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CNN-Based Approach for Segmentation of Brain and Lung MRI Images

M. Duraisamy
Associate Professor, Department of Computer Applications
Dr NGP Institute of Technology, Coimbatore - 641 048
E-mail: mduraisamyphd@gmail.com

S. Duraisamy
Professor and Head, Department of Computer Applications
Sri Krishna College of Engineering and Technology, Coimbatore -641 008
E-mail: sdsamy.s@gmail.com

Abstract

Magnetic Resonance Imaging (MRI) has become an efficient instrument for clinical diagnoses and research in recent years. It has become a very useful medical modality for the detection of various diseases through segmentation methods. In this paper, we have presented an effective CNN based segmentation method with lung and brain MRI images. This approach hits the target with the aid of the following major steps, which includes, 1) Pre-processing of the brain and lung images, 2) Segmentation using cellular neural network. Initially, the MRI image is pre-processed to make it fit for segmentation. Here, in the pre-processing step, image de-noising is done using the linear smoothing filters, such as Gaussian Filter. Then, the pre-processed image is segmented according to our proposed technique, CNN-based image segmentation. Finally, the different MRI images (brain and lung) are given to the proposed approach to evaluate the performance of the proposed approach in segmentation process. The Comparative analysis is carried out Fuzzy C-means (FCM) and K-means classification. From the comparative analysis, the accuracy of proposed segmentation approach produces better results (83.7% for lung and 93% for brain images) than that of existing Fuzzy C-means (FCM) and K-means classification.

Keywords: Brain and Lung MRI image, Cellular neural network, template design, Gaussian filter, employed bee, onlooker bee, scout bee

1. Introduction

As numerous cases of brain and lung cancer are rising day by day, so diagnosis of these threats has become much popular in advanced countries. The identification of these diseases at an early stage is of much concern to cure it. Researchers have been studying how to apply the technique of image processing to the medical imaging field for getting better medical imaging in clinical diagnoses. In Image segmentation the digital images are partitioned into disjoint regions. For medical image, image segmentation is the key method in target region extraction, giving tissue measuring and three dimensional reconstructions [10]. Segmentation of tissues and structures from medical images is the first step in many image analysis applications developed for medical diagnosis. Advancement of treatment plans and evaluation of disease progression are other applications. These applications stem from the fact that diseases affect specific tissues or structures, lead to loss, atrophy (volume loss), and abnormalities. Therefore, an accurate, reliable, and automatic segmentation of these tissues and structures can improve diagnosis and treatment of diseases.

Moreover, identification and analysis of the scrape manually from MR brain and lung images are generally time consuming, expensive and can produce unacceptably high intraobserver and interobserver variability [40]. The segmented MR images used in the medical diagnostic process depends on a combination of two, often conflicting, requirements, that is, the removal of the unnecessary information present in the original MR images and the maintenance of the significant details in the resulting segmented images [41] [42]. MR-image segmentation methods are usually examined on the basis of their ability to differentiate between i) cerebro-spinal fluid (CSF), white matter, and gray matter and between ii) normal tissues and abnormal tissues [43].

In the recent years various methods have been presented for the segmentation of brain tissues from MR image, those are classical pattern recognition methods, image analysis methods, rule-based systems, crisp and fuzzy clustering procedures, feed-forward neural networks, fuzzy reasoning, geometric models to determine scrape boundaries, connected component analysis, deterministic annealing, atlas based methods and contouring approaches [44] [45]. Also some more researches have been done for the segmentation of normal and abnormal tissues in MRI brain images. Some of the recent related works regarding the segmentation of brain tissues are discussed in the following section.

Chua and Yang [9] discovered a new model called the Cellular Neural Network (CNN) model, which permits certain new prospectives in signal processing and which can be appropriately implemented as an integrated circuit. The CNN is formed in a way that it is able to make simultaneous signal processing as the cells are connected in a two-dimensional (2D) network structure [11, 12]. The cells in the network structure are connected only with the neighboring cells by means of a certain set of parameters. These set of parameters verifies the dynamic behavior of the CNN and are known as “cloning template”. One of the major functions of CNN is image processing which is obtained by the two dimensional network architecture of CNNs that provides a convenient structure for image processing applications and also for the real time imaging sensors [13, 14]. Complex image processing tasks can also be accomplished successfully through CNN-based imaging sensors & circuits as it operates at a considerably higher speed. For realizing complex image processing applications based on the CNN structure, preliminary image processing techniques such as edge detection, diffusion and dilation must be used. Hence the overall performance of such task depends strongly on the quality of the preliminary process.

In our proposed technique, initially the input MRI image is pre-processed in order to eliminate the noise and make the image fit for rest of the processes. Here we use the Gaussian filter in the pre-processing stage. Subsequently, the pre-processed image is segmented according to our proposed technique, CNN-based image segmentation. Due to the lack of a robust and effective structure in determining the cloning template, template designing studies are one of the most attractive research areas in the CNN field and this study aims to design the segmenting CNN template through ABC algorithm. The CNN template generated by the ABC algorithm is tested by using segmentation of lung and brain images.

The organization of the paper is as follows: firstly related works are explained in section 2.Secondly, in section 2, CNN structure and cell concept are explained in Section 3. Section 4 includes problem description information about template design. Section 5 is explained our proposed approach and pseudocode of ABC algorithm. The detailed experimental results and discussions are given in Section 6. The conclusions are summed up in Section 7.

2. Related Works

Plentiful of researches have been presented by researchers regarding MRI brain and lung image segmentation techniques. A brief review of some of the recent researches is presented here.

Rajeev Ratan *et al* [1] have proposed a two dimensional MRI data which helps in detecting (10-15 minutes operator time) the tumor tissue with a better accuracy and reproducibility comparable to manual segmentation (2-6 hours operator time) making the automatic segmentation practically real for malignant tumors. In this system, after a manual segmentation process the tumor identification has been made for the potential use of MRI data for improving the approximate brain tumor shape and 2D visualization for surgical planning.

Ahmed Kharrat *et al.* [2] have presented a hybrid approach for classification of brain tissues in magnetic resonance images (MRI) based on genetic algorithm (GA) and support vector machine (SVM). A wavelet based texture feature set is derived. By using spatial gray level dependence method (SGLDM) the optimal texture & features are extracted from normal and tumor regions. These features are given as input to the SVM classifier. The choice of features, which constitute a big problem in classification techniques, is solved by using GA. These optimal features are used to classify the brain tissues into normal, benign or malignant tumor. The performance of the algorithm is evaluated on a series of brain tumor images.

Shafaf Ibrahim *et al*. [3] have introduced a paper that exposed the comparison between the performances of Seed-Based Region Growing (SBRG), Adaptive Network-Based Fuzzy Inference System (ANFIS) and Fuzzy c-Means (FCM) in brain abnormalities segmentation. The prior knowledge of size of the abnormalities was known by using controlled experimental data and the way in which they have been designed. This was done by cutting various sizes of abnormalities and pasting it onto normal brain tissues. The normal tissues or the background were divided into three different categories. The segmentation was done with fifty seven data of each category. The knowledge of the size of the abnormalities by the number of pixels was then compared with segmentation results of three techniques proposed. It was proven that the ANFIS returns the best segmentation performances in light abnormalities, whereas the SBRG on the other hand performed all in dark abnormalities segmentation.

AmirEhsan Lashkari [4] has discovered an automatic brain tumor detection method that uses T1, T2_weighted and PD, MR images to determine any kind of abnormality in brain tissues. In this technique, Gabor wavelets, energy, entropy, contrast and some other statistic features such as mean, median, variance, correlation, values of maximum and minimum intensity etc. has been used to obtain a clear description from brain tissues. It was used from a feature selection method to reduce the feature space too. This method used from neural network to do this classification. The purpose of this project was to classify the brain tissues to normal and abnormal classes automatically, that saved the radiologist time, increases accuracy and yield of diagnosis.

Murat Ceylan *et al.* [5] have derived an efficient method known as Complex-Valued Artificial Neural Network with Complex Wavelet Transform (CWT-CVANN) for the segmentation of lung region on chest CT images. In that method the combined architecture was composed of two cascade stages: feature extraction with various levels of complex wavelet transform and segmentation with complex-valued artificial neural network. Here, 32 CT images of 6 female and 26 male patients were recorded from Baskent University Radiology Department. (This collection includes 10 images with benign nodules and 22 images with malign nodules. Averaged age of patients is 64. Each CT slice used in this study has dimensions of 752\times 752 pixels with grey level) In only two seconds of processing time per each CT image, 99.79% averaged accuracy rate is obtained using 3rd level CWT-CVANN for segmentation of the lung region. Thus, it was concluded that CWT-CVANN was a comprising method in lung region segmentation problem.

Chuin-Mu Wang and Ruey-Maw Chen [6] have presented a classification approach; it is known as Vector Seeded Region Growing (VSRG). The VSRG basically selects seed pixel vectors by means of standard deviation and relative Euclidean distance. Data dimensionality of MRI can be decreased and the desired target of interest can be classified with the brain tissue and brain tumor segmentation. A series of experiments are conducted and compared to the commonly used c-means method for performance evaluation. The results indicate the possible usefulness of this method for MR image classification.

Chunming Li et al. [7] have found out a region-based process for image segmentation, which was able to deal with the intensity of inhomogeneities in the segmentation. First, based on the model of images with intensity inhomogeneities, local clustering criterion function for the image intensities in a neighborhood of each point is derived. This local clustering criterion function was then integrated with respect to the neighborhood center to give a global criterion of image segmentation. In a level set formulation, this criterion defined an energy in terms of the level set functions that represented a partition of the image domain and a bias field that accounted for the intensity inhomogeneity of the image. Therefore, by minimizing this energy, the method was able to simultaneously segment the image and estimate the bias field, and the estimated bias field can be used for intensity inhomogeneity correction (or bias correction). The method was validated on synthetic images and real images of various modalities and obtained desirable performance in the presence of intensity inhomogeneities. Through several experiments it is been found that the proposed method is robust to initialization, faster and accurate.

Manisha Sutar, and N. J. Janwe [8] have introduced a new segmentation technique which was based on an extension to the traditional C-means (FCM) clustering algorithm. A neighborhood attraction, which was dependent on the relative location and features of neighboring pixels was considered. Particle Swarm Optimization model (PSO) was used to optimize the degree of attraction. The introduced paper demonstrated the superiority of the proposed technique to FCM-based method. That segmentation method was a component of an MR image-based classification system for tumors, which was being developed.

3. Background

3.1. Cellular Neural Network (CNN)

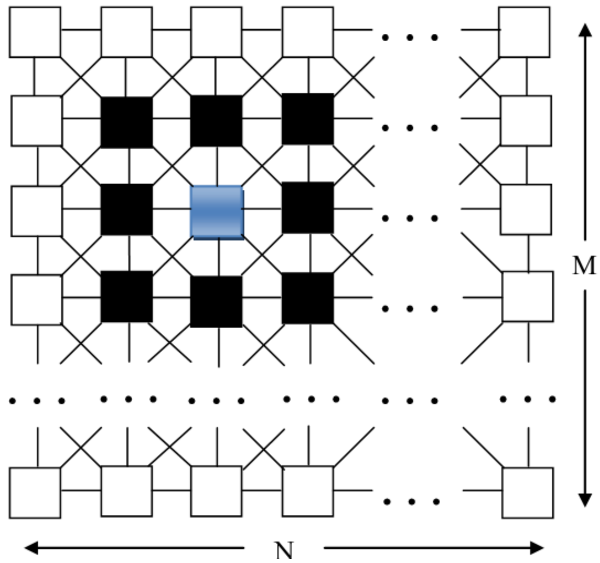
Chua and Yang [9] at the University of California, invented the Cellular Neural networks (CNN) in 1988, by using certain regular (rectangular, hexagonal, etc) group of mainly identical dynamical systems called cells which satisfy two properties: where most interactions are local within a finite radius and all state values are continuous valued signals.

Following are the Chua-Yang definition [9]:

- A CNN is an N-dimensional regular array of elements (cells) as shown in figure 1.
- The cell grid can be a planar array for example with rectangular, triangular or hexagonal geometry, a 2-D or 3-D torus, a 3-D finite array or a 3-D sequence of 2-D arrays (layers)
- Cells are multiple input & single output processors that are described by one or just few parametric functions.
- A cell is characterized by an internal state variable, but sometimes it cannot be observable directly from outside the cell.
- More than one connection network can be present, with different neighborhood sizes.
- A CNN dynamical system can operate both in continuous (CT-CNN) or discrete time (DT-CNN).
- CNN data and parameters are typically continuous values.
- CNN operate typically with more than one interaction i.e. they are recurrent networks.

In terms of speed and capability CNN has several advantages over others. A general architectural structure for CNNs is shown in Figure 1.

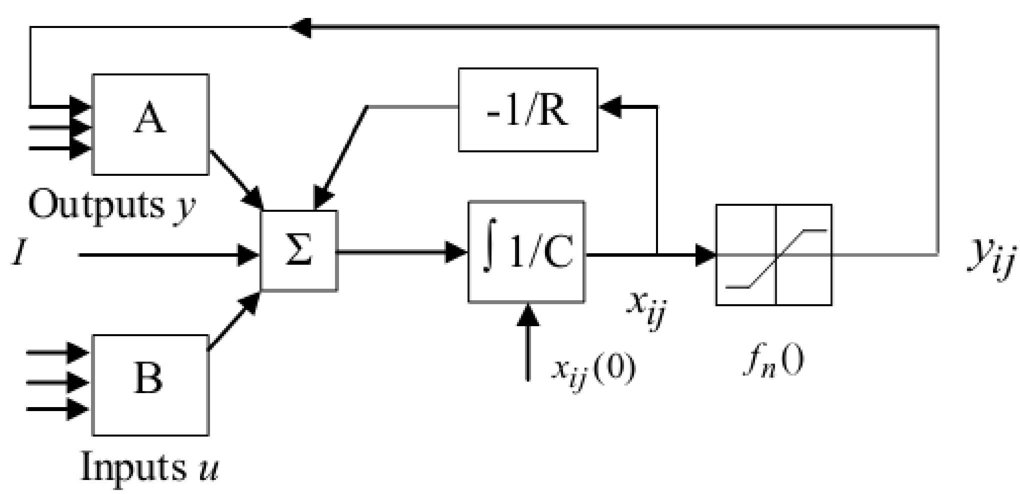
Figure 1: Cellular Neural Network with a 3×3 neighborhood



As shown in Figure 1, each cell in a CNN is directly connected only with the neighboring cells. Due to the regional inner-cell connections in CNNs, a cell directly affects only its neighbor cells. Cells which are not directly connected to this cell are indirectly affected while transiting from the initial phase to a stable phase as a result of the propagation of CNNs continuous time dynamics [9]. The cell concept and the cloning template terms are defined in the following subsections.

***Cell*:** The cell, which is the basic element of the CNN structure, is composed of structurally linear and non-linear circuit elements, such as capacitors, linear resistances, linear and non-linear controlled sources and independent sources. The first CNN cell structure in the literature proposed by Chua-Yang [9] is shown in Figure 2. Each cell has a state x, a constant input u and an output y. The equivalent block diagram of a continuous time cell is shown in figure 2 below.

Figure 2: Block diagram of one cell



State equation:

$$C\frac{dv_{xij}(t)}{dt} = -\frac{1}{R_x}v_{xij}(t) + \sum_{C(k,l)\in N(i,j)} A(i,j;k,l)v_{ykl}(t) + \sum_{C(k,l)\in N(i,j)} B(i,j:k,l)v_{ukl}(t) + I \tag{1}$$

Output equation

$$v_{yij}(t)=\frac{1}{2}\left(\left|v_{xij}(t)+1\right|-\left|v_{xij}(t)-1\right|\right) \tag{2}$$

Input equation

$$v_{uij}(t)=E_{ij} \tag{3}$$

Constraint conditions:

$$\left|v_{xij}(0)\right|\leq 1\ ,\quad \left|v_{uij}\right|\leq 1 \tag{4}$$

4. Problem Description

Template design: Designing a CNN template is one of the most important research topics in this field to achieve different behaviors effectively. If CNN is interpreted in terms of image processing, the operation principle of CNN differs from the operation of standard image processing techniques. The CNN cloning template is designed according to the CNN structure due to the fact that the mask parameter of well-known classical segmentation is not used in the CNN structure. Design of the cloning template which determines the dynamic behaviour of CNN is an important difficulty as there doesn't exist a generalized template design method. Several methods have been proposed to determine such templates. These methods can be classified as analytical methods [22-25], local learning algorithms [26, 27] and global learning algorithms [28, 29]. Depending on the number of variables and the type of data in all developed methods the difficulty level of the problem increases. However the solution for such problems using deterministic methods includes difficulties in both the modeling and solution processes, depending on the structure of the problem. Heuristic methods have been developed so as to overcome these disadvantages and produce a general solution that does not depend on the problem structure. The heuristic methods, which are based on population, can reach a solution fast, due to multiple search procedures [30]. If a suitable quality metric to be used in the heuristic methods can be defined, the optimal cloning template of CNNs, that must be adjusted correctly to realize the desired image processing practice, or else it can be designed effectively by using the heuristic algorithms. For determining the cloning template of CNNs it has been dealt with an important optimization study and therefore several artificial intelligence based methods (such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Differential Evolution (DE), *etc*.) has been proposed [31-39]. However, it is a shortcoming of these studies that results have not been assessed or compared visually or numerically with known classical techniques and previous studies made in the CNN area. It is required that the problem to be solved and the artificial intelligent optimization method should be in conformity and the control parameters of the optimization method should be set effectively. Since the results obtained with a single run are not sufficient to give a reliable interpretation of the technique used and the results obtained, determining optimal control parameter values of the optimization algorithm is possible by examining of results obtained with multiple running on different control parameter values of optimization. In this way, an idea can be suggested about whether the optimization technique selected is appropriate for the problem.

5. Proposed Approach of Lung and Brain MRI Image Segmentation using Cellular Neural Network

Segmentation of medical imagery is a knotty and challenging process due to the complexity of the images and lack of models of the anatomy that completely capture the possible deformations in each structure. It is well-known that brain and lung tissue has a complex structure, and thus, its segmentation is an essential step for our proposed method. Our proposed method consists of two phases namely, preprocessing and CNN based segmentation. In pre-processing phase, applying Gaussian filtering is done using remove unwanted noise. In segmentation phase, lung and brain tissues segmentation has done using cellular neural network and CNN template design process is designed using artificial bee colony algorithm. The Block diagram of the proposed technique is shown schematically in Figure 3.

Figure 3: Overall block diagram of our proposed approach

5.1. Pre-Processing using Gaussian Filter

For the proposed technique, MRI lung and brain images cannot be directly given as the input. Therefore, it is indispensable to perform pre-processing on the input image, so that the image gets transformed to be relevant for the further processing. The pre-processing is carried out for loading the input MRI images to the MATLAB environment and also it eradicates any type of noise present in the input images. Here, the input image is passed through a Gaussian filter to diminish the noise in order to obtain a better image. Also, passing the image via the Gaussian filter improves the image quality.

Gaussian Filter: A Gaussian filter [34] is a filter whose impulse response is a Gaussian function. Gaussian filters are created to shunt overshoot of step function input while reducing the rise and fall time. Gaussian filter has the minimum possible group delay. In mathematical terms, a Gaussian filter changes the input signal by convolution with a Gaussian function and this change is also called as Weierstrass transform. The Gaussian function is non-zero for $x \in [-\infty, \infty]$ and would notionally necessitate an infinite window length. The filter function is said to be the kernel of an integral transform. The Gaussian kernel is continuous, not discrete. The cut-off frequency of the filter is taken from the ratio between the sample rate F_s and the standard deviation σ .

$$F_c = \frac{F_s}{\sigma}$$

The 1D Gaussian filter is given as,

$$g(x) = \frac{1}{\sqrt{2\Pi}\sigma} e^{\frac{-x^2}{2\sigma^2}}$$

The impulse response of the 1D Gaussian Filter is given as,

$$g(x) = \frac{1}{\sqrt{2\Pi}\sigma} e^{\frac{-\sigma^2 u^2}{2}}$$

Here, in the pre-processing stage, the input image is passed through a Gaussian filter, which results in the reduction of noise in the input image as well as obtains a better quality image for further processing.

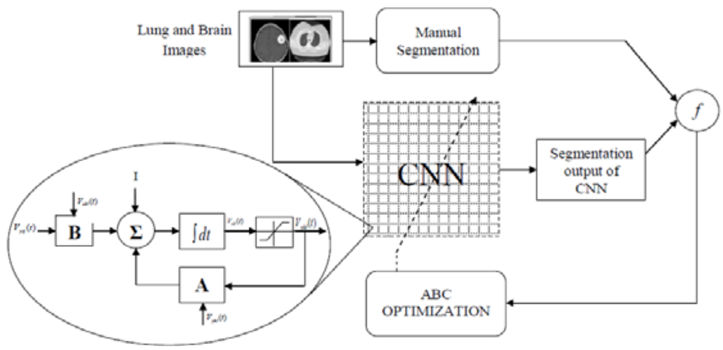
5.2. CNN Image Segmentation

The aim of the proposed approach is to effectively determine the segmentation template design of the CNN with an optimization mechanism set up by using suitable quality metric and training images.

5.2.1. Designing the CNN Template Using ABC Algorithm

In this section, the working mechanism of the ABC is presented and explained as a new approach to design templates in this section.

Figure 4: Template design mechanism of the ABC based CNN segmentation



The ABC design mechanism of the CNN template is shown in Figure 4. In this mechanism, the output image of the CNN converges to the preferred image by adjusting the template of the CNN by means of the ABC algorithm. The ABC algorithm produces template set and sends this set to the CNN. CNN runs by using this set and training image (manual segmented image), and it generates an output image. The fitness value of the objective function is calculated by comparing the output image of the CNN and the manual segmented image. The ABC algorithm evaluates with this fitness value in order to obtain better results.

ABC Optimization

- ***Assign the control parameter values***

  Control parameters of ABC algorithm are set as;

  Colony size, CS=5

- ***Initialize the population of solutions***

  The colony size of employed bees (n_e) is equal to the colony size of onlooker bees (n_o) in the population.

Fitness function $= \dfrac{A \cap B}{A \cup B}$

Where, $A \rightarrow Manually\ \ segmented\ \ image$

$B \rightarrow CNN\ \ segmented\ \ image$

Running of ABC optimization can be explained as follows: First, we initialize the positions of five $D \times SN$ matrix of employed bees, randomly using uniform distribution in the range (0, 1) and each row of the matrix represents a template set, a possible solution to the problem, in the ABC optimization. D is the dimension of the problem and SN is the size of the colony. Consider five $D \times SN$ initial templates matrix of employed bees are given below,

$$\text{Initial Templates} = \begin{bmatrix} a_{1,1} & a_{1,2} & a_{1,3} \\ a_{1,4} & a_{1,5} & a_{1,6} \\ a_{1,7} & a_{1,8} & a_{1,9} \end{bmatrix} \begin{bmatrix} a_{2,1} & a_{2,2} & a_{2,3} \\ a_{2,4} & a_{2,5} & a_{2,6} \\ a_{2,7} & a_{2,8} & a_{2,9} \end{bmatrix} \begin{bmatrix} a_{3,1} & a_{3,2} & a_{3,3} \\ a_{3,4} & a_{3,5} & a_{3,6} \\ a_{3,7} & a_{3,8} & a_{3,9} \end{bmatrix}$$
$$\begin{bmatrix} a_{4,1} & a_{4,2} & a_{4,3} \\ a_{4,4} & a_{4,5} & a_{4,6} \\ a_{4,7} & a_{4,8} & a_{4,9} \end{bmatrix} \begin{bmatrix} a_{5,1} & a_{5,2} & a_{5,3} \\ a_{5,4} & a_{5,5} & a_{5,6} \\ a_{5,7} & a_{5,8} & a_{5,9} \end{bmatrix}$$

ABC algorithm process basically consists of many cycles. Each cycle is mainly composed of three phases; the employed bees phase, the onlooker bees phase and the scout bees phase. For the first phase, the employed bees are sent to the sources and the nectar amounts of the sources visited are calculated. For the second phase, onlooker bees are sent to their sources and their nectar amounts are determined. For the third phase, it is ensured that the scout bee is located on a randomly selected new source.

Firstly, the position of a food source (*xi*) represents a feasible solution of problem and the amount of nectar of the food source indicates the fitness value of the associated solution in the ABC algorithm. A set of food sources positions $\{x_1,...,x_{ne}\}$ is produced randomly:

$$x_i = x_j^{\min} + rand(0,1)(x_j^{\max} - x_j^{\min})$$

Where $i = 1, ..., SN$ and $j = 1,..., D$ is the number of food sources and D is number of optimization parameters. Also, it must be noted that $SN = n_e = n_o$.All counters associated with solutions are reset to 0 in this phase. After initialization, the fitness value of each solution is calculated and is obtained. The fitness value of the objective function is calculated by comparing the output image of the CNN and the manual segmented image. The ABC algorithm evaluates with this fitness value in order to obtain better results.

Cycle =1

- ***Employed Bees phase***

The colony of employed bees can be expressed by n_c dimension vector $\bar{x}(n) = (x_1(n),..., x_{n_e}(n))$, where n is cycle value of ABC algorithm. To evolve quality of solutions, employed bees change their position from the current position to neighboring source positions by using the following equation:

$$v_{ij} = x_{ij} + \varphi(x_{ij} - x_{kj}) \tag{5}$$

Where, $j \in \{1,..., D\}, k \in \{1,..., SN\}, k \neq j,$ j and k are randomly chosen index. φ_{ij} is a real number produced randomly in the range [0,1]. After producing v_i, to select better solution for next generation, greedy selection operator is applied. Probability distribution of this operator can be given as follows:

$$P\{x_i, v_i\} = \begin{Bmatrix} 1, f(v_i) \geq f(x_i) \\ 0, f(v_i) < f(x_i) \end{Bmatrix}$$

where $f(v_i)$ and $f(x_i)$ are nectar amounts of food sources at v_i and x_i, respectively. If v_i is better solution than x_i, the employed bee memorizes position of v_i, otherwise position of x_i is retained. In the end of this process, if a better solution cannot be obtained, the trials counter associated with the solution is incremented by 1, and otherwise it is reset to 0.Finally, we obtain three $D \times SN$ template from the employed bee phase can be given as follows.

Employed bee templates = $\begin{bmatrix} e_{1,1} & e_{1,2} & e_{1,3} \\ e_{1,4} & e_{1,5} & e_{1,6} \\ e_{1,7} & e_{1,8} & e_{1,9} \end{bmatrix} \begin{bmatrix} e_{2,1} & e_{2,2} & e_{2,3} \\ e_{2,4} & e_{2,5} & e_{2,6} \\ e_{2,7} & e_{2,8} & e_{2,9} \end{bmatrix} \begin{bmatrix} e_{3,1} & e_{3,2} & e_{3,3} \\ e_{3,4} & e_{3,5} & e_{3,6} \\ e_{3,7} & e_{3,8} & e_{3,9} \end{bmatrix}$

- ***The Onlooker Bees Phase***

After completion of the employed bees phase, the phase of onlooker bees is started by selecting an employed bee from the colony. The onlooker bees phase is similar to the previous phase. The probability of the selection process depends on the fitness values of the solutions and many selection schemas such as roulette wheel and stochastic universal sampling can be used. Fitness function of ABC can be described as follows:

$$\text{Fitness function} = \frac{A \cap B}{A \cup B} \tag{6}$$

This function means that, if the fitness value of a solution increases, the visiting number of onlooker bees to that source also increases. To decide whether a modification is to be made on an onlooker bee position, a random real number within the range [0, 1] is generated for each source. If the generated number is less than the fitness value in Equation (6), then the onlooker bee changes position by using Equation (5) to find new solutions. Greedy selection is applied to the modified source and then if the new position is better than the old position, the memory of the onlooker bee is updated, otherwise the old position is kept. According to the result of this process, the counter associated with onlooker bees is incremented by 1 or reset to 0 similar to the operation in the employed bee phase. To end a cycle, if a counter value of employed bees and onlooker bees reaches its "limit" value, the source of this counter is abandoned. A new food source is discovered by the scout bee and it replaces the abandoned source. This operation can be defined as follows:

$$x_i(n+1) = \begin{cases} x_{\min} + ramd(0,1)(x_{\max} - x_{\min}), & counter \geq \lim it \\ x_i(n), & counter < \lim it \end{cases}$$

Finally, we obtain three $D \times SN$ template from the onlooker bee phase can be given as follows.

$$\text{Onlooker bee templates} = \begin{bmatrix} o_{1,1} & o_{1,2} & o_{1,3} \\ o_{1,4} & o_{1,5} & o_{1,6} \\ o_{1,7} & o_{1,8} & o_{1,9} \end{bmatrix} \begin{bmatrix} o_{2,1} & o_{2,2} & o_{2,3} \\ o_{3,4} & o_{1,5} & o_{1,6} \\ o_{1,7} & o_{1,8} & o_{1,9} \end{bmatrix} \begin{bmatrix} o_{1,1} & o_{1,2} & o_{1,3} \\ o_{1,4} & o_{1,5} & o_{1,6} \\ o_{1,7} & o_{1,8} & o_{1,9} \end{bmatrix}$$

- ***Scout Bees Phase***

In the scout bees phase, which template is removed from population is arranged by controlling the testing counters by comparing these counters with the parameter named "*limit*". If the testing counter value of a template set reaches the *limit* value, this set is removed from the population and a new template set produced randomly is replaced instead of the removed templates. Finally, we obtain one new $D \times SN$ template from the scout bee phase can be given as follows.

$$\text{Scout bee template} = \begin{bmatrix} s_{1,1} & s_{1,2} & s_{1,3} \\ s_{1,4} & s_{1,5} & s_{1,6} \\ s_{1,7} & s_{1,8} & s_{1,9} \end{bmatrix}$$

Subsequently, we determine quality matrix from seven templates (employed bee phase=3, onlooker bee phase =3 and scout bee phase=1), and we choose best one template from these seven templates. Consequently, this best template and another two templates (randomly selected) are given to the employed bee phase. The above process is repeated again for every cycle.

Pseudocode of Artificial Bee Colony Algorithm

Figure 5: Pseudocode of ABC algorithm

- Initialize the population of templates $[M \times N]_i .....[M \times N]_n$
- Evaluate the population
- cycle=1
- repeat
- Produce new solutions (template positions) $v_{i,j}$ in the neighbourhood of $x_{i,j}$ for the employed bees using the formula $v_{i,j} = x_{i,j} + \phi_{ij}(x_{i,j} - x_{k,j})$ (k is a solution in the neighbourhood of i, ϕ is a random number in the range [k,l])and evaluate them
- Apply the greedy selection process between $x_{i,j}$ and $v_{i,j}$.
- Calculate the probability values $P\{x_i\}$ for the solutions x_i by means of their fitness values using the equation (1)

$$P\{x_i\} = \frac{f(x_i)}{\sum_{i=1}^{SN} f(x_i)} \quad (1)$$

- In order to calculate the fitness values of solutions we employed the following equation (eq. 2):

$$\text{Fitness function} = \frac{A \cap B}{A \cup B} \quad (2)$$

- Produce the new solutions (new positions) v_i for the onlookers from the solutions x_i, selected depending on $P\{x_i\}$, and evaluate them
- Apply the greedy selection process for the onlookers between x_i and v_i
- Determine the abandoned solution (source), if exists, and replace it with a new randomly produced solution x_i for the scout using the equation (3)

$$x_i = x_j^{\min} + rand(0,1)(x_j^{\max} - x_j^{\min}) \quad (3)$$

- Memorize the best template (solution) achieved so far
- cycle=cycle+1
- until cycle= Maximum Cycle Number (MCN)

5.3.2. CNN Segmentation using the Optimal Template

After template design process is completed, CNN image segmentation will be subsequently conducted. In order to segment the lung and brain region," n" neighborhoods were used for the CNN templates A and B, which represent the feedback and feed-forward connections, respectively. Another CNN template I was used as an offset matrix. According to eqn (1), the output of CNNs lies on the feedback template A, control template B and I. They are set as below in our experiment:

$$A=\begin{bmatrix} T_{1,1} & T_{1,2} & T_{1,3} \\ T_{1,4} & T_{1,5} & T_{1,6} \\ T_{1,7} & T_{1,8} & T_{1,9} \end{bmatrix},\ B=\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix},\ I=0.6$$

Then Eq. (1) is rewritten as follows:

$$dv_{xij}(t)=\sum_{C(k,l)\in N(i,j)} A(i,\, j;k,l)v_{ykl}(t)+0.6$$

Finally, the overall segmentation process is explained as follows,

$$dx=-x+con(x,template)+con(x,zero\,matrix\,template)+I$$

Where,

$dx \rightarrow$ segmented image

$x \rightarrow$ is the original image,

$$con(x,template)=\sum_{k_1=-\infty}^{\infty}\sum_{k=-\infty}^{\infty} a(k_1,k_2)b(x-k_1,template-k_2)$$

$$con(x,zeromateix\,template)=\sum_{k_1=-\infty}^{\infty}\sum_{k=-\infty}^{\infty} a(k_1,k_2)b(x-k_1,zeromatrix\,template-k_2)$$

and $I \rightarrow$ is bias (offset matrix)

6. The Simulation Results and Discussion

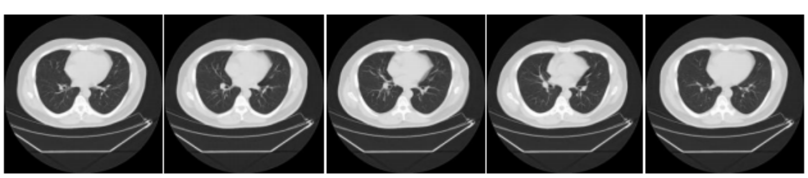
In this section the Segmentation technique using lung and brain MRI images and the experimental results are described. The proposed approach is implemented in MATLAB (matlab version 7.10). Here, the proposed lung and brain MRI image segmentation technique is tested by using medical images taken from the publicly available sources.

6.1. MRI Image Dataset Description

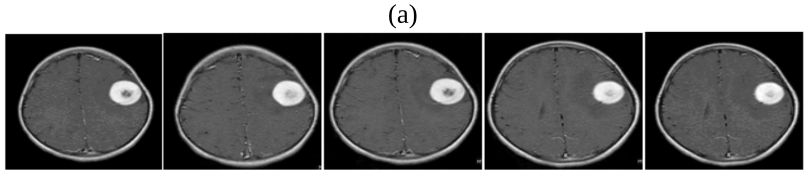
The MRI image dataset that we have utilized in our proposed lung and brain image segmentation technique is taken from the publicly available sources. This image dataset contains 20 brain MRI images in which 10 lung images and the other 10 brain images. The Brain and lung image dataset are used to analyze the performance of the proposed technique. In this, the 10 images are utilized for the training purpose and the remaining 10 images are utilized for testing purpose.

The figure 6 shows some of the sample lung and brain MRI images

Figure 6: MRI sample image dataset, (a) Lung MRI images (b) Brain MRI images



(a)



(b)

6.2. Experimental Results

Image segmentation denotes a process of partitioning an image into distinct regions. Manual segmentation of brain and lung from MR images is a challenging and time consuming task. An efficient CNN based method is proposed to segment brain and lung from MR images.

Brain Image Section

The obtained experimental results such as, initial population templates, fitness and corresponding segmented lung and brain images are shown in below figures. Figure 7 shows 5 initial templates and its corresponding best fitness and segmented image and Figure 8. shows 50 and 100 iteration template and its corresponding best fitness and segmented image.

Figure 7: Initial templates and its corresponding best fitness and segmented image

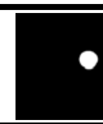
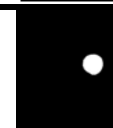
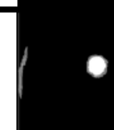
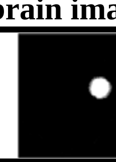
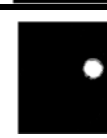
Initial population-templates	Fitness	Segmented brain image
$\begin{bmatrix} 0.306349 & 0.508509 & 0.510772 \\ 0.817628 & 0.794831 & 0.644318 \\ 0.378609 & 0.81158 & 0.532826 \end{bmatrix}$	0.88489	
$\begin{bmatrix} 0.350727 & 0.939002 & 0.875943 \\ 0.550156 & 0.622475 & 0.587045 \\ 0.207742 & 0.301246 & 0.470923 \end{bmatrix}$	0.771154	
$\begin{bmatrix} 0.230488 & 0.844309 & 0.194764 \\ 0.225922 & 0.170708 & 0.227664 \\ 0.435699 & 0.311102 & 0.92338 \end{bmatrix}$	0.828846	
$\begin{bmatrix} 0.430207 & 0.184816 & 0.904881 \\ 0.979748 & 0.43887 & 0.111119 \\ 0.258065 & 0.40872 & 0.594896 \end{bmatrix}$	0.853571	
$\begin{bmatrix} 0.262212 & 0.602843 & 0.711216 \\ 0.221747 & 0.117418 & 0.296676 \\ 0.318778 & 0.424167 & 0.507858 \end{bmatrix}$	0.827473	

Figure 8: After 50 and 100 iteration template and its corresponding best fitness and segmented image

Iteration	Template	Best Fitness	Segmented brain image
After 50 Iteration	$\begin{bmatrix} 0.309839 & 0.441236 & 0.453132 \\ 0.589509 & 0.658036 & 0.536471 \\ 0.486967 & 0.360163 & 0.395219 \end{bmatrix}$	0.917307	
After 100 Iteration	$\begin{bmatrix} 0.487710 & 0.435105 & 0.477025 \\ 0.432391 & 0.722428 & 0.515227 \\ 0.540652 & 0.447265 & 0.433043 \end{bmatrix}$	0.918681	

Lung Image Section

Figure 9 shows 5 initial templates and its corresponding best fitness and segmented image and Figure 10. shows 50 and 100 iteration template and its corresponding best fitness and segmented image.

Figure 9: Initial templates and its corresponding best fitness and segmented image

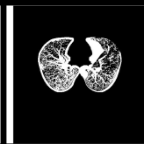
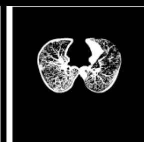
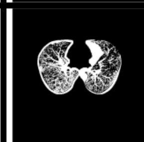
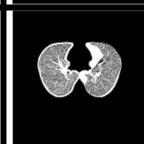
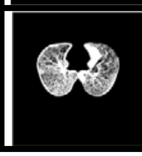
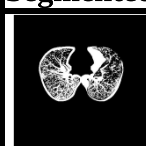
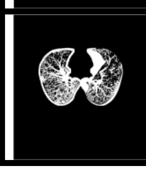
Initial population-templates	Fitness	Segmented lung image
$\begin{bmatrix} 0.164926 & 0.157413 \\ 0.0116 & 0.721248 \end{bmatrix}$	0.85057	
$\begin{bmatrix} 0.203168 & 0.271168 \\ 0.179885 & 0.635345 \end{bmatrix}$	0.738467	
$\begin{bmatrix} 0.204295 & 0.223705 \\ 0.08595 & 0.814716 \end{bmatrix}$	0.749261	
$\begin{bmatrix} 0.202001 & 0.202127 \\ 0.455025 & 0.504538 \end{bmatrix}$	0.724929	
$\begin{bmatrix} 0.228317 & 0.194636 \\ 0.459448 & 0.52145 \end{bmatrix}$	0.722758	

Figure 10: After 50 and 100 iteration template and its corresponding best fitness and segmented image

Iteration	Template	Best Fitness	Segmented lung image
After 50 Iteration	$\begin{bmatrix} 0.164926 & 0.157413 \\ 0.011600 & 0.721248 \end{bmatrix}$	0.85057	
After 100 Iteration	$\begin{bmatrix} 0.058005 & 0.084342 \\ 0.242027 & 0.713906 \end{bmatrix}$	0.855123	

6.3. Comparative Analysis

We have compared our proposed segmentation technique of CNN against the Fuzzy C-means and K-means clustering techniques. The classification techniques we have utilized for comparative analysis are Fuzzy C-means clustering and K-means clustering. The comparative analysis of the different classification methods against our approach is presented in this section. For comparative analysis we have taken three images (3 lung images and 3 brain images). For brain section, by analyzing the figure 11, our proposed approach achieves better accuracy (93.4%) in first image, (95.1%) in second image and (92.1%) in third image. For lung section, by analyzing the figure 12, our proposed approach achieves better accuracy (79.1%) in first image, (90.3%) in second image and (82.2%) in third image. Totally, our approach performs significantly better than fuzzy c-means clustering and K-means clustering. The accuracy values of three methods are plotted as a graph shown in Figure 11.

Figure 11: Comparative analysis graph of Brain images

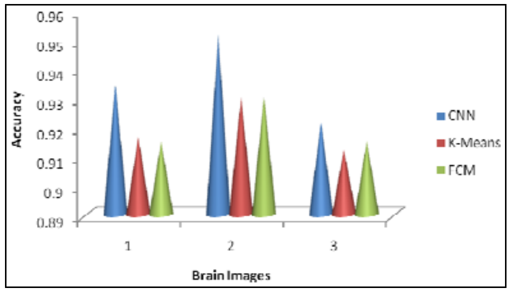
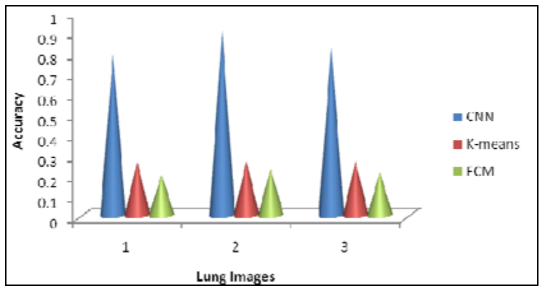


Figure 12: Comparative analysis graph of Lung images



7. Conclusion

Lung and Brain MRI Image segmentation is an important and challenging factor in the medical field. In this paper, we have presented an effective lung and brain images segmentation approach with MRI images. The efficiency is achieved with brain and lung MRI images, and the segmentation based on cellular neural network. The Comparative analysis is carried out Fuzzy C-means (FCM) and K-means classification. From the comparative analysis, the accuracy of proposed segmentation approach produces better results than that of existing Fuzzy C-means (FCM) and K-means classification.

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