is investigated.

Genetic Algorithm (GA) is a population-based stochastic search procedure to find exact or approximate solutions to optimization and search problems. Modelled on the mechanisms of evolution and natural genetics, genetic algorithms provide an alternative to traditional optimization techniques by using directed random searches to locate optimal solutions. Each chromosome in the population is a potential solution to the problem. Genetic Algorithm creates a sequence of populations for each successive generation by using a selection mechanism and uses operators such as crossover and mutation as principal search mechanisms - the aim of the algorithm being to optimize a given objective or fitness function. An encoding mechanism maps each potential solution to a chromosome. An objective function or fitness function is used to evaluate the ability of each chromosome to provide a satisfactory solution to the problem. The selection procedure, modelled on nature's survival-of-the fittest mechanism, ensure that the fitter chromosomes have a greater number of offspring in the subsequent generations. For crossover, two chromosomes are randomly chosen from the population. Assuming the length of the chromosome to be L, this process randomly chooses a point between L and L-1 and swaps the content of the two chromosomes beyond the crossover point to obtain the offspring. A crossover between a pair of chromosomes is affected only if they satisfy the crossover probability. Mutation is the second operator, after crossover, which is used for randomizing the search. Mutation involves altering the content of the chromosomes at a randomly selected position in the chromosome, after determining if the chromosome satisfies the mutation probability. In order to terminate the execution of GA, a stopping criterion is specified. Specifying the number of iterations of the generational cycle is one common technique of achieving this end. Some studies on GA incorporated FCM can be found in the literature [4]-[5].

Canny edge detection algorithm is one of the most eminent methodologies which give a good corollary compared to others. The recent works on modified Canny algorithm are presented by the authors in [6]-[8].

II. FUZZY C MEANS ALGORITHM

Segmentation is greatly being improved by using the FCM algorithm [3]-[5] instead of using K-Means Clustering algorithm. It divides the images into number of homogenous classes effectively. It has some success to detect the noise from an image.

The Traditional FCM algorithm is an iterative algorithm that produces optimal C partitions, centers $V = \{v_1, v_2, \dots, v_c\}$. Let unlabelled data set $X = \{x_1, x_2, \dots, x_n\}$ be the pixel intensities, where n is the number of image pixels to determine their membership. The FCM algorithm tries to partition the dataset X into C clusters. The standard FCM objective function is defined as follows.

$$J_m(U, V) = \sum_{i=1}^c \sum_{k=1}^n (u_{ik})^m d^2(x_k, v_i) \quad (1)$$

where $d^2(x_k, v_i)$ represents the square of the Euclidean distance between the pixel intensity value x_k and the centroid value v_i along with constraint $\sum_{i=1}^c u_{ik} = 1$, and the degree of fuzzification $m \geq 1$. A data point x_k belongs to the specific cluster v_i that is given by the membership value u_{ik} of the data point to that cluster. Local minimization of the objective function $J_m(U, V)$ is accomplished by repeatedly adjusting the values of u_{ik} and v_i according to the following equations.

$$U_{ik} = \left[\sum_{j=1}^c \left(\frac{d^2(x_k, v_i)}{d^2(x_k, v_j)} \right)^{\frac{1}{m-1}} \right]^{-1} \quad (2)$$

Where V_i is calculated using the following equation

$$V_i = \frac{\sum_{k=0}^n (u_{ik})^m x_k}{\sum_{k=0}^n (u_{ik})^m} \quad (3)$$

As J_m is iteratively minimized, the centroid matrix is more stable. This iteration is terminated when the difference between the maximum of current centroid value, maximum of previous iteration centroid value is less than the 0.0001. The value 0.0001 is predefined termination threshold. Finally, all homogeneous pixels are grouped into the same class to evaluate the Fuzzy C-means algorithm.

III. GENETIC ALGORITHM INCORPORATING FUZZY C MEANS ALGORITHM (GAFCM)

Most of the clustering methods minimize the objective function J_m . Genetic algorithm (GA) is an optimization problem to minimize the objective function. Three major functions are carried out by the genetic algorithm such as initialization, mutation and cross over. The cluster centers are assigned as the Initialization vector from the uniform distribution. Suppose it reaches the local minima, GA selects the mutation method to take off it. The incorporation of mutation enhances the ability of the genetic algorithm to find near optimal solutions. The pixel intensity is converted in to the bit strings. The mutation operator in this bit string flip search bit of the bit string with a small probability. The roulette wheel selection method which is used for selecting a small probability value.

Consider the chromosomes of the data set. We can create the new chromosome from the existing chromosomes during the reproduction is the process of crossover. The basic of the crossover is as follows: consider $a_1 = 10001111$, $a_2 = 10110011$ then derive the new chromosomes from the a_1 and a_2 namely a_{1new} and a_{2new} .

$a_{1new} = 1000001$

(first 4 bits from a_1 and last 4 bits from a_2).

$a_{2new} = 11111011$

(last 4 bits from a_1 and first 4 bits from a_2).

In this way we generate the new chromosome by using the crossover operator. Where a_1 , a_2 are the parent chromosomes of the a_{1new} and a_{2new} . This two are the children of the parent chromosomes. Well the mutation method flips the bit string of the pixel intensity value. Example consider the a_1 value it may be flipped like 10001001. The GAFCM based segmentation algorithm is given below.

A. GAFCM Algorithm

i) ENCODING: Each chromosome represents a solution which is a sequence of cluster centers. For an N-dimensional space, each cluster center is mapped to N consecutive genes in the chromosome. For image datasets each gene is an integer representing an intensity value.

ii) POPULATION INITIALISATION: Set chromosomes as vector containing the centroids of the clusters. In our implementation, we set population as 10 and the number of generations as 40.

iii) EVALUATION OF FITNESS FUNCTION: Using the roulette wheel selection, it ensures that the chromosomes with higher fitness values have better chance to get selected. We set the fitness function as the inverse of the objective function used in FCM algorithm, i.e. Fitness function = $1/J_m$.

iv) Crossover: The Crossover step recombines the bits (genes) of the two selected strings or chromosomes. Out of the two Crossover methods i.e. Single point and two points we have selected single point crossover operator for our project.

v) **MUTATION:** The next operation mutation is performed in a bit-by-bit basis. Let $p_m = 0.01$, i.e. we expect on an average 1% bit mutation. There exist altogether 10 chromosomes*5 bits/chromosomes = 50 bits in the whole population. 1% bit mutation thus means $50*0.01=0.5$ bit mutation. Since every bit has an equal chance of mutation, we generate a random number in $[0, 1]$ and if the generated number is $p_m < 0.01$, we select the chromosomes for mutation. Thus for each chromosomes, we test the feasibility of the chromosome for mutation. To identify the bit position of mutation, we generate a random number in $[0, n-1]$, where n is the word-length of the chromosomes. If random number generated is p , the p^{th} bit of the selected chromosomes will be mutated. Mutation ensures that the algorithm converges to the global minima instead of getting stuck in local minima

IV. SIMULATION RESULTS

In this section we present the simulation results of the MRI image edge detection problem. The performance of GAFCM based edge detection algorithm is compared with the ordinary Canny algorithm for three different MRI images as shown in figure 1-3 respectively. The simulation is performed in MATLAB environment.

The comparison result shows that GA- FCM based Canny edge detection method yield the better result than ordinary Canny edge detection algorithm. We can also notice that in GAFCM the image is segmented or clustered properly; each and every edge is fetched without missing even a single curve. This algorithm gets into the delicate parts of the image for extracting the edges and its analysis with an outstanding performance. The result shows that MRI Brain edge detection using GAFCM segmentation and Canny algorithm is the best edge detection technique compared to ordinary Canny edge detection algorithm.

V. CONCLUSION

In this study we have proposed a novel approach for edge detection technique, which on comparison with ordinary

canny edge detection yields excellent results. The resulted final images with their best edge details are very much essential and helpful for further brain MRI image processing and analysis. Further other population based algorithms like particle swarm optimization (PSO) may incorporated in FCM may be investigated and the effect of changing the cluster size on the problem should be checked.

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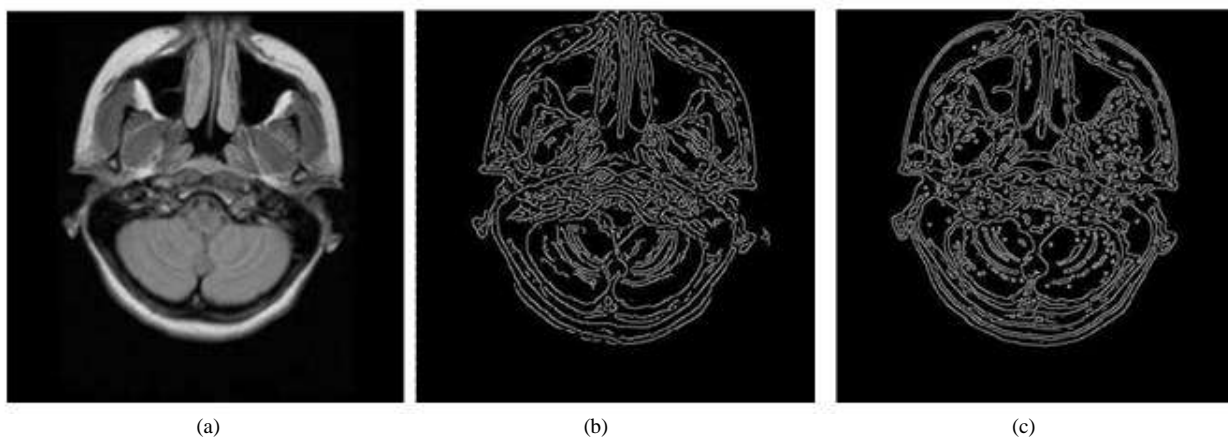
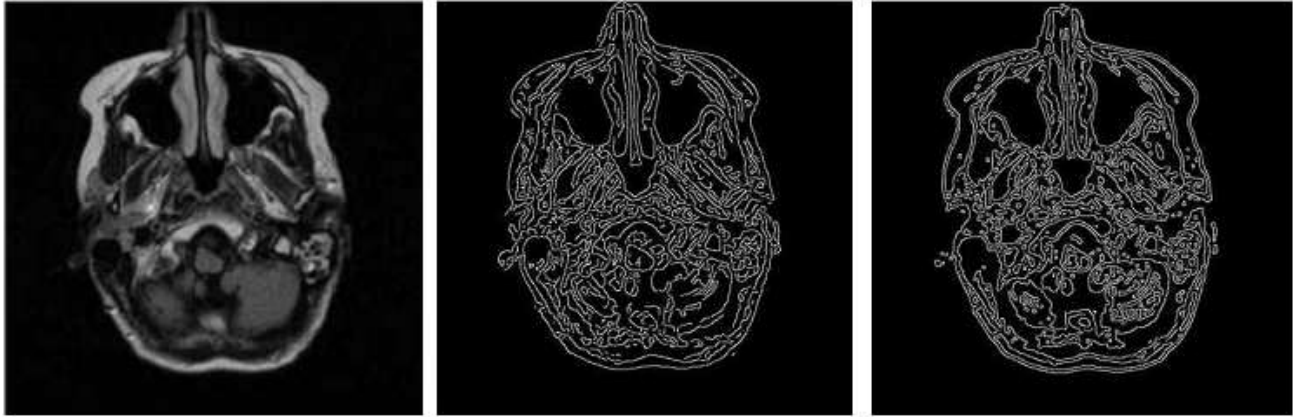


Figure 1. (a) Original Image (b) Ordinary Canny Algorithm (c) GAFCM with Canny algorithm



(a) (b) (c)
Figure 2. (a) Original Image (b) Ordinary Canny Algorithm (c) GAFCM with Canny algorithm



(a) (b) (c)
Figure 3. (a) Original Image (b) Ordinary Canny Algorithm (c) GAFCM with Canny algorithm