Mammographic Images Interpretation Using Neural-Evolutionary Approach

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Abstract

In this paper, we propose a hybrid approach for mammographic images interpretation in order to detect the benign and malignant anomalies. Using a neural evolutionary approach based on the Radial Basis Function neural *network* (*RBF*) and the evolutionary strategy (ES).

After applying the growing region algorithm in segmentation stage, the RBF neural network detects the suspect regions. The inference system specifies the type of the anomaly. Some of experimental results on mammographic images show the success of the proposed approach.

Keywords: *Interpretation, RBF Neural Network, Evolutionary Strategy, Growing Regions***,** *Mammographic Images.*

1. Introduction

The interpretation of the medicals images is an important stage in any medical system; it consists to give a description of pathological anatomy present in these images. It plays an important part in the establishment of early diagnosis and many decisions and therapeutic follow-ups. Various radiological exploitation techniques which give a visual representation of human anatomy are existed among the mammography.

Several methods are proposed in the literature to realize this task; we quote the connectionist approaches (Neural Network: NN), optimization methods (evolutionary algorithm: EA) and the artificial intelligence methodologies which includes fuzzy logic and expert systems [1][2]. Although these metaphors carry out the task of interpretation with some success, they present also disadvantages. To avoid these disadvantages; the hybrid architectures are proposed.

The training of the NN is carried out on the variety basis of anomalies examples; however the no- interpretability of its layers decreases its capacities of generalization [3]; from where this fuzzy logic intervenes in order to solve this problem thanks to its capacities of modelling of unclear and uncertain knowledge [4].

Other hybridizations were realized, which gathers the advantages of the neural networks, fuzzy logic and the algorithms genetic, this parallel neuronal hybrid approach arrive to control RNs black box dimension by specialized neurons introduction [5] [6]. Thus, the final adjustment of the parameters of the fuzzy system is realized by the neuronal training means [7]. The Genetics algorithms (GA) are used as initialization of the training step which is doing by the gradient retro propagation algorithm in order to adjust the fuzzy system parameters [8].

In order to determinate the nature of the lesions in medical image; hybridization between fuzzy logic, neuronal networks and the expert system is achieved, where the fuzzy-neural approach detects the areas suspect which will be after validate by an expert system [2].

The training of the neural network weights is formulated as the error function minimization, such as the *average quadratic error* between the required output and that obtained by the network [9]. This error function is calculated by the training on image basis examples by adjusting the weights of connection repeatedly. Majority of the training algorithms are based on the gradient descent which is often on the local minimum of the error function.

The EA training is used to find, an optimal and global connection weight set [10]. This approach completely independent of any gradient information, extended on complex spaces, not differentiable, continuous and multimodal was widely applied [11].

In this paper, the idea is to hybrid three techniques: RBF Neural network, ES and the inference system for medical images interpretation.
Section 2 presents the proposed approach of which we briefly define the RBF network and ES, detail there after the suggested hybridization. In section 3, we will present the inference system followed by the section 4 devoted to the experimental results. Conclusion and some prospects are given in the last section.

2. Proposed approach

2.1 RBF network

The original idea of the RBF networks derives from the theory of approximation functions; these networks are a powerful Feed forward architecture. This type of networks was introduced for the first time by Hardy, and the corresponding theory was developed by Powell [12], then, these networks took the name of neural networks thanks to Broomhead and Lowe [13].
Without forget works of MOODY and DARKEN [11], and POOGGIO and GIROSI [14]. The reason of its name is that the network uses standard Gaussian functions which are with radial symmetry.

2.2 Evolutionary algorithm

The EA are stochastic methods of optimization for very complex problems and are used in various field of application.
Based on the evolution of the solutions population of treated problem, the evolution is guided by a fitness function which is maximized during the process. The evolutionary methods ensure a research in the complete field. Progressively through generations, this research space is refined towards potentially powerful subspaces.
The ES was developed by two young engineers working on numerical problems. The context was the parametric optimization, and the evolution diagrams are $(\mu, +\lambda)$ - ES. A big progress was made by the *adaptive* techniques of mutation parameters adjustment, and it is the best algorithms for the numerical problems.

Evolutionary Operator: The ESs are applied in a field contained in **Ω** research space which is included in $\mathbf{R^n}$.. The individuals in the ESs contain their position in space and also some information concerning their mutation. Every individual is represented in a space of dimension **n** with the form:

$$X = (x1, x2, ..., xn) \qquad (1)$$

The evolutionary strategy has three genetic operators: selection, crossover and mutation [1].

Mutation: In the ES the mutation is carried outwards (in the structure general case), by adding a random vector which follows a normal law with an average "0". This information is incorporated in each individual. The parameters of the mutation space *S* are composed by a standard deviation σ and the rotation angles α which represent the covariance values.
n_σ and n_α represent respectively the number of standard deviation and covariance used, so the individual is represented in a space Ω * S.
There are several types of ESs by exploiting these two variables n_σ and the $n_{\alpha.}$
We used the general case when:

$$n_\sigma = n \quad et \quad n_\alpha = \frac{n.(n-1)}{2} \qquad (2)$$

What differentiates **ESs** from **GAs** is the change of the parameters at the evolution.
For our case the mutation is defined as follows:

$$\begin{cases} \sigma_i' = \sigma_i . \exp(\tau' . N(0,1) + \tau . Ni(0,1)) . \\ \alpha_j' = \alpha_j + \beta . N_i(0,1). \\ x' = x + N(0, c'). \end{cases} \qquad (3)$$

The standard deviations are muted as well as the covariance values. In this case, the values of τ and τ' are identical and the value of B is equal to 0.0873 (corresponding to the 5° rotation). The matrix « c'» is the covariance matrix reverse and the elements can be calculated by using the parameters α_{ij} (vector α must be transformed into a matrix).

$$\mathbf{C_{ij}} = \begin{cases} \sigma_{I2} & \text{if } i=j \\ {}^1/_2 (\sigma^2_i - \sigma j^2) \tan(2\alpha_{ij}) & \text{else} \end{cases} \qquad (4)$$

The vector N (0, c') is created by the first vector Z_U for N (0,σ) (σ representS a Diagonal matrix (σ[i]= σ[i][i])) and the rotation matrix R is used:

$$Z_c = \prod_{i-1}^{n} \prod_{j=j+1}^{n} R(\alpha_{ij}).Z_U \qquad (5)$$

The rotation matrix R (α_{ij}) = [r_{ij}] for i,j=1…n, are the matrix of unit modified by:
$r_{ii} = \cos(\alpha_{ii})$ and $r_{ij} = r_{ji} = -\sin(\alpha_{ii})$, It is important to note that the modification of the values of covariance (in this case) keep a positive definite matrix.

Crossover: The cross over operates here seldom on the genotype containing the problem variables. However, it seems very useful for the mutation parameters evolution.

Selection: The selection is another component of ESs. In ESs, the size of the parents population is noted by μ and the created descendants number by λ. One of the important characteristics in ESs is the fact that the selection is deterministic. Two principal selection mechanism types are distinguished: represented by (μ,λ) and (μ+λ).
The (μ,λ) selection consist that the next population contain the μ better individuals of the children, and the (λ+μ) selection consists that the best individuals of the μ parents and the λ children are selected for the next generation.

2.3 Hybrid system

The choice of the neural network was made on the radial basic function network; the RBF has as characteristic its radial activated functions which give useful answers only in a restricted field of values: the receptive field.
The RBFs networks are much used considering their important advantages in front of the traditional NN [15].
The evolutionary methods ensure a research in the complete field. Progressively with the generations, this research space is refined towards potentially powerful subspaces.
However the ESs find a solution near the best without ever reaching it; the combination between a total research (ESs) and a local one (RBF) gives an interesting results. It suggests that ESs find a good configuration of the network weights.
So the use of ESs should make it possible to identify the space areas which give an optimal convergence to a solution.

Structure of the RBF neural network: The network structure suggested is illustrated in figure 1; it includes an input layer (E), a hidden and an output layer (S1, S2). The input layer contains 9 neurons; each neuron corresponds to an attribute characterizing an image area, such as the variance, surface, elongation, average gray level, compactness. These attributes are extracted from the image segmentation stage by the region growing approach.
Four other texture attributes are extracted by superposition of the segmented image on the initial one using cooccurrence matrix. These attributes are: homogeneity, contrast, entropy and directivity.

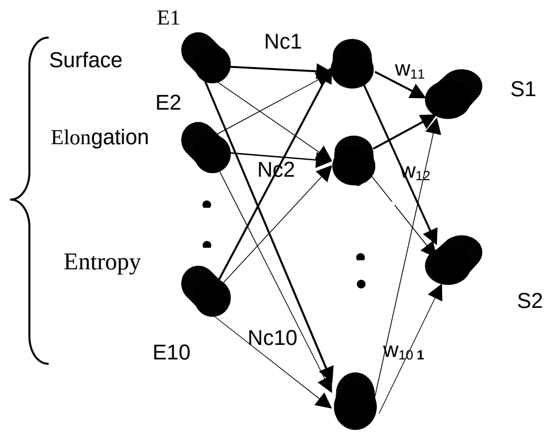

Fig .1 Structure of our RBF neural network
Wii: represents the weights of the hidden layer towards the output ones.
Nci: the weights of input layer toward the hidden ones.

The hidden layer contains 10 neurons, and finally the output layer contains two neurons, it represents a linear combination of the output value multiplied by the weights of their connection.
Among the principal parameters to regulate in a RBF, we quote two of them:

- The number of neuron in the hidden layer.
- The Gaussian centroid position which represents a major problem of the network, to solve this problem, we decide use the k-means algorithm.

Algorithm k-means: Is a fast and simple clustering algorithm, which has been applied to many applications inspired from an intuitive approach and based on the minimal distance principle.
The suppose observations are {x_i : i=1,…,L}. The goal of K-means algorithm is to partition the observations into K groups with means $'x_1, 'x_2, \ldots, 'x_k$ such that :

$$D(K) = \sum_{i-1}^{L} \min_{1 \le j \le K} (x - 'x)^2 \qquad (6)$$

is minimized. K is gradually increased and the algorithm stops when a criterion is met.
The initialization method is random partition; first it randomly assigns a cluster to each observation and then proceeds to the update step.

Network training: The training of the RBF network is hybrid; not supervises at the centroid determination step and supervises at the synaptic weights determination.

It is realized according to a training set which is formed by three images containing three anomalies.
Once the centroids are calculated and the neurons weights are adapted, weights and centroid are stored in a file.

Modeling: The realization of hybridization consists to define the various modifications necessary to the ESs to handle the NN. It is necessary in particular to determinate a coding in order to make the NN manipulated by the ES.
We will have to define also the various steps of the ESs and to build operators (crossover, mutation) adapted to the given structure coding types.
The ESs will see the NN as an individual of a population, each population is formed by chromosomes, and each chromosome represents a juxtaposition of the matrix weights elements.

Adaptation "fitness": The adaptation (fitness) describes the individual adequacy with its environment.
It is required to evaluate the solution domain.
Precisely, more the individual will have a low adaptation; it will be considered us a good solution for the optimization problem of the neural network. We want to quantify the capacity of the neural network to learn, the adaptation of an individual will be taken us the average quadratic error.

Representation of the individuals "coding": we are confronted in the individual coding step, with the problem of choice between a binary or real representation.
Traditionally GAs work on binary research spaces $[0, 1]^n$, where the ES work directly in R^n. And if our choice were a binary representation, it is necessary to decode weights before every training operation and before recognition stage.

Strategy of selection "elitist political": Various selection strategy existing, the elitist selection is the best one. In the passage from generation to another; part of individual survives to ensure their descents. This part, which represents the best elements, are selected by applying the rule: "it is the better which survive".
In practice at one time *t*, we select a strong part of the population, this part is consisted by the most powerful elements, with the meaning of the required criterion (the average quadratic error).
The remainder of the population will be replaced by other individuals at the time *t+1*.these new individuals are obtained by combination of the selected individuals. This operation of combination is containing several under operations: crossover, mutation which is the most current.
The speed convergence of the elitist selection compared to others strategies make it powerful, advantageous and explains our choice of this method.

Detection and specification: Detection consists to obtain a network answer by comparing the two output layer neurons values; if the first neuron activation (Neur1) is lower than the second neuron activation (Neur2); the area of the image presented as input is tumor, else this area is not tumor. After detection, if we have infection we can pass to the specification and we determinate the type of the tumor (malignant or benign).

3. The system of inference

To specify the type of the anomaly detected by the RBF network, we conceived a system of inferences to specify malignant or benign aspect; basing on the morphological and the textual characteristics used in the neurons network.

Base of facts: It represents the various region characteristics to be specified. These characteristics are those provided by the segmentation file and those extracted from texture.
A list of rule is given by an expert in mammographic image anomaly.
These rules are considering the Size of the anomaly, its contour, regularity or not, the homogeneity or heterogeneity which is defined by a factor of density and other tumor characteristics.

4. Experimental results

The proposed approach was tested on mammographic images (see figure 2). The segmented images present a set of homogeneous areas; each area is characterized by a whole of attributes. The tumor areas are presented to the system during the training stage, other are presented at the test step and generalization stage; after they are classified according to the malignant or benign aspect. The rate of recognition reached 100%.

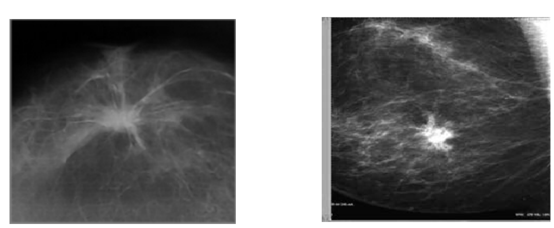

Fig .2 Initial mammographic images

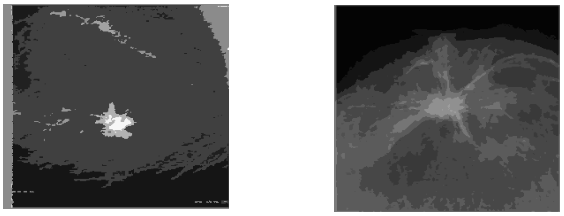

Fig .3 Segmented mammographic images

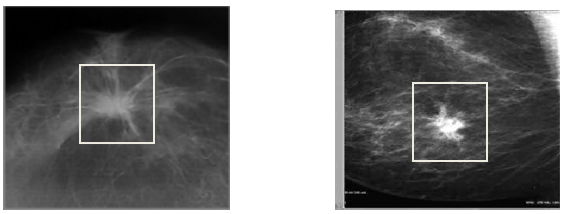

Fig .4 Images with detection (100%) and specification (100%) of one malignant tumor.

5. Conclusion and prospect

In this paper, we have proposed a hybrid approach for image interpretation. The proposed hybridizing strategy combines three different metaphors NNs, ES and Inference System in one hybrid architecture. NNs had to adopt themselves under unknown situations by the means their training property. The evolutionary algorithms are very powerful; the search for a solution require generally a longer training time, but can give better results than the traditional methods of training like the propagation of the gradient and the inference system is used to determinate the type of the anomaly.

The ES adds to the NN the possibility of doing global search., Its capacity to work directly on real number set without any coding reduce its execution time. This hybridizing could deal with several problems caused by the local search training algorithm based on the back propagation of error gradient.

The final proposed system could perform the task of interpreting the medical images. It is very important to notice that the choice of suitable set of regions attributes helps the task of discriminating the healthy tissues from the suspected one and to discriminate also, the malignancy nature of the tumors. The proposed approach has been tested on mammographic images.

The results of tumors detection and specification are very satisfactory; they were done with very high performances (100% to 100%).

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