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A Weighted Particle Swarm Optimization (WPSO) technique for accurate breast cancer detection

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Abstract:- *Microcalcifications are one of the key symptoms facilitating early detection of breast cancer. In this paper, textural features are extracted from the segmented mammogram image to classify the microcalcifications into benign, malignant or normal. The tumor part of the breast region is extracted by the reduction algorithm. Initially the reduced features are normalized between zero and one. The normalized feature values are given as input to a three-layer BPN to classify the microcalcifications into benign, malignant or normal. The network is trained to produce the output value for normal images. In this research proposed an image extraction method with reduced computation time was proposed. The computational time of proposed approach is obtained by use of Particle Swarm Optimization (PSO) algorithm. The membership function of this conventional algorithm is sensitive to the outline and does not integrate the spatial information in the image. To resolve existing disadvantages in classification algorithms like sensitivity, noise and in-homogeneties are overcome in proposed approach. Existing drawbacks are overcome in our algorithm takes also into consideration the spatial neighborhood information. To resolve existing limitation in this research proposed a weighted particle swarm optimization technique for cancer extraction. Based on the weighted function in optimization algorithm images are clustered and extracted. Simulation results of the proposed approach are comparatively examined with existing approaches naive bayes, Adaboost and SVM. Comparison of results demonstrated that proposed approach exhibits effective performance than existing classification algorithm.*

Keywords: *Optimization Technique, PSO, Breast cancer, Image Classification*

Introduction

Image analysis generally refers to preparing of images by computer with the objective of discovering what objects are exhibited in the image (Zhang., 1996). Image segmentation is the procedure that divides up an image into its constituent parts. It is a standout among the most critical tasks in automatic image analysis because the segmentation results will influence all the following tasks, for example, feature extraction & object classification (Zhang&Gerbrands., 1994). Because of its significance, much effort has been given to the segmentation procedure & method improvement in the last decades (Riseman&Arbib., 1977). This has effectively brought a quite a lot of (over and above thousands) different algorithms, & the number is still growing. A few survey papers have also been published, but they just partially cover the vast number of methods developed. As not any of the suggested segmentation algorithms are usually appropriate for all images & dissimilar algorithms are not similarly appropriate for a particular application, the performance assessment of segmentation algorithms is indispensable & in this manner a vital subject in the study of segmentation. More generally, performance assessment is vital for all computer vision algorithms from research to application, while image segmentation is a crucial & important step of low-level vision (Shi&Malik., 2000; Felzenszwalb&Huttenlocher., 2004).

Fuzzy c-means (FCM) clustering is an unsupervised method that has been effective functional to feature analysis, clustering, & classifier designs in fields, for example, astronomy, geology, medical imaging, target recognition, & image segmentation. An image can be categorized in different feature spaces, & the FCM algorithm categorizes the image by grouping similar data points in the feature space into clusters. This clustering is accomplished by iteratively minimizing a cost function that is reliant on the distance of the pixels to the cluster centers in the feature domain (Chuang et al., 2006; Bezdek et al., 1993; Iyer et al., 2000). An image's pixels are very much correlated, i.e. the pixels in the close neighborhood have almost same feature data. In this way, spatial relationship of neighboring pixels is a significant characteristic that can be of awesome guide in imaging segmentation. On the other hand, the conventional FCM algorithm does not completely use this spatial information (Chuang et al., 2006). In this way, a spatial FCM method has been utilized in this paper. Particle Swarm Optimization (PSO) is an evolutionary computation method. In Particle Swarm Optimization method, every individual of the population, which is also known as a particle, has an adaptable velocity, according to which it moves over the search space. Every particle keeps track of its coordinates in hyperspace, which are linked with the solution (fitness) it has accomplished so far. There are some disadvantages in image segmentation using PSO (Yang et al., 2002). Some pixels used to miss during image segmentation using conventional PSO. So, this paper has introduced a weightage based modified PSO to get access those missed pixels.

Related Works

Akhilesh Chander et al., 2011 have demonstrated another variation of Particle Swarm Optimization (PSO) for image segmentation utilizing optimum multi-level thresholding. This paper has additionally proposed an iterative technique that is practically more appropriate for getting initial values A Novel Method for Image Processing Using Particle Swarm Optimization Technique of candidate multilevel thresholds. This self-iterative method has been suggested to discover the suitable number of thresholds that ought to be utilized to segment an image. This iterative method was built on the renowned Otsu's technique, which demonstrates a linear progress of computational complexity. The thresholds that came from the iterative scheme have been taken as initial thresholds & the particles have been made arbitrarily nearby these thresholds, for the suggested PSO variation. Suggested PSO algorithm has made a new impact in adapting 'social' & 'momentum' factors of the velocity equation for particle move updates. Suggested segmentation technique has been applied for four benchmark images & the performances achieved outperform results got with recognized methods, like Gaussian smoothing method. Madhubanti Maitra & Amitava Chatterjee., 2008 have proposed an optimum multilevel thresholding algorithm for histogram-based image segmentation. This suggested algorithm presented an enhanced variant of PSO, a comparatively recently presented stochastic optimization strategy. This hybrid methodology has utilized both cooperative learning & comprehensive learning alongside with some extra modifications. Cooperative learning has been utilized to overcome the "curse of dimensionality" through decomposing a high-dimensional swarm into several one-dimensional swarms. Then the thorough learning has been utilized to discourage premature convergence in each one-dimensional swarm. Capability of this hybrid PSO (also known as HCOCLPSO) has been further improved through cloning of fitter particles, at the expense of worst particles, determined depend on their fitness values. HCOCLPSO algorithm has been applied for quite a few benchmark images & that exhibited significant improvement in performance compared to several other popular contemporary methods, applied for segmenting the same images. A.N.

Benaichouche et al., 2016 proposed an enhancement method for image segmentation utilizing the fuzzy c-means clustering algorithm. Also the paper has suggested further enhancing these outcomes by acting at three different levels. The first was connected to the fuzzy cmeans algorithm itself by enhancing the initialization step utilizing a meta-heuristic optimization. The second level was concerned with the incorporation of the spatial greylevel information about the image in clustering segmentation procedure & the utilization of Mahalanobis distance to decrease the impact of geometrical shape of dissimilar classes. Last level relates to refining the segmentation results by fixing errors of clustering through reallocating potentially misclassified pixels. The suggested technique, named enhanced spatial fuzzy c-means IFCMS, has been assessed on a number of test images, as well as both synthetic images & simulated breastmammogram images from McConnell breast Imaging Centre (breast Web) database. The proposed technique has been made a comparison with the most used FCM-based algorithms of literature. Outcomes has showed the efficiency of the ideas presented.

Bing Nan Li et al. 2014 have presented another fuzzy level set algorithm to simplify medical image segmentation. The proposed method has been capable of directly evolve from initial segmentation by spatial fuzzy clustering. Controlling parameters of the level set evolution have additionally been assessed from the outcomes of fuzzy clustering. Furthermore, fuzzy level set algorithm has boosted with locally regularized evolution. Such enhancements enable level set manipulation & point towards more robust segmentation. Performance evaluation of this suggested algorithm done on medical images from dissimilar modalities. The outcomes approve its efficiency for medical image segmentation. Khang Siang Tan & Nor Ashidi Mat Isa., 2012 have presented a new histogram thresholding fuzzy C-means hybrid (HTFCM) method that could find diverse application in pattern recognition & also in computer vision, especially in colour image segmentation. The suggested method applies the histogram thresholding method to achieve all possible uniform regions in the colour image. Then, Fuzzy C-means algorithm has been utilized to increase the compactness of clusters forming these uniform regions. Trial results have shown that low complexity of the suggested HTFCM methodology can achieve better cluster quality & segmentation outcomes than other segmentation methods that using an ant colony algorithm.

Maoguo Gong et al presented an enhanced fuzzy C-means algorithm for image segmentation by presenting a trade-off weighted fuzzy factor & a kernel metric. Trade-off weighted fuzzy factor relied on space distance of every neighbouring pixels & their gray-level dissimilarity at the same time. Through utilizing this factor, new algorithm can correctly evaluate the damping extent of neighbouring pixels. In order to further improve its robustness to noise & outliers, a kernel distance measure to its objective function has been introduced. The proposed algorithm adaptively decides the kernel parameter through utilizing a fast bandwidth selection rule built on distance variance of all data points in the collection. Moreover, trade-off weighted fuzzy factor & kernel distance measure are both parameter free. Trial results on synthetic & real images have demonstrated that the new algorithm is effective & efficient, & is comparatively independent of this kind of noise. Long Chen et al., 2016 have presented a generalized multiplekernel fuzzy C-means (MKFCM) technique as a framework for image-segmentation issues. In the system, beside from the point that the composite kernels has been used kernels has been suggested & the updating rules for the linear coefficients of the composite kernel has been implemented derived as well. The suggested MKFCM algorithm has given a novel flexible vehicle to fuse dissimilar pixel information on image-segmentation issues. That is, distinctive pixel data represented by dissimilar kernels is combined in the kernel space to make a novel kernel. It has been shown that two successful improved KFCM-based image-segmentation algorithms have special cases of MKFCM.

Problem Statement

Breast cancer would be considered as one of the most frequent and serious forms of women cancer that could cause death of an important statistic all over the world. In order to reduce the causes of mortality rate, an early detection of the cancer is considered so necessary and thisrequires an accurate and reliable diagnosis (Sellami et al., 2015). Several imaging modalities have been used to assess soft tissue tumors and the ultrasound modality would be among the most useful and powerful technique thank to its effectiveness for imaging organs and soft tissue structures in the human body (Taylor et al., 2002). Nowadays, an essential and important medical image processing scientific research domain has been emerged from medical imaging analysis which is referred to as Computer Aided Diagnosis (CAD) (Joo et al., 2004; Ikedo et al., 2007; Shen et al., 2007). CAD systems have been intensively developed for different breast imaging modalities offering and providing several essential aids and and more accuracy during clinical exploration even in the case limited performances apparatus. For breast ultrasound imaging we found that most of the works about CAD conception deal with 2D images (Chen et al., 2009) . Some recent works are performed in automated 3D images. In fact, the 3D ultrasound images can improve the performance over it by exploiting the correlation between the whole tumor in three dimensions (Shi et al., 2010; Sahinern et al., 2009). In order to overcome existing drawbacks in this paper proposed a optimization algorithm for image extraction.

Breast Cancer Detection Algorithm

Breast cancer is the most common cancer among women with over 220,000 women being diagnosed annually, and is the second most common cause of death from cancer among women with over 40,000 yearly deaths. Currently the most common breast cancer screening technology is Conventional Mammography (CM) which produces 2D images. Digital Breast Tomosynthesis (DBT) offers a significant advantage over CM because it generates 3D volumetric slice images (Rappaport et al., 2014). Both of these methods use X-ray technology and are therefore subject to the relatively low radiological contrast (~1%) between cancerous lesions and healthy high water content tissue. A Hybrid DBT Microwave Nearfield-Radar-Imaging (NRI) method has been proposed (Obermeier et al., 2014; Lorenzo., 2013) which takes advantage of the relatively high dielectric contrast (~10%) between cancerous lesions and other high water content breast tissue in the microwave band. In this method, the DBT image is used as a prior 3D background geometry for a NRI model which accurately predicts electromagnetic wave propagation in healthy inhomogeneous tissue. The simulated healthy case can then be subtracted from the measured case to highlight any anomalies generated by the cancerous lesion. The forward model currently used to establish a numerical Green's function for the NRI imaging algorithm is 3D Finite Difference Frequency Domain (FDFD) which is able to accurately predict the propagation of electromagnetic waves in inhomogeneous media (Dong et al., 2007). However, when dealing with high resolution medical images, the computational resources required for FDFD are prohibitively high for clinical applications. The need for a faster imaging algorithm has led to a the development of a 3D Fan-Beam model which sacrifices an acceptable level of accuracy, for a computation routine that is several orders of magnitude faster than 3D FDFD.

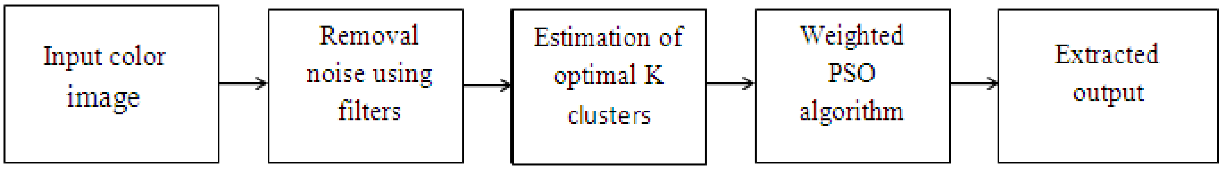
Optimization Algorithm in Image Processing

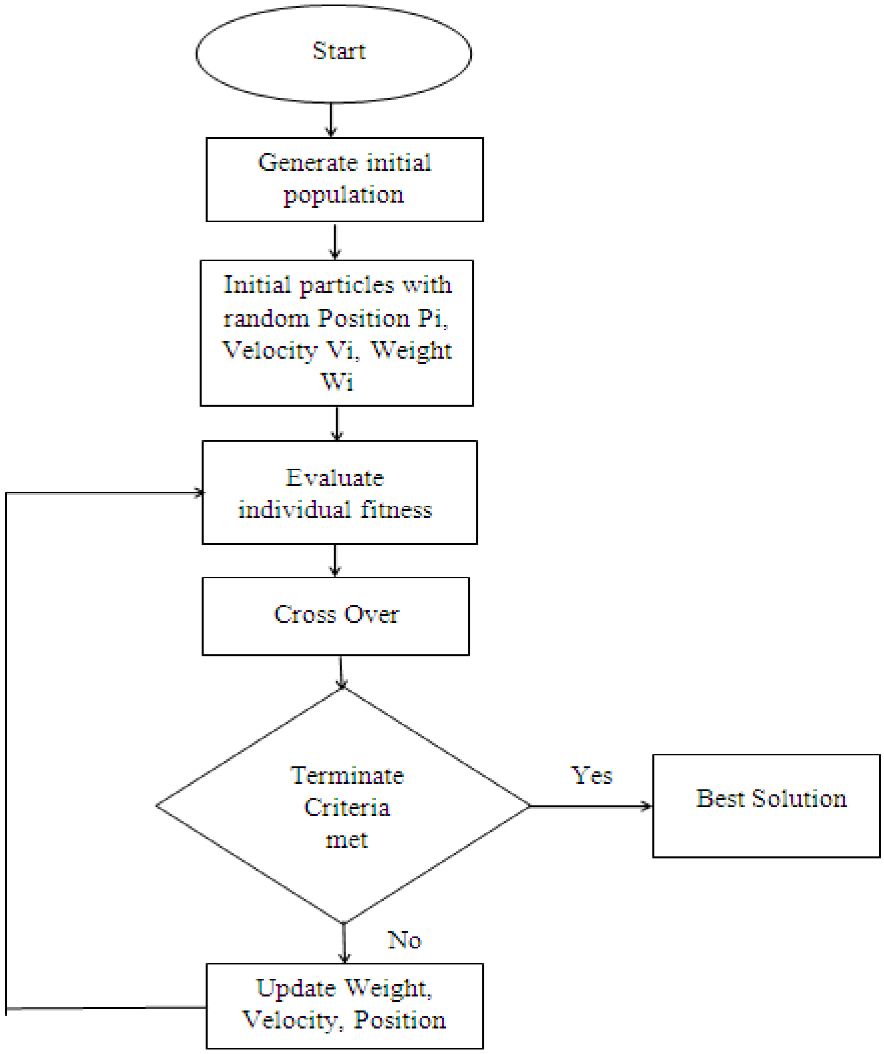
A metaheuristic therefore a general algorithmic framework, which can be applied to different optimization problems with relatively few modifications to make them, adapted to a specific problem. The use of metaheuristics has significantly increased the ability of finding very high-quality solutions to hard, practically relevant combinatorial optimization problems in a reasonable time. This is particularly true for large and poorly understood problems. Several meta-heuristics, such as Genetic Algorithms, Tabu Search and Simulated Annealing , have been proposed to deal with the computationally intractable problems. Particle Swarm Optimization (PSO) is a new meta-heuristic developed for composing approximate solutions.

Over the years, numerous techniques have been developed to solve such optimization. This study investigates the most effective optimization method, known as Particle Swarm Optimization (PSO) is introduced in the field of Medical Image Processing. The suspicious region is segmented using two algorithms GA and PSO. New CAD System is developed for verification and comparison of breast tumor detection algorithm. PSO and GA automatically determine the optimal threshold value of given image to select the initial cluster seed point then the clustering algorithm Fuzzy C Means calculates the adaptive threshold for the breast tumor segmentation. The results are compared with the existing approaches (Sivasangareswari& Kumar., 2014). Computational result indicates that the Particle Swarm Optimization algorithm improves the performances of the segmentation and can find the optimum solution faster than the other two methods. The similarity between segmented results using various segmented algorithm with the Radiologist tumor identification report as per the hospital database is used to classify the images. The GA with Fuzzy and PSO with Fuzzy algorithms are used to identify tumor position and pixel similarities are measured with Radiologist report (Chen et al., 2011). The true positive detection rate and the number of false positive detection rate at various thresholds of the images are used to measure the algorithm's performance. These rates are represented using Free-Response Receiver Operating Characteristic (FROC) graph.

Proposed Method

The modular structure of proposed methodology has been shown in figure.





Implementation of Proposed Methodology

The concept of PSO was first suggested by Kennedy and Eberhart in 1995. Particle swarm optimization (PSO) is inspired by the social behavior observed in flocks of birds and schools of fish. In nature, there is a leader who leads the bird or fish group to move. Most members of the group follow the leader. In PSO, a potential solution to the considered problem is represented by a particle, similar to the individuals in the bird and fish group. Each particle travels in the solution space and attempts to move toward a better solution by changing its direction and speed based on its own past experience and the information from the current best particle of the swarm.

The procedure of WPSO is described as follows:

Particle initialization:

An initial swarm of particles is generated in search space. Usually, the population size is decided by the dimension of problems.

Weight, Velocity and position update:

It is the velocity of the moving particles represented by a d- dimensional vector. At time t, the ith particle velocity Vi(t) can be described as Vi(t) = [Vi1 (t), Vi2(t)…….. Vid(t)], where V_{id} is the velocity of ith particle with respect to the dth dimension. The velocity update step is specified separately for each dimension d€ 1…n, so that V_{id} denotes the dth dimension of the velocity vector associated with the ith particle.

$$V_{id}^{(t+1)} = w\, V_{id}^{t} + c_1\, rand_1\, (p_{best\ id}^{\ t} - X_{id}^{t}) + c_2\, rand_2\, (g_{bestid}^{t} - X_{id}^{t})$$

Where V_{id}^t and X_{id}^t are the velocity and position of particle i, in d dimensional space respectively. $p_{best\ id}^{\ t}$ best position of individual i in d dimensional space until generation t; g_{bestid}^t is the best position of the group in d dimension until generation t; w is the inertia weight factor controlling the dynamics of flying; c_1 cognitive parameter and c_2 social parameter; rand1 and rand2 are random variables in the range[0,1].

From the definition of the velocity in the equation it is clear that c_2 regulates the maximum step service in the direction of the global best particle, and c_1 regularizes the step size in the direction of the personal best position of the particle. The value of V_{id} is clamped to the range [-Vimax,Vimax] to reduce the likelihood that the particle might leave the search space. The position of each particle is updated using the new velocity vector for that particle, so that

$$X_{id}^{(t+1)} = X_{id}^{t} + V_{id}^{(t+1)}$$

The weight controls the exploration and exploitation of the search space because it dynamically adjusts velocity. The weight is employed to control the effect of the previous velocities on the current velocity. This makes compromise between a global and (wide ranging) and local (nearby) exploration abilities of the swarm. A large weight facilitates global exploration (searching new areas) while a small one tend to facilitate local exploration. A properly chosen weight can provide balance between the global and local exploration of the swarm, which leads to a better solution. It is better to initially set the weight to a large value in order to make better global exploration of the search space and gradually decrease it to get more refined solution. A linearly decreasing weight changes the search from global to local linearly. Many problems require the search algorithm to have nonlinear search ability. By deriving some statistical features from the obtained result, in any iteration will help to understand the PSO search and calculate the proper weight for next iteration. Here weight w will decrease when the number of generation increases. It decreases linearly during the optimization run according to

$$W = w_{max} - ((w_{max}-w_{min})/iter_{max})*iter$$

Where w_{max} is the maximum value of inertia weight and w_{min} is the minimum value, iter is the current iteration and $iter_{max}$ is the maximum number of iterations.

The best position associated with the particle i is the best position that the particle has visited (a previous value of Xi), yielding the highest fitness value for that particle. For a minimization task, a position yielding the smaller function value is regarded as having fitness. The symbol f(X) will be used to denote the objective function that is being minimized. The update equation is

$$P_{bestid}^{(t+1)} = \{x_{id}\, t \quad if\ \ f(x_{id}(t+1) \geq p_{bestid}\, t$$

Or

$$P_{bestid}^{(t+1)} = \{x_{id}(t+1) \quad if\ \ f(x_{id}(t+1) < p_{bestid}\, t$$

The g_{best} offers a faster rate of convergence at the expense of robustness. This gbest maintains only a single best solution called the global best particle, across the entire particle in the swarm. This particle acts like an attractor, pulling all the particles towards it. Eventually all particles will converge to this position, so if it is not updated regularly, the swarm may converge prematurely

Evaluation and update of best locations: The fitness value of each particle is calculated by the objective function. The values of Pid and Pgd are then evaluated and replaced if better particle best position or global best position is obtained.

Pseudo code for Proposed Approach

Initialize the function
  Create objective function
    Objective function is based on intensity of pixel
  Set iteration count = 1000
  Calculate pixel intensity of images
  Optimize the cancer image pixel intensity
  Calculate optimal value for input image pixel
  Extract tumor part with maximum pixel intensity
  Calculate accuracy

Simulation Results

The optimization network is tested by using a Ten fold validation method. In the proposed weighted PSO optimization technique evaluate the objective function based on the weights of the evaluated image datasets. In this section presented about the simulation results obtained for proposed weighted PSO and comparatively examined with other classification techniques.

The neural network classifies cancer part with respect to the inter pixel distance d and the number of hidden neurons. The optimal performances are achieved when d is one and the number of hidden neurons is ten for the WPSO. The performance decreases as the inter pixel distance d increases.

The data set of 320 samples of mammogram images are divided into 10 equal size folders, such that a single folder is used for testing the model that has been developed from the remaining nine sets. This method is ideal for small data sets that cannot be split into training and test subsets. The advantage of cross-validation is that it increases the number of data patterns available for training, while using every data pattern available for testing. The evaluation statistics then assessed as an average of 10 experiments. The images that are used in this work were taken from the Mammography Image Analysis Society (MIAS).

Findings of Research

In this section, the results of WPSO algorithm are presented and compared to the most known algorithms: FCM, FCM S1, RFCM, and KPCM. The different algorithms are implemented in Matlab version 2010 and run on a 3.10 GHz Pentium CoreTM i3-2100 CPU, under Microsoft Windows 7 operating system. For synthetic data, we used a set of two images corrupted by different levels and types of noise. Simulated mammogram breast images and real medical images are also used.We use a first synthetic image (128 × 128) with two gray levels at different levels (1%, 5% and 9%), located at the image center. For the first synthetic image, although the FCM algorithm can segment the image into two regions, noise remains. For noisy images, FCM S1, RFCM and KPCM algorithms outperform the conventional FCM. From the figures, we see clearly that the proposed WPSO gives the best results. For the second synthetic image, corrupted with salt & pepper (5% noise level), Gaussian (variance = 0.02) or uniform (variance = 0.01) noises, However, artifacts are still present in the case of uniform noise, but it still outperforms the other algorithms. To evaluate the clustering performances, we use two functions: partition entropy Vpe and partition coefficient Vpc [29]They are defined as follows

$$V_{pe} = \frac{1}{n}\sum_{i=1}^{c}\sum_{j=1}^{n}\mu_{ij}^{2}$$

$$V_{pc} = \frac{1}{n}\sum_{i=1}^{c}\sum_{j=1}^{n}\mu_{ij}\log\left(\mu_{ij}\right)$$

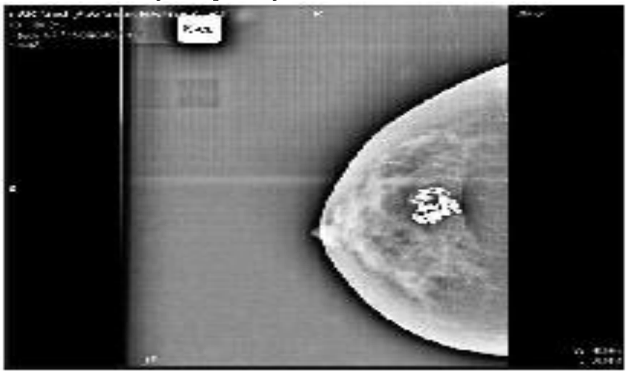
These validity functions are used to compare the results of the different algorithms. A best clustering is achieved if the value Vpe is minimal or Vpc is maximal. Another validity function based on the features structure is used [29]:

$$V_{xb} = \frac{\sum_{i=1}^{c} n \sum_{j=1} \mu_{ij}^{2} \left\| x_j - V_i \right\|}{n\left(\min_{i \neq k}\left\{\left\| x_k - V_i \right\|^2\right\}\right)}$$

Our proposed WPSO outperforms rather than other algorithm even in presence of noise. The quantitative comparisons of the algorithms confirm the visual evaluation.

Simulated breast images

Healthy breast matter can be classified into three tissues are classified based on the accumulated white matter (WM), cerebro-spinal fluid (CSF) and gray matter (GM). Because of the non availability of segmentation ground truth for real mammogram images, we use simulated mammogram breast images from the breast Web Simulated breast Database. This database is used since the scientific community frequently uses it as a benchmark.



The parameters ofthe proposed weighted PSO algorithm,namely the values of m, the number of clusters c, and finally the vectors form representing the image pixels are defined. The above figure presents the segmentation results using pre-processed image with breast cancer without noise. Comparison of the traditional approaches with proposed approach stated that traditional approaches are not suitable to classify the images but proposed weighted PSO gives good results despite the fact that the images were affected by noise. Because of its ability to cope with noise, weighted PSO gives better results than other optimization approaches. Obviously, with an increase of the noise level, the segmentation results degrade rapidly.

Tissues extraction

In this experiment we proceed to the extraction of the breast images (WM, GM and CSF). For a quantitative evaluation of the results, a pixel based evaluation approach is used. A comparison is made between pixels of the resulting image (Rt) and the ground truth (Rg). The following measures are used; Dice index, Jaccard index, True Positive Fraction (TPF), False Negative Fraction (FNF), False Positive Fraction (FPF) and True Negative Fraction (TNF) [31–33].

$$Dice = \frac{2\left|R_t \cap R_g\right|}{\left|R_t\right| + \left|R_g\right|}$$

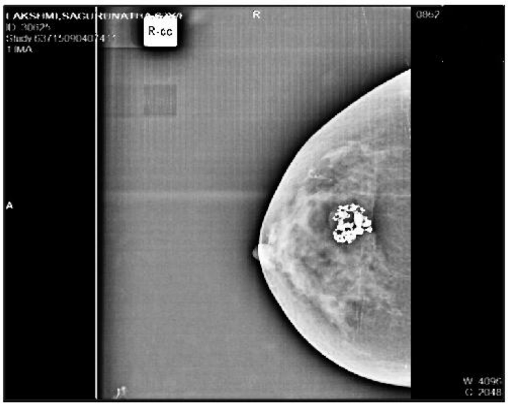
$$Jaccard = \frac{R_t \cap R_g}{R_t \cup R_g}$$

$$TPF = \frac{R_t \cap R_g}{R_g}$$

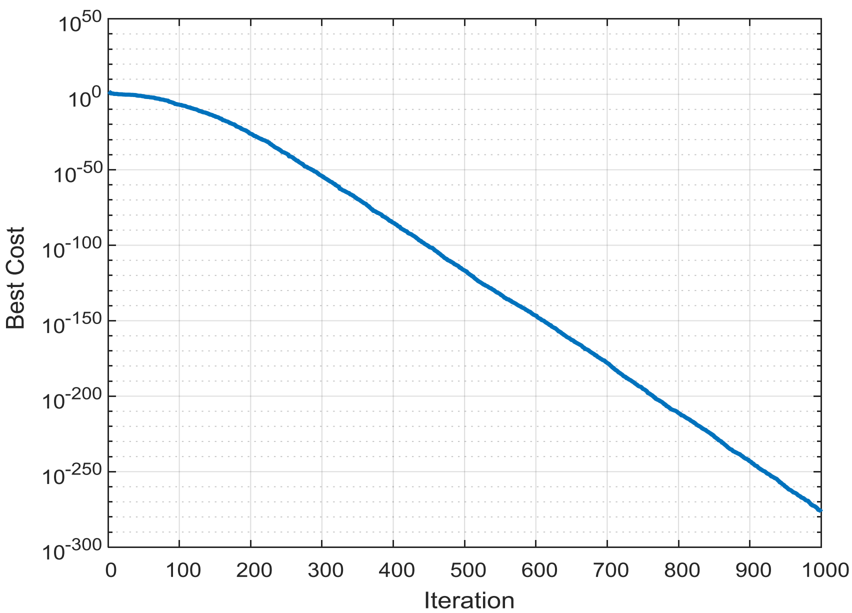
$$FNF = \frac{R_g \cap R_t}{R_g}$$

$$FPF = \frac{R_t \cap R_g}{R_g}$$

$$TNF = 1 - \frac{R_t \cap R_g}{R_g}$$



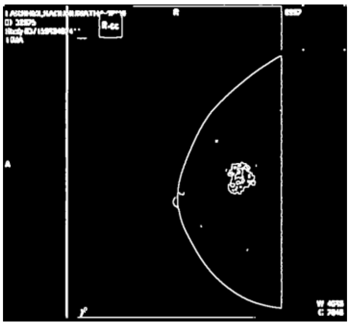
Better performances are achieved for high values of the Dice index, Jaccard index, TPF and TNF measures. However, higher values of MCR, FNF and FPF lead to worst performances.



Iteration	Cost Value
200	10
400	0.002
600	10^{-150}
800	10^{-220}
1000	10^{-250}

Level set segmentation

Usually, it is difficult to initialize manually the level set initial contour. The goals of the third step of our algorithm is to, automatically, initialize the level set initial contour using the resulting clustering obtained by weighted PSO. To evaluate the performance followed by pre-processing segmentation is performed and the experiments were carried on firstly mammogram images with tumor and non-tumor breast images.



Classification Approach	Accuracy	
	Non - Segmented	Segmented
Naive Bayes	-	97.356
SVM	-	94.792
Adaboost	-	95.197
WPSO	-	98.1

Accuracy for Segmented Image

The above figure present the results after several iterations. A good segmentation is achieved thanks to the use of an initial weighted PSO clustering step for the initialization of the level set. The initial contour issued from the weighted PSO is close to the final contour using the level set evolution. Because of the weak and irregular boundaries of the cancerous tissues, the segmentation is difficult.

Moreover, due to blood vessels, the tissue itself is inhomogeneous. It is often difficult to choose an optimal initialization for the level set

Conclusion

The experiments and results show that weighted PSO performs better than other existing algorithms. It was observed that proposed weighted PSO outperforms the existing methods. Comparatively the approach Feature Extraction using naive bayes, SVM and Adaboost proposed weighted PSO has higher accuracy rate of 98.1.

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